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ABSTRACT

Econometrics: A Bird's Eye View*

As a unified discipline, econometrics is still relatively young and has been transforming and expanding very rapidly over the past few decades. Major advances have taken place in the analysis of cross sectional data by means of semi-parametric and non-parametric techniques. Heterogeneity of economic relations across individuals, firms and industries is increasingly acknowledged and attempts have been made to take them into account either by integrating out their effects or by modeling the sources of heterogeneity when suitable panel data exists. The counterfactual considerations that underlie policy analysis and treatment evaluation have been given a more satisfactory foundation. New time series econometric techniques have been developed and employed extensively in the areas of macroeconometrics and finance. Non-linear econometric techniques are used increasingly in the analysis of cross section and time series observations. Applications of Bayesian techniques to econometric problems have been given new impetus largely thanks to advances in computer power and computational techniques. The use of Bayesian techniques have in turn provided the investigators with a unifying framework where the tasks of forecasting, decision making, model evaluation and learning can be considered as parts of the same interactive and iterative process; thus paving the way for establishing the foundation of "real time econometrics". This paper attempts to provide an overview of some of these developments.

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1 What is Econometrics?

Broadly speaking, econometrics aims to give empirical content to economic relations for testing economic theories, forecasting, decision making, and for ex post decision/policy evaluation. The term 'econometrics' appears to have been first used by Pawel Ciompa as early as 1910, although it is Ragnar Frisch who takes the credit for coining the term, and for establishing it as a subject in the sense in which it is known today (see Frisch, 1936, p. 95, and Bjerkholt, 1995). By emphasizing the quantitative aspects of economic relationships, econometrics calls for a 'unification' of measurement and theory in economics. Theory without measurement can only have limited relevance for the analysis of actual economic problems. Whilst measurement without theory, being devoid of a framework necessary for the interpretation of the statistical observations, is unlikely to result in a satisfactory explanation of the way economic forces interact with each other. Neither 'theory' nor 'measurement' on their own is sufficient to further our understanding of economic phenomena.

As a unified discipline, econometrics is still relatively young and has been transforming and expanding very rapidly over the past two decades since an earlier version of this entry was published in the New Palgrave in 1987. Major advances have taken place in the analysis of cross sectional data by means of semi-parametric and non-parametric techniques. Heterogeneity of economic relations across individuals, firms and industries is increasingly acknowledged and attempts have been made to take them into account either by integrating out their effects or by modeling the sources of heterogeneity when suitable panel data exists. The counterfactual considerations that underlie policy analysis and treatment evaluation have been given a more satisfactory foundation. New time series econometric techniques have been developed and employed extensively in the areas of macroeconometrics and finance. Non-linear econometric techniques are used increasingly in the analysis of cross section and time series observations. Applications of Bayesian techniques to econometric problems have been given new impetus largely thanks to advances in computer power and computational techniques. The use of Bayesian techniques have in turn provided the investigators with a unifying framework where the tasks of forecasting, decision making, model evaluation and learning can be considered as parts of the same interactive and iterative process; thus paving the way for establishing the foundation of "real time econometrics". See Pesaran and Timmermann (2005a).

This entry attempts to provide an overview of some of these developments. But to give an idea of the extent to which econometrics has been transformed over the past decades we begin with a brief account of the literature that pre-dates econometrics, discuss the birth of econometrics and its subsequent developments to the present. Inevitably, our accounts will be brief and non-technical. Readers interested in more details are advised to consultant the specific entries provided in the New Palgrave and the excellent general texts by Maddala (2001), Greene (2003), Davidson and MacKinnon (2004), and Wooldridge (2006), as well as texts on specific topics such as: Cameron and Trivedi (2005) on microeconometrics, Maddala (1983) on econometric models involving limited-dependent and qualitative variables, Arellano (2003), Baltagi (2005), Hsiao (2003), and Wooldridge (2002) on panel data econometrics, Johansen (1995) on cointegration analysis, Hall (2005) on generalized method of moments, Bauwens et al. (2001), Koop (2003), Lancaster (2004), and Geweke (2005) on Bayesian econometrics, Bosq (1996), Fan and Gijbels (1996), Horowitz (1998), Härdle (1990,1994), and Pagan and Ullah (1999) on non-parametric and semiparametric econometrics, Campbell, Lo and MacKinlay (1997) and Gourieroux and Jasiak (2001) on financial econometrics, Granger and Newbold (1986), Lűtkepohl (1991) and Hamilton (1994) on time series analysis.

2 Quantitative Research in Economics: Historical Backgrounds

Empirical analysis in economics has had a long and fertile history, the origins of which can be traced at least as far back as the work of the 16th-century Political Arithmeticians such as William Petty, Gregory King and Charles Davenant. The political arithmeticians, led by Sir William Petty, were the first group to make systematic use of facts and figures in their studies. They were primarily interested in the practical issues of their time, ranging from problems of taxation and money to those of international trade and finance. The hallmark of their approach was undoubtedly quantitative and it was this which distinguished them from the rest of their contemporaries. Although the political arithmeticians were primarily and understandably preoccupied with statistical measurement of economic phenomena, the work of Petty, and that of King in particular, represented perhaps the first examples of a unified quantitative/theoretical approach to economics. Indeed Schumpeter in his History of Economic Analysis (1954) goes as far as to say that the works of the political arithmeticians 'illustrate to perfection, what Econometrics is and what Econometricians are trying to do' (p. 209).

The first attempt at quantitative economic analysis is attributed to Gregory King, who was the first to fit a linear function of changes in corn prices on deficiencies in the corn harvest, as reported in Charles Davenant (1698). One important consideration in the empirical work of King and others in this early period seems to have been the discovery of 'laws' in economics, very much like those in physics and other natural sciences.

This quest for economic laws was, and to a lesser extent still is, rooted in the desire to give economics the status that Newton had achieved for physics. This was in turn reflected in the conscious adoption of the method of the physical sciences as the dominant mode of empirical enquiry in economics. The Newtonian revolution in physics, and the philosophy of 'physical determinism' that came to be generally accepted in its aftermath, had far-reaching consequences for the method as well as the objectives of research in economics. The uncertain nature of economic relations only began to be fully appreciated with the birth of modern statistics in the late 19th century and as more statistical observations on economic variables started to become available.

The development of statistical theory in the hands of Galton, Edgeworth and Pearson was taken up in economics with speed and diligence. The earliest applications of simple correlation analysis in economics appear to have been carried out by Yule (1895, 1896) on the relationship between pauperism and the method of providing relief, and by Hooker (1901) on the relationship between the marriage-rate and the general level of prosperity in the United Kingdom, measured by a variety of economic indicators such as imports, exports, and the movement in corn prices.

Benini (1907), the Italian statistician was the first to make use of the method of multiple regression in economics. But Henry Moore (1914, 1917) was the first to place the statistical estimation of economic relations at the centre of quantitative analysis in economics. Through his relentless efforts, and those of his disciples and followers Paul Douglas, Henry Schultz, Holbrook Working, Fred Waugh and others, Moore in effect laid the foundations of 'statistical economics', the precursor of econometrics. The monumental work of Schultz, *The Theory and the Measurement of Demand* (1938), in the United States and that of Allen and Bowley, Family Expenditure (1935), in the United Kingdom, and the pioneering works of Lenoir (1913), Wright (1915, 1928), Working (1927), Tinbergen (1929-30) and Frisch (1933) on the problem of 'identification' represented major steps towards this objective. The work of Schultz was exemplary in the way it attempted a unification of theory and measurement in demand analysis; whilst the work on identification highlighted the importance of 'structural estimation' in econometrics and was a crucial factor in the subsequent developments of econometric methods under the auspices of the Cowles Commission for Research in Economics.

Early empirical research in economics was by no means confined to demand analysis. Louis Bachelier (1900), using time series data on French equity prices recognized the random walk character of equity prices which proved to be the precursor to the vast empirical literature on market efficiency hypothesis that has evolved since the early 1960's. Another important area was research on business cycles, which provided the basis of the later development in time-series analysis and macroeconometric model building and forecasting. Although, through the work of Sir William Petty and other early writers, economists had been aware of the existence of cycles in economic time series, it was not until the early 19th century that the phenomenon of business cycles began to attract the attention that it deserved. Clement Juglar (1819–1905), the French physician turned economist, was the first to make systematic use of time-series data to study business cycles, and is credited with the discovery of an investment cycle of about 7–11 years duration, commonly known as the Juglar cycle. Other economists such as Kitchin, Kuznets and Kondratieff followed Juglar's lead and discovered the inventory cycle (3–5 years duration), the building cycle (15–25 years duration) and the long wave (45–60 years duration), respectively. The emphasis of this early research was on the morphology of cycles and the identification of periodicities. Little attention was paid to the quantification of the relationships that may have underlain the cycles. Indeed, economists working in the National Bureau of Economic Research under the direction of Wesley Mitchell regarded each business cycle as a unique phenomenon and were therefore reluctant to use statistical methods except in a non-parametric manner and for purely descriptive purposes (see, for example, Mitchell, 1928 and Burns and Mitchell, 1947). This view of business cycle research stood in sharp contrast to the econometric approach of Frisch and Tinbergen and culminated in the famous methodological interchange between Tjalling Koopmans and Rutledge Vining about the roles of theory and measurement in applied economics in general and business cycle research in particular. (This interchange appeared in the August 1947 and May 1949 issues of The Review of Economics and Statistics.)

3 The Birth of Econometrics

Although, quantitative economic analysis is a good three centuries old, econometrics as a recognized branch of economics only began to emerge in the 1930s and the 1940s with the foundation of the Econometric Society, the Cowles Commission in the United States, and the Department of Applied Economics in Cambridge, England.[1] This was largely due to the multi-disciplinary nature of econometrics, comprising of economic theory, data, econometric methods, and computing techniques. Progress in empirical economic analysis often requires synchronous developments in all these four components.

Initially, the emphasis was on the development of econometric methods. The first major debate over econometric method concerned the applicability of the probability calculus and the newly developed sampling theory of R.A. Fisher to the analysis of economic data. Frisch (1934) was highly skeptical of the value of sampling theory and significance tests in econometrics. His objection was not, however, based on the epistemological reasons that lay behind Robbins's and Keynes's criticisms of econometrics. He was more concerned with the problems of multicollinearity and measurement errors which he believed were pervasive in economics and to deal with the measurement error problem he developed his

[1] An account of the founding of the first two organizations can be found in Christ (1952, 1983), while the history of the DAE is covered in Stone (1978).

confluence analysis and the method of 'bunch maps'. Although used by some econometricians, notably Tinbergen (1939) and Stone (1945), the bunch map analysis did not find much favour with the profession at large. Instead, it was the probabilistic rationalizations of regression analysis, advanced by Koopmans (1937) and Haavelmo (1944), that formed the basis of modern econometrics.

Koopmans did not, however, emphasize the wider issue of the use of stochastic models in econometrics. It was Haavelmo who exploited the idea to the full, and argued for an explicit probability approach to the estimation and testing of economic relations. In his classic paper published as a supplement to *Econometrica* in 1944, Haavelmo defended the probability approach on two grounds: firstly, he argued that the use of statistical measures such as means, standard errors and correlation coefficients for inferential purposes is justified only if the process generating the data can be cast in terms of a probability model. Secondly, he argued that the probability approach, far from being limited in its application to economic data, because of its generality is in fact particularly suited for the analysis of 'dependent' and 'non-homogeneous' observations often encountered in economic research.

The probability model is seen by Haavelmo as a convenient abstraction for the purpose of understanding, or explaining or predicting events in the real world. But it is not claimed that the model represents reality in all its details. To proceed with quantitative research in any subject, economics included, some degree of formalization is inevitable, and the probability model is one such formalization. The attraction of the probability model as a method of abstraction derives from its generality and flexibility, and the fact that no viable alternative seems to be available.

Haavelmo's contribution was also important as it constituted the first systematic defence against Keynes's (1939) influential criticisms of Tinbergen's pioneering research on business cycles and macroeconometric modelling. The objective of Tinbergen's research was twofold. Firstly, to show how a macroeconometric model may be constructed and then used for simulation and policy analysis (Tinbergen, 1937). Secondly, 'to submit to statistical test some of the theories which have been put forward regarding the character and causes of cyclical fluctuations in business activity' (Tinbergen, 1939, p. 11). Tinbergen assumed a rather limited role for the econometrician in the process of testing economic theories, and argued that it was the responsibility of the 'economist' to specify the theories to be tested. He saw the role of the econometrician as a passive one of estimating the parameters of an economic relation already specified on *a priori* grounds by an economist. As far as statistical methods were concerned he employed the regression method and Frisch's method of confluence analysis in a complementary fashion. Although Tinbergen discussed the problems of the determination of time lags, trends, structural stability and the choice of functional forms, he did not propose any systematic methodology for dealing with them. In short, Tinbergen approached the problem of testing theories from a rather weak methodological position. Keynes saw these weaknesses and attacked them with characteristic insight (Keynes, 1939). A large part of Keynes's review was in fact concerned with technical difficulties associated with the application of statistical methods to economic data. Apart from the problems of the 'dependent' and 'non-homogeneous' observations mentioned above, Keynes also emphasized the problems of misspecification, multi-collinearity, functional form, dynamic specification, structural stability, and the difficulties associated with the measurement of theoretical variables. By focussing his attack on Tinbergen's attempt at testing economic theories of business cycles, Keynes almost totally ignored the practical significance of Tinbergen's work for econometric model building and policy analysis (for more details, see Pesaran and Smith, 1985a).

In his own review of Tinbergen's work, Haavelmo (1943) recognized the main burden of the criticisms of Tinbergen's work by Keynes and others, and argued the need for a general statistical framework to deal with these criticisms. As we have seen, Haavelmo's response, despite the views expressed by Keynes and others, was to rely more, rather than less, on the probability model as the basis of econometric methodology. The technical problems raised by Keynes and others could now be dealt with in a systematic manner by means of formal probabilistic models. Once the probability model was specified, a solution to the problems of estimation and inference could be obtained by means of either classical or of Bayesian methods. There was little that could now stand in the way of a rapid development of econometric methods.

4 Early Advances in Econometric Methods

Haavelmo's contribution marked the beginning of a new era in econometrics, and paved the way for the rapid development of econometrics, with the likelihood method gaining importance as a tool for identification, estimation and inference in econometrics.

4.1 Identification of Structural Parameters

The first important breakthrough came with a formal solution to the identification problem which had been formulated earlier by Working (1927). By defining the concept of 'structure' in terms of the joint probability distribution of observations, Haavelmo (1944) presented a very general concept of identification and derived the necessary and sufficient conditions for identification of the entire system of equations, including the parameters of the probability distribution of the disturbances. His solution, although general, was rather difficult to apply in practice. Koopmans, Rubin and Leipnik (1950) used the term 'identification' for the first time in econometrics, and gave the now familiar rank and order conditions for the identification of a single equation in a system of simultaneous *linear* equations. The solution of the identification problem by Koopmans (1949) and Koopmans, Rubin and Leipnik (1950), was obtained in the case where there are *a priori* linear restrictions on the structural parameters. They derived rank and order conditions for identifiability of a single equation from a complete system of equations without reference to how the variables of the model are classified as endogenous or exogenous. Other solutions to the identification problem, also allowing for restrictions on the elements of the variance-covariance matrix of the structural disturbances, were later offered by Wegge (1965) and Fisher (1966).

Broadly speaking, a model is said to be identified if all its structural parameters can be obtained from the knowledge of its implied joint probability distribution for the observed variables. In the case of simultaneous equations models prevalent in econometrics the solution to the identification problem depends on whether there exists a sufficient number of *a priori* restrictions for the derivation of the structural parameters from the reduced-form parameters. Although the purpose of the model and the focus of the analysis on explaining the variations of some variables in terms of the unexplained variations of other variables is an important consideration, in the final analysis the specification of a minimum number of identifying restrictions was seen by researchers at the Cowles Commission to be the function and the responsibility of 'economic theory'. This attitude was very much reminiscent of the approach adopted earlier by Tinbergen in his business cycle research: the function of economic theory was to provide the specification of the econometric model, and that of econometrics to furnish statistically optimal methods of estimation and inference. More specifically, at the Cowles Commission the primary task of econometrics was seen to be the development of statistically efficient methods for the estimation of structural parameters of an *a priori* specified system of simultaneous stochastic equations.

More recent developments in identification of structural parameters in context of semi-parametric models is discussed below in Section 12. See also Manski (1995).

4.2 Estimation and Inference in Simultaneous Equation Models

Initially, under the influence of Haavelmo's contribution, the maximum likelihood (ML) estimation method was emphasized as it yielded consistent estimates. Anderson and Rubin (1949) developed the Limited Information Maximum Likelihood (LIML) method, and Koopmans and others (1950) proposed the Full Information Maximum Likelihood (FIML). Both methods are based on the joint probability distribution of the endogenous variables conditional on the exogenous variables and yield consistent estimates, with the former utilizing all the available *a priori* restrictions and the latter only those which related to the equation being estimated. Soon other computationally less demanding estimation methods followed, both for a fully efficient estimation of an entire system of equations and for a consistent estimation of a single equation from a system of equations.

The Two-Stage Least Squares (2SLS) procedure was independently proposed by Theil (1954, 1958) and Basmann (1957). At about the same time the instrumental variable (IV) method, which had been developed over a decade earlier by Reiersol (1941, 1945), and Geary (1949) for the estimation of errors-in-variables models, was generalized and applied by Sargan (1958) to the estimation of simultaneous equation models. Sargan's generalized IV estimator (GIVE) provided an asymptotically efficient technique for using surplus instruments in the application of the IV method to econometric problems, and formed the basis of subsequent developments of the generalized method of moments (GMM) estimators introduced subsequently by Hansen (1982). A related class of estimators, known as k-class estimators, was also proposed by Theil (1958). Methods of estimating the entire system of equations which were computationally less demanding than the FIML method were also advanced. These methods also had the advantage that unlike the FIML did not require the full specification of the entire system. These included the Three-Stage Least Squares method due to Zellner and Theil (1962), the iterated instrumental variables method based on the work of Lyttkens (1970), Brundy and Jorgenson (1971), Dhrymes (1971); and the system k-class estimators due to Srivastava (1971) and Savin (1973). Important contributions have also been made in the areas of estimation of simultaneous non-linear (Amemiya 1983), the seemingly unrelated regression model proposed by Zellner (1962), and the simultaneous rational expectations models (see Section 7.1 below).

Interest in estimation of simultaneous equation models coincided with the rise of Keynesian economics in early 1960's, and started to wane with the advent of the rational expectations revolution and its emphasis on the GMM estimation of the structural parameters from the Euler equations (first order optimization conditions). See Section 7 below. But with the rise of the dynamic stochastic general equilibrium models in macroeconometrics a revival of interest in identification and estimation of non-linear simultaneous equation models seems quite likely. The recent contribution of Fernandez-Villaverde and Rubio-Ramirez (2005) represents a start in this direction.

4.3 Developments in Time Series Econometrics

While the initiative taken at the Cowles Commission led to a rapid expansion of econometric techniques, the application of these techniques to economic problems was rather slow. This was partly due to a lack of adequate computing facilities at the time. A more fundamental reason was the emphasis of the research at the Cowles Commission on the simultaneity problem almost to the exclusion of other econometric problems. Since the early applications of the correlation analysis to economic data by Yule and Hooker, the serial dependence of economic time series and the problem of nonsense or spurious correlation that it could give rise to had been the single most important factor explaining the profession's scepticism concerning the value of regression analysis in economics. A satisfactory solution to the spurious correlation problem was therefore needed before regression analysis of economic time series could be taken seriously. Research on this topic began in the mid–1940s at the Department of Applied Economics (DAE) in Cambridge, England, as a part of a major investigation into the measurement and analysis of consumers' expenditure in the United Kingdom (see Stone and others, 1954). Although the first steps towards the resolution of the spurious correlation problem had been taken by Aitken (1934/35) and Champernowne (1948), the research in the DAE introduced the problem and its possible solution to the attention of applied economists. Orcutt (1948) studied the autocorrelation pattern of economic time series and showed that most economic time series can be represented by simple autoregressive processes with similar autoregressive coefficients. Subsequently, Cochrane and Orcutt (1949) made the important point that the major consideration in the analysis of stationary time series was the autocorrelation of the error term in the regression equation and not the autocorrelation of the economic time series themselves. In this way they shifted the focus of attention to the autocorrelation of disturbances as the main source of concern. Although, as it turns out, this is a valid conclusion in the case of regression equations with strictly exogenous regressors; in more realistic set ups where the regressors are weakly exogenous the serial correlation of the regressors are also likely to be of concern in practice. See, for example, Stambaugh (1999).

