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REPORT NO. DOT-TSC-OST-76-49

MAXIMUM LIKELIHOOD AS AN OPERATIONAL TOOL IN SOCIO-ECONOMIC MODELING

As Outlined in a Recent Thesis of D.W. Peterson

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FEBRUARY 1977

FINAL REPORT

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INFORMATION SERVICE, SPRINGFIELD,
VIRGINIA 22161

Prepared for

U.S. DEPARTMENT OF TRANSPORTATION
OFFICE OF THE SECRETARY
Office of the Assistant Secretary for
Systems Development and Technology
Office of Systems Engineering
Washington DC 20590

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Technical Report Documentation Page

1. Report No.
DOT-TSC-OST-76-49

2. Government Accession No.

3. Recipient's Catalog No.

4. Title and Subtitle
MAXIMUM LIKELIHOOD AS AN OPERATIONAL TOOL IN SOCIO-ECONOMIC MODELING: As Outlined in a Recent Thesis of D.W. Peterson

5. Report Date
February 1977

6. Performing Organization Code

7. Author(s)
Diarmuid O'Mathuna

8. Performing Organization Report No.
DOT-TSC-OST-76-49

9. Performing Organization Name and Address
U.S. Department of Transportation
Transportation Systems Center
Kendall Square
Cambridge MA 02142

10. Work Unit No. (TRAIS)
OS750/R7502

11. Contract or Grant No.

12. Sponsoring Agency Name and Address
U.S. Department of Transportation
Office of the Secretary
Office of the Asst. Sec'y for Sys. Dev. and Tech.
Office of Systems Engineering
Washington DC 20590

13. Type of Report and Period Covered
Final Report
July 1975-Sept. 1976

14. Sponsoring Agency Code

15. Supplementary Notes

16. Abstract

The limitations of currently used estimation procedures in socio-economic modeling have been highlighted in the ongoing work of Senge, in which it is shown where more sophisticated estimation procedures may become necessary. One such advanced method (FIMLOF) based on the maximum likelihood procedure has been developed by Peterson and incorporated in a computer program, GPSIE. The present report gives a review of this development and includes a discussion of the relevant conclusions from the work of Senge.

17. Key Words
Maximum Likelihood
Estimation
Statistics
Socio-Economic Modeling

18. Distribution Statement
DOCUMENT IS AVAILABLE TO THE U.S. PUBLIC THROUGH THE NATIONAL TECHNICAL INFORMATION SERVICE, SPRINGFIELD, VIRGINIA 22161

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	24	

Form DOT F 1700.7 (8-72)

Reproduction of completed page authorized

PREFACE

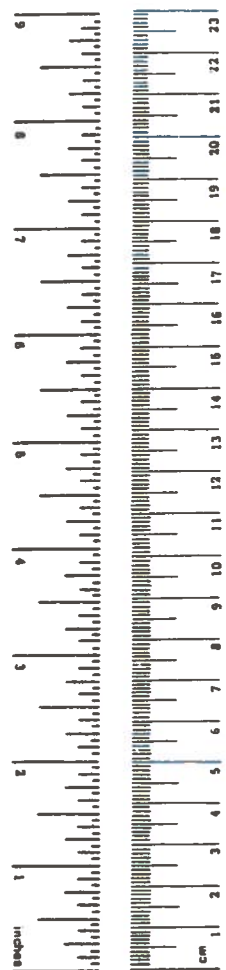
The work described in this report was performed at the Transportation Systems Center as an independent project in support of the Office of the Secretary in the area of Socio-Economic Analysis and Planning.

The project was sponsored by the Office of the Secretary through the Transportation Advanced Research Program (TARP) for the application of advanced technology to large-scale systems.

METRIC CONVERSION FACTORS

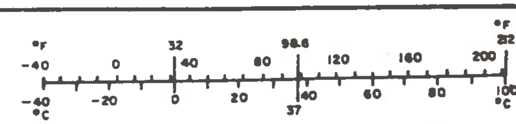
Approximate Conversions to Metric Measures

