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Policy Simulation Experiments with Macroeconometric Models: The State of the Art

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In recent years economists have made increasing use of policy simulation experiments with macroeconometric models to evaluate the effects of alternative economic policies on the behavior of the economy of an entire country. Although econometricians have devoted considerable time and effort to the solution of a multiplicity of problems related to the estimation of the parameters of econometric models, they have almost totally ignored some relatively serious methodological problems associated with policy simulation experiments with given econometric models. But some very real methodological problems do exist when one attempts to design and implement a simulation experiment with a large-scale, macroeconometric model. What are some of these problems? What are the possible consequences of ignoring these problems? What alternatives are available for circumventing these problems? In this paper we shall attempt to answer some of these questions.

Definition of the Policy Problem

Three alternative approaches have been proposed by economists for using macroeconometric models to evaluate the effects of alternative economic policies on the behavior of an economic system: (1) the Theil approach, (2) the Tinbergen approach, and (3) the policy simulation approach. Each approach assumes that we begin with a given econometric model of the economy to be investigated. That is, it is assumed that the economy of the country in question can be described by a set of simultaneous equations of the following form:[1]

$$(1) \quad AX_t + BY_t + \sum_{j=1}^{p} B_j Y_{t-j} + CZ_t + D = U_t$$

where

X_t = an $m \times 1$ vector of exogenous variables

Y_t = an $n \times 1$ vector of endogenous variables

Y_{t-j} = an $n \times 1$ vector of lagged endogenous variables when $j = 1, \ldots, p$

Z_t = $aq \times 1$ vector of policy instruments

U_t = an $n \times 1$ vector of stochastic disturbance terms

A, B, C, D = coefficient matrices whose parameters have been estimated by standard econometric techniques.

Theil approach [15]

Theil assumes that we know the social welfare function W of the policy maker and that it may be expressed as a function of the target (endogenous) variables and the policy instruments:

$$(2) \quad W_t = W_t(Y_t, Z_t).$$

The problem of the policy maker is defined as one of finding the values of Y_t and Z_t that will

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[1] Of course, the model may also be nonlinear.

maximize W_t subject to the constraints imposed by the econometric model (1) and given values of X_t, Y_{t-j}, and U_t.

This approach suffers from one major shortcoming, namely, that in the real world we simply do not know the parameters or even the functional form of W_t for governmental policy makers. The von Neumann-Morgenstern utility index and other techniques that have been proposed by economists for quantifying utility simply require too much information in order to obtain meaningful results—information that is not likely to be forthcoming from either present or future policy makers on the national, state, or local governmental levels. A policy maker whose principal concern is his own political survival is not going to reveal his utility function to you or me or any other economist.

Fromm [17, 19] and Shupp [43] have proposed several examples of hypothetical utility functions for national policy makers. While these exercises may be of some interest to academic economists, they are not likely to do much for real world policy makers.

In summary, the Theil approach to the evaluation of economic policies with macroeconometric models is little more than an interesting exercise which offers only limited promise as a policy-making tool. Economists would do well to spend less time trying to specify the social welfare functions of policy makers and spend more time seeking solutions to some of the problems of policy makers.

Tinbergen approach [15]

With the Tinbergen approach no knowledge of the policy maker's welfare function is assumed. This approach eliminates the maximization problem and instead assumes that the policy maker has specified a fixed target value for each of the endogenous variables. For given values of the exogenous, lagged endogenous, and stochastic variables, the equations of the econometric model (1) are then solved simultaneously for the set of values of the policy variables Z_t that is consistent with the targets.

If there are fewer policy variables than targets, the number of unknowns (policy instruments) in the econometric model (1) is smaller than the number of equations, and a solution is impossible except for special cases. On the other hand, if the number of policy instruments exceeds the number of targets, the number of unknowns will exceed the number of equations, and an infinite number of solutions will be possible. Within the Tinbergen framework the first of these two problems can be resolved only by either increasing the number of policy instruments or reducing the number of target variables until there is an equal number of equations and unknowns in the system. When there are more policy instruments than equations, the policy maker can assign arbitrary values to $q - n$ of the policy variables, and the equation system can be solved for the remaining n policy variables.

