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Quantitative Methods in Agricultural Economics, 1940s to 1970s


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Part I. Estimation and Statistical Inference in Economics
This essay is dedicated to those members of the economics and statistics faculties at Iowa State University who during the 1940s and 1950s did so much to make statistical inferences an operational tool in economics and to give meaning and context to the phrase “measurement with theory.”

Dennis Aigner, George E. Brandow, John P. Doll, Richard J. Foote, Wayne A. Fuller, Stanley R. Johnson, George W. Ladd, Lee R. Martin, Gordon C. Rausser, Earl R. Swanson, Takashi Takayama, Gerhard Tintner, Thomas D. Wallace, Fred V. Waugh, and Arnold Zellner read an earlier draft of this paper and made a larger number of useful comments, many of which in one way or another found their way into the final copy.

G. G. J.
This essay is focused on attempts over the last three decades to cope with the problem of measurement in economics. In particular, it is directed to a review of analytical methods developed and employed in analyzing and learning from economic data. To some extent, it is a report of an experiment—an experiment in nonexperimental model building. The achievements realized through a systematic use of economic and statistical models, methods, and data give empirical content to economic theory and practice and bring out clearly the complementarity between theory and measurement, and these achievements have made economics a leader of the nonexperimental sciences. Therefore, it is with great pleasure that I take this intellectual trek through time.

Perhaps during the first half of this century it was possible to summarize, as many tried to do, the theory and method of economics, but I doubt if any economist in his right mind would attempt to do so today. The virtual explosion of knowledge over the past few decades has made this impossible. My task is only to review a subset of quantitative economic knowledge, but in this area the pace of development is so rapid I have a feeling that if I do not hurry and finish this paper I too shall be accused of not being in my right mind.

This literature review is a brief, personal, partially documented statement of one man's view of the development of econometric theory and applications and cannot and should not be considered exhaustive or all-inclusive. Rather, it is only a subjective sampling of some of the creative analytical and
empirical work done over the last thirty years. Others who have looked back
over the field and have viewed with alarm and pointed with pride, as they em­
phasized various aspects of the evolution of econometrics, include Tintner
[1966], Wold [1969], Leser [1968], and Klein [1971]. Since the economet­
ric methods and applications I will discuss cut across subject matter areas, I
have chosen time as a frame on which to hang and contrast the developments.
Other subject matter survey papers have been commissioned that will include
detailed reviews of applied econometric results, and for this reason I have
been very selective in the application references noted.

The Pre-1940 Period

At the close of the 1930s economists had available to them the following
tools in their search for knowledge: an economic theory developed over the
decennia which included, among other things, the general equilibrium theory
of Walras, the partial equilibrium theories of Marshall, and the aggregative eco­
nomic theory of Keynes; a steady flow of economic data from the developed
countries; the elements of classical statistical theory and scientific method
that appeared sometime between 1880 and 1920 and developed under the in­
fluence of such men as Pearson [1938] and Fisher [1935]; the concept of
least squares estimation supported by a theory that dates back to around
1800 and owes its conceptual base to Gauss [1821] and Legendre [1805];
and the wonderful statistical tool known as multiple correlation and regres­
sion (Ezekiel [1930]). Armed with these tools, economists and statisticians in
the twentieth century, after the casual empiricism of the nineteenth century,
made systematic and scientific use of statistical data (1) to give empirical con­
tent to economic theory by refuting, refining, or modifying the conclusions
reached from abstract reasoning, and (2) to estimate the parameters of de­
mand, supply, production, cost, consumption, and investment relations so
they could be used as a basis for decision making.

Although linear statistical models and estimators have existed since 1800,
the lack of the currently fashionable sampling theory concepts of gauging the
statistical consequences of model misspecification and comparing the perfor­
mance of estimators via defined properties or risk functions caused the early
applied econometricians little or no pain at all. By and large, the following
linear statistical model or a slightly transformed variant was the workhorse of
the day:

\[
(1) \quad y = X\beta + u
\]

where \( y \), called a dependent variable, was a \( (T \times 1) \) vector of observations, \( X \)
was a \( (T \times K) \) matrix of observations on \( K \) independent (usually nonstochas-
tic) variables, $\beta$ was the $(K \times 1)$ vector of unknown parameters (coefficients), and $u$, called the error term, was a $(T \times 1)$ vector of unobservable (normal) random variables with mean zero and scalar identity covariance $\sigma^2 I_T$. It was not until the 1930s that the statisticians and some workers in applied economics became very precise about the stochastic assumptions underlying the error term. The Gauss-Markoff Theorem, specified and proved by Aitken [1934] and by David and Neyman [1938], resulted in the conclusion that out of the class of linear unbiased estimators the least squares estimator, $\hat{\beta} = (X'X)^{-1}X'y$, was best (minimum variance). Also, under the quadratic loss measure of goodness for evaluating estimator performance that is so popular today, the least squares estimator is minimax (minimizes the maximum expected loss over the parameter space $\beta$).

The statistical study of demand, which started with Moore [1914], culminated with Schultz's classic work *The Theory and Measurement of Demand* [1938]. Schultz's work was concerned with making use of economic theory, mathematical economics, the regression statistical model (1), and the data of the day in specifying and estimating the parameters of the demand relations for agricultural commodities. Ezekiel, Bean, Warren, Pearson, and the Workings were important contributors to the development of demand analysis in the 1920s and 1930s. In his paper "What Do Statistical 'Demand Curves' Show?" E. J. Working [1926] looked at this activity which made use of data passively generated by society and questioned the possibility of deducing statistically the Cournot-Marshall demand curve when only the coordinates of intersection of the demand and supply relations were given for a series of points in time. In addition, the least squares approach to estimation was a method in which different estimates were obtained for a given parameter, depending on which variable was chosen to play the dependent role. Demand theory unfortunately gave little help on this problem since it was stated in functional terms and hence treated all variables symmetrically. Investigators faced the multiple-parameter dilemma and reacted to the problem by reporting two relations for each commodity analyzed—one for price and one for quantity.

On the supply side, the focus was on agricultural commodities and much of the work concerned single equation economic and statistical models, involving the variables acreage and lagged price. This work was summarized by Black [1924] in an article in the *Journal of Farm Economics*, and several years later Bean [1929] published his famous article, "The Farmers' Response to Price."

Also during the 1920s and 1930s Black, Jensen, Spillman, and others attempted to estimate production functions for the technical units and pro-
cesses in agriculture, and Cobb and Douglas [1928] worked on industry rela-
tions. Dean [1936] specified and estimated statistical cost functions, and
Bressler [1942] and his associates were generating the data for and estimating
cost-output functions. Stone and Stone [1938-39] made a statistical study of
the macro consumption function, and S. Kuznets [1935] and Tinbergen
[1938] used statistical evidence to reject Clark's accelerator model of invest-
ment.

As the first forty years of this century came to a close, attempts were be-
ing made to deal with the endogenous generation of economic data, and multi-
relation models came to the foreground in econometric research. Wright
[1934] put forth the method of path analysis to reflect interdependencies in
social processes. Frisch [1934] extended his work to complete regression sys-
tems, and Tinbergen [1939] developed his macroeconomics model for the
Netherlands and the United States. About the same time Leontief [1937]
completed the work started by the Physiocrats in the eighteenth century and
developed input-output analysis to make it possible to take into account the
interdependence between the sectors of an economy and permit structural
analysis. Although they could not satisfactorily solve the puzzle, many inves-
tigators during this period were aware of the conceptual problems of using
single equation regression models, and in order to patch up the regression
method they proposed and applied a variety of procedures such as canoni-
cal correlation (Hotelling [1936]), the variate difference method (Tintner
[1940]), confluence analysis (Frisch [1934]), principal components (Hotel-
ling [1933] and Girschick [1936]), and weighted regression (Koopmans
[1937]).

The Decade of the 1940s

The early 1940s marks the beginning of the era of modern econometrics. The
conceptual problems raised by E. J. Working [1926], Frisch [1934], Tinber-
gen [1938], and others emphasized among other things that economic data
are generated by systems of economic relations that are stochastic, dynamic,
and simultaneous and pointed to the many unsolved problems of statistical
inference, from the observed data to the relations. It was fully realized that if
the results of econometric ventures were to reflect desired properties in esti-
mation and inference, there must be consistency between the statistical mod-
el employed and the sampling model by which the data were generated.