Symbol	When You Know	Multiply by	To Find	Symbol
		LENGTH		
in	inches	2.5	centimeters	cm
ft	feet	30	centimeters	cm
yd	yards	0.9	meters	m
mi	miles	1.6	kilometers	km
		AREA		
in^2	square inches	6.5	square centimeters	cm^2
ft^2	square feet	0.09	square meters	m^2
yd^2	square yards	0.8	square meters	m^2
mi^2	square miles	2.6	square kilometers	km^2
	acres	0.4	hectares	ha
		MASS (weight)		
oz	ounces	28	grams	g
lb	pounds	0.45	kilograms	kg
	short tons (2000 lb)	0.9	tonnes	t
		VOLUME		
tsp	teaspoons	5	milliliters	ml
Tbsp	tablespoons	15	milliliters	ml
fl oz	fluid ounces	30	milliliters	ml
c	cups	0.24	liters	l
pt	pints	0.47	liters	l
qt	quarts	0.95	liters	l
gal	gallons	3.8	liters	l
ft^3	cubic feet	0.03	cubic meters	m^3
yd^3	cubic yards	0.76	cubic meters	m^3
		TEMPERATURE (exact)		
°F	Fahrenheit temperature	5/9 (after subtracting 32)	Celsius temperature	°C



Approximate Conversions from Metric Measures

Symbol	When You Know	Multiply by	To Find	Symbol
		LENGTH		
mm	millimeters	0.04	inches	in
cm	centimeters	0.4	inches	in
m	meters	3.3	feet	ft
m	meters	1.1	yards	yd
km	kilometers	0.6	miles	mi
		AREA		
cm^2	square centimeters	0.16	square inches	in^2
m^2	square meters	1.2	square yards	yd^2
km^2	square kilometers	0.4	square miles	mi^2
ha	hectares (10,000 m^2)	2.5	acres	
		MASS (weight)		
g	grams	0.035	ounces	oz
kg	kilograms	2.2	pounds	lb
t	tonnes (1000 kg)	1.1	short tons	
		VOLUME		
ml	milliliters	0.03	fluid ounces	fl oz
l	liters	2.1	pints	pt
l	liters	1.06	quarts	qt
l	liters	0.26	gallons	gal
m^3	cubic meters	35	cubic feet	ft^3
m^3	cubic meters	1.3	cubic yards	yd^3
		TEMPERATURE (exact)		
°C	Celsius temperature	9/5 (then add 32)	Fahrenheit temperature	°F



CONTENTS

1. PREAMBLE: SOCIO-ECONOMIC MODELS AND STATISTICAL PROCEDURES

At certain stages of development, scientific investigation appears to follow a general pattern where ever-greater precision is sought through the more intensive use of quantitative methods and sophisticated techniques. The pitfalls and limitations inherent in such a tendency are not always fully or consistently recognized even in the more exact sciences - the Michelson-Morley experiment is still being performed with the latest instrumentation. The sciences considered less exact generally also have more immediate social impact so that the recognition of such limitations is all the more necessary.

In many problem areas arising in the socio-economic field, a reasonably accurate qualitative prediction of the overall performance of a system frequently makes better scientific sense and also generally is far more useful than an over-refined precision in the estimation of parameters that all too frequently are not quite as precisely defined. The fact that the latter occupation attracts a far greater number of adherents has recently evoked strong expressions of concern from some professionsl leaders regarding the weakness of the socio-economic profession for over-indulgence in statistical methods:

> Where, as so often, the fluctuations of different series (of statistical data) respond in common to the pulse of the economy, it is fatally easy to get a good fit, and get it for quite a number of different equations. Nor in any case do I see how statistical procedure can enable us to distinguish causal from merely contingent relations, so as to "explain" or "account for" the variables taken as dependent.
>
> E. H. Phelps Brown: "The Underdevelopment of Economics," The Economic Journal, March 1972.

> The validity of these statistical tools depends itself on certain convenient assumptions ... that can seldom be verified.
>
> W. Leontief: "Theoretical Assumptions and Nonobserved Facts," American Economic Review, March 1971.*

Among such assumptions underlying any statistical technique there must be included the fidelity of the modeler's conception of the system structure, since sophistication of technique is ancillary to, but not a substitute for, adequate comprehension of the problem.

These and other factors related to restraint in the use of statistical methods in socio-economic research are fully discussed in the reports of Senge.** There is noted therein an extreme example of the almost religious attachment of large segments of the profession to statistical methods without regard to their relevance, as reflected in an attitude that regards such methods not as discretionary tools but rather as essential components in modeling. In the Systems Dynamics approach† the emphasis is on modeling the dynamic behavior - particularly the essentially nonlinear feedback effects - of the system under consideration. Although Forrester has repeatedly pointed out that the commonly used statistical techniques are incapable of adequate parameter estimation in nonlinear dynamic feedback models, his work has been repeatedly criticized for not using statistical techniques!

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*Further comments on this theme are noted in the appendix.