Although the problem of balancing the number of equations and the number of policy variables may prove to be a serious limitation of the Tinbergen approach, there is, in my opinion, another problem which is even more serious. The assumption that in a country like the United States a policy maker is willing to commit himself to a specific set of target values for the endogenous variables is highly questionable.[2] Just as the policy maker is unlikely to provide the economist with enough information to glean his utility function, it is doubtful that the policy maker will reveal in a very precise manner the values of his targets. A methodology based on information (e.g., values of target variables) that is simply not available to the analyst cannot be expected to yield results that are particularly useful to the policy maker.

Policy simulation approach

There is yet a third approach to the problem of evaluating the effects of alternative economic policies on the behavior of the economy which does not assume prior knowledge of either the social welfare function or the targets of the policy maker. This approach is known in the literature as simulation. With simulation we can solve the set of simultaneous equations given by (1) for Y_t in terms of X_t, Y_{t-j}, Z_t, and U_t and generate the time path of Y_t for as long a period as we desire. The exogenous variables X_t are read into the computer as data, the values of Y_{t-j} were generated in previous periods and are fed back into the model in period t, the policy variables are specified by the analyst, and the stochastic disturbances may either be suppressed or generated by an appropriate computer subroutine [38]. In the case of a linear econometric model, the solution of the econometric model takes the following form:

$$Y_t = -B^{-1}AX_t - B^{-1}\sum_{j=1}^{p} B_j Y_{t-j} - B^{-1}CZ_t - B^{-1}D + B^{-1}U_t \tag{3}$$

where B^{-1} is the inverse of B. Since it is possible to invert very large matrices on today's digital computers in only a few seconds, it is relatively easy to generate the time paths of Y_t for linear models through the use of computer simulation techniques.

Therefore, for any given values of the policy instruments, we can generate the time paths of the endogenous variables. In other words, when we approach the policy maker we ask him only two questions. First, "What output variables are of particular interest to you?" Second, "What sets of policy variables appear to be politically feasible?" With simulation we can then show the policy maker the consequences of the proposed policies. In addition, the economist may propose a few policies of his own for consideration by the policy maker. These policies may be put to a similar test. The policy maker then selects the policies that are most compatible with his preference function (which is unknown to the economist). The results of initial simulation runs may suggest other policy variable configurations to try.

There are two advantages of the policy simulation approach. First, it does not assume the availability of information about the policy maker's preferences that is impossible to obtain. Second, it provides the policy maker with the type of information that he is most likely to require in order to make decisions. In summary, while the Theil-Tinbergen approaches may be of considerable interest to economists from a purely theoretical standpoint, neither of these approaches provides operational solutions to policy problems. Therefore, policy simulation experiments may represent the only methodology currently available for obtaining practical solutions to real world policy problems.

We now turn our attention to several methodological problems associated with policy simulation experiments with macroeconometric models.

Solution of the Model

If our econometric model is linear, the solution is quite straightforward and is given by (3). Unfortunately, realistic econometric models are seldom linear. One example of nonlinearity which arises frequently in econometric models is the use of price times quantity terms in the identity defining gross national product in current prices. The Wharton model [10, 13] contains several other examples of nonlinearities, including: (1) relative prices in the consumption functions; (2) logarithmic treatment of the production function; (3) nonlinearity of the wage rate and capacity term in some of the price formation equations.

With the rediscovery by economists of the Gauss-Seidel method for solving systems of simultaneous nonlinear equations, nonlinearity no longer represents a serious computational problem. The paper by Evans [10] and the book by Klein and Evans [31] provide complete descriptions of the Gauss-Seidel method. Although the convergence of this algorithm is influenced by (1) the type of normalization procedure used and (2) the ordering of the equations, practical experience with the algorithm indicates that convergence is usually not a problem.