In formulating statistical models consistent with the way economic data
are visualized as being generated, a milestone was reached in 1943 when two
articles were published in Econometrica by Haavelmo [1943] and Mann and
Wald [1943], and Haavelmo wrote a monograph entitled The Probability Ap-
Haavelmo converted the economist's simultaneous equation model to a statistical model by assuming a random disturbance for each equation and specifying the distribution of these random variables. This specification resulted in the following so-called simultaneous system of equations statistical model:

\[ Y \Gamma + X B = U \]

where \( Y \) is a \( T \times G \) matrix of jointly determined or endogenous variables, \( \Gamma \) is a \( G \times G \) matrix of parameters, \( X \) is a \( T \times K \) matrix of exogenous and predetermined variables, \( B \) is a \( K \times G \) matrix of parameters, and \( U \) is a \( T \times G \) matrix of disturbances or, in the early language, latent variables or shocks. Classical assumptions were made about the stochastic properties of the disturbances and thus, \( E(u_j) = 0 \), for \( j = 1, 2, \ldots, G \), and \( E(u_j u_{j'}) = \sigma_{jj'}I_T \) for \( j, i = 1, 2, \ldots, G \), and the \( G \times G \) symmetric and positive semidefinite variance-covariance matrix \( \Sigma \). Since \( \Gamma \) is assumed to be nonsingular, the structural equation statistical model (2) was also expressed in the statistically equivalent "reduced form" format.

\[ Y = -X B \Gamma^{-1} + U \Gamma^{-1} = X I + V. \]

Mann and Wald suggested a large sample solution to the estimation problem arising from the new systems of equations formulation. Marschak and Andrews [1944] pointed out the simultaneous nature of production decisions leading to the determination of input levels in the production function. Anderson and Rubin [1949] developed the "limited information" maximum likelihood estimators for estimating the parameters of an equation in a system of equations and derived corresponding large sample properties and statistical tests. Koopmans [1949] faced up to the problem first raised by Working [1926] and developed, with the aid of zero linear restrictions on \( \Gamma \), \( B \), and \( \Sigma \), necessary and sufficient conditions for identifying each mathematical equation as a definite economic relation and discriminating between alternative competing structures. Vining and Koopmans [1949] debated the question of measurement without theory as one goes about searching for knowledge. Marschak [1947, 1953] made clear the need for structural estimation if the results were to be useful for policy purposes and suggested decision models for making use of empirical results. In two important articles which appeared in the Journal of Farm Economics Cooper [1948] made clear the role of the econometric model in inference and D. G. Johnson [1948] discussed the use of econometric models in the study of agricultural policy. The work of the 1940s, which was based squarely on economic and statistical theory, was to a large extent centered in the Cowles Commission at the University of Chicago. A monograph edited by Koopmans [1950] summarized
the state of the tools of quantitative knowledge after the developments of the 1940s.

Girshick and Haavelmo [1947] beautifully integrated economic theory and inferential statistics in their classic five-equation model concerned with the demand for food. Haavelmo [1947] made use of a system of equations in estimating the parameters of the consumption function. Klein [1950] completed his work on a sophisticated macroeconometric model of the United States economy. Judge [1949], under the direction of Hurwicz and Thompson, completed a simultaneous systems of equations analysis of the feeder cattle sector; Ogg [1949], working with Hildreth, completed a simultaneous equation analysis of the production relation for a sample of firms; French [1950] made a statistical analysis of the demand for meat; and G. Johnson [1952] made a statistical analysis of the burley tobacco sector. Computational burdens with the new techniques were significant since the desk calculator was still the main tool of the "estimators." Anyone who has inverted a 10 X 10 matrix on a hand calculator can attest to the reality of this computing restriction and to the impossibility of the data dredging and mining activities that many currently engage in.

At the end of the 1940s Samuelson published his book on the Foundations of Economic Analysis [1948], Von Neumann and Morgenstern [1947] introduced the profession to game theory, Wald [1950] alerted us to statistical decision theory, Dantzig [1951a, 1951b] developed the simplex algorithm for use with linear optimizing models, and Koopmans [1951] and his cohorts were putting together the conceptual basis for the activity analysis approach to price and allocation problems in economics. Each of these creative efforts had a significant impact on the demand for and structure of econometric efforts in the 1950s and 1960s. Economists interested in agriculture were leaders in applying the new statistical procedures for estimation and prediction, and at the end of this period there was great optimism that we were on the road to making mathematical economics and econometrics into tools that would serve the needs and aspirations of the discipline and society.

The Decade of the 1950s

As the decade opened, Haavelmo's view [1943] of endogenous data generation was questioned by Wold [1956]. Wold proposed the recursive or causal chain economic and statistical models which were characterized by a triangular \( \Gamma \) matrix of coefficients for the endogenous variables and diagonal covariance matrix \( \Sigma \). The term "single equation or least square bias" became firmly implanted in the literature (Bronfenbrenner [1953]). The argument of single versus simultaneous system of equations estimators was launched and reasons
were advanced why single equation techniques were or were not satisfactory for a wide variety of agricultural commodities or sectors (Bentzel and Hanson [1954], Fox [1953], Foote [1955a], G. Kuznets [1955]). Hood and Koopmans [1953] published their book on studies in econometrics, and Tintner [1952] and Klein [1953] published textbooks which gathered together the theory and practice of the techniques that today we call econometrics. Most economics and agricultural economics departments with an emphasis on graduate work introduced a course or courses in econometrics. "How to" handbooks appeared (Foote [1958], Friedman and Foote [1955]), and there was hardly an agricultural commodity that was not statistically analyzed as Hildreth and Jarrett [1955], Judge [1954], Nordin, Judge, and Wahby [1954], Fox [1951], Foote [1952, 1953a, 1953b, 1955b], E. J. Working [1954], Rojko [1953, 1957a, 1957b], Cromarty [1959a, 1959b, 1962], Meinken [1953, 1955], Harlow [1960], King [1958], Gerra [1959a, 1959b], Shuffett [1954], and many others (for example, Buchholz, Judge, and West [1962]) specified and estimated systems of equations. These econometric ventures, which involved systems of behavioral, technical, definitional, and institutional equations, did much to increase our understanding of the economic process and institutions underlying each of the agricultural sectors, the interactions among the agricultural sectors, and to a limited degree the interactions between the agricultural sector and the other sectors of the economy. In addition, the econometric results sometimes generated numbers that were useful for choice purposes at one or more of the structural decision-making levels. At the macro or economy level almost every major country had one or more simultaneous equation models constructed, estimated, and used, with perhaps the Dutch being the most conscientious in using econometric results for economic policy and planning purposes.

Chernoff and Divinsky [1953] specified the "full maximum likelihood method," which in contrast to the limited information system used information concerning the structure and data from all of the variables in the system. Unfortunately, since the estimating equations involved were nonlinear, with this procedure numerical methods had to be used for solution purposes, and in the 1950s the method was impractical.

As an alternative estimator for the parameters of an equation in a system of equations, Theil [1954] and Basmann [1957] proposed the generalized classical or two-stage least squares estimator, and Theil [1954] the k-class estimator. In this procedure an equation from the system of equations (2) was written as

\[(4a) \quad \gamma_j = [Y_j X_j] \begin{bmatrix} \gamma_j \\ B_j \end{bmatrix} + u_j = Z_j \delta_j + u_j\]
or equivalently as

\[(4b) \quad y_j = [E(Y_j), X_j] \begin{bmatrix} \gamma_j \\ \beta_j \end{bmatrix} + (Y_j - E(Y_j)) \gamma_j + u_j.\]

Since the expectation operator makes the observation matrix \([E(Y_j), X_j]\) non-stochastic, the reduced form equation (3) may be used to estimate the unknown \(E(Y_j)\) and then least squares may be applied to the resulting equation to yield a consistent estimator.

The addition of these estimators to the econometrician's tool chest meant that we had reached the stage of multiple parameters estimates for any given economic model, and just as early econometricians had asked the question "Which regression?" we now had to ask "Which estimator?" The choice of estimator question was a difficult one since for the system of equations estimators only the asymptotic properties were available, and many estimators were asymptotically equivalent. For economists who usually have to work with small samples of data, however, finite sample results are essential. In order to get some idea of the performance of the alternative estimators in finite samples, simulation or sampling experiments were proposed and carried through by Ladd [1957], Wagner [1958], Neiswanger and Yancey [1959], Summers [1965], and others for certain specialized models, some of which involved measurement and specification errors. The progress via this route was slow, and at its 1958 winter meetings the Econometric Society sponsored a panel discussion under the pleading title, "Simultaneous Equation Estimators—Any Verdict Yet?" At that time the final verdict was not in (and in some respects it still is not in). In the 1950s the electronic computer became a reality and put system of equations estimators within the reach of the individual researcher.

The decade of the 1940s made us acutely aware of the necessity for consistency between the assumptions underlying economic and statistical models. When models are correctly specified and sufficiently simple, statistical theory provides procedures for obtaining point and interval estimates and evaluating the performance of various linear estimators. Unfortunately, we seldom work with true models and a method was not available for drawing inferences based on "false" models. Because statistical theory provided inferential statements conditioned on true models and investigators in the main were working with false models, a large amount of effort was devoted to if-then types of questions: if relevant variables are omitted from an equation, what is the impact on the properties of the estimates and how will the inferences be distorted (Griliches [1957], Theil [1957])? If the disturbances are autocorrelated and, for example, the disturbance \(u_t\) of (1) follows a first-order autoregressive scheme \(u_t = \rho u_{t-1} + e_t\) where \(e_t\) has mean zero and scalar identity covariance, how will the efficiency of the estimator be affected
and how can we mitigate the impact of this specification error (Hildreth and Liu [1960], Cochrane and Orcutt [1949], Durbin and Watson [1950, 1951])?

What is the inferential impact of not fulfilling the assumption of the disturbances being identically (homoscedasticity) as well as independently distributed? What are the implications of stochastic rather than fixed regressors?

What are the statistical implications of using variables that contain a measurement error (Durbin [1954])?