**P. M. Senge, "Evaluating the Validity of Econometric Methods for Estimation and Testing of Dynamical Systems," Systems Dynamics Group, Sloan School, MIT, Cambridge, February 1974, Memo D-1944-2; P. M. Senge, "An Experimental Evaluation of Generalized Least Square Estimation," System Dynamics Group, Sloan School, MIT, Cambridge, November 1974, Memo D-1944-6.

†See for example J. W. Forrester, Industrial Dynamics, MIT Press, Cambridge, 1961; J. W. Forrester, Urban Dynamics, MIT Press, Cambridge, 1969.

In specifying the proper role for statistical estimation in dynamic social models Senges's reports constitute a first step. Recognizing the need for clarifying such issues as:

1. Which statistical techniques are applicable for socio-economic models
2. Under what conditions are the respective techniques appropriate
3. How they should be applied,

it is acknowledged that a thorough assessment of existing techniques is necessary. Senge develops a general method, based on a laboratory technique, designed to assess the performance of estimation procedures under realistic conditions. While the method is in principle applicable to any statistical estimation procedure, Senge in the initial phase has confined his application to Ordinary Least Square (OLS) and Generalized Least Square (GLS) procedures, which are widely used in socio-economic modeling practice. These two procedures are tested against data generated from a sample model of Forester's describing market growth and capital investment in a typical firm. His results show that:

1. Both procedures are extremely sensitive to moderate measurement (data) errors
2. This sensitivity is considerably amplified in the presence of slight imperfections in the model structure.

This means that the investigator may be misled in either of two ways:

1. Discarding a reasonably good model structure in favor of an inferior one
2. Unjustified confidence in the parameters estimated.

Under such conditions, it appears it would be safer to rely on a model that merits a reasonable degree of confidence and accept an empirical guess on the parameters.

Senge is continuing his investigation with the aim of:

1. Defining the range and limits of applicability of OLS and GLS techniques in social modeling

2. Defining the applicability of other techniques through a corresponding evaluation.

Corroboration from other models is also necessary to ensure that the conclusions drawn are not due to some peculiarities in the particular Forrester model considered. It is also pointed out that if no acceptable results can be expected from the current single-equation econometric estimation methods, it will be necessary to extend the scheme in order to assess estimation procedures applicable to simultaneous systems of equations. One such estimation procedure, FIMLOF - Full Information Maximum Likelihood using Optimal Filter - has been developed as an operational tool and incorporated in a computer program (GPSIE) by D. W. Peterson.*

In the particular example considered by Peterson, the FIMLOF procedure has yielded highly accurate estimates even when measurement errors are on the order of 10 percent. In this respect it can be considered more reliable when compared with OLS and GLS methods. What the sensitivity of the results may be to model specification has not been completed; however, the thesis does include a very worthwhile discussion of the whole problem of modeling.

A summary of Peterson's work follows.

*D.W. Peterson, "Hypothesis, Estimation and Validation of Dynamic Social Models - Energy Demand Modeling," Ph.D. Thesis, MIT, June 1975.

2. INTRODUCTION

Noting the factors already discussed, the development of the FIMLOF procedure was motivated by the following considerations:

1. Models hypothesized in socio-economic sciences are often not linear in the parameters and thus do not lend themselves to the traditional single equation methods of statistical estimation.

2. Much of the available data is prone to significant levels of measurement error which, as noted by Senge, can under traditional (OLS and WLS) estimation procedures result in misleading conclusions.

3. The method allows the inclusion of variables for which no direct measurements are available - so frequently desirable in socio-economic modeling.

The thesis reviews the procedure termed Full Information Maximum Likelihood Estimation via Optimal Filtering (FIMLOF, developed by Schweppe) and extends the method so as to make it applicable to dynamic social models. The operation is demonstrated both in controlled simulation experiments and on real data - the modeling of energy demand: the software is available as a computer program GPSIE (General Purpose System Identifier and Evaluator) designed for easy coupling with a program describing the model under consideration.

The following simple example gives a good intuitive feeling for the issues involved. Consider the system:

$$x(n) = rx\,(n-1) + w(n)$$
$$z(n) = x(n) + v(n)$$

where, $x(n)$ and $z(n)$ are the state and observation at stage (time) n, while w and v represent the driving and measurement noise respectively. The problem is to estimate the parameter r.