Another important and related development was the work of Durbin and Watson (1950, 1951) on the method of testing for residual autocorrelation in the classical regression model. The inferential breakthrough for testing serial correlation in the case of observed time-series data had already been achieved by von Neumann (1941, 1942), and by Hart and von Neumann (1942). The contribution of Durbin and Watson was, however, important from a practical viewpoint as it led to a bounds test for residual autocorrelation which could be applied irrespective of the actual values of the regressors. The independence of the critical bounds of the Durbin-Watson statistic from the matrix of the regressors allowed the application of the statistic as a general diagnostic test, the first of its type in econometrics. The contributions of Cochrane and Orcutt and of Durbin and Watson marked the beginning of a new era in the analysis of economic time-series data and laid down the basis of what is now known as the 'time-series econometrics' approach.

5 Consolidation and Applications

The work at the Cowles Commission on identification and estimation of the simultaneous equation model and the development of time series techniques paved the way for widespread application of econometric methods to economic and financial problems. This was helped significantly by the rapid expansion of computing facilities, advances in financial and macroeconomic modelling, and the increased availability of economic data sets, cross section as well as time series.

5.1 Macroeconometric Modelling

Inspired by the pioneering work of Tinbergen, Klein (1947, 1950) was the first to construct a macroeconometric model in the tradition of the Cowles Commission. Soon others followed Klein's lead. Over a short space of time macroeconometric models were built for almost every industrialized country, and even for some developing and centrally planned economies. Macroeconometric models became an important tool of *ex ante* forecasting and economic policy analysis, and started to grow both in size and sophistication. The relatively stable economic environment of the 1950s and 1960s was an important factor in the initial success enjoyed by macroeconometric models. The construction and use of large-scale models presented a number of important computational problems, the solution of which was of fundamental significance not only for the development of macroeconometric modelling, but also for econometric practice in general. In this respect advances in computer technology were clearly instrumental, and without them it is difficult to imagine how the complicated computational problems involved in the estimation and simulation of large-scale models could have been solved. The increasing availability of better and faster computers was also instrumental as far as the types of problems studied and the types of solutions offered in the literature were concerned. For example, recent developments in the area of microeconometrics (see section 6.3 below) could hardly have been possible if it were not for the very important recent advances in computing facilities.

5.2 Dynamic Specification

Other areas where econometrics witnessed significant developments included dynamic specification, latent variables, expectations formation, limited dependent variables, discrete choice models, random coefficient models, disequilibrium models, non-linear estimation, and the analysis of panel data models. Important advances were also made in the area of Bayesian econometrics. largely thanks to the publication of Zellner's 1971 textbook, which built on his earlier work including important papers with George Tiao. The Seminar on Bayesian Inference in Econometrics and Statistics (SBIES) was founded shortly after the publication of the book, and was key in the development and diffusion of Bayesian ideas in econometrics. It was, however, the problem of dynamic specification that initially received the greatest attention. In an important paper, Brown (1952) modelled the hypothesis of habit persistence in consumer behaviour by introducing lagged values of consumption expenditures into an otherwise static Keynesian consumption function. This was a significant step towards the incorporation of dynamics in applied econometric research and allowed the important distinction to be made between the short-run and the long-run impacts of changes in income on consumption. Soon other researchers followed Brown's lead and employed his autoregressive specification in their empirical work.

The next notable development in the area of dynamic specification was the distributed lag model. Although the idea of distributed lags had been familiar to economists through the pioneering work of Irving Fisher (1930) on the relationship between the nominal interest rate and the expected inflation rate, its application in econometrics was not seriously considered until the mid 1950s. The geometric distributed lag model was used for the first time by Koyck (1954) in a study of investment. Koyck arrived at the geometric distributed lag model via the adaptive expectations hypothesis. This same hypothesis was employed later by Cagan (1956) in a study of demand for money in conditions of hyperinflation, by Friedman (1957) in a study of consumption behaviour and by Nerlove (1958a) in a study of the cobweb phenomenon. The geometric distributed lag model was subsequently generalized by Solow (1960), Jorgenson (1966) and others, and was extensively applied in empirical studies of investment and consumption behaviour. At about the same time Almon (1965) provided a polynomial generalization of Fisher's (1937) arithmetic lag distribution which was later extended further by Shiller (1973). Other forms of dynamic specification considered in the literature included the partial adjustment model (Nerlove, 1958b; Eisner and Strotz, 1963) and the multivariate flexible accelerator model (Treadway, 1971) and Sargan's (1964) work on econometric time series analysis which formed the basis of error correction and cointegration analysis that followed next. Following the contributions of Champernowne (1960), Granger and Newbold (1974) and Phillips (1986) the spurious regression problem was better understood, and paved the way for the development of the theory of cointegration. For further details see Section 8.3 below.

5.3 Techniques for Short-term Forecasting

Concurrent with the development of dynamic modelling in econometrics there was also a resurgence of interest in time-series methods, used primarily in short-term business forecasting. The dominant work in this field was that of Box and Jenkins (1970), who, building on the pioneering works of Yule (1921, 1926), Slutsky (1927), Wold (1938), Whittle (1963) and others, proposed computationally manageable and asymptotically efficient methods for the estimation and forecasting of univariate autoregressive-moving average (ARMA) processes. Time-series models provided an important and relatively simple benchmark for the evaluation of the forecasting accuracy of econometric models, and further highlighted the significance of dynamic specification in the construction of time-series econometric models. Initially univariate time-series models were viewed as mechanical 'black box' models with little or no basis in economic theory. Their use was seen primarily to be in short-term forecasting. The potential value of modern time-series methods in econometric research was, however, underlined in the work of Cooper (1972) and Nelson (1972) who demonstrated the good forecasting performance of univariate Box-Jenkins models relative to that of large econometric models. These results raised an important question mark over the adequacy of large econometric models for forecasting as well as for policy analysis. It was argued that a properly specified structural econometric model should, at least in theory, yield more accurate forecasts than a univariate time-series model. Theoretical justification for this view was provided by Zellner and Palm (1974), followed by Trivedi (1975), Prothero and Wallis (1976), Wallis (1977) and others. These studies showed that Box-Jenkins models could in fact be derived as univariate final form solutions of linear structural econometric models. In theory, the pure time-series model could always be embodied within the structure of an econometric model and in this sense it did not present a 'rival' alternative to econometric modelling. This literature further highlighted the importance of dynamic specification in econometric models and in particular showed that econometric models that are out-performed by simple univariate time-series models most probably suffer from specification errors.

The papers in Elliott, Granger and Timmermann (2006) provide excellent reviews of recent developments in economic forecasting techniques.

6 A New Phase in Development of Econometrics

With the significant changes taking place in the world economic environment in the 1970s, arising largely from the breakdown of the Bretton Woods system and the quadrupling of oil prices, econometrics entered a new phase of its development. Mainstream macroeconometric models built during the 1950s and 1960s, in an era of relative economic stability with stable energy prices and fixed exchange rates, were no longer capable of adequately capturing the economic realities of the 1970s. As a result, not surprisingly, macroeconometric models and the Keynesian theory that underlay them came under severe attack from theoretical as well as from practical viewpoints. While criticisms of Tinbergen's pioneering attempt at macroeconometric modelling were received with great optimism and led to the development of new and sophisticated estimation techniques and larger and more complicated models, the disenchantment with macroeconometric models in 1970's prompted a much more fundamental reappraisal of quantitative modelling as a tool of forecasting and policy analysis.

At a theoretical level it was argued that econometric relations invariably lack the necessary 'microfoundations', in the sense that they cannot be consistently derived from the optimizing behaviour of economic agents. At a practical level the Cowles Commission approach to the identification and estimation of simultaneous macroeconometric models was questioned by Lucas and Sargent and by Sims, although from different viewpoints. (Lucas, 1976, Lucas and Sargent (1981), and Sims (1980)). There was also a move away from macroeconometric models and towards microeconometric research with greater emphasis on matching of econometrics with individual decisions.

It also became increasingly clear that Tinbergen's paradigm where economic relations were taken as given and provided by 'economic theorist' was not adequate. It was rarely the case that economic theory could be relied on for a full specification of the econometric model. (Leamer, 1978). The emphasis gradually shifted from estimation and inference based on a given tightly parameterized specification to diagnostic testing, specification searches, model uncertainty, model validation, parameter variations, structural breaks, semi-parametric and nonparametric estimation. The choice of approach often governed by the purpose of the investigation, the nature of the economic application, data availability, computing and software technology.

What follows is a brief overview of some of the important developments. Given space limitations there are inevitably significant gaps. These include the important contributions of Granger (1969), Sims (1972) and Engle and others (1983) on different concepts of 'causality' and 'exogeneity', the literature on disequilibrium models (Quandt, 1982; Maddala, 1983, 1986), random coefficient models (Swamy, 1970, Hsiao and Pesaran, 2006), unobserved time series models (Harvey, 1989), count regression models (Cameron and Trivedi, 1986, 1998), the weak instrument problem (Stock, Wright and Yogo, 2002), small sample theory (Phillips, 1983; Rothenberg, 1984), econometric models of auction pricing (Hendricks and Porter, 1988, and Laffont, Ossard, and Vuong, 1995).

7 Rational Expectations and the Lucas Critique

Although the Rational Expectations Hypothesis (REH) was advanced by Muth in 1961, it was not until the early 1970s that it started to have a significant impact on time-series econometrics and on dynamic economic theory in general. What brought the REH into prominence was the work of Lucas (1972, 1973), Sargent (1973), Sargent and Wallace (1975) and others on the new classical explanation of the apparent breakdown of the

Phillips curve. The message of the REH for econometrics was clear. By postulating that economic agents form their expectations *endogenously* on the basis of the true model of the economy and a *correct* understanding of the processes generating exogenous variables of the model, including government policy, the REH raised serious doubts about the invariance of the structural parameters of the mainstream macroeconometric models in the face of changes in government policy. This was highlighted in Lucas's critique of macroeconometric policy evaluation. By means of simple examples Lucas (1976) showed that in models with rational expectations the parameters of the decision rules of economic agents, such as consumption or investment functions, are usually a mixture of the parameters of the agents' objective functions and of the stochastic processes they face as historically given. Therefore, Lucas argued, there is no reason to believe that the 'structure' of the decision rules (or economic relations) would remain invariant under a policy intervention. The implication of the Lucas critique for econometric research was not, however, that policy evaluation could not be done, but rather than the traditional econometric models and methods were not suitable for this purpose. What was required was a separation of the parameters of the policy rule from those of the economic model. Only when these parameters could be identified separately given the knowledge of the joint probability distribution of the variables (both policy and non-policy variables), would it be possible to carry out an econometric analysis of alternative policy options.

There have been a number of reactions to the advent of the rational expectations hypothesis and the Lucas critique that accompanied it.

7.1 Model Consistent Expectations

The least controversial has been the adoption of the REH as one of several possible expectations formation hypotheses in an otherwise conventional macroeconometric model containing expectational variables. In this context the REH, by imposing the appropriate cross-equation parametric restrictions, ensures that 'expectations' and 'forecasts' generated by the model are consistent. In this approach the REH is regarded as a convenient and effective method of imposing cross-equation parametric restrictions on time series econometric models, and is best viewed as the 'model-consistent' expectations hypothesis. There is now a sizeable literature on solution, identification, and estimation of linear RE models. The canonical form of RE models with forward and backward components is given by

$$\mathbf{y}_t = \mathbf{A}\mathbf{y}_{t-1} + \mathbf{B}E\left(\mathbf{y}_{t+1}\left|F_t\right.\right) + \mathbf{w}_t,$$

where $\mathbf{y}_t$ is a vector of endogenous variables, $E\left(.\left|F_t\right.\right)$ is the expectations operator, F_t the publicly available information at time t, and $\mathbf{w}_t$ is a vector of forcing variables. For example, log-linearized version of dynamic general equilibrium models (to be discussed) can all be written as a special case of this equation with plenty of restrictions on the coefficient matrices A and B. In the typical case where $\mathbf{w}_t$ are serially uncorrelated and the solution of the RE model can be assumed to be unique the RE solution reduces to the vector autoregression (VAR)

$$\mathbf{y}_t = \mathbf{\Phi}\mathbf{y}_{t-1} + \mathbf{G}\mathbf{w}_t,$$

where $\mathbf{\Phi}$ and $\mathbf{G}$ are given in terms of the structural parameters:

$$\mathbf{B\Phi}^2 - \mathbf{\Phi} + \mathbf{A} = \mathbf{0}, \text{ and } \mathbf{G} = (\mathbf{I} - \mathbf{B\Phi})^{-1}.$$

The solution of the RE model can, therefore, be viewed as a restricted form of VAR popularized in econometrics by Sims (1980) as a response in macroeconometric modelling to the rational expectations revolution. The nature of restrictions are determined by the particular dependence of A and B on a few "deep" or structural parameters. For general discussion of solution of RE models see, for example, Broze, Gouriéroux, and Szafarz (1985) and Binder and Pesaran (1995). For studies of identification and estimation of linear RE models see, for example, Hansen and Sargent (1980), Wallis (1980), Wickens (1982) and Pesaran (1981,1987). These studies show how the standard econometric methods can in principle be adapted to the econometric analysis of rational expectations models.

7.2 Detection and Modelling of Structural Breaks

Another reaction to the Lucas critique has been to treat the problem of 'structural change' emphasized by Lucas as one more potential econometric 'problem'. Clements and Hendry (1998, 1999) provide a taxonomy of factors behind structural breaks and forecast failures. Stock and Watson (1996) provide extensive evidence of structural break in macroeconomic time series. It is argued that structural change can result from many factors and need not be solely associated with intended or expected changes in policy. The econometric lesson has been to pay attention to possible breaks in economic relations. There now exists a large body of work on testing for structural change, detection of breaks (single as well as multiple), modelling of break processes by means of piece-wise linear or non-linear dynamic models. (Chow, 1960, Brown, Durbin and Evans, 1975, Nyblom, 1989, Andrews, 1993, Andrews and Ploberger, 1994, Bai and Perron, 1998, Pesaran and Timmermann, 2005b, 2006. See also the surveys by Stock (1994) and Clements and Hendry (2006). The implications of breaks for short term and long term forecasting have also begun to be addressed. McCulloch, and Tsay (1993) ,Koop and Potter (2004a, 2004b), Pesaran, Pettenuzzo and Timmermann (2006).

8 VAR Macroeconometrics

8.1 Unrestricted VARs

The Lucas critique of mainstream macroeconometric modelling also led some econometricians, notably Sims (1980, 1982), to doubt the validity of the Cowles Commission style of achieving identification in econometric models. He focussed his critique on macroeconometric models with a vector autoregressive (VAR) specification, which was relatively simple to estimate and its use soon became prevalent in macroeconometric analysis. The view that economic theory cannot be relied on to yield identification of structural models was not new and had been emphasized in the past, for example, by Liu (1960). Sims took this viewpoint a step further and argued that in presence of rational expectations *a priori* knowledge of lag lengths is indispensable for identification, even when we have distinct strictly exogenous variables shifting supply and demand schedules. (Sims, 1980, p. 7). While it is true that the REH complicates the necessary conditions for the identification of structural models, the basic issue in the debate over identification still centres on the validity of the classical dichotomy between exogenous and endogenous variables. (Pesaran, 1981). In the context of closed economy macroeconometric models where all variables are treated as endogenous other forms of identification of the structure will be required. Initially, Sims suggested a recursive identification approach where the matrix of contemporaneous effects were assumed to be lower (upper) triangular and the structural shocks orthogonal. Other non-recursive identification schemes soon followed.

8.2 Structural VARs

One prominent example was the identification scheme developed in Blanchard and Quah (1989) who distinguished between permanent and transitory shocks and attempted to identify the structural models through long-run restrictions. For example, Blanchard and Quah argued that the effect of a demand shock on real output should be temporary (namely it should have a zero long run impact), whilst a supply shock should have a permanent effect. This approach is known as 'structural VAR' (SVAR) and has been used extensively in the literature. It continues to assume that structural shocks are orthogonal, but uses a mixture of short-run and long-run restrictions to identify the structural model. In their work Blanchard and Quah considered a bivariate VAR model in real output and unemployment. They assumed real output to be integrated of order 1, or $I(1)$, and viewed unemployment as an $I(0)$, or a stationary variable. This allowed them to associate the shock to one of the equations as permanent, and the shock to the other equation as transitory. In more general settings, such as the one analyzed by Gali (1992) and Wickens and Motta (2001), where there are m endogenous variables and r long-run or cointegrating relations, the SVAR approach provides $m(m-r)$ restrictions which are not sufficient to fully identify the model, unless $m = 2$ and $r = 1$ which is the simple bivariate model considered by Blanchard and Quah. (Pagan and Pesaran, 2006). In most applications additional short term restrictions are required. More recently, attempts have also been made to identify structural shocks by means of qualitative restrictions, such as sign restrictions. Notable examples include Canova and de Nicolo (2002), Uhlig (2005) and Peersman (2005).

The focus of the SVAR literature has been on impulse response analysis and forecast error variance decomposition, with the aim of estimating the time profile of the effects of monetary policy, oil price or technology shocks on output and inflation, and deriving the relative importance of these shocks as possible explanations of forecast error variances at different horizons. Typically such analysis is carried out with respect to a single model specification and at most only parameter uncertainty is taken into account. (Kilian, 1998). More recently the problem of model uncertainty, and its implications for impulse response analysis and forecasting, has been recognized. Bayesian and classical approaches to model and parameter uncertainty have been considered. Initially, Bayesian VAR models were developed for use in forecasting as an effective shrinkage procedure in the case of high dimensional VAR models. (Doan, Litterman and Sims, 1984, and Litterman, 1985). The problem of model uncertainty in cointegrating VARs has been addressed in Garrett, Lee, Pesaran and Shin (2003b, 2006), and Strachan and van Dijk (2006).

8.3 Structural Cointegrating VARs

This approach provides the SVAR with the decomposition of shocks into permanent and transitory and gives economic content to the long-run or cointegrating relations that underlie the transitory components. In the simple example of Blanchard and Quah this task is trivially achieved by assuming real output to be I(1) and the unemployment rate to be an I(0) variable. To have shocks with permanent effects some of the variables in the VAR must be non-stationary. This provides a natural link between the SVAR and the unit root and cointegration literature. Identification of the cointegrating relations can be achieved by recourse to economic theory, solvency or arbitrage conditions. (Garrett, Lee, Pesaran and Shin, 2003a). Also there are often long-run over-identifying restrictions that can be tested. Once identified and empirically validated, the long-run relations can be embodied within a VAR structure, and the resultant structural vector error correction model identified using theory-based short-run restrictions. The structural shocks can be decomposed into permanent and temporary components using either the multivariate version of the Beveridge and Nelson (1981) decompositions, or the one more recently proposed by Garrett, Robertson and Wright (2006).

Two or more variables are said to be cointegrated if they are individually integrated (or have a random walk component), but there exists a linear combination of them which is stationary. The concept of cointegration was first introduced by Granger (1986) and more formally developed in Engle and Granger (1987). Rigorous statistical treatments followed in the papers by Johansen (1988, 1991) and Phillips (1991). Many further developments and extensions have taken place with reviews provided in Johansen (1995), Juselius (2006) and Garret, Lee, Pesaran and Shin (2006). The related unit root literature is reviewed by Stock (1994) and Phillips and Xiao (1998).

8.4 Macroeconometric Models with Microeconomic Foundations

For policy analysis macroeconometric models need to be based on decisions by individual households, firms and governments. This is a daunting undertaking and can be achieved only by gross simplification of the complex economic interconnections that exists across millions of decision makers worldwide. Dynamic Stochastic General Equilibrium (DSGE) modelling approach attempts to implement this task by focussing on optimal decisions of a few representative agents operating with rational expectations under complete learning. Initially, DSGE models were small and assumed complete markets with instantaneous price adjustments, and as a result did not fit the macroeconomic time series (Kim and Pagan, 1995). More recently, Smets and Wouters (2003) have shown that DSGE models with sticky prices and wages along the lines developed by Christiano, Eichenbaum and Evans (2005) are sufficiently rich to match most of the statistical features of the main macro-economic time series. Moreover, by applying Bayesian estimation techniques, these authors have shown that even relatively large models can be estimated as a system. Bayesian DSGE models have also shown to perform reasonably level in forecasting as compared to standard and Bayesian vector autoregressions. It is also possible to incorporate long run cointegrating relations within Bayesian DSGE models. The problems of parameter and model uncertainty can also be readily accommodated using data coherent DSGE models. Other extensions of the DSGE models to allow for learning, regime switches, time variations in shock variances, asset prices, and multi-country interactions are likely to enhance their policy relevance. (Del Negro and Schorfheide, 2004, Del Negro, Schorfheide, Smets and Wouters, 2005, An and Schorfheide, 2006, Pesaran and Smith, 2006). Further progress will also be welcome in the area of macroeconomic policy analysis under model uncertainty, and robust policy making (Brock and Durlauf, 2006, Hansen and Sargent, 2006).