Since some progress was being made in formulating statistical models to cope with the simultaneous and stochastic nature of economic data, attention was directed to the dynamic aspects of economic models and data. The question of how to specify models consistent with the dynamic characteristics of economic data led to the consideration of the autoregressive case and the specification of somewhat ad hoc distributed lag economic models based on vague notions such as inertia and habit formation and their attendant problems of estimation. The work of Koyck [1954], Cagan [1956], and Nerlove [1958a, 1958b, 1958c] stand out in this development and their formulations led to the application of the distributed lag model (Nerlove and Addison [1958]) with emphasis on estimating the short-run and long-run parameters of behavior patterns. The conventional distributed lag model as a variant of (1) may be written as

\[ y_t = \beta \sum_{j=0}^{\infty} \lambda^j x_{t-j} + u_t \]

where \(|\lambda| < 1\). Subtracting from (5a), \(\lambda y_{t-1}\), yields

\[ y_t = \beta x_t + \lambda y_{t-1} + u_t - \lambda u_{t-1}, \]

which is used for estimation purposes. This result, (5b), is also consistent with the behavioral hypothesis of adaptive expectations. There were several techniques for estimating \(\beta\) and \(\lambda\) (for example, Koyck [1954] and Klein [1958]), some of which were not consistent or asymptotically efficient. The practical difficulties of distinguishing between different lag schemes when using nonexperimental data were early recognized and to a large extent the problem still exists today.

In the demand area, in addition to the commodity analyses already alluded to, Stone [1954] estimated a system of expenditure functions which satisfied various theoretical conditions, Frisch [1959] developed a scheme for computing cross elasticities of substitution, and Brandow [1961] completed his work concerned with the interrelations among demands for farm products. There was a feeling during this decade, well expressed by T. W. Schultz, that we had made more progress in capturing the parameters of demand relations than had been made with those for supply relations. This realization generat-
ed a flurry of activity led by W. Cochrane [1955], Nerlove [1958c], and others, and the debate of positive versus normative supply response functions began.

Questions relating to the economic and statistical impact of using aggregate economic data and relations have an early origin and intuitively most analysts feel that aggregation involves a loss of information. An important work in this area was the book by Theil [1954], *Linear Aggregation of Economic Relations*, in which he dealt with the problem of interpreting the parameters of macro relations estimated from aggregate data, when the observed data are generated from a set of micro relations. One of his major results, assuming the micro coefficients are constant, was that when macro variables are obtained by simple aggregation (the aggregate result postulated to hold independently of the micro relations), the expectation of the macro coefficient estimator will depend on a complicated combination of corresponding and noncorresponding micro coefficients. This result may be seen in terms of (1) by writing the micro statistical model as

\[(6a)\quad y_i = X_i \beta_i + u_i, \text{ for } i = 1, 2, \ldots, N,\]

where the usual definitions hold for \(y_i, X_i\) and \(u_i\). If by simple aggregation we use the macro variables \(Y = \frac{1}{N} \sum_i y_i\) and \(X = \frac{1}{N} \sum_i X_i\), the statistical model \(Y = X \beta + u\), with usual definitions for the variables and the least squares estimator, then

\[(6b)\quad E(\beta) = E[(X'X)^{-1} X'Y] = (X'X)^{-1} X' \left( \frac{1}{N} \sum_i X_i \beta_i \right) \neq \frac{1}{N} \sum \beta_i.\]

Given this result, Theil [1954] raised the question of whether we should abolish the macro models and estimates. Alternatively, Klein [1953] showed that when the macro and micro relations are derived so that they are consistent, then the macro variables are weighted averages of the micro coefficients. If the weights are stable over time, then no aggregation bias results. The usual case, however, is for the weights to change over time. Grunfeld and Griliches [1960] answered no to the question "Is aggregation necessarily bad?" but the outcome was as many had suspected—the question should have been answered yes (Zellner [1962b]). It is interesting to note that in spite of the discouraging words of Theil, Klein, and Zellner, during the 1950s macroeconometric model building and estimation continued at full pace.

Given the questionable virtue of the macro data, in the 1950s much effort by persons such as Orcutt, Greenberger, Korbel, and Rivlin [1961] went into specifying a framework for and actually generating more complete micro data over time. Data panels and banks were set up and sample surveys were conducted to capture these data. From the point of view of estimation, this expanded data base made it imperative to develop estimating methods which
would permit the combining of cross-section and time series data. In the 1950s covariance analysis, usually through the use of dummy (zero-one) variables, provided the major estimating technique, although extraneous estimators were being talked about and actually applied by Tobin [1950] and others.

Much econometric activity in estimating production and cost functions was evident during this decade. Heady and Baker [1954], in an article on resource adjustments to equate productivities in agriculture, exemplified the techniques employed in estimating the parameters of aggregate production and the uses to which they were put. Swanson [1956], in an article concerned with the optimum size of business, gave a good example of some of the problems of empirical production function analysis. Hoch [1958], Mundlak [1961], and others investigated the sampling properties of conventional parameter estimates of production functions for total farm or nonexperimental situations. Assuming that the income share accruing to each production factor is equal or proportionate to the respective output elasticity, Solow [1957] estimated (and started the debate about how to measure) the impact of technical progress on output or growth.

Concern over the richness of macro data or relations also raised questions about the necessity of generating data via controlled experiments. Within this context it was realized by Heady and Dillon [1961] and others that, in estimating production functions, if we were to trace out the parameters of the production surface in order to estimate isoproduct and production possibility relations, data from controlled experiments would be necessary. This generated work on the appropriate experimental design to employ (Heady and Dillon [1961]) and the actual applications of these designs to generate the experimental data.

At about the same time many questions were being raised about the use of passively generated data in estimating the parameters of price-consumption response relations. This led Godwin [1952], Brunk [1958], Franzmann and Judge [1957], and others to design and carry out controlled experiments in retail markets and to develop parameter estimates for an array of commodity response relations. Questions about the generalizability of these results to a wider range of data were raised, and by the end of the decade the generation and use of experimental price-consumption data trended downward.

Friedman [1957] put forth his permanent income hypothesis and separated income and consumption for behavior purposes into the unobservable permanent and transitory components. Houthakker [1958], Eisner [1958], Nerlove [1958d], and others investigated the implications of this framework and how to measure these nonobservable variables and to test the permanent income hypothesis in Friedman's consumption function model.
Given the development in the 1950s of various linear and nonlinear decision and simulation models under certainty and uncertainty (Batchelor [1959-64]) and the evolution of operations research and management science, the need for hard quantitative knowledge at all structural decision levels was emphasized and econometrics started serving these new masters.

In spite of the rapid pace of developments in theory and application, econometrics was, as the decade ended, an essay in persuasion. The alternative choices or permutations regarding the model, method, and data facing an investigator were many (Booth and Judge [1956]), and in many cases one had the feeling in reading an article or bulletin that the investigator had searched over a variety of models, methods, and data to find a set of numbers satisfying a theory or his own intuition. In some examples of data dredging the investigator reported many alternative results and in a sense appealed to the reader to make a choice among the possibilities. In the 1950s, as in the 1940s, economists interested in agriculture took the lead in applying and sharpening the new and old econometric tools. Many of these results were seldom if ever used for decision purposes.

The Decade of the 1960s

If the role of the economic model (the prototype of the sampling model that generated the data) in determining appropriate statistical models became evident in the 1940s and 1950s, the 1960s made us aware of the necessity of developing statistical models which (1) provide systematic ways of combining sample and a priori information and (2) are appropriate for economic decision problems—the fruit of an idea introduced by Wald [1950] in the 1940s. As some have implied, in a sense the respectability of probability as a state of mind was reestablished. It was suggested that if econometric models are constructed and estimated as a source of information for decision making or choice, the theory of statistical decision, based on an analysis of losses due to incorrect decisions, can and should be used. In addition, it was argued that, since nonexperimental observations are the main data source of the economist, the criterion of using performance in repeated trials, and thus, unobserved samples as a basis for rationalizing sampling theory approaches, should be questioned.

For economic data, which are by and large nonexperimental in nature, the statistical decision theory problem is that of making the “best” decision on the basis of a given set of data, when $\theta$, the true state of the world (parameter), is unknown. A number of solutions have been proposed and used for this statistical decision problem. Traditionally, the class of decision rules (estimators) is typically restricted to those that are linear and unbiased, and in con-
conventional estimation theory where a quadratic loss function is assumed, this approach leads to minimum variance unbiased estimators. In spite of the near godly stature of unbiasedness that one gets from economic literature, the notion of unbiasedness, although intuitively plausible, is an arbitrary restriction and has no connection with the loss due to incorrect decisions and is thus unsatisfactory from a decision theory point of view. In any event, as the decision theorists note, the conventional sampling theory approach does not always lead to an optimal decision rule (estimator) and, as W. Fisher [1962] and Zellner [1972] have shown, may not in some cases satisfy even certain minimal properties.