In the absence of noise (i.e., $w(n) = 0$, $v(n) = 0$) a straightforward simulation will work and give consistent results. However, when driving noise is admitted ($w(n) \neq 0$) the system can drift from the determined trajectory and give a misleading result - zero error for wrong guess on r. In such a case, the OLS procedure can be used with consistent results as long as $v(n) = 0$. However, as already noted, OLS can be extremely sensitive to measurement noise ($v(n) \neq 0$), so that an alternative procedure becomes necessary. The FIMLOF procedure explicitly takes account of the variance of both error sources.

Consider the following iteration scheme inherent in the three estimation procedures mentioned above.

1. Compute predicted measure $\hat{z}(n/n-1)$ (predicted estimate of nth observation given all information up to stem (n-1))

2. Square and accumulate error residual $z(n) - \hat{z}(n/n-1)$ (difference between actual observation and estimate of observation)

3. Reinitialize [set $x(n) = \hat{x}(n/n)$ (estimate of state variable, given all information up to step n)] and repeat procedure.

The difference in the procedures lies in Step 3.

1. The straightforward simulation "reinitializes" by leaving the model state at the value determined by the prior simulation - ignoring the data $z(n)$; it is entirely model-based and hence vulnerable to driving noise in the model.

2. The OLS procedure reinitializes the model state at $z(n)$ - ignoring the previous state completely; it is entirely data-based and hence vulnerable to measurement error.

3. The aim of FIMLOF is to strike an optimum balance between these extremes by basing the reinitialization on estimates of the variances of the two error sources.

In general, the FIMLOF procedure reinitializes the system at the best Bayesian estimate x(n) given all prior information z(1)...z(n).

3. FIMLOF FOR NONLINEAR DYNAMIC SOCIAL MODELS

The procedure is designed to deal with models which can be reduced to the following standard form:

$$\underline{x}(n) = \underline{f}[\underline{x}(n-1), \underline{u}(n), \underline{w}(n), n]$$

$$\underline{z}(n) = \underline{h}[\underline{x}(n), \underline{v}(n), n] \qquad 1 \leq n \leq N$$

where n is the index of time-points at which data is available - a uniform time-step is not assumed; in the above, $\underline{x}$ and $\underline{u}$ are the state and control vectors, respectively, while $\underline{z}$ denotes the vector of observations, all three having a distinct dimension. The vectors $\underline{w}$ and $\underline{v}$ are the driving and measurement noise, respectively, both of which are assumed to be white Gaussian processes with zero mean. The initial conditions $\underline{x}(0)$ are uncertain and are characterized by having mean $\underline{x}$ and co-variance Ψ.

It is shown that the above system covers an extremely wide class of problems including cases involving missing observations and systems involving lagged variables and inputs as well as variables for which no observations are available, all these situations being particularly relevant to socio-economic modeling. Moreover, by suitable adjustment and augmentation, uncertainty can be admitted in the control vector and the assumptions on the noise components - white Gaussian, zero-mean - can be dispensed with.

The FIMLOF procedure may be summarized as follows. Let $\underline{z}_n$ denote the vector of accumulated observations up to the nth, i.e.,

$$\underline{z}_n = \{\underline{z}(1), \underline{z}(2), \ldots \underline{z}(n)\}.$$

Then, $\underline{z}_n$ is a random variable which, under the hypothesis of a given model identified by the subscript j, has probability density $p_j(\underline{z}_n)$ which represents the value of the likelihood function for that set of observations under the hypothesized model. Moreover, by Bayes' rule we note:

$$P_j(\underline{z}_n) = P_j(\underline{z}_{n-1}) \cdot P_j(\underline{z}_n/\underline{z}_{n-1}).$$

If we denote the log likelihood functions by $\underline{\xi}(n)$ so that

$$\underline{\xi}_j(n) = \ln P_j\ (\underline{z}_n)$$

then we have

$$\underline{\xi}_j(n) = \underline{\xi}_j(n-1) + \ln P_j(\underline{z}_n/z_{n-1})$$

Thus, the crux of computing the log-likelihood function is reduced to evaluating the second term on the right. If we introduce the residuals:

$$\underline{\delta}_z(n) = \underline{z}\ (n) - \hat{\underline{z}}(n/n-1)$$

where $\hat{\underline{z}}(n/n-1)$ is the predicted measurement, and use K_z to denote the dimension of $\underline{z}(n)$, then under the Gaussian assumption, we have

$$\ln P_j\ (\underline{z}_n/\underline{z}_{n-1}) = -\frac{1}{2}K_z \ln(2\pi)\ -\frac{1}{2}\ \ln\ [\det\{\underline{\Sigma}_z(n/n-1)\}]$$

$$-\frac{1}{2}\underline{\delta}_z'(n)\ \underline{\Sigma}_z^{-1}(n/n-1)\ \underline{\delta}_z(n)$$

where the predicted measurement and associated covariance

$$\hat{\underline{z}}(n/n-1) = E(z_n/z_{n-1})$$

$$\underline{\Sigma}_z(n/n-1) = E[\underline{\delta}_z(n)\delta_z'(n)]$$

are to be determined through the standard Kalman filter procedures.