9 Model and Forecast Evaluation

While in the 1950s and 1960s research in econometrics was primarily concerned with the identification and estimation of econometric models, the dissatisfaction with econometrics during the 1970s caused a shift of focus from problems of estimation to those of model evaluation and testing. This shift has been part of a concerted effort to restore confidence in econometrics, and has received attention from Bayesian as well as classical viewpoints. Both these views reject the 'axiom of correct specification' which lies at the basis of most traditional econometric practices, but differ markedly as how best to proceed.

It is generally agreed, by Bayesians as well as by non-Bayesians, that model evaluation involves considerations other than the examination of the statistical properties of the models, and personal judgements inevitably enter the evaluation process. Models must meet multiple criteria which are often in conflict. They should be relevant in the sense that they ought to be capable of answering the questions for which they are constructed. They should be consistent with the accounting and/or theoretical structure within which they operate. Finally, they should provide adequate representations of the aspects of reality with which they are concerned. These criteria and their interaction are discussed in Pesaran and Smith (1985b). More detailed breakdowns of the criteria of model evaluation can be found in Hendry and Richard (1982) and McAleer, Pagan, and Volker (1985). In econometrics it is, however, the criterion of 'adequacy' which is emphasized, often at the expense of relevance and consistency.

The issue of model adequacy in mainstream econometrics is approached either as a model selection problem or as a problem in statistical inference whereby the hypothesis of interest is tested against general or specific alternatives. The use of absolute criteria such as measures of fit/parsimony or formal Bayesian analysis based on posterior odds are notable examples of model selection procedures, while likelihood ratio, Wald and Lagrange multiplier tests of nested hypotheses and Cox's centred log-likelihood ratio tests of non-nested hypotheses are examples of the latter approach. The distinction between these two general approaches basically stems from the way alternative models are treated. In the case of model selection (or model discrimination) all the models under consideration enjoy the same status and the investigator is not committed *a priori* to any one of the alternatives. The aim is to choose the model which is likely to perform best with respect to a particular loss function. By contrast, in the hypothesis-testing framework the null hypothesis (or the maintained model) is treated differently from the remaining hypotheses (or models). One important feature of the model-selection strategy is that its application always leads to one model being chosen in preference to other models. But in the case of hypothesis testing, rejection of all the models under consideration is not ruled out when the models are non-nested. A more detailed discussion of this point is given in Pesaran and Deaton (1978).

Broadly speaking, classical approaches to the problem of model adequacy can be classified depending on how specific the alternative hypotheses are. These are the *general specification tests, the diagnostic tests*, and the *non-nested tests*. The first of these, pioneered by Durbin (1954) and introduced in econometrics by Ramsey (1969), Wu (1973), Hausman (1978), and subsequently developed further by White (1981, 1982) and Hansen (1982), are designed for circumstances where the nature of the alternative hypothesis is kept (sometimes intentionally) rather vague, the purpose being to test the null against a *broad* class of alternatives. (The pioneering contribution of Durbin (1954) in this area has been documented by Nakamura and Nakamura (1981)). Important examples of general specification tests are Ramsey's regression specification error test (RESET) for omitted variables and/or misspecified functional forms, and the Durbin-Hausman-Wu test of misspecification in the context of measurement error models, and/or simultaneous equation models. Such general specification tests are particularly useful in the preliminary stages of the modelling exercise.

In the case of diagnostic tests, the model under consideration (viewed as the null hypothesis) is tested against more specific alternatives by embedding it within a general model. Diagnostic tests can then be constructed using the likelihood ratio, Wald or Lagrange multiplier (LM) principles to test for parametric restrictions imposed on the general model. The application of the LM principle to econometric problems is reviewed in the papers by Breusch and Pagan (1980), Godfrey and Wickens (1982), Engle (1984). An excellent review is provided in Godfrey (1988). Examples of the restrictions that may be of interest as diagnostic checks of model adequacy include zero restrictions, parameter stability, serial correlation, heteroskedasticity, functional forms, and normality of errors. The distinction made here between diagnostic tests and general specification tests is more apparent than real. In practice some diagnostic tests such as tests for serial correlation can also be viewed as a general test of specification. Nevertheless, the distinction helps to focus attention on the purpose behind the tests and the direction along which high power is sought.

The need for non-nested tests arises when the models under consideration belong to separate parametric families in the sense that no single model can be obtained from the others by means of a suitable limiting process. This situation, which is particularly prevalent in econometric research, may arise when models differ with respect to their theoretical underpinnings and/or their auxiliary assumptions. Unlike the general specification tests and diagnostic tests, the application of non-nested tests is appropriate when specific but rival hypotheses for the explanation of the same economic phenomenon have been advanced. Although non-nested tests can also be used as general specification tests, they are designed primarily to have high power against specific models that are seriously entertained in the literature. Building on the pioneering work of Cox (1961, 1962), a number of such tests for single equation models and systems of simultaneous equations have been proposed. (Pesaran and Weeks, 2001).

The use of statistical tests in econometrics, however, is not a straightforward matter and in most applications does not admit of a clear-cut interpretation. This is especially so in circumstances where test statistics are used not only for checking the adequacy of a *given* model but also as guides to model construction. Such a process of model construction involves specification searches of the type emphasized by Leamer (1978) and presents insurmountable pre-test problems which in general tend to produce econometric models whose 'adequacy' is more apparent than real. As a result, in evaluating econometric models less reliance should be placed on those indices of model adequacy that are used as guides to model construction, and more emphasis should be given to the performance of models over other data sets and against rival models.

A closer link between model evaluation and the underlying decision problem is also needed. Granger and Pesaran (2000a, 2000b) discuss this problem in the context of forecast evaluation. A recent survey of forecast evaluation literature can be found in West (2006). Pesaran and Skouras (2002) provide a review from a decision-theoretic perspective.

The subjective Bayesian approach to the treatment of several models begins by assigning a prior probability to each model, with the prior probabilities summing to one. Since each model is already endowed with a prior probability distribution for its parameters and for the probability distribution of observable data conditional on its parameters, there is then a complete probability distribution over the space of models, parameters, and observable data. (No particular problems arise from non-nesting of models in this framework.) This probability space can then be augmented with the distribution of an object or vector of objects of interest. For example, in a macroeconomic policy setting the models could include VARs,. DSGEs, and traditional large-scale macroeconomic models, and the vector of interest might include future output growth, interest rates, inflation and unemployment, whose distribution is implied by each of the models considered. Implicit in this formulation is the conditional distribution of the vector of interest conditional on the observed data. Technically, this requires the integration (or marginalization) of parameters in each model as well as the models themselves. As a practical matter this usually proceeds by first computing the probability of each model conditional on the data, and then using these probabilities as weights in averaging the posterior distribution of the vector of interest in each model. It is not necessary to choose one particular model, and indeed to do so would be suboptimal. The ability to actually carry out this simultaneous consideration of multiple models has been enhanced greatly by recent developments in simulation methods, surveyed in Section 15 below; recent texts by Koop (2003), Lancaster (2004) and Geweke (2005) provide technical details. Geweke and Whiteman (2006) specifically outline these methods in the context of economic forecasting.

10 Microeconometrics: An Overview

Partly as a response to the dissatisfaction with macroeconometric time-series research and partly in view of the increasing availability of micro-data and computing facilities, over the past two decades significant advances have been made in the analysis of micro-data. Important micro-data sets have become available on households and firms especially in the United States in such areas as housing, transportation, labour markets and energy. These data sets include various longitudinal surveys (e.g. University of Michigan Panel Study of Income Dynamics and Ohio State National Longitudinal Study Surveys), cross-sectional surveys of family expenditures, population and labour force surveys. This increasing availability of micro-data, while opening up new possibilities for analysis, has also raised a number of new and interesting econometric issues primarily originating from the nature of the data. The errors of measurement are likely to be important in the case of some micro data sets. The problem of the heterogeneity of economic agents at the micro level cannot be assumed away as readily as is usually done in the case of macro-data by appealing to the idea of a 'representative' firm or a 'representative' household.

The nature of micro-data, often being qualitative or limited to a particular range of variations, has also called for new econometric models and techniques. Examples include categorical survey responses ('up', 'same' or 'down'), and censored or truncated observations. The models and issues considered in the micro-econometric literature are wide ranging and include fixed and random effect panel data models (e.g. Mundlak, 1961, 1978), logit and probit models and their multinominal extensions, discrete choice or quantal response models (Manski and McFadden, 1981), continuous time duration models (Heckman and Singer, 1984), and micro-econometric models of count data (Hausman et al., 1984 and Cameron and Trivedi, 1986).

The fixed or random effect models provide the basic statistical framework and will be discussed in more detailed below. Discrete choice models are based on an explicit characterization of the choice process and arise when individual decision makers are faced with a finite number of alternatives to choose from. Examples of discrete choice models include transportation mode choice (Domenich and McFadden, 1975), labour force participation (Heckman and Willis, 1977), occupation choice (Boskin, 1974), job or firm location (Duncan 1980), and models with neighborhood effects (Brock and Durlauf, 2002). Limited-dependent variables models are commonly encountered in the analysis of survey data and are usually categorized into truncated regression models and censored regression models. If all observations on the dependent as well as on the exogenous variables are lost when the dependent variable falls outside a specified range, the model is called *truncated*, and, if only observations on the dependent variable are lost, it is called *censored*. The literature on censored and truncated regression models is vast and overlaps with developments in other disciplines, particularly in biometrics and engineering. Maddala (1983, ch. 6) provides a survey.

The censored regression model was first introduced into economics by Tobin (1958) in his pioneering study of household expenditure on durable goods where he explicitly allowed for the fact that the dependent variable, namely the expenditure on durables, cannot be negative. The model suggested by Tobin and its various generalizations are known in economics as Tobit models and are surveyed in detail by Amemiya (1984), and more recently in Cameron and Trivedi (2005, ch. 14).

Continuous time duration models, also known as survival models, have been used in analysis of unemployment duration, the period of time spent between jobs, durability of marriage, etc. Application of survival models to analyse economic data raises a number of important issues resulting primarily from the non-controlled experimental nature of economic observations, limited sample sizes (i.e. time periods), and the heterogeneous nature of the economic environment within which agents operate. These issues are clearly not confined to duration models and are also present in the case of other microeconometric investigations that are based on time series or cross section or panel data.

Partly in response to the uncertainties inherent in econometric results based on non-experimental data, there has also been a significant move towards social experimentation, and experimental economics in general. A social experiment aims at isolating the effects of a policy change (or a treatment effect) by comparing the consequences of an exogenous variation in the economic environment of a set of experimental subjects known as the 'treatment' group with those of a 'control' group that have not been subject to the change. The basic idea goes back to the early work of R.A. Fisher (1928) on randomized trials and have been applied extensively in agricultural and biomedical research. The case for social experimentation in economics is discussed in Burtless (1995). Hausman and Wise (1985) and Heckman and Smith (1995) consider a number of actual social experiments carried out in the US and discuss their scope and limitations.

Experimental economics tries to avoid some of the limitations of working with observations obtained from natural or social experiments by using data from laboratory experiments to test economic theories by fixing some of the factors and identifying the effects of other factors in a way that allows *ceteris paribus* comparisons. A wide range of topics and issues are covered in this literature such as individual choice behaviour, bargaining, provision of public goods, theories of learning, auction markets, and behavioral finance. A comprehensive review of major areas of experimental research in economics is provided in Kagel and Roth (1995).

These developments have posed new problems and challenges in the areas of experimental design, statistical methods and policy analysis. Another important aspect of recent developments in microeconometric literature relates to the use of microanalytic simulation models for policy analysis and evaluation to reform packages in areas such as health care, taxation, social security systems, and transportation networks. Cameron and Trivedi (2005) review the recent developments in methods and application of microeconometrics. Some of these topics will be discussed in more detail below.

11 Econometrics of Panel Data

Panel data models are used in many areas of econometrics, although initially they were developed primarily for the analysis of micro behavior, and focussed on panels formed from cross-section of N individual households or firms surveyed for T successive time periods. These types of panels are often refereed to as 'micropanels'. In social and behavioral sciences they are also known as longitudinal data or panels. The literature on micropanels typically takes N to be quite large (in hundreds) and T rather small, often less than 10. But more recently, with the increasing availability of financial and macroeconomic data, analyses of panels where both N and T are relatively large have also been considered. Examples of such data sets include time series of company data from Datastream, country data from International Financial Statistics or the Penn World Table, and county and state data from national statistical offices. There are also pseudo panels of firms and consumers composed of repeated cross sections that cover cross section units that are not necessarily identical but are observed over relatively long time periods. Since the available cross section observations do not (necessarily) relate to the same individual unit, some form of grouping of the cross section units is needed. Once the grouping criteria are set, the estimation can proceed using fixed effects estimation applied to group averages if the number of observations per group is sufficiently large, otherwise possible measurement errors of the group averages also need to be taken into account. Deaton (1985) pioneered the econometric analysis of pseudo panels. Verbeek (2006) provides a recent review.

Use of panels can enhance the power of empirical analysis and allows estimation of parameters that might not have been identified along the time or the cross section dimensions alone. These benefits come at a cost. In the case of linear panel data models with a short time span the increased power is usually achieved under assumptions of parameter homogeneity and error cross section independence. Short panels with autocorrelated disturbances also pose a new identification problem, namely how to distinguished between dynamics and state dependence. (Arellano, 2003, ch. 5). In panels with fixed effects the homogeneity assumption is relaxed somewhat by allowing the intercepts in the panel regressions to vary freely over the cross section units, but continues to maintain the error cross section independence assumption. The random coefficient specification of Swamy (1970) further relaxes the slope homogeneity assumption, and represents an important generalization of the random effects model (Hsiao and Pesaran, 2006). In micropanels where T is small cross section dependence can be dealt with if it can be attributed to spatial (economic or geographic) effects. Anselin (1988) and Anselin, Le Gallo and Jaye (2006) provide surveys of the literature on spatial econometrics. A number of studies have also used measures such as trade or capital flows to capture economic distance, as in Conley and Topa (2002), Conley and Dupor (2003), and Pesaran, Schuermann and Weiner (2004).

Allowing for dynamics in panels with fixed effects also present additional difficulties; for example the standard within-group estimator will be inconsistent unless $T \to \infty$. (Nickell, 1981). In linear dynamic panels the incidental parameter problem (the unobserved heterogeneity) can be resolved by first differencing the model and then estimating the resultant first-differened specification by instrumental variables or by the method of transformed likelihood. (Anderson and Hsiao, 1981,1982, Holtz-Eakin, Newey and Rosen, 1988, Arellano and Bond, 1991, and Hsiao, Pesaran and Tahmiscioglu, 2002). A similar procedure can also be followed in the case of short T panel VARs. (Binder, Hsiao and Pesaran, 2005). But other approaches are needed for non-linear panel data models. See, for example, Honore and Kyriazidou (2000) and review of the literature on non-linear panels in Arellano and Honoré (2001). Relaxing the assumption of slope homogeneity in dynamic panels is also problematic, and neglecting to take account of slope heterogeneity will lead to inconsistent estimators. In the presence of slope heterogeneity Pesaran and Smith (1995) show that the within group estimator remains inconsistent even if both N and $T \to \infty$. A Bayesian approach to estimation of micro dynamic panels with random slope coefficients is proposed in Hsiao, Pesaran and Tahmiscioglu (1999).

To deal with general dynamic specifications, possible slope heterogeneity and error cross section dependence large T and N panels are required. In the case of such large panels it is possible to allow for richer dynamics and parameter heterogeneity. Cross section dependence of errors can also be dealt with using residual common factor structures. These extensions are particularly relevant to the analysis of purchasing power parity hypothesis (O'Connell, 1998, Imbs, Mumtaz, Ravn and Rey, 2005, Pedroni, 2001, Smith, Leybourne, Kim and Newbold, 2004), output convergence (Durlauf, Johnson, and Temple, 2005, Pesaran, 2006c), the Fisher effect (Westerlund, 2005), house price convergence (Holly, Pesaran, and Yamagata, 2006), regional migration (Fachin, 2006), and uncovered interest parity (Moon and Perron, 2006). The econometric methods developed for large panels has to take into account the relationship between the increasing number of time periods and cross section units (Phillips and Moon 1999). The relative expansion rates of N and T could have important consequences for the asymptotic and small sample properties of the panel estimators and tests. This is because fixed T estimation bias tend to magnify with increases in the cross section dimension, and it is important that any bias in the T dimension is corrected in such a way that its overall impact disappears as both N and $T \to \infty$, jointly.

The first generation panel unit root tests proposed, for example, by Levin, Lin and Chu (2002) and Im, Pesaran and Shin (2003) allowed for parameter heterogeneity but assumed errors were cross sectionally independent. More recently, panel unit root tests that allow for error cross section dependence have been proposed by Bai and Ng (2004), Moon and Perron (2004) and Pesaran (2006b). As compared to panel unit root tests, the analysis of cointegration in panels is still at an early stages of its developments. So far the focus of the panel cointegration literature has been on residual based approaches, although there has been a number of attempts at the development of system approaches as well. (Pedroni, 2004). But once cointegration is established the long-run parameters can be estimated efficiently using techniques similar to the ones proposed in the case of single time series models. These estimation techniques can also be modified to allow for error cross section dependence. (Pesaran, 2006a). Surveys of the panel unit root and cointegration literature are provided by Banerjee (1999), Baltagi and Kao (2000), Choi (2006) and Breitung and Pesaran (2006).

The micro and macro panel literature is vast and growing. For the analysis of many economic problems further progress is needed in the analysis of non-linear panels, testing and modelling of error cross section dependence, dynamics, and neglected heterogeneity. For general reviews of panel data econometrics see Arellano (2003), Baltagi (2005), Hsiao (2003) and Wooldridge (2002).

12 Nonparametric and Semiparametric Estimation

Much empirical research is concerned with estimating conditional mean, median, or hazard functions. For example, a wage equation gives the mean, median or, possibly, some other quantile of wages of employed individuals conditional on characteristics such as years of work experience and education. A hedonic price function gives the mean price of a good conditional on its characteristics. The function of interest is rarely known a priori and must be estimated from data on the relevant variables. For example, a wage equation is estimated from data on the wages, experience, education and, possibly, other characteristics of individuals. Economic theory rarely gives useful guidance on the form (or shape) of a conditional mean, median, or hazard function. Consequently, the form of the function must either be assumed or inferred through the estimation procedure.

The most frequently used estimation methods assume that the function of interest is known up to a set of constant parameters that can be estimated from data. Models in which the only unknown quantities are a finite set of constant parameters are called parametric. A linear model that is estimated by ordinary least squares is a familiar and frequently used example of a parametric model. Indeed, linear models and ordinary least squares have been the workhorses of applied econometrics since its inception. It is not difficult to see why. Linear models and ordinary least squares are easy to work with both analytically and computationally, and the estimation results are easy to interpret. Other examples of widely used parametric models are binary logit and probit models if the dependent variable is binary (e.g., an indicator of whether an individual is employed or not or whether a commuter uses automobile or public transit for a trip to work) and the Weibull hazard model if the dependent variable is a duration (e.g., the duration of a spell of employment or unemployment).

Although parametric models are easy to work with, they are rarely justified by theoretical or other *a priori* considerations and often fit the available data badly. Horowitz (2001), Horowitz and Savin (2001), Horowitz and Lee (2002), and Pagan and Ullah (1999) provide examples. The examples also show that conclusions drawn from a convenient but incorrectly specified model can be very misleading.

Of course, applied econometricians are aware of the problem of specification error. Many investigators attempt to deal with it by carrying out a specification search in which several different models are estimated and conclusions are based on the one that appears to fit the data best. Specification searches may be unavoidable in some applications, but they have many undesirable properties. There is no guarantee that a specification search will include the correct model or a good approximation to it. If the search includes the correct model, there is no guarantee that it will be selected by the investigator's model selection criteria. Moreover, the search process invalidates the statistical theory on which inference is based.