As a means of facing up to some of these objections, the use of Bayes's rule for handling inference and decision problems was revived and developed in the 1960s. If we let \( p(y,\theta) \) denote the joint probability density function of the observation vector \( y \) and the parameter vector \( \theta \) and use the definition of conditional probability for \( y \) and \( \theta \) which implies \( p(\theta|y)p(y) = p(y|\theta)p(\theta) \), we may write the posterior probability density function for the parameter vector \( \theta \), given the sample information as

\[
(7) \quad p(\theta|y) = \frac{p(y|\theta)p(\theta)}{p(y)} \propto p(y|\theta)p(y)
\]

where \( \alpha \) denotes proportionality. Equation (7) is a statement of Bayes's rule or the principle of inverse probability, and in this approach the decision maker's prior information about the state of the world or parameter \( \theta \) is combined with the sample information \( y \) to make the "best decision." Within the context of (7) it is assumed that the investigator's information or uncertainty about some parameter \( \theta \) can be summarized in a prior probability function \( p(\theta) \). This information is then combined with the sample density function \( p(y|\theta) \) to yield a posterior probability density function \( p(\theta|y) \). Then, given a loss function, say \( L = L(\theta, \hat{\theta}) \), which reflects the losses due to an incorrect estimation, the Bayesian choice of a point estimate \( \hat{\theta} \) is the one that minimizes the expected loss, where the posterior distribution of \( \theta \) is used in the expectation, i.e.,

\[
(8) \quad \min_{\hat{\theta}} E[L(\hat{\theta}, \theta)] = \min_{\hat{\theta}} \int L(\hat{\theta}, \theta)p(\theta|y)d\theta.
\]

Thus, the posterior probability density function combines both prior and sample information, and it is this distribution which is employed in estimation and to make inferences about the parameters.

Given this framework and building on the work of Jeffreys [1961] and Savage [1954], Raiffa and Schlaifer [1961], Dreze [1962], and Zellner [1971] and his associates developed a Bayesian formulation of the regression model with extensions to cover the problems of autocorrelated errors, distrib-
uted lags, errors in the variables, prediction and decision, and multiple equation systems. One problem of applying Bayesian decision theory is the need to find a set of prior distributions rich enough to incorporate the investigator's knowledge but simple enough to be algebraically tractable. Modern methods of numerical analysis, however, have done much to change the definition of what is tractable. Much of the theory and practice of Bayesian inference in econometrics which took place in the sixties has been summarized in a recent book by Zellner [1971], and some of the elements of the debate still raging between the Bayesians and the non-Bayesians are contained in articles by Zellner [1972] and Rothenberg [1972]. One major restriction on the application of Bayesian estimation and inference procedures to variants of the linear statistical model is the almost complete nonavailability of viable computer programs.

Within the spirit of combining prior and sample information, several sampling theory estimators were developed for the regression model, and the alternative specifications have been analyzed and applied:

(i) When the prior knowledge concerning an individual or group of coefficient(s) is exact in nature, for the linear regression statistical model (1), this external information or hypothesis may appear as \( R\beta = r \), where \( R \) is a \((J \times K)\) matrix of known elements with rank \( J \) and \( r \) is a \((J \times 1)\) vector of known elements (hypotheses). Under this specification the methods and test statistics proposed by Wilks [1947], Tintner [1940], and Chipman and Rao [1964] may be employed. Either the conventional likelihood ratio test or the Toro-Vizcarrondo and Wallace [1968] or Wallace [1972] tests may be used with this model for deciding when, under a mean square error or squared error loss criterion, the restricted least squares estimator on possibly incorrect, although exact, prior information is superior to the conventional estimator using only sample data.

(ii) If the prior information on an individual coefficient or group of coefficients is of a statistical nature, the stochastic linear hypotheses or prior information may be specified for statistical model (1) as \( r = R\beta + v \), where \( r \) is a \((J \times 1)\) mean vector of known constants, \( R \) is a \((J \times K)\) matrix of known constants, \( v \) is a \((J \times 1)\) unobservable normally distributed random vector with mean \( \delta \), which is usually assumed to be zero, and covariance \( \sigma^2v \). Under this specification, i.e., stochastic linear hypotheses with known finite mean and variance, the methods and test statistics proposed by Durbin [1953], Theil and Goldberger [1961], and Theil [1963], which make use of Aitken's generalized least squares technique, may be employed to estimate the parameters and test the compatibility of the prior and sample information. It should be noted that this estimator yields the same results as the mean of the limiting
distribution for the Bayesian formulation assuming a locally uniform prior for $\beta$ and $\sigma^2$.

(iii) When the prior knowledge is less complete and information exists only in the form of inequality restraints, $R\beta \leq r$, where all symbols have been previously defined, one possibility when placing a prior upper and lower bound on a coefficient is to specify a mean and variance for the parameter which would give a very low probability to values outside this range. Under this specification, the resulting information could be used in the same way as Theil and Goldberger [1961] use prior knowledge of a statistical type and Aitken's generalized least squares estimator could be applied. Alternatively, when the prior information consists of linear inequality restraints on the individual coefficients or combinations thereof, following Zellner [1963] and Judge and Takayama [1966], the problem may be specified and solved as a quadratic programming problem. The minimum absolute deviations (linear programming) estimator whose properties have been analyzed by Ashar and Wallace [1963], Blattberg and Sargent [1971], and Smith and Hall [1972] is still another alternative specification for handling the linear inequality parameter restriction problem.

These Bayesian and non-Bayesian formulations (Judge and Yancey [1969]) permit the investigator to take account of prior information about the unknown parameters that exist via the routes of postulation, experimentation, or "revelation." When a certain minimum amount of information is available concerning the structure of the relation(s), these estimators, either through restrictions or other outside information, may offer one way of coping with the troublesome problem of multicollinearity. The sampling properties of the inequality restricted least squares estimator are yet to be established, but initial Monte Carlo sampling studies, such as those by Thornber [1967] and Lee, Judge, and Zellner [1970], yield encouraging results relative to its performance. Both the Bayesian and sampling theory estimating methods can handle the cases for a multivariate regression system and a simultaneous equation system.

In deriving new estimators during the decades of the 1950s and 1960s the standard practice appears to have been: (1) to change the statistical model, (2) to change the prior information or the way to use prior information, or (3) to change the loss function or measure of goodness. Although not all of the inferential and philosophical problems in this area were solved in the 1960s, these procedures appear to offer promise in our search for "optimum" estimators and suggest systematic ways for proceeding as we attempt to learn from experience and data.

In the early 1960s Graybill's book [1961] on linear statistical models was published and provided the theoretical base and format for the econometric
texts of this era. The volumes by Johnston [1963] and Goldberger [1964] were the two outstanding textbooks of the period, and their appearance along with other econometric texts had much impact on the quality of instruction and the level of the econometric sophistication of students.

In the 1960s systems analysis and control theory provided a framework for combining into one package automatic or adaptive control, estimation, prediction, and some utility functional or optimality criterion (Pontryagin et al. [1962], Aoki [1967]) and thus the possible joining of optimization, estimation, and the design of experiments. These methods, especially in the discrete form, suggested, for example, ways to deal with the effects of lags and uncertainty on the conduct of stabilization policy and permitted one basis for following up the early contributions of Phillips [1954]. Bayesian methods, as outlined by W. Fisher [1962], Zellner and Geisel [1968], and Prescott [1967] provide a systematic way of handling control problems since they permit optimal, computable solutions which use both prior and past sample information, take account of uncertainty about parameter values, make use of new information as it becomes available, and, in an experimental design sense, provide a basis for making settings for the control variables.

Meanwhile in the area of classical sampling theory Zellner and Theil [1962], within the two-stage least squares framework, specified the system of simultaneous equations as

\[
\begin{bmatrix}
  y_1 \\
  y_2 \\
  \vdots \\
  y_G
\end{bmatrix} =
\begin{bmatrix}
  Z_1 & 0 & \ldots & 0 \\
  0 & Z_2 & 0 & \ldots \\
  \vdots & \ddots & \ddots & \ddots \\
  0 & 0 & \ldots & Z_G
\end{bmatrix}\begin{bmatrix}
  \delta_1 \\
  \delta_2 \\
  \vdots \\
  \delta_G
\end{bmatrix} +
\begin{bmatrix}
  u_1 \\
  u_2 \\
  \vdots \\
  u_G
\end{bmatrix}
\]

or

\[
y = Z\delta + u,
\]

where \(Z_j = [Y_j, X_j]\) and \(\delta_j = [y_j, \beta_j]\) were defined in conjunction with (4). Each \(u_j\) is assumed to have a zero mean vector with the conventional covariance \(\text{E}[u_j, u_k'] = \sigma_{jj} I\) and covariance matrix \(\text{E}[uu'] = X \otimes I\), where \(\otimes\) represents the Kronecker product symbol. With proper transformations relative to the system of equations (9), involving \(X\), the observation matrix of all of the exogenous and predetermined variables in the system, and use of the Aitken least squares procedure applied to the resulting set of equations, Zellner and Theil [1962] developed the three-stage least squares estimator

\[
\hat{\delta} = \left[Z' (\Sigma^{-1} \Theta X (X'X)^{-1} X') \Sigma^{-1} Z' (\Sigma^{-1} \Theta X (X'X)^{-1} X') \right]^{-1} Z' (\Sigma^{-1} \Theta X (X'X)^{-1} X') y.
\]

Since \(\Sigma\) is normally unknown, Zellner and Theil suggested estimating it from the two-stage least squares residuals. It should perhaps be noted that two-stage least squares is nothing more than the application of Aitken's general-
ized least squares to (9), when the equations are appropriately transformed, and three-stage least squares involves the double application of the Aitken generalized least squares procedure.