When the log-likelihood function has been thus numerically determined, a hill-climbing algorithm is used to determine the maximum - which gives the FIMLOF estimate. Certain properties of the likelihood function (e.g., the two-sigma-two property of the likelihood function and the statistical character of the residual process) are especially useful in checking the consistency of the model and procedure with the data. The residuals also provide a convenient check for the determination and identification of bad data points resulting from such factors as typographical errors or sensor failures. The adverse effect of such readings can then be eliminated by such devices as converting these readings to the status of missing data points.

The computer program GPSIE, embodying procedures for:

1. Loading data
2. Computing the likelihood function point-by-point, via optimal filtering
3. Searching for the maximum of the likelihood function
4. Computing statistics as independent checks for consistency
5. Detecting bad data and identifying and eliminating their adverse effects

is designed for easy coupling with the program describing the particular model under consideration and embodies a high degree of flexibility for dealing with special cases.

4. FEASIBILITY OF PROCEDURE

Although the general procedure was first developed by Schweppe in 1965, applications of the FIMLOF methods have been relatively few, probably for two reasons:

1. High computational cost
2. Availability of some special-case simplifications.

Some engineering applications have demonstrated the feasibility of the model as well as giving some insight into the problem of numerical error in the method. When considering the application to the socio-economic problem area, it is well to bear in mind such features as:

1. Greater flexibility in model structure
2. Usually lower density in the data spectrum
3. Much broader selection of measured variables for which data are available

which distinguish it from engineering application.

The soundness of the approach was demonstrated by an application to a simple first-order linear system, where it yielded consistent accurate estimates in spite of extremely high noise content in both dynamic and measurement equations. A similar test was made on a more realistic model - Forrester's nonlinear dynamic model of a firm which permits comparison with the work of Senge on the same model.

As already noted, Senge's test of OLS and GLS estimation procedures showed that a 10 percent measurement error can lead to large errors in the parameter estimates. On the other hand, Peterson's test of FIMLOF as implemented by GPSIE yielded accurate results under the same conditions.

These results indicate that FIMLOF may yield accurate results even in the presence of system nonlinearities and measurement errors which cause difficulties with the traditional estimation techniques. This merely confirms that the GPSIE program gives results consistent with the theoretical considerations already discussed. A fuller understanding of the efficiencies and limitations of the various estimation techniques requires further such comparisons; a clearer definition of the conditions of success or failure of the various methods merits further investigation.

5. MODEL STRUCTURE

That the method is applicable to a wide class of nonlinear problems - where the distinction between structure and parameters is not clear as it is in the linear systems - removes many of the currently accepted restrictions in model construction largely dictated by the limitations in the estimation techniques. The fewer constraints in model structure as permitted by the power of the procedure in estimating parameters and structure in turn increases the role of experience, logic, theory, and judgment in model building. In particular, it should be noted that the procedure permits the inclusion in the model structure of such factors as:

1. Variables for which there are no data
2. Data of varying sampling frequency
3. Time-intervals not coincident with sampling intervals
4. Measurement errors in the data
5. Non-linear dependence in parameters

excluded by traditional estimation techniques, but so much a feature of socio-economic problem areas. The reduction of the traditional constraints makes dominant the implicit considerations inherent in model building - the judgment of choices exercised by the modeler.

As an example, rather than model an economic system in equilibrium, it would be more instructive to model the recognized cyclic features of the system and estimate the conditions under which a certain degree of equilibrium is achieved.

6. APPLICATION - ENERGY DEMAND

In illustrating the application of the procedure to specific examples, two models of fuel demand in the residential-commercial sector of the economy (as formulated by Baughman and Joskow) were considered. Both models include the same three components of fuel - natural gas, fuel-oil, and electricity.

In the simpler model the results from the checking procedures of GPSIE indicated the model was inconsistent with the data: in fact, the most acceptable maximum likelihood estimate resulted when the coefficient representing the lag-effect in fuel demand assumed an unrealistic value. There was, however, a certain consistency in the results which implied uncoupling of the electricity component from the rest of the system. The fact that GPSIE tended to ignore the other two components merely reflected its recognition of the much poorer quality of the data associated with the oil and gas consumption compared with that of electricity.