Given this situation, it is reasonable to ask whether conditional mean and other functions of interest in applications can be estimated nonparametrically, that is without making *a priori* assumptions about their functional forms. The answer is clearly yes in a model whose explanatory variables are all discrete. If the explanatory variables are discrete, then each set of values of these variables defines a data cell. One can estimate the conditional mean of the dependent variable by averaging its values within each cell. Similarly, one can estimate the conditional median cell by cell.

If the explanatory variables are continuous, they cannot be grouped into cells. Nonetheless, it is possible to estimate conditional mean and median functions that satisfy mild smoothness conditions without making *a priori* assumptions about their shapes. Techniques for doing this have been developed mainly in statistics, beginning with Nadaraya's (1964) and Watson's (1964) nonparametric estimator of a conditional mean function. The

Nadaraya-Watson estimator, which is also called a kernel estimator, is a weighted average of the observed values of the dependent variable. More specifically, suppose that the dependent variable is Y, the explanatory variable is X, and the data consist of observations $\{Y_i, X_i : i = 1, ..., n\}$. Then the Nadaraya-Watson estimator of the mean of Y at $X = x$ is a weighted average of the Y_i's. Y_i's corresponding to X_i's that are close to x get more weight than do Y_i's corresponding to X_i's that are far from x. The statistical properties of the Nadaraya-Watson estimator have been extensively investigated for both cross-sectional and time-series data, and the estimator has been widely used in applications. For example, Blundell, Browning and Crawford (2003) used kernel estimates of Engel curves in an investigation of the consistency of household-level data and revealed preference theory. Hausman and Newey (1995) used kernel estimates of demand functions to estimate the equivalent variation for changes in gasoline prices and the deadweight losses associated with increases in gasoline taxes. Kernel-based methods have also been developed for estimating conditional quantile and hazard functions.

There are other important nonparametric methods for estimating conditional mean functions. Local linear estimation and series or sieve estimation are especially useful in applications. Local linear estimation consists of estimating the mean of Y at $X = x$ by using a form of weighted least squares to fit a linear model to the data. The weights are such that observations (Y_i, X_i) for which X_i is close to x receive more weight than do observations for which X_i is far from x. In comparison to the Nadaraya-Watson estimator, local linear estimation has important advantages relating to bias and behavior near the boundaries of the data. These are discussed in the book by Fan and Gijbels (1996), among other places.

A series estimator begins by expressing the true conditional mean (or quantile) function as an infinite series expansion using basis functions such as sines and cosines, orthogonal polynomials, or splines. The coefficients of a truncated version of the series are then estimated by ordinary least squares. The statistical properties of series estimators are described by Newey (1997). Hausman and Newey (1995) give an example of their use in an economic application.

Nonparametric models and estimates essentially eliminate the possibility of misspecification of a conditional mean or quantile function (that is, they consistently estimate the true function), but they have important disadvantages that limit their usefulness in applied econometrics. One important problem is that the precision of a nonparametric estimator decreases rapidly as the dimension of the explanatory variable X increases. This phenomenon is called the curse of dimensionality. It can be understood most easily by considering the case in which the explanatory variables are all discrete. Suppose the data contain 500 observations of Y and X. Suppose, further, that X is a K-component vector and that each component can take five different values. Then the values of X generate 5^K cells. If $K = 4$, which is not unusual in applied econometrics, then there are 625 cells, or more cells than observations. Thus, estimates of the conditional mean function are likely to be very imprecise for most cells because they will contain few observations. Moreover, there will be at least 125 cells that contain no data and, consequently, for which the conditional mean function cannot be estimated at all. It has been proved that the curse of dimensionality is unavoidable in nonparametric estimation. As a result of it, impracticably large samples are usually needed to obtain acceptable estimation precision if X is multidimensional.

Another problem is that nonparametric estimates can be difficult to display, communicate, and interpret when X is multidimensional. Nonparametric estimates do not have simple analytic forms. If X is one- or two-dimensional, then the estimate of the function of interest can be displayed graphically, but only reduced-dimension projections can be displayed when X has three or more components. Many such displays and much skill in interpreting them can be needed to fully convey and comprehend the shape of an estimate.

A further problem with nonparametric estimation is that it does not permit extrapolation. For example, in the case of a conditional mean function it does not provide predictions of the mean of Y at values of x that are outside of the range of the data on X. This is a serious drawback in policy analysis and forecasting, where it is often important to predict what might happen under conditions that do not exist in the available data. Finally, in nonparametric estimation, it can be difficult to impose restrictions suggested by economic or other theory. Matzkin (1994) discusses this issue.

The problems of nonparametric estimation have led to the development of so-called semiparametric methods that offer a compromise between parametric and nonparametric estimation. Semiparametric methods make assumptions about functional form that are stronger than those of a nonparametric model but less restrictive than the assumptions of a parametric model, thereby reducing (though not eliminating) the possibility of specification error. Semiparametric methods permit greater estimation precision than do nonparametric methods when X is multidimensional. Semiparametric estimation results are usually easier to display and interpret than are nonparametric ones and provide limited capabilities for extrapolation.

In econometrics, semiparametric estimation began with Manski's (1975, 1985) and Cosslett's (1983) work on estimating discrete-choice random-utility models. McFadden had introduced multinomial logit random utility models. These models assume that the random components of the utility function are independently and identically distributed with the Type I extreme value distribution. The resulting choice model is analytically simple but has properties that are undesirable in many applications (e.g., the well-known independence-of-irrelevant-alternatives property). Moreover, estimators based on logit models are inconsistent if the distribution of the random components of utility is not Type I extreme value. Manski (1975, 1985) and Cosslett (1983) proposed estimators that do not require *a priori* knowledge of this distribution. Powell's (1984, 1986) least absolute deviations estimator for censored regression models is another early contribution to econometric research on semiparametric estimation. This estimator was motivated by the observation that estimators of (parametric) Tobit models are inconsistent if the underlying normality assumption is incorrect. Powell's estimator is consistent under very weak distributional assumptions.

Semiparametric estimation has continued to be an active area of econometric research. Semiparametric estimators have been developed for a wide variety of additive, index, partially linear, and hazard models, among others. These estimators all reduce the effective dimension of the estimation problem and overcome the curse of dimensionality by making assumptions that are stronger than those of fully nonparametric estimation but weaker than those of a parametric model. The stronger assumptions also give the models limited extrapolation capabilities. Of course, these benefits come at the price of increased risk of specification error, but the risk is smaller than with simple parametric models. This is because semiparametric models make weaker assumptions than do parametric models and contain simple parametric models as special cases.

Semiparametric estimation is also an important research field in statistics, and it has led to much interaction between statisticians and econometricians. The early statistics and biostatistics research that is relevant to econometrics was focused on survival (duration) models. Cox's (1972) proportional hazards model and the Buckley and James (1979) estimator for censored regression models are two early examples of this line of research. Somewhat later, Stone (1985) showed that a nonparametric additive model can overcome the curse of dimensionality. Since then, statisticians have contributed actively to research on the same classes of semiparametric models that econometricians have worked on.

13 Theory-Based Empirical Models

Many econometric models are connected to economic theory only loosely or through essentially arbitrary parametric assumptions about, say, the shapes of utility functions. For example, a logit model of discrete choice assumes that the random components of utility are independently and identically distributed with the Type I extreme value distribution. In addition, it is frequently assumed that the indirect utility function is linear in prices and other characteristics of the alternatives. Because economic theory rarely, if ever, yields a parametric specification of a probability model, it is worth asking whether theory provides useful restrictions on the specification of econometric models and whether models that are consistent with economic theory can be estimated without making non-theoretical parametric assumptions. The answers to these questions depend on the details of the setting being modeled.

In the case of discrete-choice, random-utility models, the inferential problem is to estimate the distribution of (direct or indirect) utility conditional on observed characteristics of individuals and the alternatives among which they choose. More specifically, in applied research one usually is interested in estimating the systematic component of utility (that is, the function that gives the mean of utility conditional on the explanatory variables) and the distribution of the random component of utility. Discrete-choice is present in a wide range of applications, so it is important to know whether the systematic component of utility and the distribution of the ransom component can be estimated nonparametrically, thereby avoiding the non-theoretical distributional and functional form assumptions that are required by parametric models. The systematic component and distribution of the random component cannot be estimated unless they are identified. However, economic theory places only weak restrictions on utility functions (e.g., shape restrictions such as monotonicity, convexity, and homogeneity), so the classes of conditional mean and utility functions that satisfy the restrictions are large. Indeed, it is not difficult to show that observations of individuals' choices and the values of the explanatory variables, by themselves, do not identify the systematic component of utility and the distribution of the random component without making assumptions that shrink the class of allowed functions.

This issue has been addressed in a series of papers by Matzkin that are summarized in Matzkin (1994). Matzkin gives conditions under which the systematic component of utility and the distribution of the random component are identified without restricting either to a finite-dimensional parametric family. Matzkin also shows how these functions can be estimated consistently when they are identified. Some of the assumptions required for identification may be undesirable in applications. Moreover, Manski (1988) and Horowitz (1998) have given examples in which infinitely many combinations of the systematic component of utility and distribution of the random component are consistent with a binary logit specification of choice probabilities. Thus, discrete-choice, random-utility models can be estimated under assumptions that are considerably weaker than those of, say, logit and probit models, but the systematic component of utility and the distribution of the random component cannot be identified using the restrictions of economic theory alone. It is necessary to make additional assumptions that are not required by economic theory and, because they are required for identification, cannot be tested empirically.

Models of market-entry decisions by oligopolistic firms present identification issues that are closely related to those in discrete-choice, random utility models. Berry and Tamer (2005) explain the identification problems and approaches to resolving them.

The situation is different when the economic setting provides more information about the relation between observables and preferences than is the case in discrete-choice models. This happens in models of certain kinds of auctions, thereby permitting nonparametric estimation of the distribution of values for the auctioned object. An example is a first-price, sealed bid auction within the independent private values paradigm. Here, the problem is to infer the distribution of bidders' values for the auctioned object from observed bids. A game-theory model of bidders' behavior provides a characterization of the relation between bids and the distribution of private values. Guerre, Perrigne, and Vuong (2000) showed that this relation nonparametrically identifies the distribution of values if the analyst observes all bids and certain other mild conditions are satisfied. Guerre, Perrigne, and Vuong (2000) also showed how to carry out nonparametric estimation of the value distribution.

Dynamic decision models and equilibrium job search models are other examples of empirical models that are closely connected to economic theory, though they also rely on non-theoretical parametric assumptions. In a dynamic decision model, an agent makes a certain decision repeatedly over time. For example, an individual may decide each year whether to retire or not. The optimal decision depends on uncertain future events (e.g., the state of one's future health) whose probabilities may change over time (e.g., the probability of poor health increases as one ages) and depend on the decision. In each period, the decision of an agent who maximizes expected utility is the solution to a stochastic, dynamic programming problem. A large body of research, much of which is reviewed by Rust (1994), shows how to specify and estimate econometric models of the utility function (or, depending on the application, cost function), probabilities of relevant future events, and the decision process.

An equilibrium search model determines the distributions of job durations and wages endogenously. In such a model, a stochastic process generates wage offers. An unemployed worker accepts an offer if it exceeds his reservation wage. An employed worker accepts an offer if it exceeds his current wage. Employers choose offers to maximize expected profits. Among other things, an equilibrium search model provides an explanation for why seemingly identical workers receive different wages. The theory of equilibrium search models is described in Albrecht and Axell (1984), Mortensen (1990), and Burdett and Mortensen (1998). There is a large body of literature on the estimation of these models. Bowlus, Kiefer, and Neumann (2001) provide a recent example with many references.

14 The Bootstrap

The exact, finite-sample distributions of econometric estimators and test statistics can rarely be calculated in applications. This is because except in special cases and under restrictive assumptions (e.g., the normal linear model), finite sample distributions depend on the unknown distribution of the population from which the data were sampled. This problem is usually dealt with by making use of large-sample (asymptotic) approximations. A wide variety of econometric estimators and test statistics have distributions that are approximately normal or chi-square when the sample size is large, regardless of the population distribution of the data. The approximation error decreases to zero as the sample size increases. Thus, asymptotic approximations can to be used to obtain confidence intervals for parameters and critical values for tests when the sample size is large.

It has long been known, however, that the asymptotic normal and chi-square approximations can be very inaccurate with the sample sizes encountered in applications. Consequently, there can be large differences between the true and nominal coverage probabilities of confidence intervals and between the true and nominal probabilities with which a test rejects a correct null hypothesis. One approach to dealing with this problem is to use higher-order asymptotic approximations such as Edgeworth or saddlepoint expansions. These received much research attention during 1970s and 1980s, but analytic higher-order expansions are rarely used in applications because of their algebraic complexity.

The bootstrap, which is due to Efron (1979), provides a way to obtain sometimes spectacular improvements in the accuracy of asymptotic approximations while avoiding algebraic complexity. The bootstrap amounts to treating the data as if they were the population. In other words, it creates a pseudo-population whose distribution is the empirical distribution of the data. Under sampling from the pseudo-population, the exact finite sample distribution of any statistic can be estimated with arbitrary accuracy by carrying out a Monte Carlo simulation in which samples are drawn repeatedly from the empirical distribution of the data. That is, the data are repeatedly sampled randomly with replacement. Since the empirical distribution is close to the population distribution when the sample size is large, the bootstrap consistently estimates the asymptotic distribution of a wide range of important statistics. Thus, the bootstrap provides a way to replace analytic calculations with computation. This is useful when the asymptotic distribution is difficult to work with analytically.

More importantly, the bootstrap provides a low-order Edgeworth approximation to the distribution of a wide variety of asymptotically standard normal and chi-square statistics that are used in applied research. Consequently, the bootstrap provides an approximation to the finite-sample distributions of such statistics that is more accurate than the asymptotic normal or chi-square approximation. The theoretical research leading to this conclusion was carried out by statisticians, but the bootstrap's importance has been recognized in econometrics and there is now an important body of econometric research on the topic. In many settings that are important in applications, the bootstrap essentially eliminates errors in the coverage probabilities of confidence intervals and the rejection probabilities of tests. Thus, the bootstrap is a very important tool for applied econometricians.

There are, however, situations in which the bootstrap does not estimate a statistic's asymptotic distribution consistently. Manski's (1975, 1985) maximum score estimator of the parameters of a binary response model is an example. All known cases of bootstrap inconsistency can be overcome through the use of subsampling methods. In subsampling, the distribution of a statistic is estimated by carrying out a Monte Carlo simulation in which the subsamples of the data are drawn repeatedly. The subsamples are smaller than the original data set, and they can be drawn randomly with or without replacement. Subsampling provides estimates of asymptotic distributions that are consistent under very weak assumptions, though it is usually less accurate than the bootstrap when the bootstrap is consistent.

15 Program Evaluation and Treatment Effects

Program evaluation is concerned with estimating the causal effect of a treatment or policy intervention on some population. The problem arises in many disciplines, including biomedical research (e.g., the effects of a new medical treatment) and economics (e.g., the effects of job training or education on earnings). The most obvious way to learn the effects of treatment on a group of individuals by observing each individual's outcome in the both the treated and the untreated states. This is not possible in practice, however, because one virtually always observes any given individual in either the treated state or the untreated state but not both. This does not matter if the individuals who receive treatment are identical to those who do not, but that rarely happens. For example, individuals who choose to take a certain drug or whose physicians prescribe it for them may be sicker than individuals who do not receive the drug. Similarly, people who choose to obtain high levels of education may be different from others in ways that affect future earnings.

This problem has been recognized since at least the time of R.A. Fisher. In principle, it can be overcome by assigning individuals randomly to treatment and control groups. One can then estimate the average effect of treatment by the difference between the average outcomes of treated and untreated individuals. This random assignment procedure has become something of a gold standard in the treatment effects literature. Clinical trials use random assignment, and there have been important economic and social experiments based on this procedure. But there are also serious practical problems. First, random assignment may not be possible. For example, one cannot assign high-school students randomly to receive a university education or not. Second, even if random assignment is possible, post-randomization events may disrupt the effects of randomization. For example, individuals may drop out of the experiment or take treatments other than the one to which they are assigned. Both of these things may happen for reasons that are related to the outcome of interest. For example, very ill members of a control group may figure out that they are not receiving treatment and find a way to obtain the drug being tested. In addition, real-world programs may not operate the way that experimental ones do, so real-world outcomes may not mimic those found in an experiment, even if nothing has disrupted the randomization.

Much research in econometrics, statistics, and biostatistics has been aimed at developing methods for inferring treatment effects when randomization is not possible or is disrupted by post-randomization events. In econometrics, this research dates back at least to Gronau (1974) and Heckman (1974). The fundamental problem is to identify the effects of treatment or, in less formal terms, to separate the effects of treatment from those of other sources of differences between the treated and untreated groups. Manski (1995), among many others, discusses this problem. Large literatures in statistics, biostatistics, and econometrics are concerned with developing identifying assumptions that are reasonable in applied settings. However, identifying assumptions are not testable empirically and can be controversial. One widely accepted way of dealing with this problem is to conduct a sensitivity analysis in which the sensitivity of the estimated treatment effect to alternative identifying assumptions is assessed. Another possibility is to forego controversial identifying assumptions and to find the entire set of outcomes that are consistent with the joint distribution of the observed variables. This approach, which has been pioneered by Manski and several co-investigators, is discussed in Manski (1995, 2003), among other places. Hotz, Mullin, and Sanders (1997) provide an interesting application of bounding methods to measuring the effects of teen pregnancy on the labor market outcomes of young women.

16 Integration and simulation methods in econometrics

The integration problem is endemic in economic modeling, arising whenever economic agents do not observe random variables and the behavior paradigm is the maximization of expected utility. The econometrician inherits this problem in the expression of the corresponding econometric model, even before taking up inference and estimation. The issue is most familiar in dynamic optimization contexts, where it can be addressed by a variety of methods. Taylor and Uhlig (1990) present a comprehensive review of these methods, and for later innovations see Keane and Wolpin (1994), Rust (1997) and Santos and Vigo-Aguiar (1998).

In econometrics the problem is more pervasive than in economic modeling, because it arises, in addition, whenever economic agents observe random variables that the econometrician does not. For example, the economic agent may form expectations conditional on an information set not entirely accessible to the econometrician, such as personal characteristics or confidential information. Another example arises in discrete choice settings, where utilities of alternatives are never observed and the prices of alternatives often are not. In these situations the economic model provides a probability distribution of outcomes conditional on three classes of objects: observed variables, available to the econometrician; latent variables, unobserved by the econometrician; and parameters or functions describing the preferences and decision-making environment of the economic agent. The econometrician typically seeks to learn about the parameters or functions given the observed variables.

There are several ways of dealing with this task. Two approaches that are closely related and widely used in the econometrics literature generate integration problems. The first is to maintain a distribution of the latent variables conditional on observed variables, the parameters in the model, and additional parameters required for completing this distribution. (This is the approach taken in maximum likelihood and Bayesian inference.) Combined with the model, this leads to the joint distribution of outcomes and latent variables conditional on observed variables and parameters. Since the marginal distribution of outcomes is the one relevant for the econometrician in this conditional distribution, there is an integration problem for the latent variables. The second approach is weaker: it restricts to zero the values of certain population moments involving the latent and observable variables. (This is the approach taken in generalized method of moments, which can be implemented with both parametric and nonparametric methods.) These moments depend upon the parameters (which is why the method works) and the econometrician must therefore be able to evaluate the moments for any given set of parameter values. This again requires integration over the latent variables.

Ideally, this integral would be evaluated analytically. Often – indeed, typically – this is not possible. The alternative is to use numerical methods. Some of these are deterministic, but the rapid growth in the solution of these problems since (roughly) 1990 has been driven more by simulation methods employing pseudo-random numbers generated by computer hardware and software. This section reviews the most important these methods and describes their its most significant use in non-Bayesian econometrics, simulated method of moments. In Bayesian econometrics the integration problem is inescapable, the structure of the economic model notwithstanding, because parameters are treated explicitly as unobservable random variables. Consequently simulation methods have been central to Bayesian inference in econometrics.