In addition to the Gauss-Seidel method for solving nonlinear econometric models, Charles Holt and others [25] have developed a special purpose simulation language called PROGRAM SIMULATE for generating the time paths of the endogenous variables of linear and nonlinear econometric models.

For the sake of completeness, we should mention two other computational problems associated with the generation of the time paths of the endogenous variables of an econometric model with computer simulation techniques.

First, Goldberger [22] has shown that when serial correlation is present in the error terms of an econometric model, the pattern of equation residuals over prior observations contains information that is useful in prediction. Through certain mechanical procedures that utilize information about the serial correlation in the observed residuals, it is possible to adjust the constant terms of regression equations and improve the predictive efficiency of the equations. Green [23] has reported on the results of using four different mechanical adjustment procedures in simulation experiments with the OBE model.

Second, with stochastic simulations with econometric models we frequently assume that the disturbance terms in (1) have a multivariate normal distribution with expected value of zero and a given variance-covariance matrix which has been estimated from the observed values of the residuals of the model. Provided the number of observations available to estimate the variance-covariance matrix is not less than the num-

[2] Admittedly, in a country like Holland or India, where economic planning is a generally accepted way of life, economic planners and policy makers may be willing to specify target values for the endogenous variables. But can you imagine a state legislator or even a U.S. congressman in this country being willing to specify a set of policy targets?

ber of equations, the technique for generating random variables with a multivariate normal distribution described in [38] is appropriate. However, if the number of observations is less than the number of equations, this technique breaks down and one of the procedures proposed by Nagar [36] and McCarthy [14, Appendix] will be required.

Validation

The validity of an econometric model depends on the ability of the model to predict the behavior of the actual economic system on which the model is based. In order to test the degree to which data generated by simulation experiments with econometric models conform to observed data, two alternatives are available—historical verification and verification by forecasting. The essence of these procedures is prediction, for *historical verification* is concerned with retrospective predictions (ex post simulations over the sample period) while *forecasting* is concerned with prospective predictions (ex ante simulations beyond the sample period). In the paper by Naylor and Finger [40] several criteria are suggested for deciding when the time paths generated by a simulation experiment agree sufficiently with the observed time paths so that agreement cannot be attributed merely to chance. Several specific measures and techniques are suggested for testing the "goodness-of-fit" of simulation results, i.e., the degree of conformity of simulated series to observed data.

Two recent studies by Cooper [5] and Stekler [44, 45] have attempted to evaluate the predictive behavior of several of the large-scale quarterly econometric models of the economy of the United States. Cooper uses the mean-squared error as a goodness-of-fit criterion and Stekler uses the Theil inequality coefficient. Cooper concluded:

> First, no single quarterly econometric model currently available is overwhelming superior to all other quarterly models in predicting the components of the national income and product accounts. Second, the econometric models are not, in general, superior to purely mechanical methods of forecasting. However, there are modules of the econometric models which are definitely superior to purely mechanical models. Third, the econometric models are, in general, structurally unstable [5, p. 151].

Stekler [45, p. 463] concluded that "the results suggest that econometric models have not been entirely successful in forecasting economic activity." Cooper's study examined the predictive performance of seven different models while Stekler considered only six models. Both studies included earlier versions of the OBE [33] and Wharton [13] models, but neither study treated the Brookings model [8] or the FRB-MIT-PENN model [4].

Experimental Design

In a computer simulation experiment, as in any experiment, careful thought should be given to the problem of experimental design. Among the important considerations in the design of computer simulation experiments are: (1) factor selection, (2) randomization, (3) number of replications, (4) length of simulation runs, and (5) multiple responses.