Nagar [1962] widened the class of system of equations estimators to include the double k-class variety. Rothenberg and Leenders [1964] developed the method of linearized maximum likelihood and investigated some properties of the alternative system of equations estimators. Several Monte Carlo sampling studies (Cragg [1966, 1967, 1968], Summers [1965]) and analytical studies (Basmann [1957, 1965], Dhrymes [1965], Kabe [1964], Richardson [1968], Sawa [1969], Madansky [1964]) were completed, and we have gradually learned a little more about the finite sample properties of alternative system of equations estimators. The debate on the appropriate statistical model and methods for prediction purposes was fed by Waugh's provocative article [1961] on the place of least squares in econometrics.

Shortly before and to some extent in conjunction with his three-stage least squares work, Zellner [1962a] formulated an Aitken type estimator for handling the following sets of regression equations of the form of (1):

$$\begin{bmatrix}
y_1 \\
y_2 \\
\vdots \\
y_M
\end{bmatrix} = 
\begin{bmatrix}
X_1 & 0 & \ldots & 0 \\
0 & X_2 & \ldots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \ldots & X_M
\end{bmatrix}
\begin{bmatrix}
\beta_1 \\
\beta_2 \\
\vdots \\
\beta_M
\end{bmatrix} + 
\begin{bmatrix}
u_1 \\
u_2 \\
\vdots \\
u_M
\end{bmatrix}$$

(11)

where the equations are disturbance related with a covariance matrix consistent with (9) and the regressors vary over equations. For this seemingly unrelated regression model Zellner developed a test for aggregation bias and some small sample properties.


Interest in and use of some of the multivariate techniques developed in the 1930s was revived. Discriminant analysis and linear probability functions which permit the measurement of the effect of continuous variables on group
membership were reviewed by Ladd [1966] and were used, for example, by Ladd [1967] to analyze the objectives of fluid milk cooperatives, by Adelman and Morris [1968] to explore the forces affecting a country's prospects for development, and by J. Fisher [1962] to study the purchase of durable goods. Factor analysis and principal components, inductive procedures that are used to develop (among other things) hypotheses from data, were reviewed by Scott [1966] and used by Baumer, Brandt, Jacobson, and Walker [1969] to study psychological and attitudinal differences between milk purchasers, and by Massey, Frank, and Lodahl [1968] to study various measures of consumer purchasing power.

In regard to enriching the data base by using both time series and cross-section data, Balestra and Nerlove [1966], Mundlak [1961], Wallace and Hussain [1969], and Maddala [1971] specified a components of error model whereby the regression error is assumed to be composed of three independent components—one with time, one with the cross-section, and one overall component in both the time and cross-section dimensions. Nerlove [1971] investigated, by Monte Carlo procedures, the properties of various estimators within this context and proposed a two-round estimation procedure. Chetty [1968] reformulated the cross-section/time series problem along Bayesian lines. Swamy [1971], in contrast to conventional fixed coefficient models, recognized the heterogeneity of behavior among individuals and over time (i.e., the invariance of parameter systems), by developing the random coefficient statistical model and analyzed estimation procedures for it. Within the framework of the conventional linear statistical model (1) this model may be written as

\[
y_i = X_i(\vec{\beta} + \eta_i) + \epsilon_i, \text{ for } i = 1, 2, \ldots, N,
\]

where \( \vec{\beta} \) is the mean vector of the unknown coefficients, the \( \eta_i \) are additive independent and identical distributed random variables with mean zero and covariance \( \sigma^2 \) if \( i = i' \) and zero otherwise. Hildreth and Houck [1968] and Griffiths [1970] extended the results of a variant of this statistical model. Zellner [1967] analyzed the statistical implications of the aggregation problem within the context of the random coefficient statistical model.

In classical estimation and inference in econometrics a population is postulated which is assumed to be characterized by a density function whose parameters are unknown but fixed. A sample of observations is captured and used as the basis for estimation and statistical inferences about the unknown parameters. In economics one frequently encounters a situation where the sample consists of single observations on different random variables. A sequence of such random variables is called a stochastic process and spectral analysis consists of examining various aspects of the stochastic process when
its random variables have been given a representation in the frequency domain. This tool of frequency domain analysis, which has also been referred to under topics such as harmonic, Fourier, and periodogram analysis, is based on the idea of decomposing a stochastic process into a number of orthogonal components, each of which is associated with a given frequency (Granger and Hatanaka [1964], Nerlove [1964], Fishman [1969]). These methods are in general possible when the variance and covariances are time independent. Cross-spectral methods which deal with relations between variables are of great importance to economists but at this time are the least developed. Since modern computers can easily handle these techniques, a large number of researchers have made use of spectral procedures in the time series modeling of economic phenomena (Dhrymes [1971, pp. 383-484]), and spectral methods have been extended to such areas as estimating time domain distributed lag models (Dhrymes [1971, pp. 263-325], Fishman [1969]) and evaluating the dynamic properties of structural systems of equations (Howrey [1971]). Rausser and Cargill [1970] give a survey of spectral analysis, discuss its relationship to Fourier and periodogram analysis, and apply the procedures to the study of broiler cycles.

The distributed lag or autoregressive model (5) with moving average error continued to enjoy considerable use in empirical work. Fuller and Martin [1961] considered a distributed lag model with autocorrelated errors and suggested a consistent estimator. Griliches [1967] surveyed the work in this area during the 1950s and early 1960s, concentrating his emphasis on estimating distributed lags in the form of difference equations. Since this time emphasis has shifted to estimation of distributed lags under more general stochastic assumptions about the disturbance (Hannan [1967], Amemiya and Fuller [1967], Dhrymes [1971], Fishman [1969], Hall [1971], Jorgenson [1966]), constraining the lag function to belong to a family controlled by a few parameters (parametrization) and/or treating the least squares estimates so that adjacent lag coefficients lie close to one another (smoothing). In the linear parametrization area the idea of fitting polynomials to a series of coefficients, which can be dated back to Irving Fisher, was identified as the pre-Almon [1965] approach and became the dominant method of modern empirical work in distributed lags. The work of Ladd and Tedford [1959] reflects one pre-Almon application of this procedure in the agricultural economics literature. An alternative to making exact parametric restrictions is a probabilistic (Bayesian) characterization of the lag distribution which has been proposed by Leamer [1970] and Shiller [1970]. In closing this discussion we should note the work of Box and Jenkins [1970] on time series models from the class of discrete linear stochastic processes of integrated autoregressive moving average form and the work of Aigner [1971b] in integrating this work.
with that of econometrics. The autoregressive moving average (ARMA) model may be written as

\begin{equation}
y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + u_t + \theta_1 u_{t-1} + \\
\ldots + \theta_q u_{t-q},
\end{equation}

where $y_t$ is a stochastic process defined on integral time points and generated autoregressively. The residual in (13) is defined as a moving average of well-behaved random variables, $u_{t-j}$, which are assumed to be identically and independently distributed. The regression function (13) is used in estimating the parameters of the $y_t$ process. Estimation techniques permit a $y_t$ process which is both stationary and nonstationary to be accommodated. An early application of this procedure in the form of a multiplicative seasonal model, by Leuthold [1970], provided the basis for evaluating forecasts of a structural model of the hog market.

The econometric dimensions of the consumer's problem of how to allocate income to $M$ commodities, given prices and income, was pushed forward on the theoretical, estimation, and testing fronts. Some of the major econometric contributors to the problem of estimation of demand parameters under consumer budgeting that give empirical content to the ideas of Frisch [1959], Gorman [1959], and Strotz [1959] include Barten [1968], Theil [1967, 1971], DeJanvry, Bieri, and Nuñez [1972], Powell [1966], and Boutwell and Simmons [1968].

One important activity in the 1960s was the econometric study of investment behavior which developed from empirical comparisons of alternative determinants of producer behavior. This work is important here since it has provided an important basis for the development of new econometric techniques for representing the time structure of economic behavior. Some of the contributors in this area include Meyer and Kuh [1957], Eisner and Strotz [1963], Griliches, Modigliani, Grunfeld, and especially Jorgenson [1971].

The dynamic and stochastic nature of economic data led several writers to suggest that economic observations may be viewed as being generated by a stochastic process—that is, a process that develops in time or space according to probabilistic laws. This proposition led to the use of a first-order stationary Markov process as the appropriate probability model when the observation at any time is the category in which an observation falls. The object of this type of analysis is to use the time-ordered movements of micro data as a basis for estimating the transition probability system where the transition probabilities $p_{ij}$, which are associated with a change from state $i$ ($s_i$) to state $j$ ($s_j$) for the discrete random variable $X_t$ ($t = 0, 1, 2, \ldots , T$) are generated under the assumption that $X_{t-1} = s_i$ and $X_t = s_j$, and

\begin{equation}
\Pr(X_t = s_j|X_{t-1} = s_i) = p_{ij}(t) = p_{ij}, \text{ for all } t.
\end{equation}
The parameters of the probability system, the $P_{ij}$, are used as a basis for summarizing the dynamic characteristics of the data, predicting future outcomes and the long-run equilibrium of the system. This type of model has found many applications ranging from the work of Goodman [1965] on gauging social mobility to that of Adelman [1958], Judge and Swanson [1962], Preston and Bell [1961], Steindl [1965], and Hallberg [1969] on the size distribution of firms. One problem in making use of this model is that in many cases the data for the micro units are not available and only their aggregate counterparts (proportions in each state) exist. In order to use the aggregate data as a basis for estimating the behavior system for the micro data (transition probabilities), Miller [1952] and later Telser [1963] formulated the problem within the least squares framework and assumed the sample observations were generated by the following stochastic relation:

$$X_j(t) = \sum_{i} X_i(t-1)P_{ij} + u_j(t), \text{ for } i, j = 1, 2, \ldots, r.$$ 

Building on this work Lee, Judge, and Zellner [1970] developed restricted least squares, maximum likelihood and Bayesian estimators of the transition probabilities. Simulated sampling studies with these estimators have shown that each of the estimators perform well when the aggregate data are generated by a first-order Markov process, although the Bayesian estimator, using a multivariate beta prior, appears to yield the best performance.