16.1 Deterministic approximation of integrals

The evaluation of an integral is a problem as old as the calculus itself. In well-catalogued but limited instances analytical solutions are available: Gradshteyn and Ryzhik (1965) is a useful classic reference. For integration in one dimension there are several methods of deterministic approximation, including Newton-Coates (Press et al., 1986, Chapter 4, Davis and Rabinowitz, 1984, Chapter 2), and Gaussian quadrature (Golub and Welsch, 1969, Judd, 1998, Section 7.2). Gaussian quadrature approximates a smooth function as the product a polynomial of modest order and a smooth basis function, and then uses iterative refinements to compute the approximation. It is incorporated in most mathematical applications software and is used routinely to approximate integrals in one dimension to many significant figures of accuracy.

Integration in several dimensions by means of deterministic approximation is more difficult. Practical generic adaptations of Gaussian quadrature are limited to situations in which the integrand is approximately the product of functions of single variables (Davis and Rabinowitz,1984, pp. 354-359). Even here the logarithm of computation time is approximately linear in the number of variables, a phenomenon sometimes dubbed "the curse of dimensionality." Successful extensions of quadrature beyond dimensions of four or five are rare, and these extensions typically require substantial analytical work before they can be applied successfully.

Low discrepancy methods provide an alternative generic approach to deterministic approximation of integrals in higher dimensions. The approximation is the average value of the integrand computed over a well-chosen sequence of points whose configuration amounts to a sophisticated lattice. Different sequences lead to variants on the approach, the best known being the Halton (1960) sequence and the Hammersley (1960) sequence. Niederreiter (1992) reviews these and other variants.

A key property of any method of integral approximation, deterministic or nondeterministic, is that it should provide as a byproduct some indicator of the accuracy of the approximation. Deterministic methods typically provide upper bounds on the approximation error, based on worst-case situations. In many situations the actual error is orders of magnitude less than the upper bound, and as a consequence attaining desired error tolerances may appear to be impractical whereas in fact these tolerances can easily be attained. Geweke (1996, Section 2.3) provides an example.

16.2 Simulation approximation of integrals

The structure of integration problems encountered in econometrics makes them often more amenable to attack by simulation methods than by nondeterministic methods. Two characteristics are key. First, integrals in many dimensions are required. In some situations the number is proportional to the size of the sample, and while the structure of the problem may lead to decomposition in terms of many integrals of smaller dimension, the resulting structure and dimension are still unsuitable for deterministic methods. The second characteristic is that the integration problem usually arises as the need to compute the expected value of a function of a random vector with a given probability distribution P:

$$I = \int_S g(\mathbf{x})p(\mathbf{x})d\mathbf{x}, \tag{1}$$

where p is the density corresponding to P, g is the function, $\mathbf{x}$ is the random vector, and I is the number to be approximated. The probability distribution P is then the point of departure for the simulation.

For many distributions there are reliable algorithms, implemented in widely available mathematical applications software, for simulation of random vectors x. This yields a sample $\left\{g\left(\mathbf{x}^{(m)}\right)\right\}$ $(m = 1, \ldots, M)$ whose arithmetic mean provides an approximation of I, and for which a central limit theorem provides an assessment of the accuracy of the approximation in the usual way. (This requires the existence of the first two moments of g, which must be shown analytically.) This approach is most useful when p is simple (so that direct simulation of $\mathbf{x}$ is possible) but the structure of g precludes analytical evaluation of I.

This simple approach does not suffice for the integration problem as it typically arises in econometrics. A leading example is the multinomial probit (MNP) model with J discrete choices. For each individual i the utility of the last choice u_{iJ} is normalized to be zero, and the utilities of the first $J-1$ choices are given by the vector

$$\mathbf{u}_i \sim N(\mathbf{X}_i\boldsymbol{\beta}, \boldsymbol{\Sigma}), \tag{2}$$

where $\mathbf{X}$ is a matrix of characteristics of individual i, including the prices and other properties of the choices presented to that individual, and $\boldsymbol{\beta}$ and $\boldsymbol{\Sigma}$ are structural parameters of the model. If the j'th element of $\mathbf{u}_i$ is positive and larger than all the other elements of $\mathbf{u}_i$ the individual makes choice j, and if all elements of $\mathbf{u}$ are negative the individual makes choice J. The probability that individual i makes choice j is the integral of the $(n-1)$-variate normal distribution (1) taken over the subspace $\{\mathbf{u}_i : u_{ik} \leq u_{ij} \forall k = 1, \ldots, n\}$. This computation is essential in evaluating the likelihood function, and it has no analytical solution. (For discussion and review see Sandor and Andras (2004).)

Several generic simulation methods have been used for the problem (1) in econometrics. One of the oldest is acceptance sampling, a simple variant of which is described in von Neumann (1951) and Hammersley and Handscomb (1964). Suppose it is possible to draw from the distribution Q with density q, and the ratio $p(\mathbf{x})/q(\mathbf{x})$ is bounded above by the known constant a. If $\mathbf{x}$ is simulated successively from Q but accepted and taken into the sample with probability $p(\mathbf{x})/[aq(\mathbf{x})]$, then the resulting sample is independently distributed with the identical distribution P. Proofs and further discussion are widely available, e.g. Press et al. (1992, Section 7.4), Bratley et al. (1987, Section 5.2.5), and Geweke (2005, Section 4.2.1). The unconditional probability of accepting draws from Q is $1/a$. If a is too large the method is impractical, but when acceptance sampling is practical it provides draws directly from P. This is an important component of many of the algorithms underlying the "black box" generation of random variables in mathematical applications software.

Alternatively, in the same situation all of the draws from Q are retained and taken into a stratified sample in which the weight $w\left(\mathbf{x}^{(m)}\right) = p\left(\mathbf{x}^{(m)}\right)/q\left(\mathbf{x}^{(m)}\right)$is associated with the m'th draw. The approximation of I in (1) is then the weighted average of the terms $g\left(\mathbf{x}^{(m)}\right)$. This approach dates at least to Hammersley and Handscomb (1964, Section 5.4), and was introduced to econometrics by Kloek and van Dijk (1978). The procedure is more general than acceptance sampling in that a known upper bound of w is not required, but if in fact a is large then the weights will display large variation and the approximation will be poor. This is clear in the central limit theorem for the accuracy of approximation provided in Geweke (1989a), which as a practical matter requires that a finite upper bound on w be established analytically. This is a key limitation of acceptance sampling and importance sampling.

Markov chain Monte Carlo (MCMC) methods provide an entirely different approach to the solution of the integration problem (1). These procedures construct a Markov process of the form

$$\mathbf{x}^{(m)} \sim p\left(\mathbf{x}|\mathbf{x}^{(m-1)}\right) \tag{3}$$

in such a way that

$$M^{-1}\textstyle\sum_{m=1}^{M} g(x^{(m)})$$

converges (almost surely) to I. These methods have a history in mathematical physics dating back to the algorithm of Metropolis et al. (1953). Hastings (1970) focused on statistical problems and extended the method to its present form known as the Hastings-Metropolis (HM) algorithm. HM draws a candidate $\mathbf{x}^*$ from a convenient distribution indexed by $\mathbf{x}^{(m-1)}$. It sets $\mathbf{x}^{(m)} = \mathbf{x}$ with probability $\alpha\left(\mathbf{x}^{(m-1)}, \mathbf{x}^{(m)}\right)$ and sets $\mathbf{x}^{(m)} = \mathbf{x}^{(m)-1}$ otherwise, the function α being chosen so that the process (3) defined in this way has the desired convergence property. Chib and Greenberg (1995) provide a detailed introduction to HM and its application in econometrics. Tierney (1994) provides a succinct summary of the relevant continuous state space Markov chain theory bearing on the convergence of MCMC.

A version of the HM algorithm particularly suited to image reconstruction and problems in spatial statistics, known as the Gibbs sampling (GS) algorithm, was introduced by Geman and Geman (1984). This was subsequently shown to have great potential for Bayesian computation by Gelfand and Smith (1990). In GS the vector $\mathbf{x}$ is subdivided into component vectors, $\mathbf{x}' = (\mathbf{x}_1', ..., \mathbf{x}_B')$, in such a way that simulation from the conditional distribution of each $\mathbf{x}_j$ implied by $p(\mathbf{x})$ in (1) is feasible. This method has proven very advantageous in econometrics generally, and it revolutionized Bayesian approaches in particular beginning about 1990.

By the turn of the century HM and GS algorithms were standard tools for likelihood-based econometrics. Their structure and strategic importance for Bayesian econometrics were conveyed in surveys by Geweke (1999) and Chib (2001), as well as in a number of textbooks, including Koop (2003), Lancaster (2004), Geweke (2005) and Rossi et al. (2005). Central limit theorems can be used to assess the quality of approximations as described in Tierney (1994) and Geweke (2005).

16.3 Simulation Methods in non-Bayesian Econometrics

Generalized method of moments estimation has been a staple of non-Bayesian econometrics since its introduction by Hansen (1982). In an econometric model with $k \times 1$ parameter vector $\boldsymbol{\theta}$ economic theory provides the set of sample moment restrictions

$$\mathbf{h}(\boldsymbol{\theta}) = \int_S \mathbf{g}(\mathbf{x}) p(\mathbf{x}|\boldsymbol{\theta}, \mathbf{y}) d\mathbf{x} = \mathbf{0}, \tag{4}$$

where $\mathbf{g}(\mathbf{x})$ is a $p \times 1$ vector and $\mathbf{y}$ denotes the data including instrumental variables. An example is the MNP model (2). If the observed choices are coded by the variables $d_{ij} = 1$ if individual i makes choice j and $d_{ij} = 0$ otherwise, then the expected value of d_{ij} is the probability that individual i makes choice j, leading to restrictions of the form (4).

The generalized method of moments estimator minimizes the criterion function $\mathbf{h}(\boldsymbol{\theta})'\mathbf{W}\mathbf{h}(\boldsymbol{\theta})$ given a suitably chosen weighting matrix $\mathbf{W}$. If the requisite integrals can be evaluated analytically, $p \geq k$, and other conditions provided in Hansen (1982) are satisfied, then there is a well-developed asymptotic theory of inference for the parameters that by 1990 was a staple of graduate econometrics textbooks. If for one or more elements of $\mathbf{h}$ the integral cannot be evaluated analytically, then for alternative values of it is often possible to approximate the integral appearing in (4) by simulation. This is the situation in the MNP model.

The substitution of a simulation approximation

$$M^{-1} \textstyle\sum_{m=1}^{M} \mathbf{g}(\mathbf{x}^{(m)})$$

for the integral in (4) defines the method of simulated moments (MSM) introduced by McFadden (1989) and Pakes and Pollard (1989), who were concerned with the MNP model (2) in particular and the estimation of discrete response models using cross-section data in general. Later the method was extended to time series models by Lee and Ingram (1991) and Duffie and Singleton (1993). The asymptotic distribution theory established in this literature requires that the number of simulations M increase at least as rapidly as the square of the number of observations. The practical import of this apparently severe requirement is that applied econometric work must establish that changes in M must have little impact on the results; Geweke, Keane and Runkle (1994, 1997) provide examples for MNP. This literature also shows that in general the impact of using direct simulation, as opposed to analytical evaluation of the integral, is to increase the asymptotic variance of the GMM estimator of θ by the factor , M^{-1} typically trivial in view of the number of simulations required. Substantial surveys of the details of MSM and leading applications of the method can be found in Gourieroux and Monfort (1993, 1996), Stern (1997) and Liesenfeld and Breitung (1999).

The simulation approximation, unlike the (unavailable) analytical evaluation of the integral in (4) can lead to a criterion function that is discontinuous in $\boldsymbol{\theta}$. This happens in the MNP model using the obvious simulation scheme in which the choice probabilities are replaced by their proportions in the M simulations, as proposed by Lerman and Manski (1981). The asymptotic theory developed by McFadden (1989) and Pakes and Pollard (1989) copes with this possibility, and led McFadden (1989) to used kernel weighting to smooth the probabilities. The most widely used method for smoothing probabilities in the MNP model is the GHK simulator of Geweke (1989b), Hajivassiliou et al. (1991) and Keane (1990); a full description is provided in Geweke and Keane (2001), and comparisons of alternative methods are given in Hajivassiliou et al. (1996) and Sandor and Andras (2004).

Maximum likelihood estimation of $\boldsymbol{\theta}$ can lead to first-order conditions of the form (4), and thus becomes a special case of MSM. This context highlights some of the complications introduced by simulation. While the simulation approximation of (1) is unbiased the corresponding expression enters the log likelihood function and its derivatives non-linearly. Thus for any finite number of simulations M, the evaluation of the first order conditions is biased in general. Increasing M at a rate faster than the square of the number of observations eliminates the squared bias relative to the variance of the estimator; Lee (1995) provides further details.

16.4 Simulation Methods in Bayesian Econometrics

Bayesian econometrics places a common probability distribution on random variables that can be observed (data) and unobservable parameters and latent variables. Inference proceeds using the distribution of these unobservable entities conditional on the data – the posterior distribution. Results are typically expressed in terms of the expectations of parameters or functions of parameters, expectations taken with respect to the posterior distribution. Thus whereas integration problems are application-specific in non-Bayesian econometrics, they are endemic in Bayesian econometrics.

The development of modern simulation methods had a correspondingly greater impact in Bayesian than in non-Bayesian econometrics. Since 1990 simulation-based Bayesian methods have become practical in the context of most econometric models. The availability of this tool has been influential in the modeling approach taken in addressing applied econometric problems.

The MNP model (2) illustrates the interaction in latent variable models. Given a sample of n individuals, the $(J-1)\times 1$ latent utility vectors $\mathbf{u}_1, ..., \mathbf{u}_n$ are regarded explicitly as $n(J-1)$ unknowns to be inferred along with the unknown parameters $\boldsymbol{\beta}$ and $\boldsymbol{\Sigma}$. Conditional on these parameters and the data, the vectors $\mathbf{u}_1, ..., \mathbf{u}_n$ are independently distributed. The distribution of $\mathbf{u}_i$ is (2) truncated to an orthant that depends on the observed choice j : if $j < J$ then $u_{ik} < u_{ij}$ for all $k \neq j$ and $u_{ij} > 0$, whereas for choice J, $u_{ik} < 0$ for all k. The distribution of each u_{ik}, conditional on all of the other elements of $\mathbf{u}_i$, is truncated univariate normal, and it is relatively straightforward to simulate from this distribution. (Geweke (1991) provides details on sampling from a multivariate normal distribution subject to linear restrictions.) Consequently GS provides a practical algorithm for drawing from the distribution of the latent utility vectors conditional on the parameters.

Conditional on the latent utility vectors – that is, regarding them as observed – the MNP model is a seemingly unrelated regressions model and the approach taken by Percy (1992) applies. Given conjugate priors the posterior distribution of $\boldsymbol{\beta}$, conditional on $\boldsymbol{\Sigma}$ and utilities, is Gaussian, and the conditional distribution of $\boldsymbol{\Sigma}$, conditional on $\boldsymbol{\beta}$ and utilities, is inverted Wishart. Since GS provides the joint distribution of parameters and latent utilities, the posterior mean of any function of these can be approximated as the sample mean. This approach and the suitability of GS for latent variable models were first recognized by Chib (1992). Similar approaches in other latent variable models in include McCulloch and Tsay (1994), Chib and Greenberg (1998), McCulloch, Polson and Rossi (2000) and Geweke and Keane (2001).

The Bayesian approach with GS sidesteps the evaluation of the likelihood function, and of any moments in which the approximation is biased given a finite number of simulations, two technical issues that are prominent in MSM. On the other hand, as in all MCMC algorithms, there may be sensitivity to the initial values of parameters and latent variables in the Markov chain, and substantial serial correlation in the chain will reduce the accuracy of the simulation approximation. Geweke (1992, 2005) and Tierney (1994) discuss these issues.

17 Financial Econometrics

Attempts at testing of the efficient market hypothesis (EMH) provided the impetus for the application of time series econometric methods in finance. The EMH was built on the pioneering work of Bachelier (1900) and evolved in the 1960's from the random walk theory of asset prices advanced by Samuelson (1965). By the early 1970's a consensus had emerged among financial economists suggesting that stock prices could be well approximated by a random walk model and that changes in stock returns were basically unpredictable. Fama (1970) provides an early, definitive statement of this position. He distinguished between different forms of the EMH: The "Weak" form that asserts all price information is fully reflected in asset prices; the "Semi-strong" form that requires asset price changes to fully reflect all publicly available information and not only past prices; and the "Strong" form that postulates that prices fully reflect information even if some investor or group of investors have monopolistic access to some information. Fama regarded the strong form version of the EMH as a benchmark against which the other forms of market efficiencies are to be judged. With respect to the weak form version he concluded that the test results strongly support the hypothesis, and considered the various departures documented as economically unimportant. He reached a similar conclusion with respect to the semi-strong version of the hypothesis. Evidence on the semi-strong form of the EMH was revisited by Fama (1991). By then it was clear that the distinction between the weak and the semi-strong forms of the EMH was redundant. The random walk model could not be maintained either - in view of more recent studies, in particular that of Lo and MacKinlay (1988).

This observation led to a series of empirical studies of stock return predictability over different horizons. It was shown that stock returns can be predicted to some degree by means of interest rates, dividend yields and a variety of macroeconomic variables exhibiting clear business cycle variations. See, for example, Fama and French (1989), Kandel and Stambaugh (1996), and Pesaran and Timmermann (1995) on predictability of equity returns in the US; and Clare, Thomas and Wickens (1994), and Pesaran and Timmermann (2000) on equity return predictability in the UK.

Although, it is now generally acknowledged that stock returns could be predictable, there are serious difficulties in interpreting the outcomes of market efficiency tests. Predictability could be due to a number of different factors such as incomplete learning, expectations heterogeniety, time variations in risk premia, tranaction costs, or specification searches often carried out in pursuit of predictability. In general, it is not possible to distinquish between the different factors that might lie behind observed predictability of asset returns. As noted by Fama (1991) the test of the EMH involves a joint hypothesis, and can be tested only jointly with an assumed model of market equilibrium. This is not, however, a problem that is unique to financial econometrics; almost all areas of empirical economics are subject to the joint hypotheses problem. The concept of market efficiency is still deemed to be useful as it provides a benchmark and its use in finance has led to significant insights.

Important advances have been made in the development of equilibrium asset pricing models, econometric modelling of asset return volatility (Engle, 1982, Bollerslev, 1986), analysis of high frequency intraday data, and market microstructures. Some of these developments are reviewed in Campbell, Lo and MacKinlay (1997), Cochrane (2005), Shephard (2005), and McAleer and Medeiros (2006). Future advances in financial econometrics are likely to focus on heterogenity, learning and model uncertainty, real time analysis, and further integration with macroeconometrics. Finance is particularly suited to the application of techniques developed for real time econometrics. (Pesaran and Timmermann, 2005a).

18 Appraisals and Future Prospects

has come a long way over a relatively short period. Important advances have been made in the compilation of economic data and in the development of concepts, theories and tools for the construction and evaluation of a wide variety of econometric models. Applications of econometric methods can be found in almost every field of economics. Econometric models have been used extensively by government agencies, international organizations and commercial enterprises. Macroeconometric models of differing complexity and size have been constructed for almost every country in the world. Both in theory and practice econometrics has already gone well beyond what its founders envisaged. Time and experience, however, have brought out a number of difficulties that were not apparent at the start.

Econometrics emerged in the 1930s and 1940s in a climate of optimism, in the belief that economic theory could be relied on to identify most, if not all, of the important factors involved in modelling economic reality, and that methods of classical statistical inference could be adapted readily for the purpose of giving empirical content to the received economic theory. This early view of the interaction of theory and measurement in econometrics, however, proved rather illusory. Economic theory is invariably formulated with *ceteris paribus* clauses, and involves unobservable latent variables and general functional forms; it has little to say about adjustment processes, lag lengths and other factors mediating the relationship between the theoretical specification (even if correct) and observables. Even in the choice of variables to be included in econometric relations, the role of economic theory is far more limited than was at first recognized. In a Walrasian general equilibrium model, for example, where everything depends on everything else, there is very little scope for *a priori* exclusion of variables from equations in an econometric model. There are also institutional features and accounting conventions that have to be allowed for in econometric models but which are either ignored or are only partially dealt with at the theoretical level. All this means that the specification of econometric models inevitably involves important auxiliary assumptions about functional forms, dynamic specifications, latent variables, etc. with respect to which economic theory is silent or gives only an incomplete guide.