Factor selection

In the language of experimental design, the policy variables in our model are usually called *factors* and the endogenous variables are known as *response* variables. A *full factorial* design involves selecting several values or levels for each of the factors (policy variables) in the experiment. By assigning to each factor one of its levels, we generate a design point. If all the design points obtainable in this way are used, we have a full factorial design. The total number of design points in the full factorial design is the product of the number of levels for each factor. It is clear that a full factorial design can require an unmanageably large number of design points if more than a very few factors are to be investigated. If we require a complete investigation of all the factors in the experiment, including main effects and interactions of all orders, there is no solution to the problem of "too many factors." If, however, we are willing to settle for a less than complete investigation, perhaps including main effects and two-factor interactions, there are designs which will accomplish our purpose that require fewer design points than the full factorial. Fractional factorial designs, including Latin square and Greco-Latin square designs, are examples of designs that require only a fraction of the design points required by the full factorial design. The papers by Hunter and Naylor [37] and Naylor, Burdick, and Sasser [39] describe various experimental designs which may be useful with policy simulation experiments with macroeconometric models.

Randomization

There are at least three reasons why one might want to include stochastic disturbance terms in simulation experiments with nonlinear macroeconometric models. First, as Phil Howrey has pointed out in an unpublished paper entitled "Dynamic Properties of Stochastic Linear Econometric Models," if the long-term properties of an econometric model are to be investigated,

> . . . it may not be reasonable to disregard the impact of the disturbance terms on the time paths of the endogenous variables. Neither the characteristic roots nor the dynamic multipliers provide information about the magnitude or correlation properties of deviations from the expected value of the time path.

Second, Howrey and Kelejian [27] have demonstrated that "the application of nonstochastic simulation procedures to econometric models that contain nonlinearities in the endogenous variables yields results that are not consistent with the properties of the reduced form of the model." Third, by including stochastic error terms, one can replicate the simulation experiment and make statistical inferences and test hypotheses about the behavior of the system being simulated, based on the output data generated by the simulation experiment.

Number of replications

If one is to make inferences about the effects of alternative economic policies on the behavior of an economic system based on a computer simulation experiment, the question of sample size or the number of replications of the experiment should be considered. It is well known that the optimal sample size (number of replications) depends on the answers one gives to the following questions: (1) How large a shift in population parameters do you wish to detect? (2) How much variability is present in the population? (3) What size risks are you willing to take?

Unfortunately, econometricians have tended to ignore the question of optimal sample size and to select some arbitrary number of replications for stochastic simulations with econometric models. Nagar [36], for example, used twenty replications with his stochastic simulations with the Brookings model. In more recent simulations with the Brookings [18], OBE [23], and Wharton [14] models, fifty replications were used. In none of these cases was any rationale provided for the arbitrary sample size.

The paper by Gilman [21] describes several rules for determining the number of replications of a simulation experiment when the observations are independent. (Observations obtained by replicating a simulation experiment will be independent, provided one uses a random number generator that yields independent random numbers.)

Length of simulations runs

Another consideration in the design of simulation experiments is the length of a given simulation run. This problem is more complicated than the question of the number of replications because the observations generated by a given simulation rule will typically be autocorrelated, and the application of "stopping rules" based on classical statistical techniques may underestimate the variance substantially and lead to incorrect inferences about the behavior of the system being simulated.

> In the large majority of current simulations, the required sample record length is guessed at by using some rule such as "Stop sampling when the parameter to be estimated does not change in the second decimal place when 1000 more samples are taken." The analyst must realize that makeshift rules such as this are very dangerous, since he may be dealing with a parameter whose sample values converge to a steady state solution very slowly. Indeed, his estimate may be several hundred percent in error. Therefore, it is necessary that adequate stopping rules be used in all simulations [21, p. 1].

To the best of my knowledge, econometricians have not even acknowledged that the length of the simulation run might be a relevant consideration in the design of a policy simulation experiment. Gilman [21] has described several "stopping rules" for determining the length of simulation runs with autocorrelated output data. Ling [37] has also treated this problem.