Growth theory received much emphasis during the decade of the 1960s and since the aggregate production function, which expresses the basic relationship among output, employment, and capital stock, is the engine for most of the models searching for the golden rule of accumulation, this relation provided the basis for a large number of studies on technical change and growth. As a replacement for the Cobb-Douglas specification which implies a unitary elasticity of substitution between the factors, Arrow, Chenery, Minhas, and Solow [1961] proposed the constant elasticity of substitution (CES) production function

$$Z = \left[ \beta K^{-\rho} + \alpha L^{-\rho} \right]^{1/\rho} u,$$

where $Z$ is output, $K$ is capital, and $L$ is labor, which permitted the elasticity of substitution to lie between zero and one; Dhrymes [1965] developed statistical tests for the CES production function; Revankar [1966] proposed a generalized production function which permits variable returns to scale; and Newman and Read [1961] and Ferguson and Pfouts [1962] proposed a production function that would permit variable factor shares. These specifications result in relations which are nonlinear functions of the parameter, and conventional estimation methods fail because alternative estimators lead to the problem of solving a system of nonlinear equations. Because of this result,
various attempts have been made to circumvent the problem of nonlinear estimation methods (Kmenta [1967], Bodkin and Klein [1967], and Tsang [1971]). Aigner and Chu [1968] questioned the conventional rationale used in estimating the parameters of production functions and developed and applied procedures for estimating the frontier of a production function. Meanwhile, the old problems of multicollinearity, aggregation bias, specification error, how to isolate the impacts of management and technical progress, and the question of the meaning to be attached to the parameters of macro production functions were still unsolved.

During the 1960s interest and work continued in the area of macroeconometric models (Nerlove [1966], Hallberg [1972]) and produced such outcomes as the SSRC-Brookings (Griliches [1968]), FRB-MIT-Penn (Rasche and Shapiro [1968]), and St. Louis (Anderson and Carlson [1970]) specifications. The first two of these models entailed the cooperative efforts of the theorist, applied economist, statistician, mathematician, and computer scientist in the job of model specification, estimation, and modeling. These models involved several industrial sectors, of which agriculture was one, and the national income accounting and input-output systems were combined in the specification. Thus, these efforts continued the tendency to increase the size of the macroeconometric models by a finer disaggregation of the major macro variables. Monetary sectors were added as monetary policy became more in vogue. Nonlinear systems were estimated and solved. As a sign of the times in terms of working with these econometric models, Zellner [1970a] did a paper on "The Care and Feeding of Econometric Models." The macroeconometric models were used by Goldberger [1959], Evans and Klein [1967], Fromm and Taubman [1968], and others for ex ante forecasting. Perhaps it should be noted at this point that there are three equivalent forms for a given econometric model. The structural and reduced form equation alternatives are well known and the reduced form is more convenient that the structural equations for calculating the effects of the exogenous changes on the endogenous variables. When lagged endogenous variables appear in the model, the reduced form equations are not sufficient for impact analysis purposes, and Theil and Boot [1962] use equations which are obtained by eliminating all lagged endogenous variables from the reduced form. This leads to what they term impact, interim, and total multipliers that may be used in describing the generation of the endogenous variables.

As the models got bigger, the debate between the big and the small specifications gathered steam. Within this context Cooper and Nelson [1971] compared the FRB-MIT Penn 171-equation model, the St. Louis 8-equation model, and the simple Box-Jenkins autoregressive moving average model for ex post and ex ante prediction of six endogenous variables and found that no
single model or predictor could be said to dominate the others. Given this re­
sult, they suggested a convex combination of the estimates as one superior al­
ternative. However, the debate continues, and Klein [1971] and others talk of models in the 1,000-equation range. The timid during this period contin­
ued to ask where one is to get the data base to support the parameter space for these larger and larger ventures. Unfortunately, they were not swamped with either the data or the answers to the query. At this stage, perhaps the greatest payoff is, as it was in the 1950s, in the building of the models and the identification of conceptual, data, estimation, and nonlinear system solu­
tion needs.

One break from the past, where it was conventional to toss econometric results to the masses with a plea for their use by somebody, at some place, and at some time, was to set up and carry through simulation experiments in order to see if the outcomes of the estimated systems were consistent with observed behavior and expected results. This further testing of our models through modeling did much to improve the usefulness of the results and raise the interesting philosophical question of whether simulation procedures, which iterate on parameter systems, may not be one meaningful way to cap­
ture unknown parameters or systems. Elsewhere in this volume Johnson and Rausser discuss some of the formal attempts to estimate unknown parameters on the basis of simulated results. Much of the macroeconometric estimation and modeling was made possible by advances in computer technology. What seemed beyond the reach of estimation and analysis in the 1940s and 1950s became accepted practice in the 1960s.

Since the econometric machine runs on data, we will close this section by noting that as the 1960s ended we were well on our way to creating large data banks of economic statistics, using remote access computer consoles, and we were starting to discuss seriously and to design large-scale controlled experi­
ments as a basis for understanding existing or potential economic processes and institutions.

The First Half of the 1970s

As the decade of the 1970s began, the rapid pace of econometric develop­ments started in the 1940s and 1950s continued. Methods for estimating eco­
nomic relations and testing economic hypotheses were refined and extended. The use of Bayesian estimation and inference in econometrics was firmly es­
tablished and no longer had to be justified anew each time it was mentioned or applied. Many schools introduced Bayesian techniques in their economet­
ric and economic theory courses. From an applications standpoint the lack of computer programs to handle the various data-generating processes and mar-
ginal prior densities still remained, although work currently under way at the University of Chicago (Zellner) and the Center for Operations Research and Econometrics (Drèze) will narrow if not eliminate this gap. Recent contributions to Bayesian inference in econometrics were summarized in a book (in honor of Savage) edited by Fienberg and Zellner [1974]. Several econometric texts were completed (Theil [1971], Kmenta [1971], Dhrymes [1970], Malinvaud [1970], Walters [1970], Johnston [1971], Aigner [1971a], and others), and in contrast to the situation in the 1950s the teacher and student have almost unlimited material for texts and references.

Analytical work concerning the finite sample properties of systems of equations estimators made headway in a number of special cases. Sawa [1972] evaluated the finite sample moments of the k-class estimators for $0 \leq k \leq 1$ and developed numerical calculations of the mean square error and the bias for specific cases. Mariano [1972, 1973] obtained necessary and sufficient conditions for the existence of even moments of the two-stage least squares estimator and approximated the distribution function of the two-stage least squares estimator up to the terms whose order of magnitude are $1/\sqrt{n}$, where $n$ is the sample size, Mariano and Sawa [1972] developed the exact finite sample distribution of the limited information maximum likelihood estimator when the structural equation being estimated contains two endogenous variables and is identifiable in a complete system of linear stochastic equations. Hendry [1976] explored the possibility that a simple formula could be obtained which encompassed most systems of equations and emphasized close similarities in the face of apparent diversities. Hendry concluded that most simultaneous equation estimators are really only different numerical methods for solving an expression for the full information estimator. This result helps to clarify the asymptotic equivalences of the various estimators, while permitting the alternative numerical variants to yield very different finite sample properties.

Within the context of the classical linear regression model the detection of autocorrelated errors continued to be a matter of concern, and new test statistics were proposed which had the advantage of having distributions independent of the design matrix. Durbin [1970a, 1970b] developed a test wherein the residuals are based on estimates of the parameters obtained from a derived set of regressors. Abrahamse and Louter [1971] developed a test statistic based on a new class of estimators for the disturbance vector. Berenblut and Webb [1973] developed what they called a g test statistic which is more powerful than the Durbin and Watson [1951] test for high values of autocorrelation. The tables in Durbin and Watson [1951] can be used in making the bounds for the new statistic. Smith [1973] reviewed sampling studies of autocorrelation and distribution lag models and concluded that most of the
techniques used are comparable in their performance patterns for small samples.

Box and Jenkins [1970] techniques for time series analysis were applied and evaluated, and one of the interesting and promising developments in the area centered around the analysis of dynamic simultaneous equation models within the context of general linear multiple time series processes. Zellner and Palm [1973], building on the idea that if a set of variables is generated by a multiple time series process it is often possible to solve for the processes generating individual variables, showed that if a multiple time series process is appropriately specified we can obtain the usual dynamic simultaneous equation model in structural form and then the associated reduced form and transfer functions can be derived.