The recognition that economic theory on its own cannot be expected to provide a complete model specification has important consequences for testing and evaluation of economic theories, for forecasting and real time decision making. The incompleteness of economic theories makes the task of testing them a formidable undertaking. In general it will not be possible to say whether the results of the statistical tests have a bearing on the economic theory or the auxiliary assumptions. This ambiguity in testing theories, known as the Duhem-Quine thesis, is not confined to econometrics and arises whenever theories are conjunctions of hypotheses (on this, see for example Cross, 1982). The problem is, however, especially serious in econometrics because theory is far less developed in economics than it is in the natural sciences. There are, of course, other difficulties that surround the use of econometric methods for the purpose of testing economic theories. As a rule economic statistics are not the results of designed experiments, but are obtained as by-products of business and government activities often with legal rather than economic considerations in mind. The statistical methods available are generally suitable for large samples while the economic data typically have a rather limited coverage. There are also problems of aggregation over time, commodities and individuals that further complicate the testing of economic theories that are micro-based.

Econometric theory and practice seek to provide information required for informed decision-making in public and private economic policy. This process is limited not only by the adequacy of econometrics, but also by the development of economic theory and the adequacy of data and other information. Effective progress, in the future as in the past, will come from simultaneous improvements in econometrics, economic theory, and data. Research that specifically addresses the effectiveness of the interface between any two of these three in improving policy – to say nothing of all of them – necessarily transcends traditional subdisciplinary boundaries within economics. But it is precisely these combinations that hold the greatest promise for the social contribution of academic economics.

References

[1] Aitken, A. C., 1934–5. On least squares and linear combinations of observations. Proceedings of the Royal Society of Edinbungh, 55, 42–8.

[2] Albrecht, J. W. and B. Axell, 1984. An equilibrium model of search unemployment. Journal of Political Economy, 92, 824-840.

[3] Allen, R. G. D. and A. L. Bowley, 1935. Family Expenditure. London: P.S. King.

[4] Almon, S., 1965. The distributed lag between capital appropriations and net expenditures. Econometrica, 33, 178–96.

[5] Amemiya, T., 1983. Nonlinear regression models. In Handbook of Econometrics, ed. Z. Griliches and M.D. Intriligator, Vol. 1, Amsterdam: North-Holland.

[6] Amemiya, T., 1984. Tobit models: a survey. Journal of Econometrics, 24, 3–61.

[7] An, S. and F. Schorfheide, 2006. Bayesian analysis of DSGE models, forthcoming in Econometric Reviews.

[8] Anderson, T.W. and C. Hsiao, 1981, Estimation of Dynamic Models with Error Components, Journal of the American Statistical Society, 76, 598-606.

[9] Anderson, T.W. and C. Hsiao, 1982, Formulation and Estimation of Dynamic Models Using Panel Data, Journal of Econometrics, 18, 47-82.

[10] Anderson, T.W. and H. Rubin, 1949. Estimation of the parameters of a single equation in a complete system of stochastic equations. Annals of Mathematical Statistics, 20, 46–63.

[11] Andrews, D. W. K., 1993. Tests for parameter instability and structural change with unknown change point. Econometrica, 61, 821-856.

[12] Andrews, D. W. K. and W. Ploberger, 1994. Optimal tests when a nuisance parameter is present only under the alternative. Econometrica, 62, 1383-1414.

[13] Anselin, L., (1988). Spatial Econometrics: Methods and Models, Boston: Kluwer Academic Publishers.

[14] Anselin, L., Le Gallo, J. and Jayet, H., (2006). Spatial panel econometrics. In Matyas, L. and Sevestre, P. (Eds.), The Econometrics of Panel Data, Fundamentals and Recent Developments in Theory and Practice, (3rd Edition), Dordrecht, Kluwer, forthcoming.

[15] Arellano, M., 2003. Panel Data Econometrics, Oxford University Press, Oxford.

[16] Arellano, M., and S.R. Bond, 1991. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations, Review of Economic Studies, 58, 277-297.

[17] Arellano, M., and B. Honoré, 2001. "Panel Data Models: Some Recent Developments", Chapter 53 in J.J. Heckman and E. Leamer (eds.), Handbook of Econometrics, Vol. V., Amsterdam: North-Holland, 3229-3296.

[18] Bachelier, L. J. B. A., 1900. Théorie de la Speculation, Paris: Gauthier-Villars. Reprinted in Paul H. Cootner (ed.), The Random Character of Stock Market Prices, Cambridge, M.I.T. press, 1964. pp 17-78.

[19] Bai, J. and S. Ng (2004), A Panic Attack on Unit Roots and Cointegration, Econometrica, 72, 1127–1177.

[20] Bai, J. and P. Perron, 1998. Estimating and testing linear models with multiple structural changes. Econometrica, 66, 47-78.

[21] Baltagi, B., 2005. Econometric Analysis of Panel Data, Second Edition, Wiley College Textbooks, New York.

[22] Baltagi, B.H. and C. Kao (2000), Nonstationary Panels, Cointegration in Panels and Dynamic Panels, A Survey, in: B. Baltagi (ed.), Nonstationary Panels, Panel Cointegration, and Dynamic Panels, Advances in Econometrics, Vol. 15, Amsterdam: JAI Press, 7–52.

[23] Banerjee, A., 1999. Panel data unit roots and cointegration: an overview, Oxford Bulletin of Economics and Statistics, 61, 607–629.

[24] Basmann, R. L., 1957. A generalized classical method of linear estimation of coefficients in a structural equation. Econometrica, 25, 77–83.

[25] Bauwens, L., M. Lubrano and J.F. Richard. Bayesian Inference in Dynamic Econometric Models, Oxford University Press, Oxford.

[26] Benini, R., 1907. Sull'uso delle formole empiriche a nell'economia applicata. Giornale degli economisti, 2nd series, 35, 1053–63.

[27] Berry, S. and E. Tamer, 2005. Identification in models of oligopoly entry. Paper presented at the 9th World Congress of the Econometric Society, London, Aug. 2005. Forthcoming in Advances in Economics and Econometrics: 9th World Congress, Blundell, R., W.K. Newey, and T. Persson, eds.

[28] Beveridge, S. and C. R. Nelson, 1981. A new approach to the decomposition of economic time series into permanent and transitory components with particular attention to measurement of the "business cycle". Journal of Monetary Economics, 7, 151-174.

[29] Binder, M. and M. H. Pesaran, 1995. Multivariate rational expectations models and macroeconometric modelling: A review and some new results. In Handbook of Applied Econometrics Volume 1 - Macroeconomics, M. H. Pesaran and M. R. Wickens (eds), 139-187. Basil Blackwell, Oxford.

[30] Binder, M., C. Hsiao, and M. H. Pesaran, 2005. Estimation and inference in short panel vector autoregressions with unit roots and cointegration, Econometric Theory, 21, 795-837.

[31] Bjerkholt, O., 1995. Ragnar Frisch, Editor of Econometrica, Econometrica, 63, 755-765.

[32] Blanchard, O. J. and D. Quah, 1989. The dynamic effects of aggregate demand and supply disturbances. American Economic Review, 79, 1146-1164.

[33] Blundell, R. W., M. Browning and I. A. Crawford, 2003. Nonparametric engel curves and revealed preference. Econometrica, 71, 205-240.

[34] Bollerslev, T., 1986. Generalised autoregressive conditional heteroskedasticity. Journal of Econometrics, 51, 307-327.

[35] Boskin, M. J., 1974. A conditional logit model of occupational choice. Journal of Political Economy, 82, 389–98.

[36] Bosq, D. 1996. Nonparametric Statistics for Stochastic Processes. New York: Springer.

[37] Bowlus, A. J., N. M. Kiefer and G. R. Neumann, 2001. Equilibrium search models and the transition from school to work. International Economic Review, 42, 317-343.

[38] Box, G. E. P. and G. M. Jenkins, 1970. Time Series Analysis: Forecasting and Control. San Francisco: Holden-Day.

[39] Bratley, P., B. L. Fox and L. E. Schrage, 1987. A Guide to Simulation. New York: Springer-Verlag.

[40] Breusch, T. S. and A. R. Pagan, 1980. The Lagrange multiplier test and its applications to model specification in econometrics. Review of Economic Studies, 47, 239–53.

[41] Breitung, J. and M.H. Pesaran, 2006. Unit roots and cointegration in panels, in Matyas, L. and Sevestre, P. (eds.), The Econometrics of Panel Data, Fundamentals and Recent Developments in Theory and Practice, (3rd Edition), Dordrecht, Kluwer, forthcoming.

[42] Brock, W., and S. Durlauf, 2002. A multinomial choice model with neighborhood effects, American Economic Review, 92, 298-303.

[43] Brock, W., and S. Durlauf, 2006. Macroeconomics and model uncertainty, in Post-Walrasian Macroeconomics: Beyond the Dynamic Stochastic General Equilibrium Model, D. Colander, (ed.), Cambridge University Press, New York.

[44] Broze, L., C. Gouriéroux, and A. Szafarz, 1985. Solutions of Dynamic Linear Rational Expectations Models, Econometric Theory, 1, 341 - 368.

[45] Brown, R.L., J. Durbin and J.M. Evans, 1975. Techniques for testing the constancy of regression relationships over time (with discussion). Journal of the Royal Statistical Society B, 37, 149-192.

[46] Brown, T. M., 1952. Habit persistence and lags in consumer behaviour. Econometrica, 20, 355–71.

[47] Brundy, J. M. and D. N. Jorgenson, 1971. Efficient estimation of simultaneous equations by instrumental variables. Review of Economics and Statistics, 53, 207–24.

[48] Buckley, J. and I. James, 1979. Linear regression with censored data. Biometrika, 66, 429-436.

[49] Burdett, K. and D. T. Mortensen, 1998. Wage differentials, employer size, and unemployment. International Economic Review, 39, 257-273.

[50] Burns, A. F. and W. C. Mitchell, 1947. Measuring Business Cycles. New York: Columbia University Press for the National Bureau of Economic Research.

[51] Burtless, G. 1995. The case for randomized field trials in economic and policy research, Journal of Economic Perspective, 9, 63-84.

[52] Cagan, P., 1956. The monetary dynamics of hyperinflation. In Studies in the Quantity Theory of Money, ed. M. Friedman, Chicago: University of Chicago Press.

[53] Cameron, A. C. and P. K. Trivedi, 1986. Econometric models based on count data: comparisons and applications of some estimators and tests. Journal of Applied Econometrics, 1, 29–53.

[54] Cameron, A. C. and P. K. Trivedi, 1998. Regression Analysis for Count Data, Econometric Society Monograph No. 30, Cambridge University Press, Cambridge.

[55] Cameron, A. C. and P. K. Trivedi, 2005. Microeconometrics: Methods and Applications, Cambridge University Press, Cambridge.

[56] Campbell, J. Y., A. W. Lo and A. C. MacKinlay, 1997. The Econometrics of Financial Markets, Princeton University Press, New Jersey.

[57] Canova, F. and G. de Nicolo, 2002. Monetary disturbances matter for business fluctuations in the G7", Journal of Monetary Economics, 49, 1131-1159.

[58] Champernowne, D. G., 1960. An experimental investigation of the robustness of certain procedures for estimating means and regressions coefficients. Journal of the Royal Statistical Society, 123, 398-412.

[59] Chib, S., 1992. Bayes inference in the tobit censored regression model. Journal of Econometrics, 51, 79-99.

[60] Chib, S., 2001. Markov chain Monte Carlo methods: Computation and inference. In Handbook of Econometrics, J. J. Heckman and E. Leamer, eds. Vol. 5, 3569-3649. Amsterdam: Elsevier Science.

[61] Chib, S. and E. Greenberg, 1995. Understanding the Metropolis-Hastings algorithm. The American Statistician, 49, 327-335.

[62] Chib, S. and E. Greenberg, 1998. Analysis of multivariate probit models. Biometrika, 85, 347-361.

[63] Choi, I. (2006), Nonstationary Panels, Chapter 13 in T.C. Mills and K. Patterson (eds.), Palgrave Handbooks of Econometrics, Volume 1, pp. 511-539, Palgrave, Macmillan.

[64] Chow, G.C. 1960. Tests of equality between sets of coefficients in two linear regressions. Econometrica, 28, 591-605.

[65] Christiano, L.J. , M. Eichenbaum, and C. Evans, 2005. Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy, Journal of Political Economy, 113, 1-45.

[66] Clare, A.D., Thomas, S.H., and M.R. Wickens, 1994. Is the gilt- equity yield ratio useful for predicting UK stock return?, The Economic Journal, 104, 303-15.

[67] Clements, M. P. and D. F. Hendry, 1998. Forecasting economic time series: The marshall lectures on economic forecasting. Cambridge University Press, Cambridge.

[68] Clements, M. P. and D. F. Hendry, 1999. Forecasting non-stationary economic time series. MIT Press, Cambridge, MA.

[69] Clements, M. P. and D. F. Hendry, 2006. Forecasting with breaks, Chapter 12 in Elliott, Granger and Timmermann (2006).

[70] Cochrane, J., 2005. Asset Pricing, (revised Edition), Princeton University Press, Princeton.

[71] Cochrane, P. and G. H. Orcutt, 1949. Application of least squares regression to relationships containing autocorrelated error terms. Journal of the American Statistical Association, 44, 32–61.

[72] Conley, T.G. and Dupor, B., (2003). A spatial analysis of sectoral complementarity. Journal of Political Economy, 111, 311-352.

[73] Conley, T.G. and Topa, G., (2002). Socio-economic distance and spatial patterns in unemployment. Journal of Applied Econometrics, 17, 303 - 327.

[74] Cooper, R. L., 1972. The predictive performance of quarterly econometric models of the United States. In Econometric Models of Cyclical Behavior, ed. B.G. Hickman, Studies in Income and Wealth, 36, Vol. 2, 813–925.

[75] Cosslett, S. R., 1983. Distribution free maximum likelihood estimation of the binary choice model. Econometrica, 51, 765-782.

[76] Cox, D. R., 1961. Tests of separate families of hypotheses. Proceedings of the Fourth Berkeley Symposium on Mathematical Statistics and Probability, Vol. 1, Berkeley: University of California Press, 105–23.

[77] Cox, D. R., 1962. Further results of tests of separate families of hypotheses. Journal of the Royal Statistical Society, Series B, 24, 406–24.

[78] Cox, D. R., 1972. Regression models and life tables. Journal of the Royal Statistical Society, Series B, 34, 187-220.

[79] Cross, R., 1982. The Duhem-Quine thesis, Lakatos and the appraisal of theories in macroeconomics. Economic Journal, 92, 320–40.

[80] Davenant, C., 1698. Discourses on the Publick Revenues and on the Trade of England, Vol. 1. London.

[81] Davidson, R. and J. G. MacKinnon, 2004. Econometric Theory and Methods, Oxford University Press.

[82] Davis, P. J. and P. Rabinowitz, 1984. Methods of Numerical Integration. Orlando: Academic Press.

[83] Deaton, A., 1985. "Panel data from time series of cross-sections, Journal of Econometrics, 30, 109–126.

[84] Del Negro, M. and F. Schorfheide, 2004. Priors from equilibrium models for VAR's. International Economic Review, 45, 643-673.

[85] Del Negro, M., F. Schorfheide, F. Smets and R. Wouters, 2005. On the fit and forecasting performance of new Keynesian models. European Central Bank Working Paper, No. 491.

[86] Dhrymes, P., 1971. A simplified estimator for large-scale econometric models. Australian Journal of Statistics, 13, 168–75.

[87] Doan, T., R. Litterman and C. A. Sims, 1984. Forecasting and conditional projections using realistic prior distributions. Econometric Reviews, 3, 1–100.

[88] Domenich, T. and D. McFadden, 1975. Urban Travel Demand: A Behavioral Analysis. Amsterdam: North-Holland.

[89] Duffie, D. and K. Singleton, 1993. Simulated moments estimation of Markov models of asset prices. Econometrica, 61, 929-952.

[90] Duncan, G., 1980. Formulation and statistical analysis of the mixed continuous/discrete variable model in classical production theory. Econometrica, 48, 839–52.

[91] Durbin, J. 1954., Errors in Variables, Review of the International Statistical Institute, 22, 23-32.

[92] Durbin, J. and G. S. Watson, 1950. Testing for serial correlation in least squares regression I. Biometrika, 37, 409–28.

[93] Durbin, J. and G. S. Watson, 1951. Testing for serial correlation in least squares regression II. Biometrika, 38, 159–78.

[94] Durlauf, S. N., Johnson, P. A., and Temple, J. R. W., 2005. Growth econometrics. In P. Aghion and S. N. Durlauf (eds.) Handbook of Economic Growth, Volume 1A, North-Holland: Amsterdam, 2005, pp. 555-677.

[95] Efron, B., 1979. Bootstrap methods: another look at the jackknife. Annals of Statistics, 7, 1-26.

[96] Eisner, R. and R. H. Strotz, 1963. Determinants of business investment. In Commission on Money and Credit, Impacts of Monetary Policy, Englewood Cliffs, NJ: Prentice-Hall, 59–337.

[97] Elliott, G., C.W.J. Granger, and A.Timmermann, 2006. Handbook of Economic Forecasting, Volume 1, Elsevier Science, North-Holland, Amsterdam.

[98] Engle, R.F., 1982. Autoregressive conditional heteroscedasticity, with estimates of the variance of United Kingdom inflation. Econometrica, 50, 987-1007.

[99] Engle, R. F., 1984. Wald likelihood ratio and lagrange multiplier tests in econometrics. In Handbook of Econometrics, Vol. 2, ed. Z. Griliches and M. D. Intriligator, Amsterdam: North-Holland.

[100] Engle, R. F., D. F. Hendry and J.-F. Richard, 1983. Exogeneity. Econometrica, 51, 277–304.

[101] Engle, R. F. and G. Granger, 1987. Cointegration and error-correction: Representation, estimation and testing. Econometrica, 55, 251-276.

[102] Fachin, S., 2006. Long-run trends in internal migrations in italy: a study in panel cointegration with dependent units, forthcoming in Journal of Applied Econometrics.

[103] Fama, E.F., 1970. Efficient capital markets: a review of theory and empirical work". The Journal of Finance, 25, 383-417.

[104] Fama, E.F., 1991. Efficient capital markets: II, The Journal of Finance, 46, 1575-1617.

[105] Fama, E.F. and K.R. French, 1989. Business conditions and expected returns on stocks and bonds, Journal of Financial Economics, 25, 23-49

[106] Fan, J. and I. Gijbels, 1996. Local Polynomial Modelling and Its Applications. London: Chapman & Hall.

[107] Fernandez-Villaverde, J. and J. Rubio-Ramirez, 2005. Estimating dynamic equilibrium economies: linear versus nonlinear likelihood. Journal of Applied Econometrics, 20, 891–910.

[108] Fisher, F. M., 1966. The Identification Problem in Econometrics. New York: McGraw-Hill.

[109] Fisher, I., 1930. The Theory of Interest. New York: Macmillan. Reprinted, Philadelphia: Porcupine Press, 1977.

[110] Fisher, I., 1937. Note on a short-cut method for calculating distributed lags. Bulletin de l'Institut International de Statistique, 29, 323–7.

[111] Fisher, R.A., 1928. Statistical Methods for Research Workers, 2nd Edition, Oliver and Boyd, London.

[112] Friedman, M., 1957. A Theory of the Consumption Function. Princeton: Princeton University Press.

[113] Frisch, R., 1933. Pitfalls in the Statistical Construction of Demand and Supply Curves. Leipzig: Hans Buske Verlag.

[114] Frisch, R., 1934. Statistical Confluence Analysis by Means of Complete Regression Systems. Oslo: University Institute of Economics.

[115] Gali, J., 1992. How well does the IS-LM model fit postwar US data. Quarterly Journal of Economics, 107, 709-738.

[116] Garratt, A., K. Lee, M. H. Pesaran and Y. Shin, 2003a. A long run structural macroeconometric model of the UK. Economic Journal, 113, 487, 412-455.

[117] Garratt, A., K. Lee, M. H. Pesaran and Y. Shin, 2003b. Forecast uncertainty in macroeconometric modelling: An application to the UK economy. Journal of the American Statistical Association, 98, 464, 829-838.

[118] Garratt, A., K. Lee, M. H. Pesaran and Y. Shin, 2006. Global and National Macroeconometric Modelling: A Long Run Structural Approach, Oxford University Press, Oxford.

[119] Garratt, A., D. Robertson and S. Wright (2006), "Permanent vs Transitory Components and Economic Fundamentals", Journal of Applied Econometrics.

[120] Geary, R. C., 1949. Studies in relations between economic time series. Journal of the Royal Statistical Society, Series B, 10, 140–58.