The flaws revealed by the results indicated how the model could be restructured so as to reflect more accurately the fuel-demand characteristics in spite of the drawbacks in the available data. In the second model, the demand equations are appropriately modified, and the equation for electricity demand is replaced by an equation describing total fuel demand. As a preliminary run the bad data are identified as falling into three categories:

1. Typographical errors
2. Inappropriate distribution of aggregated data
3. Anomalies.

Having corrected or disposed of the bad data points, the problem of initial conditions for cross-sectional data is dealt with through a device for setting the initial conditions for the filter. Then, using initial WLS estimates for the parameters, the model, through the FIMLOF estimation procedure, yields overall satisfactory results: the estimates from the maximum-likelihood checking schemes fall within acceptable limits, indicating that the model is consistent with the data.

7. CONCLUSIONS

The estimation procedure FIMLOF can be performed under the conditions of:

1. Nonlinearity in system dynamics and measurement functions
2. Unmeasured variables and mixed sampling intervals
3. Highly corrupted data, including measurement errors
4. Cross-sectional data
5. Short-time sequences of data.

In addition to its direct use for estimation purposes, it can be used to:

1. Detect and identify bad data
2. Check on other estimation techniques, e.g., OLS.

Futhermore, there are indications it can be used to compute statistical confidence bounds.

Perhaps the most significant implication is the substantial reduction in constraints on the model builder. However, it must not be taken as a conclusive test of model validity. The model must satisfy the more informal tests of validity as well as the numerical test of consistency. (These informal tests of model validity are discussed in Appendix B of Peterson's thesis, while the procedure for bad data identification is detailed in Appendix C; Appendix A gives a description of GPSIE.)

APPENDIX - FURTHER NOTES RELATIVE TO LEONTIEF'S REMARKS

In a more recent (December 1974) presidential address to the AEA, Walter Heller remarks:

"In one form or another, variations on Leontief's lament have been heard in many another presidential address, to wit:

> By F. H. Hahn (Econometric Society, 1968), who decried 'the spectacle of so many people refining the analysis of economic states which they give no reason to suppose will ever, or have ever, come about ...'
>
> By G. D. N. Worswich (Section F of the British Association, 1971), who viewed the performance of economics as 'curiously disappointing,' suggesting that it has 'a marvelous array of pretend tools which would perform wonders if ever a set of facts should turn up in the right form.'
>
> By E. H. Phelps Brown (Royal Economics Society, 1971), who judged the usefulness of current work in economics as 'not equal to its distinction' because it is 'built upon assumptions about human behavior that are plucked from the air.'
>
> By James H. Blackman (Southern Economic Association, 1971), who noted that models with sufficiently intriguing mathematical properties can achieve lives of their own even if they lead the investigator further away from reality and yet, 'the profession's incentive system tends perversely to reward this kind of endeavor and to deflect the attention of gifted economists from the exploration of concrete problems and the dirty work that entails.'
>
> By Serman Maisel (American Finance Association, 1973), who concluded that most of the literature of monetary economics is 'non-operational' since its prescriptions

are too often based on limited or false assumptions, it by-passes critical operational problems, and it ascribed too great validity to its statistical tests.'

By Barbara Bergmann (Eastern Economic Association, 1974), who prefaced her plea for more microsimulation to incorporate 'realistically messy information' in our economic data base with a few roundhouse swings at the economics profession and the pointed observation that instead of studying the real nature of decision making, we typically rush to make assumptions 'whose purpose in life is to let the theorem emerge, all neat and provable.'"

In the October/November 1976 issue of Technology Review there appears an illuminating and sobering discussion of nonlinearity and uncertainty by Kenneth Boulding. The article titled "Outrageous Fortune" concludes on the following note:

"Does the passion for linearity and certainty then distort scientific enterprise? One suspects that it does, especially in the social sciences where the search in dark rooms for invisible parameters that do not exist goes on constantly. This is not to deny the importance of the search for parameters that do exist, for the reduction of uncertainty, and for the pursuit of linearity wherever it may be discovered. At a certain point, however, linearity and certainty always break down and leave us with faith, hope, and charity, believing where we cannot prove, hoping against hope, and extending the blind determinism of vulgar social science into the absurd but real world of social creativity and human benevolence."

Such a buoyant conclusion cannot be improved upon.

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