Interest in optimal decisions under uncertainty continued to grow at an exponential rate and econometricians constructed models of markets in which participants act optimally over time subject to uncertainty. A survey article by Nerlove [1972] demonstrated both the level of interest and unsolved problems faced by researchers in this area. In the theory of the firm the firm's forecasts of prices play a role in generating an actual series of equilibrium prices, and it was this point that led Muth [1961] to define a rational expectation forecasting rule where the probability distribution of anticipated prices is the same as those actually generated by anticipations. Lucas and Prescott [1971] assumed that expectations of firms are rational in that anticipated price at time $t$ is the same function of the random disturbances as is the actual price. Grossman [1975] synthesized the rational expectations theory with Bayesian econometric theory to develop econometric models of competitive markets subject to uncertainty and derived optimal estimators of the parameters of the Cobb-Douglas production function and the equilibrium predictor of future prices. Rausser [1971] and Just [1972] formally incorporated variables associated with risk and uncertainty in the estimation of lag relationships pertaining to investment behavior and/or supply response. Lucas and Prescott [1974] applied these procedures in the equilibrium search and unemployment area. Obviously work that is going on in this area has important implications for specifying econometric models under uncertainty and for econometric forecasting.

In most econometric models it is customary to assume that the parameters are stationary or time invariant. Most economic systems are not time constant, however, and the response parameters do change over time. The time varying parameter problem received much attention in the early 1970s under the following three main theoretical structures: random coefficient models, systematic nonrandom variation models, and Kalman-filter models. In 1973 the National Bureau of Economic Research sponsored a symposium on time
varying parameter structures, and the papers were published in the October 1973 issue of the *Annals of Economic and Social Measurement*. The procedures discussed in the various papers offer much that can improve the econometrician's approach to the fixed coefficient limitation of conventional econometric models.

One of the problems that characterizes most econometric ventures pertains to measurement and observation errors. In most statistical models such as (1) and (2) it is assumed that errors occur in the equations and that the variables are measured without error. Unfortunately, most data that we generate or that are generated for us do not have this quality and instead of the true \( y \) and \( x \) we must work with the observed approximate measurements \( y^* \) and \( x^* \). Thus, if we consider two variables, the measurement error of the observed variables may be represented as

\[
(17) \quad x^* = X + \delta \quad \text{and} \quad y^* = y + \xi
\]

where \( \delta \) and \( \xi \) are the vectors of the error in the variables. The statistical model now contains both errors in the variables and errors in the equation and the relationship between the observable variables for the general case may be written as

\[
(18) \quad y^* = x^* \beta + u + \Delta \beta + \xi.
\]

Errors in the variables, as is well known, cause conventional estimators to give both biased and inconsistent results. Out of the procedures proposed to cope with the measurement error problem, the method of instrumental variables, which dates back to the 1930s, has probably been the most widely used. Excellent survey articles on the errors in the variables model covering the period from 1940 to 1970 may be found in Madansky [1959], Moran [1971], and Malinvaud [1970]. In making use of one of the alternative consistent estimators when measurement errors are suspected, the investigator is usually uncertain whether the virtue of consistency in his finite sample is sufficient to outweigh the increased variance from the use of instrumental variables. As an approach to this problem Feldstein [1973] suggested and evaluated alternative procedures for balancing the loss of efficiency in instrumental variables estimators against the potential gain of reduced bias. Fuller [1972] investigated the properties of the estimators of errors in the variables model when the covariance matrix is estimated. Unobservable variables, such as permanent and transitory income, are a special case of the errors in the variables model and are the subject of studies by Zellner [1970b] and Goldberger [1972]. Zellner considered a regression model containing a single unobservable variable and, for the practical situation where the variances are unknown, developed an operational version of generalized least squares where sample variances re-
place their unknown population counterparts. In customary Zellner fashion he also proposed a Bayesian analysis of the model. Goldberger [1972], building on the work of Zellner, developed a maximum likelihood procedure for the unobservable independent variable problem. The revival of econometric interest in the errors in the variables problem and realization of the possibility of identification and efficient estimation in unobservable variable models have contributed to the development of a unified statistical methodology (Goldberger [1971]) for the social sciences. Geracci [1976] examined the identification and estimation of simultaneous models which contain errors in both the equations and the variables.

In regard to sampling theory estimators, the inferential problem of making use of preliminary tests of significance, a problem first emphasized by Bancroft [1944], received new attention in the 1970s. This problem arises since in much of the work in economic measurement there is uncertainty about the agreement between the sampling model that generated the data and the statistical model that is employed for estimation and inference purposes. Statistical theory provides estimator properties and inferential statements conditioned on true models, whereas post-data model construction, by making use of preliminary tests of significance based on the data in hand, constitutes a rejection of the concept of true models. Two-stage procedures which yield an estimate after a preliminary test of significance make the estimation procedure dependent on the outcome of a test of hypothesis and lead to preliminary test or sequential estimators. Within the context of the general linear statistical model (1), the pretest estimator may be expressed as

\[
\hat{\beta} = I(0,c)^{(\omega)} \hat{\beta} + I(c,\infty)^{(\omega)} b
\]

where \(\omega\) is the usual test statistic from making use of likelihood ratio procedures, \(\hat{\beta}\) is the general linear hypothesis estimator of \(\beta\) (restricted least squares estimator or the sampling theory prior information estimators), \(b\) is the least squares estimator of \(\beta\), \(I(0,c)^{(\omega)}\) and \(I(c,\infty)^{(\omega)}\) are indicator functions which are one if \(\omega\) falls in the interval subscripted and zero otherwise, and \(c\) is the critical level of the test or the statistical significance level chosen. Although this estimator is widely used by workers in applied economics, little is known of the sampling properties of the estimator and the possible distortion of subsequent inferences when preliminary tests of significance are performed. Bancroft [1964], Sclove, Morris, and Radhakrishnan [1972], Ashar [1970], and Kennedy and Bancroft [1971] studied, usually for special cases, the properties of the resulting statistics in terms of their mean values and mean square errors and contrasted the forward and backward selection and sequential deletion model building procedures. Bock, Judge, and Yancey [1973a], building on the work of Bancroft and Sclove and using a squared
error loss measure, derived analytically the risk for the preliminary test estimator (PTE) for the general case, showed that there are points in the parameter space where the risk of the PTE exceeds that of the conventional estimator and developed the conditions necessary for the risk of the PTE to be equal to or less than that of the conventional estimator under squared error loss. Bock, Yancey, and Judge [1973b] derived the sampling properties of the PTE and considered the sampling information of the PTE under a generalized mean square error criterion. Judge, Yancey, and Bock [1973] and Yancey, Judge, and Bock [1974] extended the mean square error test of Toro-Vizcarrondo and Wallace [1968] to include stochastic linear hypotheses and developed the properties of the stochastic PTE (i.e., the sampling properties of Theil's mixed regression estimator [1963] when the compatibility test statistic is used).

At the same time that work on the preliminary test estimator was going on, renewed interest emerged in Stein-rule estimators, which lie outside of the class of linear unbiased estimators. Stein [1956] showed the conventional least squares estimator of the multivariate mean (with components greater than two) was inadmissible under the squared error loss measure of goodness. James and Stein [1961] showed that in estimation under square error loss if the number of regressors or hypotheses for the general linear regression model is equal to or greater than three (K > 3) and c* fulfills the conditions 0 < c* < 2(J-2)/T-K+2K, then the Stein-rule estimator

\[ \beta^* = (1 - c*/\omega)(b-\beta) + \hat{\beta} = b - c*/\omega(b-\hat{\beta}) \]

dominates (is uniformly superior to) the conventional least squares estimator. The optimal choice of c* was shown to be (T-K)(J-2)/(T-K+2K).

Baranchik [1964] showed that the positive part version of the Stein-rule estimator

\[ \beta^+ = 1_{(0,c^*)}(\omega)(1 - c*/\omega)(b-\hat{\beta} + \hat{\beta}), \]

which implies \( \beta^+ = \hat{\beta} \) if \( \omega < c^* \) and \( \beta^+ = \beta^* \) if \( \omega > c^* \), dominates the original James and Stein estimator \( \beta^* \). Strawderman [1971] developed, for the case when the number of parameters involved was greater than five, an estimator that was admissible and minimax. Sclove, Morris, and Radhakrishnan [1972] showed that the estimator

\[ \beta^{++} = 1_{(c,\infty)}(\omega) \beta^+, \]

which is a modified version of the James and Stein-Baranchik positive part Stein-rule estimator, dominates the preliminary test estimator (19) and is thus uniformly superior over the entire range of the parameter values. Bock [1975] generalized the results for the above estimators for cases usually found in
practice. Zellner and Vandaele [1972] developed Bayesian interpretations of and alternatives to the preliminary test and Stein-rule estimators. Hill [1975] investigated the problem of the inadmissibility of the usual multivariate estimator of a multivariate location parameter and presented a unified approach to estimation and hypothesis testing which is based directly on the concept of subjective probability. Lindley [1968] considered the analysis of data under the regression model and argued that the form of the analysis should depend on the use to be made of the results; in his approach to the variable choice problem he made use of ideas from decision theory. Although some problems remain (e.g., for the sampling theory estimators the optimal level of the test), we now have a much better idea of the sampling performance of a wide range of old and new estimators, and this should pay off in terms of improved procedures for sequential model building and learning from data.