[121] Gelfand, A. E. and A. F. M. Smith, 1990. Sampling based approaches to calculating marginal densities. Journal of the American Statistical Association, 85, 398-409.

[122] Geman, S. and D. Geman, 1984. Stochastic relaxation, Gibbs distributions and the Bayesian restoration of images. IEEE Transactions on Pattern Analysis and Machine Intelligence, 6, 721-741.

[123] Geweke, J., 1989a. Bayesian inference in econometric models using Monte Carlo integration. Econometrica, 57, 1317-1340.

[124] Geweke, J., 1989b. Efficient simulation from the multivariate normal distribution subject to linear inequality constraints and the evaluation of constraint probabilities. Discussion paper (Duke University, Durham, NC).

[125] Geweke, J., 1991. Efficient simulation from the multivariate normal and student-t distributions subject to linear constraints. In Computing Science and Statistics: Proceedings of the Twenty-Third Symposium on the Interface, E. M. Keramidas ed. 571-578. Fairfax: Interface Foundation of North America, Inc.

[126] Geweke, J., 1992. Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments. In Bayesian Statistics 4, J. M. Bernardo et al. eds. Oxford: Clarendon Press.

[127] Geweke, J., 1996. Monte Carlo simulation and numerical integration. In Handbook of Computational Economics, H. M. Amman, D. A. Kendrick and J. Rust eds. Chapter 15. Amsterdam: North-Holland.

[128] Geweke, J., 1999. Using simulation methods for Bayesian econometric models: Inference, development and communication (with discussion and rejoinder). Econometric Reviews, 18, 1-126.

[129] Geweke, J., 2005. Contemporary Bayesian Econometrics and Statistics. New York: Wiley.

[130] Geweke, J. and M. Keane, 2001. Computationally intensive methods for integration in econometrics. In Handbook of Econometrics, J. Heckman and E. E. Leamer eds. Volume 5. Amsterdam: North-Holland, 2001, 3463-3568.

[131] Geweke, J., M. Keane and D. Runkle, 1994. Alternative computational approaches to statistical inference in the multinomial probit model. Review of Economics and Statistics, 76, 609–632.

[132] Geweke, J., M. Keane and D. Runkle, 1997. Statistical inference in the multinomial multiperiod probit model. Journal of Econometrics, 80, 125–165.

[133] Geweke, J. and C. Whiteman, 2006. Bayesian forecasting. In Handbook of Economic Forecasting, G. Elliott, C.W.J. Granger and A. Timmermann eds. Chapter 1. Amsterdam: Elsevier.

[134] Godfrey, L. G., 1988. Misspecification Tests in Econometrics: The LM principle and other approaches, Cambridge University Press, Cambridge.

[135] Godfrey, L. G. and M. R. Wickens, 1982. Tests of mis-specification using locally equivalent alternative models. In Evaluation and Reliability of Macro-economic Models, eds. G. C. Chow and P. Corsi, New York: John Wiley.

[136] Golub, G. H. and J. H. Welsch, 1969. Calculation of Gaussian quadrature rules. Mathematics of Computation, 23, 221-230.

[137] Gourieroux, C. and J. Jasiak, 2001. Financial Econometrics: Problems, Models, and Methods. Oxford University Press, Oxford.

[138] Gourieroux, C. and A. Monfort, 1993. Simulation based inference, a survey with special reference to panel data models. Journal of Econometrics, 59, 5-33.

[139] Gourieroux, C. and A. Monfort, 1996. Simulation-Based Econometric Methods. New York: Oxford University Press.

[140] Gradshteyn, I. S. and I. M. Ryzhik, 1965. Tables of Integrals, Series and products. New York: Academic Press.

[141] Granger, C. W. J., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica, 37, 424–38.

[142] Granger, C.W.J. 1986. Developments in the study of co-integrated economic variables", Oxford Bulletin of Economics and Statistics, 48, 213-28.

[143] Granger, C.W.J. and P. Newbold, 1986. Forecasting Economic Time Series. Second Edition, Academic Press, San Diego.

[144] Granger, C.W.J. and P. Newbold, 1974. Spurious regressions in econometrics, Journal of Econometrics, vol. 2, 111-120.

[145] Granger, C.W.J. and M.H. Pesaran, 2000a. A Decision Theoretic Approach to Forecast Evaluation, in (eds) W.S. Chan, W.K. Li and H. Tong , Statistics and Finance: An Interface, Imperial College Press, London.

[146] Granger, C.W.J., and M.H. Pesaran, 2000b. Economic and Statistical Measures of Forecast Accuracy, Journal of Forecasting, 19, 537-560.

[147] Greene, W. H., 2003. Econometric Analysis (fifth Edition), Prentice Hall.

[148] Gronau, R., 1974. Wage comparisons – a selectivity bias. Journal of Political Economy, 82, 1119-1143.

[149] Guerre, E., I. Perrigne, and Q. Vuong, 2000. Optimal nonparametric estimation of first-price auctions, Econometrica, 68, 525-574.

[150] Haavelmo, T., 1943. Statistical testing of business cycle theories. Review of Economics and Statistics, 25, 13–18.

[151] Haavelmo, T., 1944. The probability approach in econometrics. Econometrica, 12, Supplement, 1–118.

[152] Hajivassiliou, V., D. McFadden and P. Ruud, 1991. Simulation of multivariate normal rectangle probabilities: Methods and programs, mimeo.

[153] Hajivassiliou V., D. McFadden and P. Ruud, 1996. Simulation of multivariate normal rectangle probabilities and their derivatives – Theoretical and computational results. Journal of Econometrics, 72, 85-134.

[154] Hall, A.R., 2005. Generalized Method of Moments, Oxford University Press, Oxford.

[155] Halton, J. M., 1960. On the efficiency of evaluating certain quasi-random sequences of points in evaluating multi-dimensional integrals. Numerische Mathematik, 2, 84-90.

[156] Hamilton, J. D., 1994. Time Series Analysis, Princeton University Press.

[157] Hammersley, J. M., 1960. Monte Carlo methods for solving multivariate problems. Annals of the New York Academy of Sciences, 86, 844-874.

[158] Hammersley, J. M. and D. C. Handscomb, 1964. Monte Carlo Methods. London: Methuen.

[159] Hansen, L. P., 1982. Large sample properties of generalized method of moments. Econometrica, 50, 1029–54.

[160] Hansen, L. P. and T. J. Sargent, 1980. Formulating and estimating dynamic linear rational expectations models. Journal of Economic Dynamics and Control, 2, 7–46.

[161] Hansen, L.P. and Sargent, T.J. (2006), Robustness, forthcoming in Princeton University Press, New Jersey.

[162] Hart, B. S. and J. von Neumann, 1942. Tabulation of the probabilities for the ratio of mean square successive difference to the variance. Annals of Mathematical Statistics, 13, 207–14.

[163] Harvey, A., 1989. Forecasting, Structural Time Series Models and Kalman Filter, Cambridge University Press, Cambridge.

[164] Härdle, W., 1990. Applied Nonparametric Estimation, Cambridge: Cambridge University Press.

[165] Härdle, W. and O. Linton, 1994. Applied nonparametric methods, in R.F. Engle and D. McFadden, eds, Handbook of Econometrics, vol. 4, Ch. 38. Amsterdam: Elsevier.

[166] Hastings, W. K., 1970. Monte Carlo sampling methods using Markov chains and their applications. Biometrika, 57, 97-109.

[167] Hausman, J. A., 1978. Specification tests in econometrics. Econometrica, 46, 1251–72.

[168] Hausman, J. A., B. H. Hall and Z. Griliches, 1984. Econometric models for count data with application to the patents - R & D relationship. Econometrica, 52, 909–1038.

[169] Hausman, J.A. and W.K. Newey, 1995. Nonparametric estimation of exact consumers surplus and deadweight loss, Econometrica, 63, 1445-1476.

[170] Hausman, J. A. and D. A. Wise, 1985. Social Experimentation, editors, National Bureau of Economic Research Conference Report, University of Chicago Press, Chicago.

[171] Heckman, J. J., 1974. Shadow prices, market wages, and labor supply. Econometrica, 42, 679-694.

[172] Heckman, J. J. and A. J. Smith, 1995. Assesing the case for social experimentation, Journal of Economic Perspective, 9, 85–110.

[173] Heckman, J. J. and B. Singer, 1984. Econometric duration analysis. Journal of Econometrics, 24, 63–132.

[174] Heckman, J. J. and R. Willis, 1977. A beta-logistic model for the analysis of sequential labour force participation by married women. Journal of Political Economy, 85, 27–58.

[175] Hendricks, K., R. H. Porter, 1988. An empirical study of an auction with asymmetric information. The American Economic Review, 78, 865-883.

[176] Hendry, D. F. and J.-F. Richard, 1982. On the formulation of empirical models in dynamic econometrics. Journal of Econometrics, 20, 3–33.

[177] Holly, S., Pesaran, M.H. and Yamagata, T., (2006). A spatio-temporal model of house prices in the US. mimeo, University of Cambridge.

[178] Holtz-Eakin, D., W.K. Newey, and H.S. Rosen, 1988. Estimating vector autoregressions with panel data, Econometrica, 56, 1371-1395.

[179] Honore, B. and E. Kyriazidou, 2000. Panel data discrete choice models with lagged dependent variables, Econometrica, 68, 839-74.

[180] Hooker, R. H., 1901. Correlation of the marriage rate with trade. Journal of the Royal Statistical Society, 44, 485–92.

[181] Horowitz, J. L., 1998. Semiparametric Methods in Econometrics. New York: Springer-Verlag.

[182] Horowitz, J. L., 2001. Semiparametric Models. In International Encyclopedia of Behavioral and Social Sciences, N. J. Smelser and P. B. Baltes eds. Elsevier, 13891-13897.

[183] Horowitz, J. L. and S. Lee, 2002. Semiparametric Methods in Applied Econometrics: Do the Models Fit the Data? Statistical Modelling, 2, 3-22.

[184] Horowitz, J. L. and N. E. Savin, 2001. Binary response models: Logits, probits, and semiparametrics. Journal of Economic Perspectives, 15, 43-56.

[185] Hotz, V. J., C. H. Mullin and S. G. Sanders, 1997. Bounding causal effects using data from a contaminated natural experiment: analyzing the effects of teenage childbearing. Review of Economic Studies, 64, 575-603.

[186] Hsiao, C., 2003. Analysis of Panel Data, second edition,Cambridge University Press, Cambridge.

[187] Hsiao, C., M.H. Pesaran and A.K. Tahmiscioglu, 1999. Bayes estimation of short-run coefficients in dynamic panel data models", in C. Hsiao, L.F. Lee, K. Lahiri and M.H. Pesaran (eds.), Analysis of Panels and Limited Dependent Variables Models, Cambridge: Cambridge University press, 268-296.

[188] Hsiao, C., M.H. Pesaran, and A.K. Tahmiscioglu, 2002. Maximum Likelihood Estimation of Fixed Effects Dynamic Panel Data Models Covering Short Time Periods, Journal of Econometrics, 109, 107-150.

[189] Hsiao, C., and M. H. Pesaran, 2006. Random coefficient panel data models, in L. Matyas and P. Sevestre, (eds.), The Econometrics of Panel Data, Kluwer Academic Publishers (forthcoming).

[190] Im, K.S., M.H. Pesaran, and Y. Shin, 2003. Testing for unit roots in heterogenous panels, Journal of Econometrics, 115, 53–74.

[191] Imbs, J., H. Mumtaz, M.O. Ravn and H. Rey, 2005. PPP strikes back, aggregation and the real exchange rate, Quarterly Journal of Economics, 120, 1-43.

[192] Johansen, S., 1988. Statistical analysis of cointegration vectors. Journal of Economic Dynamics and Control, 12, 231-254. Reprinted in Long-run economic relationships, 131-152, Engle. R. F and C. W. J. Granger (eds.) 1991. Oxford University Press, Oxford.

[193] Johansen, S., 1991. Estimation and hypothesis testing of cointegrating vectors in Gaussian vector autoregressive models. Econometrica, 59,1551-1580.

[194] Johansen, S., 1995. Likelihood-based inference in cointegrated vector autoregressive models. Oxford University Press, Oxford.

[195] Jorgenson, D. W., 1966. Rational distributed lag functions. Econometrica, 34, 135–49.

[196] Judd, K. L., 1998. Numerical Methods in Economics. Cambridge: MIT Press.

[197] Juselius, K., 2006. The Cointegrated VAR Model: Econometric Methodology and Macroeconomic Applications, Oxford University Press, Oxford.

[198] Kagel, J. and A. E. Roth, 1995. The Handbook of Experimental Economics, editors, Princeton University Press, 1995.

[199] Keane, M. P., 1990. A computationally practical simulation estimator for panel data, with applications to estimating temporal dependence in employment and wages. Discussion paper (University of Minnesota, Minneapolis, MN).

[200] Keane, M. and K. I. Wolpin, 1994. The solution and estimation of discrete choice dynamic programming models by simulation: Monte Carlo evidence. Review of Economics and Statistics, 76, 648-672.

[201] Kandel, S. and Stambaugh, R.F., 1996. On the predictability of stock returns: an asset-allocation perspective". The Journal of Finance, 51, 385-424

[202] Keynes, J. M., 1939. The statistical testing of business cycle theories. Economic Journal, 49, 558–68.

[203] Klein, L. R., 1947. The use of econometric models as a guide to economic policy. Econometrica, 15, 111–151.

[204] Klein, L. R., 1950. Economic Fluctuations in the United States 1921–1941. Cowles Commission Monograph No. 11, New York: John Wiley.

[205] Kilian, L., 1998. Small-sample confidence intervals for impulse response functions. The Review of Economics and Statistics, 80, 218-229.

[206] Kim, K. and A.R. Pagan, 1995. The econometric analysis of calibrated macroeconomic models", Chapter 7 in M.H. Pesaran and M. Wickens (eds.) Handbook of Applied Econometrics: Macroeconomics. Basil Blackwell: Oxford.

[207] Kloek, T. and H. K. van Dijk, 1978. Bayesian estimates of equation system parameters: An application of integration by Monte Carlo. Econometrica, 46, 1-20.

[208] Koop, G., M. H. Pesaran and S. M. Potter, 1996. Impulse response analysis in nonlinear multivariate models. Journal of Econometrics, 74, 119-147.

[209] Koop, G., 2003. Bayesian Econometrics. West Sussex UK: Wiley.

[210] Koop, G. and S. Potter, 2004a. Forecasting and estimating multiple change-point models with an unknown number of change-points. Mimeo, University of Leicester and Federal Reserve Bank of New York.

[211] Koop, G. and S. Potter, 2004b. Prior elicitation in multiple change-point models. Mimeo, University of Leicester and Federal Reserve Bank of New York.

[212] Koopmans, T. C., 1937. Linear Regression Analysis of Economic Time Series. Haarlem: De Erven F. Bohn for the Netherlands Economic Institute.

[213] Koopmans, T. C., 1949. Identification problems in economic model construction. Econometrica, 17, 125–44.

[214] Koopmans, T. C., H. Rubin and R. B. Leipnik, 1950. Measuring the equation systems of dynamic economics. In Statistical Inference in Dynamic Economic Models, ed. T.C. Koopmans, Cowles Commission Monograph No. 10, New York: John Wiley.

[215] Koyck, L. M., 1954. Distributed Lags and Investment Analysis. Amsterdam: North-Holland.

[216] Laffont, J-J., Ossard, H., Q., Vuong, 1995. Econometrics of first-price auctions, Econometrica, 63, 953-980.

[217] Lancaster, T., 2004. An Introduction to Modern Bayesian Econometrics. Malden MA: Blackwell.

[218] Leamer, E. E., 1978. Specification Searches: Ad Hoc Inference with Non-experimental Data. New York: John Wiley.

[219] Lee, B. S. and B. Ingram, 1991. Simulation estimation of time-series models. Journal of Econometrics, 47, 197-205.

[220] Lee, L.F., 1995. Asymptotic bias in simulated maximum likelihood estimation of discrete choice models. Economic Theory, 11, 437-483.

[221] Lenoir, M., 1913. Etudes sur la formation et le mouvement des prix. Paris: Giard et Brière.

[222] Lerman, S. and C. S. Manski, 1981. On the use of simulated frequencies to approximate choice probabilities. In Structural Analysis of Discrete Data with Econometric Applications, C.F. Manski and D. McFadden eds. Cambridge: MIT Press.

[223] Levin, A., C. Lin, and C.J. Chu (2002), Unit Root Tests in Panel Data: Asymptotic and Finite-sample Properties, Journal of Econometrics, 108, 1–24.

[224] Liesenfeld, R. and J. Breitung, 1999. Simulation based method of moments. In Generalized Method of Moment Estimation, L. Tatyas, ed. Cambridge: Cambridge University Press.

[225] Litterman, R. B., 1985. Forecasting with Bayesian vector autoregressions: five years of experience. Journal of Business and Economic Statistics, 4, 25–38.

[226] Liu, T. C., 1960. Underidentification, structural estimation and forecasting. Econometrica, 28, 855–65.

[227] Lucas, R. E., 1972. Expectations and the neutrality of money. Journal of Economic Theory, 4, 103–24.

[228] Lucas, R. E., 1973. Some international evidence on output-inflation tradeoffs. American Economic Review, 63, 326–34.

[229] Lucas, R. E., 1976. Econometric policy evaluation: a critique. In The Phillips Curve and Labor Markets, ed. K. Brunner and A. M. Meltzer, Carnegie-Rochester Conferences on Public Policy, Vol. 1, Amsterdam: North-Holland, 19–46.

[230] Lucas, R. E., and T. Sargent, 1981. Rational Expectations and Econometric Practice, Introductory Essay to: Rational Expectations and Econometric Practice, University of Minnesota Press, p. xi-x1.

[231] Lűtkepohl, H. 1991. Introduction to multiple time series analysis. Springer-Verlag, New York.

[232] Lyttkens, E., 1970. Symmetric and asymmetric estimation methods. In Interdependent Systems, ed. E. Mosback and H. Wold, Amsterdam: North-Holland.

[233] Maddala, G. S., 1983. Limited Dependent and Qualitative Variables in Econometrics. Cambridge: Cambridge University Press.

[234] Maddala, G. S., 1986. Disequilibrium, self-selection, and switching models. In Handbook of Econometrics, Vol. 3, ed. Z. Griliches and M.D. Intriligator, Amsterdam: North-Holland.

[235] Maddala, G.S., 2001. Introduction to Econometrics (third edition), John Wiley and Sons.

[236] Manski, C. F., 1975. Maximum score estimation of the stochastic utility model of choice. Journal of Econometrics, 3, 205-228.

[237] Manski, C. F., 1985. Semiparametric analysis of discrete response: asymptotic properties of the maximum score estimator. Journal of Econometrics, 27, 313-334.

[238] Manski, C. F., 1988. Identification of binary response models. Journal of the American Statistical Association, 83, 729-738.

[239] Manski, C. F., 1995. Identification Problems in the Social Sciences. Cambridge, MA: Harvard University Press.

[240] Manski, C. F., 2003. Partial Identification of Probability Distributions. New York: Springer-Verlag.

[241] Manski, C. F. and D. McFadden, 1981. Structural Analysis of Discrete Data with Econometric Applications. Cambridge, Mass: MIT Press.

[242] Matzkin, R. L., 1994. Restrictions of economic theory in nonparametric methods. In Handbook of Econometrics, R. F. Engle and D. L. McFadden eds. Vol. 4. North-Holland, Amsterdam, pp. 2523-2558.

[243] McAleer, M., A. R. Pagan and P. A. Volker, 1985. What will take the con out of econometrics? American Economic Review, 75, 293–307.

[244] McAleer, M. and M.C. Medeiros, 2006. Realized volatility: a review, forthcoming in Econometric Reviews.

[245] McCulloch, R. E. and P. E. Rossi, 1994. An exact likelihood analysis of the multinomial probit model. Journal of Econometrics, 64, 207-240.

[246] McCulloch, R.E. and R. Tsay, 1993. Bayesian inference and prediction for mean and variance shifts in autoregressive time series. Journal of the American Statistical Association, 88, 965-978.

[247] McCulloch, R.E. and R.S. Tsay, 1994. Bayesian analysis of autoregressive time series via the Gibbs sampler. Journal of Time Series Analysis, 15, 235-250.

[248] McCulloch, R. E., N.G. Polson and P. E. Rossi, 2000. A Bayesian analysis of the multinomial probit model with fully identified parameters. Journal of Econometrics, 99, 173-193.