Multiple responses

The multiple response problem arises when we wish to observe and evaluate many different response variables in a given simulation experiment. We previously alluded to this problem in our discussion of the Theil-Tinbergen approaches to the theory of quantitative economic policy. The multiple response problem is particularly acute with the Brookings, OBE, and Wharton models, each of which has over fifty response variables. A question arises as to how one goes about validating multiple response simulation experiments and how one evaluates the results of the use of alternative policies in the case of policy simulation experiments. To solve the multiple response problem, the analyst must devise some technique for assigning weights to the different response variables before applying specific statistical tests. Fromm [17, 19] has proposed the use of utility theory to evaluate the results of policy simulation experiments with the Brookings model. The approach taken by most econometricians to the multiple response problem is to present the results of their experiments and let the policy maker assign his own weights to the different response variables. Given the practical and theoretical problems involved in assigning weights or utilities to different response variables, this approach is likely to prevail in the near future.

Data Analysis

In a well designed simulation experiment, consideration must be given to methods of analyzing data generated by the experiment. Most of the classical experimental design techniques described in the literature are used in the expectation that the data will be analyzed by one or both of the following—regression analysis and analysis of variance. Regression analysis is a collection of techniques for data analysis which utilizes the numerical properties of the levels of quantitative factors. The analysis of variance is a collection of techniques for data analysis that are appropriate when qualitative factors are present, although quantitative factors are not excluded.

The papers by Burdick, Hunter, and Naylor in [37] describe the use of response surface designs and regression analysis with computer simulation experiments with econometric models.

Several special cases of the analysis of variance have been applied to the analysis of data generated by simulation experiments with macroeconometric models. These techniques include the F-test, multiple comparisons, multiple ranking procedures, and spectral analysis. Although the F-test and multiple comparisons are well known to most economists, economists have made only limited use of multiple ranking procedures [28].

Frequently, the objective of a computer simulation experiment with an econometric model is to find the "best," "second best," "third best," etc. policy. Although multiple comparison methods of estimating the sizes of differences between policies (as measured by population means) are often used as a way of attempting, indirectly, to achieve goals of this type, multiple ranking methods represent a more direct approach to the solution of the ranking problem. A good estimate of the rank of a set of economic policies is simply the ranking of the sample means associated with the given policies. Because of random error, however, sample rankings may yield incorrect results. With what probability can we say that a ranking of sample means represents the true ranking of population means? It is basically this question that multiple ranking procedures attempt to answer.

The F-test, multiple comparisons, and multiple ranking procedures have been used by Naylor, Wertz, and Wonnacott [41] to evaluate the effects of alternative monetary and fiscal policies on the variance of national income with a simulation experiment with a macroeconometric model.

Another technique that has proved to be useful in analyzing data generated by computer simulation experiments with econometric models is spectral analysis. Spectral analysis was developed specifically to analyze time series data that are autocorrelated. For the purpose of describing the behavior of a stochastic variate (e.g., GNP) over time, the information content of spectral analysis is greater than that of sample means and variances. With spectral analysis it is relatively easy to construct confidence bands and to test hypotheses for the purpose of comparing the simulated results of the use of two or more alternative economic policies. Frequently, it is impossible to detect differences in time series generated by simulation experiments when one restricts himself to simple graphical analysis. Spectral analysis provides a means of objectively comparing time series generated with a computer model. Spectral analysis can also be used as a technique for validating an econometric model of an economic system. By comparing the estimated spectra of simulated data and corresponding real world data, one can infer how well the model resembles the system it was designed to emulate.

Naylor, Wertz, and Wonnacott [42] have used spectral analysis to analyze data generated by a simulation experiment with an econometric model. Spectral analysis was employed to compare the effects of alternative economic policies on national income generated by the simulation experiment.

Some Unresolved Problems

We shall conclude this paper by summarizing a number of methodological problems associated with policy simulation experiments with macroeconomic models for which solutions do not presently exist.

