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## EDITOR'S CORNER

This issue of the *Annals* contains a diverse collection of articles. The lead article by Michael Grossman and Victor Fuchs extends some of the latter's path-breaking work on *The Service Economy*. The authors examine the secular trend toward service employment and its effect upon aggregate productivity change over the long run and during business cycles. Computer simulations with reasonable parameter values are used to identify the quantitative importance of these effects.

The second article by Raford Boddy and Michael Gort is also in the mainstream of the NBER research tradition, as it involves the estimation of "Capital Expenditures and Capital Stocks." They compare their estimates for 1947-1963 with earlier estimates by Daniel Creamer and Bert Hickman, and obtain higher growth rates in capital stocks than the previous estimates. Although one may always question specific assumptions, the annual estimates for thirty major industry sectors for 1921-1963 should prove useful to applied researchers in this area of economic measurement and analysis.

Next, Jack Triplett and Stephen Merchant of the Bureau of Labor Statistics examine two measures of aggregate price change for consumption goods and services—the Consumer Price Index and the Implicit Price Deflator for Personal Consumption Expenditures. By using statistical tests of the relationships between the counterpart series in the two price indexes, they conclude that weighting, *per se*, and non-CPI indexes, are not the only sources of divergencies in the two measures. Allan Young, in his comment, questions two aspects of the Triplett-Merchant study: their selection of CPI data and the need for "matched" components to correspond exactly. In their reply, the authors reiterate their conclusion that something other than the CPI is moving components of the PCE deflator. We hope that the exchange will stimulate further work in this important area.

Thomas Sargent, in the next article, "What Do Regressions of Interest on Inflation Show?", explores whether an estimate of the distributed lag on inflation captures the speed with which expectations of inflation are formed. He concludes that the necessary restrictions for consistency are stringent, and that a long lag may be estimated even when the lag is actually short. The six equation model which he develops contains feedbacks which give this result. Sargent's article is part of a series supported by the NBER which attempt to merge advanced econometric techniques with economic theory.

This issue's *Programming Software Notes* contains an extended announcement of a "Microdata Processing Package" developed at the NBER and a series of notes on programs and methods for input-output analysis, several of which were written by persons affiliated with the NBER. Since Clopper Almon was willing to introduce the series of four contributions, we need not contrast them in detail here. Edward Wolf's IOPE and Gholam Mustafa and Lonnie L. Jones' RIMLOC are two programming packages designed for input-output analysis described in notes. Virginia Klema, in her "Note on Matrix Factorization," surveys alternatives to the matrix inversion techniques used in these programs.

The last contribution in this series, by Stephen Dresch and Robert Goldberg, describes IDIOM, an input-out model of the economy which has been designed to address a number of complex issues. The case of reduced military expenditures is used to illustrate the employment, output and environmental effects of alternative compensatory policies. It is clear from this series of notes that hardware, software, and advanced mathematical and analytical techniques give researchers an extremely powerful set of tools for interindustry analysis.

The two sections that follow report upon a number of NBER conference activities. Cynthia Taeuber, rapporteur for a Conference on Research and the Public Use Samples, describes the problems and potentials of the census Public Use Samples from the viewpoints of a wide variety of users. This conference, which was co-sponsored by the Conference on the Computer in Economic and Social Research and the Southern Regional Demographic Group, dealt with both analytical and technical problems encountered with these data bases. Another conference series, the NBER-NSF Conference on Econometrics and Mathematical Economics is described in the following notes, with the Seminar on Bayesian Inference in Econometrics given detailed coverage.

The last section reports on developments at the NBER Computer Research Center for Economics and Management Science. The next issue of the *Annals* (contents listed below) will be devoted to papers presented at a NBER Computer Research Center Workshop. We hope that these notes on conferences and other NBER activities, as well as non-NBER research, will help keep interested researchers informed of developments in the area of computers, data retrieval, and research methodology.

SVB

FORTHCOMING

*Annals of Economic and Social Measurement*

Volume 2, Number 4, October 1973

SPECIAL ISSUE ON  
TIME-VARYING PARAMETERS

- Edwin Kuh and "Estimates of Time Varying Parameter Structures—An Overview"  
David A. Belsley  
Barr Rosenberg "A Survey of Time-Varying Parameter Structures"

*Random Coefficient Models*

- P. A. V. B. Swamy "Criteria, Constraints and Multicollinearity in a Random Coefficient Regression Model"  
Barr Rosenberg "The Analysis of a Cross Section of Time Series by a Stochastically Convergent Parameter Regression"  
Swarnjit S. Arora "Error Component Regression Models and Their Applications"

*Systematic (non-random) Variation Models*

- Thomas Cooley and "Varying Parameter Regression: A Theory and Some Applications"  
Edward Prescott  
Stephen M. Goldfeld and "The Estimation of Structural Shifts by Switching Regressions"  
Richard Quandt  
David Belsley "On the Determination of Systematic Parameter Variations in the Linear Regression Model"  
David Belsley "A Test for Systematic Variates in Regression Coefficients"

*Kalman Filter Models*

- Alexander H. Sarris "A Bayesian Approach to Estimation of Non-Constant Regression Parameters"  
J. Phillip Cooper "Time-Varying Regression Coefficients: A Mixed Estimation Approach and Operational Limitations of the General Markov Structure"

"On the Applicability of the Kalman Filter to the Determination of Systematic Parameter Variation"

The Kalman filter is a recursive algorithm for estimating the state of a dynamic system from a series of noisy observations. It is widely used in control systems, navigation, and signal processing. The filter consists of two main steps: prediction and correction. In the prediction step, the state is estimated based on the previous state and the system's dynamics. In the correction step, the estimate is updated based on the current observation and the Kalman gain, which determines the weight given to the observation.

The Kalman filter is based on the assumption that the system's state and the observation noise are Gaussian. This assumption allows for the use of linear algebra to compute the Kalman gain and the updated state estimate. The filter is optimal in the sense that it provides the minimum variance unbiased estimate of the state given the observations up to that point.

The Kalman filter is a special case of the more general Bayesian filter. The Bayesian filter uses Bayes' theorem to update the probability density function of the state given the observations. The Kalman filter uses the Kalman gain to update the state estimate, which is equivalent to using the Bayesian filter with a Gaussian prior and likelihood.

The Kalman filter is a powerful tool for state estimation in many applications. It is used in navigation systems to estimate the position and velocity of a vehicle. It is also used in control systems to estimate the state of a process and to compute the control signal. The filter is a key component of many modern control systems.

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