[249] McFadden, D., 1989. A method of simulated moments for estimation of multinomial probits without numerical integration. Econometrica, 57, 995–1026.

[250] Metropolis, N., A. W. Rosenbluth, M. N. Rosenbluth, A. H.Teller and E. Teller, 1953. Equation of state calculations by fast computing machines. The Journal of Chemical Physics, 21, 1087-1092.

[251] Mitchell, W. C., 1928. Business Cycles: the problem in its setting. New York: National Bureau of Economic Research.

[252] Moon, R. and B. Perron, 2004. Testing for unit root in panels with dynamic factors, Journal of Econometrics, 122, 81–126.

[253] Moon, R. and B. Perron, 2006. An empirical analysis of nonstationarity in a panel of interest rates with factors. Journal of Applied Econometrics, forthcoming.

[254] Moore, H. L., 1914. Economic Cycles: Their Law and Cause. New York: Macmillan Press.

[255] Moore, H. L., 1917. Forecasting the Yield and the Price of Cotton. New York: Macmillan Press.

[256] Mortensen, D. T., 1990. Equilibrium wage distributions: a synthesis. In Panel Data and Labor Market Studies, Hartog, J., G. Ridder, and J. Theeuwes eds. New York: North Holland, pp. 279-296.

[257] Mundlak, Y., 1961. Empirical production function free of management bias. Journal of Farm Economics, 43, 44–56.

[258] Mundlak, Y., 1978. On the pooling of time series and cross section data. Econometrica, 46, 69–85.

[259] Muth, J. F., 1961. Rational expectations and the theory of price movements. Econometrica, 29, 315–35.

[260] Nelson, C. R., 1972. The prediction performance of the FRB-MIT-Penn model of the US economy. American Economic Review, 62, 902–17.

[261] Nadaraya, E. A., 1964. On estimating regression. Theory of Probability and Its Applications, 10, 141-142.

[262] Nakamura A. and M. Nakamura, 1981. On the Relationships Among Several Specification Error Tests Presented by Durbin, Wu, and Hausman, Econometrica, 49, 1583-1588.

[263] Nerlove, M., 1958a. Adaptive expectations and the cobweb phenomena. Quarterly Journal of Economics, 72, 227–40.

[264] Nerlove, M., 1958b. Distributed Lags and Demand Analysis. USDA, Agriculture Handbook No. 141, Washington, DC.

[265] Neumann, J. von., 1941. Distribution of the ratio of the mean square successive difference to the variance. Annals of Mathematical Statistics, 12, 367–95.

[266] Neumann, J. von., 1942. A further remark on the distribution of the ratio of the mean square successive difference to the variance. Annals of Mathematical Statistics, 13, 86–8.

[267] Newey, W. K., 1997. Convergence rates and asymptotic normality for series estimators, Journal of Econometrics, 79, 147-168.

[268] Nickell, S., 1981. Biases in dynamic models with fixed effects", Econometrica, 49, 1399-1416.

[269] Niederreiter, H., 1992. Random Number Generation and Quasi-Monte Carol Methods. Philadelphia: SIAM.

[270] Nyblom, J., 1989. Testing for the constancy of parameters over time. Journal of the American Statistical Association, 84, 223-230.

[271] O'Connell, P, 1998. The Overvaluation of Purchasing Power Parity, Journal of International Economics, 44, 1–19.

[272] Orcutt, G. H., 1948. A study of the autoregressive nature of the time series used for Tinbergen's model of the economic system of the United States, 1919–1932. Journal of the Royal Statistical Society, Series B 10, 1–45 (Discussion, 46–53).

[273] Pagan, A. R. and M.H. Pesaran, 2006. On Econometric Analysis of Structural Systems with Permanent and Transitory Shocks and Exogenous Variables, unpublished manuscript.

[274] Pagan, A. and A. Ullah, 1999. Nonparametric Econometrics. Cambridge: Cambridge University Press.

[275] Pakes, A. and D. Pollard, 1989. Simulation and the asymptotics of optimization estimators. Econometrica, 57, 5 1027–1058.

[276] Peersman, G., 2005. What caused the early millenium slowdown? evidence based on autoregressions, Journal of Applied Econometrics, 20, 185-207.

[277] Pedroni, P., 2001. Purchasing power parity tests in cointegrated panels, Review of Economics and Statistics, 83, 727–731.

[278] Pedroni, P., 2004. Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis, Econometric Theory, 20, 597–625.

[279] Percy, D. F., 1992. Prediction for seemingly unrelated regressions. Journal of the Royal Statistical Society, Series B, 54, 243-252.

[280] Pesaran, M. H., 1981. Identification of rational expectations models. Journal of Econometrics, 16, 375–98.

[281] Pesaran, M. H., 1987. The Limits to Rational Expectations. Oxford: Basil Blackwell.

[282] Pesaran, M.H., (2006a), Estimation and Inference in Large Heterogeneous Panels with Cross Section Dependence, Econometrica, 74, 967-1012.

[283] Pesaran, M.H. (2006b), A Simple Panel Unit Root Test in the Presence of Cross Section Dependence, Cambridge Working Papers in Economics 0346, revised Version, University of Cambridge.

[284] Pesaran, M.H. (2006c), A pair-wise approach to testing for output and growth convergence, forthcoming in Journal of Econometrics.

[285] Pesaran, M. H. and A. S. Deaton, 1978. Testing non-nested nonlinear regression models. Econometrica, 46, 677–94.

[286] Pesaran, M. H., D. Pettenuzzo and A. Timmermann, 2006. Forecasting Time Series Subject to Multiple Structural Breaks. Forthcoming in Review of Economic Studies.

[287] Pesaran, M. H., T. Schuermann and S. M. Weiner, 2004. Modelling regional interdependencies using a global error-correcting macroeconometric model (with discussion). Journal of Business and Economic Statistics, 22, 129-162 and 175-181.

[288] Pesaran, M. H. and S. Skouras, 2002. Decision-based methods for forecast evaluation. In A Companion to Economic Forecasting, M. P. Cements and D. F. Hendry (eds.). Blackwell Publishing: Oxford.

[289] Pesaran, M. H. and R. P. Smith, 1985a. Keynes on econometrics. In Keynes' Economics: methodological issues, ed. T. Lawson and M. H. Pesaran, London: Croom Helm.

[290] Pesaran, M. H. and R. P. Smith, 1985b. Evaluation of macroeconometric models. Economic Modelling, April, 125–34.

[291] Pesaran, M.H., Smith, R. (1995), Estimating Long-run Relationships from Dynamic Heterogeneous Panels, Journal of Econometrics, 68, 79-113.

[292] Pesaran, M. H. and R. P. Smith, 2006. Macroeconometric modelling with a global perspective. The Manchester School, Supplement, pp. 24-49.

[293] Pesaran, M.H. and Timmermann, A., 1995. The robustness and economic significance of predictability of stock returns, The Journal of Finance, 50, 1201-1228.

[294] Pesaran, M.H. and Timmermann, A., 2000. A recursive modelling approach to predicting UK stock returns, The Economic Journal ,110, 159-191.

[295] Pesaran, M. H. and A. Timmermann, 2005a. Real Time Econometrics. Econometric Theory, 21, 212-231.

[296] Pesaran, M. H. and A. Timmermann, 2005b. Small sample properties of forecasts from autoregressive models under structural breaks. Journal of Econometrics, 129, 183-217.

[297] Pesaran, M. H. and A. Timmermann, 2006. Model instability and choice of observation window. Forthcoming in Journal of Econometrics.

[298] Pesaran, M.H., D. Pettenuzzo and A. Timmermann, 2006. Forecasting Time Series Subject to Multiple Structural Breaks. Forthcoming in Review of Economic Studies.

[299] Pesaran, M. H., and M.Weeks, 2001. Non-nested hypothesis testing: an overview, in B. H. Baltagi (ed.), Companion to Theoretical Econometrics, Basil Blackwell, Oxford.

[300] Phillips, P. C. B., 1983. Exact small sample theory in the simultaneous equations model. In Handbook of Econometrics, ed. Z. Griliches and M. D. Intrilgator, Vol. 1, Amsterdam: North-Holland.

[301] Phillips, P. C. B., 1986. Understanding spurious regressions in econometrics. Journal of Econometrics 33, 311–40.

[302] Phillips, P. C. B., 1991. Optimal inference in cointegrated systems. Econometrica, 59, 283-306.

[303] Phillips, P.C.B. and H.R. Moon (1999), Linear Regression Limit Theory for Nonstationary Panel Data, Econometrica, 67, 1057–1111.

[304] Phillips, P. C. B. and Z. Xiao, 1998. A primer on unit root testing, Journal of Economic Surveys, 12, 423-469.

[305] Powell, J. L., 1984. Least absolute deviations estimation for the censored regression model. Journal of Econometrics, 25, 303-325.

[306] Powell, J. L., 1986. Censored regression quantiles. Journal of Econometrics, 32, 143-155.

[307] Press, W. H., B. P. Flannery, S. A. Teukolsky and W. T. Vetterling 1986. Numerical Recipes: The Art of Scientific Computing. Cambridge: Cambridge University Press.

[308] Prothero, D. L. and K. F. Wallis, 1976. Modelling macroeconomic time series. Journal of the Royal Statistical Society, Series A 139, 468–86.

[309] Quandt, R. E., 1982. Econometric disequilibrium models. Econometric Reviews 1, 1–63.

[310] Ramsey, J. B., 1969. Tests for specification errors in classical linear least squares regression analysis. Journal of the Royal Statistical Society, Series B 31, 350–71.

[311] Reiersol, O., 1941. Confluence analysis by means of lag moments and other methods of confluence analysis. Econometrica, 9, 1–24.

[312] Reiersol, O., 1945. Confluence Analysis by Means of Instrumental Sets of Variables. Stockholm.

[313] Rossi, P. E., G. M. Allenby and R. McCulloch, 2005. Bayesian Statistics and Marketing. Chichester: John Wiley & Sons.

[314] Rothenberg, T. J., 1984. Approximating the distributions of econometric estimators and test statistics. In Handbook of Econometrics, ed. Z. Griliches and M. D. Intriligator, Vol. 2, Amsterdam: North-Holland.

[315] Rust, J., 1994. Structural estimation of Markov decision processes. In Handbook of Econometrics, R.F. Engle and D. L. McFadden, eds. Vol. 4. North-Holland, Amsterdam, pp. 3081-3143.

[316] Rust, J., 1997. Using randomization to break the curse of dimensionality. Econometrica, 65, 487-516.

[317] Samuelson, P., 1965. Proof that properly anticipated prices fluctuate randomly", Industrial Management Review, Spring 6, 41-49.

[318] Sandor, Z. and P. Andras, 2004. Alternative sampling methods for estimating multivariate normal probabilities. Journal of Econometrics, 120, 207-234.

[319] Santos, M. S. and J. Vigo-Aguiar, 1998. Analysis of a numerical dynamic programming algorithm applied to economic models. Econometrica, 66, 409-426.

[320] Sargan, J. D., 1958. The estimation of economic relationships using instrumental variables. Econometrica, 26, 393–415.

[321] Sargan, J. D., 1964. Wages and prices in the United Kingdom: a study in econometric methodology. In Econometric Analysis for National Economic Planning, ed. P. E. Hart, G. Mills and J. K. Whitaker, London: Butterworths.

[322] Sargent, T. J., 1973. Rational expectations, the real rate of interest and the natural rate of unemployment. Brookings Papers on Economic Activity, No. 2, 429–72.

[323] Sargent, T. J. and N. Wallace, 1975. Rational expectations and the theory of economic policy. Journal of Monetary Economics, 2, 169–84.

[324] Savin, N. E., 1973. Systems k-class estimators. Econometrica, 41, 1125–36.

[325] Schultz, M., 1938. The Theory and Measurement of Demand. Chicago: University of Chicago Press.

[326] Schumpeter, J. A., 1954. History of Economic Analysis. London: George Allen & Unwin.

[327] Shephard, N., 2005. Stochastic Volatility: Selected Readings, edited volume, Oxford University Press.

[328] Shiller, R. J., 1973. A distributed lag estimator derived from smoothness priors. Econometrica, 41, 775–88.

[329] Sims, C. A., 1972. Money, income and causality. American Economic Review, 62, 540–52.

[330] Sims, C. A., 1980. Macroeconomics and reality. Econometrica, 48, 1–48.

[331] Sims, C. A., 1982. Policy analysis with econometric models. Brookings Papers on Economic Activity, No. 1, 107–64.

[332] Slutsky, E., 1927. The summation of random causes as the source of cyclic processes. In Problems of Economic Conditions, Vol. 3, Moscow. English trans. in Econometrica, 5, (1937), 105–46.

[333] Smets, F. and R. Wouters, 2003. An estimated stochastic dynamic general equilibrium model of the euro area. Journal of the European Economic Association, 1, 1123-1175.

[334] Smith, V., S. Leybourne, T.-H. Kim and P. Newbold, 2004. More powerful panel data unit root tests with an application to mean reversion in real exchange rates, Journal of Applied Econometrics, 19, 147–170.

[335] Solow, R. M., 1960. On a family of lag distributions. Econometrica, 28, 393–406.

[336] Srivastava, V. K., 1971. Three-stage least-squares and generalized double k-class estimators: a mathematical relationship. International Economic Review, 12, 312–16.

[337] Stambaugh, R. F., 1999. Predictive regressions. Journal of Financial Economics, 54, 375-421.

[338] Stern, S., 1997. Simulation-based estimation. Journal of Economic Literature, 35, 2006-2039.

[339] Stock, J. H., 1994. Unit roots, structural breaks and trends. In Handbook of Econometrics, Engle, R. F. and D. L. McFadden (eds.), 2739-2841. North-Holland, Amsterdam.

[340] Stock, J. H. and M. W. Watson, 1996. Evidence on structural instability in macroeconomic time series relations. Journal of Business and Economic Statistics, 14, 11-30.

[341] Stock, J.H. , J.H. Wright and M. Yogo, 2002. A survey of weak instruments and weak identification in generalized method of moments, Journal of Business and Economic Statistics, 20, 518-529.

[342] Stone, C. J., 1985. Additive regression and other nonparametric models. Annals of Statistics, 13, 689-705.

[343] Stone, J. R. N., 1945. The analysis of market demand. Journal of the Royal Statistical Society, Series A 108, 286–382.

[344] Stone, J. R. N. et al., 1954. Measurement of Consumers' Expenditures and Behavior in the United Kingdom, 1920–38, Vols 1 and 2. London: Cambridge University Press.

[345] Strachan R. W. and H. K. van Dijk, (2006). "Model Uncertainty and Bayesian Model Averaging in Vector Autoregressive Processes," Discussion Papers in Economics 06/5, Department of Economics, University of Leicester.

[346] Swamy, P.A.V.B., 1970. Efficient inference in a random coefficient regression model", Econometrica, 38, 311-323.

[347] Taylor, J. B. and H. Uhlig, 1990. Solving nonlinear stochastic growth models: A comparison of alternative solution methods. Journal of business and Economic Statistics, 8, 1-18.

[348] Theil, H., 1954. Estimation of parameters of econometric models. Bulletin of International Statistics Institute, 34, 122–8.

[349] Theil, H., 1958. Economic Forecasts and Policy. Amsterdam: North-Holland; 2nd edn, 1961.

[350] Tierney, L., 1994. Markov chains for exploring posterior distributions with discussion and rejoinder. Annals of Statistics, 22, 1701-1762.

[351] Tinbergen, J., 1929–30. Bestimmung und Deutung von Angebotskurven: ein Beispiel. Zeitschrift für Nationalökonomie, 1, 669–79.

[352] Tinbergen, J., 1937. An Econometric Approach to Business Cycle Problems. Paris: Herman & Cie Editeurs.

[353] Tinbergen, J., 1939. Statistical Testing of Business Cycle Theories. Vol. 1: A Method and its Application to Investment activity; Vol. 2: Business Cycles in the United States of America, 1919–1932. Geneva: League of Nations.

[354] Tobin, J., 1958. Estimation of relationships for limited dependent variables. Econometrica, 26, 24–36.

[355] Treadway, A. B., 1971. On the multivariate flexible accelerator. Econometrica, 39, 845–55.

[356] Trivedi, P. K., 1975. Time series analysis versus structural models: a case study of Canadian manufacturing behaviour. International Economic Review, 16, 587–608.

[357] Uhlig H., 2005. What are the effects of monetary policy: results from an agnostic indentification approach, Journal of Monetary Economics, 52, 381-419.

[358] Verbeek, M., 2006. Pseudo panels and repeated cross-sections, forthcoming in The Econometrics of Panel Data, edited by L. Matyas and P. Sevestre, 3rd ed. Kluwer Academic Publishers.

[359] Von Neumann, J., 1951. Various techniques used in connection with random digits. National Bureau of Standards Applied Mathematics, Series 12, 36-38.

[360] Wallis, K. F., 1977. Multiple time series analysis and the final form of econometric models. Econometrica, 45, 1481–97.

[361] Wallis, K., 1980. Econometric implications of the Rational Expectations Hypothesis. Econometrica, 48, 49–73.

[362] Watson, G. M., 1964. Smooth regression analysis. Sankhyâ, Series A, 26, 359-372.

[363] Watson, M. W., 1994. Vector autoregressions and cointegration. Chapter 47 in Handbook of Ecometrics, Vol. 4, R. F. Engle and D. L. McFadden (eds.). North Holland Elsevier: Amsterdam.

[364] Wegge, L. L., 1965. Identifiability criteria for a system of equations as a whole, The Australian Journal of Statistics, 7, 67-77.

[365] West, K.D., 2006. Forecast evalution, in Handbook of Economic Forecasting, Volume 1, in G. Elliott, C. Granger, and A. Timmermann (eds.), North Holland Elsevier: Amsterdam.

[366] Westerlund, J., 2005., Panel cointegration tests of the Fisher effect, Working Papers 2005:10, Lund University, Department of Economics.

[367] White, H., 1981. Consequences and detection of misspecified nonlinear regression models. Journal of the American Statistical Association, 76, 419–33.

[368] White, H., 1982. Maximum likelihood estimation of misspecified models. Econometrica, 50, 1–26.

[369] Whittle, P., 1963. Prediction and Regulation by Linear Least-squares Methods. London: English Universities Press.

[370] Wickens, M., 1982. The efficient estimation of econometric models with rational expectations. Review of Economic Studies, 49, 55–68.

[371] Wickens, M.R. and R. Motto, 2001. Estimating shocks and impulse response functions", Journal of Applied Econometrics, 16, 371-387.

[372] Wold, H., 1938. A Study in the Analysis of Stationary Time Series. Stockholm: Almqvist and Wiksell.

[373] Wooldridge, J. M., 2002. Econometric Analysis of Cross Section and Panel Data, MIT Press.

[374] Wooldridge, J. M., 2006, Introductory Econometrics: A Modern Approach (third edition), South-Western.

[375] Working, E. J., 1927. What do statistical 'demand curves' show? Quarterly Journal of Economics, 41, 212–35.

[376] Wright, P. G., 1915. Review of economic cycles by Henry Moore. Quarterly Journal of Economics 29, 631–41.

[377] Wright, P. G., 1928. The Tariff on Animal and Vegetable Oils. London: Macmillan for the Institute of Economics.

[378] Wu, D. 1973. Alternatives Tests of Independence between Stochastic Regressor and Disturbances. Econometrica, 41, 733-750.

[379] Yule, G. U., 1895, 1896. On the correlation of total pauperism with proportion of out-relief. Economic Journal, 5, 603–11; 6, 613–23.

[380] Yule, G. U., 1921. On the time-correlation problem, with special reference to the variate-difference correlation method. Journal of the Royal Statistical Society, 84, 497–526.

[381] Yule, G. U., 1926. Why do we sometimes get nonsense correlations between time-series? A study in sampling and the nature of time-series. Journal of the Royal Statistical Society, 89, 1–64.

[382] Zellner, A., 1962. An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. Journal of the American Statistical Association, 57, 348–68.

[383] Zellner, A., 1984. Basic Issues in Econometrics. Chicago: University of Chicago Press.

[384] Zellner, A., 1985. Bayesian econometrics. Econometrica, 53, 253–70.

[385] Zellner, A. and F. Palm, 1974. Time series analysis and simultaneous equation econometric models. Journal of Econometrics, 2, 17–54.

[386] Zellner, A. and H. Theil, 1962. Three-stage least squares: simultaneous estimation of simultaneous equations. Econometrica, 30, 54–78.