The work on post-data model evaluation or discriminating among alternative admissible economic and statistical models has continued. Some of the hypothesis and decision rule procedures referred to earlier have implications for post-data model evaluation and choice. Dhrymes et al. [1972] surveyed the alternative and to some extent ad hoc procedures for the parametric evaluation of econometric models and noted the unsatisfactory nature of econometric practice and the state of the art. Beale [1970] summarized many of the most commonly used regression model building procedures, many of which are based only on intuitive appeal, and lends support to the backward stepwise method of variable elimination. Kennedy and Bancroft [1971] consider the forward selection and sequential deletion model building procedures and via numerical sampling experiments study the relative efficiency of the two procedures and recommend significance levels to use in confronting the best subset problem. Much work has been done using Bayesian procedures for comparing alternative models, and some of the productive efforts that stand out in this context are Box and Hill [1967], Geisel [1970], Thornber [1966], and Zellner [1971]. An excellent survey of these and other procedures for model selection is given in Gaver and Geisel [1973]. In spite of these advances in both the Bayesian and non-Bayesian areas, much remains to be done since we know little of (1) the sensitivity of these procedures to specification errors, (2) the finite sample behavior of these procedures, and (3) the implications for multiple equation models.

In the 1970s, in addition to adding to the stock of econometric tools, much effort went into evaluating through error analysis and impact multipliers the performance of ongoing econometric models specified and estimated in the 1960s and 1970s. Some of the major macroeconometric models include the Bureau of Economic Analysis Model, the Brookings Model, the University of Michigan Model, the Data Resources, Inc., Model, the Fair Model,
the Federal Reserve Bank of St. Louis Model, the MIT-Pennsylvania-SSRC Model, the Wharton Mark III and Anticipation Version Model, the Stanford University Model, the Wharton Annual Model, and the Cornell University Model. Descriptions and evaluations of each of these models are given in the *International Economic Review* (June 1974, October 1974, and February 1975 issues) and in Fromm [1973] and Fromm and Klein [1976]. Each of the models offers a different approximation to reality and each has its own characteristics and insights. No one model appears to dominate. As Nelson [1972] puts it, "some combination of the models is needed for effective interpretation of movements of the important economic variables." While not wanting to add to the critical voices surrounding the specification and estimation of econometric models and the uses to which they are put, may I suggest we perhaps expect too much from these quantitative ventures. Because of the nature of the models most are designed for short-run forecasting purposes. If this is true perhaps, as Lucas [1973] suggests, the model characteristics which lead to forecasting success are unrelated to quantitative policy evaluation and simulations involving these traditional models can in principle provide no useful information about the actual consequences of alternative economic policies.

The Economic Research Service of the United States Department of Agriculture continued to improve the econometric models underlying the economic information it provides on near-term agricultural outlook and long-run projections. The various models and efforts of the price analysis and forecast group are well described in a paper by Boutwell and his colleagues [1976]. Two symposiums involving ERS and university researchers in the econometric area were held in 1975 and 1976 to consider cooperative efforts in developing, implementing, and using an ongoing comprehensive econometric model of the United States agricultural sector.

**The Future**

Having enumerated some of the elements and events in the econometric set which help us to determine where we have been and where we are, let us now turn to the future and engage in a little ex ante prediction as it relates to econometrics.

Unfortunately, most of the problems of measurement in economics that have been raised over the last half century remain. Although we more clearly understand the inferential implications of what we do when "measuring with or without theory," the models and methods that we have developed and the questions that remain suggest that we are only at the beginning of our science. If the paths we have taken and the successes we have achieved are in
any way a prologue, it seems apparent that we will continue to refine and develop our economic and statistical models to cope with the special problems of our sample data and the decision problems for which the results are to be used. We will continue to improve our knowledge of the finite sample properties of sampling theory estimators and learn more of the implications and possibilities for combining prior and sample information for the purposes of estimation, prediction, and control. Nonlinear estimators and their stochastic properties and random coefficient statistical models will be further developed and become standard equipment in the econometrician's tool chest. We will improve by both sampling theory and Bayesian procedures our ability to handle the distributed lag estimation problem and to transform the distributed lag model into the frequency domain. The progress to date in the area of post-data model evaluation, while to a large degree ad hoc and unsatisfactory in nature, warrants an optimistic forecast that the development and extension of useful selection methods will continue. Computer programs for alternative Bayesian estimators will become available and the use of Bayesian inference, estimation, and decision processes will grow rapidly in our search for "optimal" actions (estimators). There will continue to be a significant growth in the average level of sophistication of economists with respect to econometric techniques, and perhaps ten years from now everyone will be at least a residual Bayesian. The gap or lag between theory and analytical tools and application should continue to narrow.

The communalities between problems and methods in the social sciences will become more apparent, and we will move toward a unified set of quantitative techniques which we hope will preclude a situation in which the tools and techniques of one discipline are rediscovered twenty-five years later in another (Hauser and Goldberger [1971]). We will gradually learn that quantitative tools are less specialized than the people who use them, and we will start to make use of state space representations of our econometric models and such far-afield procedures as linear filter and prediction theory (Kalman [1960]) that have been developed by engineers to cope with the problem of estimation in dynamic systems which involve unobservable variables and non-time-constant parameters.

Dynamic and stochastic decision models will grow in sophistication and usefulness, and econometrics will serve as a foundation stone in the development of operational routines for a formal analysis of decision problem under uncertainty. The use of structural modeling and simulation procedures will continue to grow very rapidly and especially the modeling of macroeconomic models will increase in importance as a tool to gauge the relative performance of alternative estimators and models and to help us understand the results. Future methods and models will, as they become more appropriate
for economic decision problems under uncertainty, continue to emphasize
the use of systems or stochastic control theory which combines in one pack­age automatic or adaptive control, estimation, prediction, and some optimali­ty criterion (Drèze [1972]).

The acquisition or generation of appropriate data will continue to be a
problem, but since the model builders and the model users are now beginning
to coordinate their efforts, there are many reasons to be optimistic in regard
to an improvement in quantity, form, and accuracy. Quantitative economists
will realize that federal collection agencies will not supply many of their data
needs and new institutional arrangements will be specified and implemented
for acquiring the research data we need. One hopeful sign is that we are final­ly generating data from large social experiments (for example, the experi­ments in New Jersey, North Carolina, and Iowa involving the negative income
tax proposal). Thus over the next ten years we should see a flow of much
more usable experimental and survey-generated data, where data design is in­tegrated with use, and the situation relative to social statistics, where current­ly we know more about the population of hogs and cows than the population
of people, will be improved. Central files of data and prior research results
will be stored with ready access to the researcher via remote terminals. When
this information is combined with econometric programs and remote termi­nals, the individual researcher, department, or institute will have ready access
to large-scale systems now available to only a few.

Finally, since mathematical economics is one of the foundation stones of
econometrics, we note that much of our modern economic theory is a theory
of position and not of movement. This means that in order to have a concep­tual base for many of the major problems facing society we must develop a
more workable theory of change which is concerned with a feedback system
involving leads, lags, and expectations, with intertemporal relations among
phenomena and the dynamic mechanism of transmitting impulses. As Nerlove
[1972] has noted, dynamic economics is still in large part a thing of the fu­ture. Econometric procedures now available or on the horizon, along with
more and better data and computing possibilities, provide the ingredients ap­propriate for evaluating economic hypotheses and for accumulating a system
of uniformities in the form of mathematical economic theory which will per­mit us to understand better the dynamic characteristics of economic process­es and institutions and to develop a more adequate theory of quantitative
economic policy evaluation.

Concluding Remarks

We are now at the end of a very inadequate tour. When I finished putting to­gether these words and other symbols, I was impressed by how hard the prob-
lems were and how far we have come. The last thirty years have been a very important experiment in nonexperimental model building and the current interdisciplinary focus in academia has only helped to emphasize that our achievements in econometric theory and applications have made economics a leader of the social sciences. Economists interested in agriculture have had a significant role over time in testing the new methods of estimation and inference and in many cases modifying, sharpening, and extending them. The list of econometricians who cut their teeth on agricultural data, or who at least did some work on agricultural problems during their careers, is indeed an impressive one. Agricultural economics will continue to be an important testing ground for econometric work, but its uniqueness in this respect will diminish as economists get a better break at the funding table and the general economics departments continue to develop their research programs.

In a post-industrial society theoretical and empirical knowledge in economics will become a primary source of innovation and policy analysis, and academic economic research, where this knowledge is codified and tested, will assume a task greater than it has carried through history. In spite of past performances and the importance of the charge for the future, econometrics will continue to have its social and other critics and to be under suspicion to some. Some may feel that we continue to work or fiddle with the properties of esoteric estimators while the world burns and people suffer. Others may hold that we are out to violate man's sacred beliefs and deal him the final moral insult by developing schemes to manipulate or control human behavior and that we are hard at work on a set of structural equations which will capture the relevant behavioral mechanisms or processes and make the "understand, predict, and control" trichotomy operational. Our response to the charges of irrelevance and impiety and our future performance as a science will ultimately depend on how well we fulfill the prescriptive goal of helping peoples and their governments to satisfy their social, cultural, and economic aspirations. This goal is best served by a science that provides an understanding of the regularities of economic life and a framework for using this information as a basis for decision making and choice. In the quest for this kind of a science of economics the continued development and application of tools of econometric analysis are essential.

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