Simulation versus analytical solutions

Explicit analytical solutions for the reduced form of simultaneous, nonlinear, stochastic difference equations are frequently difficult, if not impossible, to obtain. For this reason economists have found it necessary to resort to numerical techniques or computer simulation experiments to validate these models and to investigate their dynamic properties. Howrey and Kelejian [27] have recently raised some very interesting questions concerning the use of computer simulation techniques with econometric models. In general, they have suggested that the role of computer simulation as a tool of analysis of econometric models should be reconsidered. They have argued "that once a *linear* econometric model has been estimated and tested in terms of the known distribution theory concerning parameter estimates, simulation experiments . . . yield *no additional information* about the validity of the model." In addition, they have pointed out that "although some of the dynamic properties of linear models can be inferred from simulation results, an analytical technique (spectral analysis) based on the model itself is available for this purpose" [27]. Since any nonlinear econometric model can be approximated by a linear model through the use of an appropriate Taylor series expansion, the arguments of Howrey and Kelejian can also be extended to include nonlinear econometric models. The questions they raise are important ones and merit further theoretical and empirical consideration. In general, the whole question of when to use simulation rather than standard mathematical techniques is a question that needs further investigation, not only with econometric models but with economic models of all types.

Perverse simulation results

Econometric models that have been estimated properly and are based on sound economic theory may yield nonsensical simulation results. That is, the simulations may "explode" and inherently positive variables may turn negative, leading to results that are in complete conflict with reality. We must learn more about the mathematical properties of our models, with the hope of devising techniques that will enable us to spot these problems with our models analytically before running simulations with them. For example, Howrey and Kelejian [27] have shown that the application of simulation techniques to nonstochastic econometric models that contain nonlinearities in the endogenous variables "yields results that are not consistent with the properties of the reduced form of the model." What other information can be gleaned from the structure of econometric models prior to conducting simulation experiments?

There appears to be a definite need to combine the approaches of the econometrician and the systems analyst in formulating models of complex economic systems. To the systems analyst, an economic model consists of a set of mathematical inequalities which reflect the various conditional statements, logical branchings, and complex feedback mechanisms that depict the economy as a dynamic, self-regulating system. Although economists have made considerable progress in building econometric models and developing techniques to estimate their parameters, little or no attention has been given to alternative model structures such as those used by systems analysts. The possibility of developing models of the economy as a whole that consist of structures other than simultaneous difference equations needs to be explored more fully. Special attention should be given to the types of logical models developed by systems analysts. To use systems analysis to build macroeconomic models that accurately reflect the underlying decision processes of the total economy, it may be necessary to draw heavily on other disciplines, including sociology, psychology, and political science.

Inadequate estimation techniques

Although the static properties of simultaneous equation estimators such as OLS, 2SLS, LISE, FIML, and 3SLS are well known, we have no assurance whatsoever from econometric theory that a model whose parameters have been estimated by one of these methods will yield valid, dynamic, closed-loop simulations. That is, it is quite possible for a model that has been estimated by one of the aforementioned techniques to yield simulations which in no sense resemble the behavior of the system that they were designed to emulate. What is needed is a new estimation technique which uses as its criterion of goodness-of-fit, "How well does the model simulate?" rather than "How well does the static model fit the historical data based on one-period predictions?" The question of whether poor simulation results with econometric models are due to improper methods of estimation or a misspecified model is one that calls for further research.

Unstable coefficients

The simulation experiments of the Adelmans [1, 2] and others have demonstrated the effects of including additive stochastic error terms in econometric models. Howrey and Kelejian [27] have also treated this question from a theoretical standpoint. What has not been considered is the question of what happens if we treat the coefficients of an econometric model as random variables in simulation experiments. Yet we know very well that these coefficients are indeed random variables and that they are not likely to remain constant over long periods of time. Preliminary experiments with this problem indicate that by shocking the coefficients of the Klein-Goldberger model [32] we encounter two different problems. First, we encounter serious difficulty in solving the model. Second, the results are quite different from the deterministic simulations as well as the simulations with additive shocks. Finally, the structure of the model may in reality evolve over time, and the assumption of constant coefficients, independent of time, may require review.

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