

The Econometric Challenge to System Dynamics and Vice Versa: Some Future Perspectives

MANFRED SOMMER

ABSTRACT

In the last years, there have been some attempts to compare different approaches for dynamic modeling of socioeconomic systems and to suggest guidelines for choosing among them. This paper continues these efforts with special emphasis on system dynamics and econometrics, which are commonly regarded as the roughest competitors in this field of simulation. It will present a detailed catalogue of model features, relevant for an adequate characterization of system dynamics and econometrics, and will stress the importance to notice the interconnections that exist between different features. The paper then gives a systematic survey of the conceivable relations between system dynamics and econometrics, and closes with a short epistemological outlook.

Introduction

Since it started as "Industrial Dynamics," System Dynamics (SD) has been under attack from followers of other modeling methodologies—at first mainly operations researchers and later (since "Urban Dynamics" and "World Dynamics") economists and econometricians (EC). In the last years, system dynamicists have launched some heavy counterblows not only to refute the EC-criticisms, but also in order to prove that EC more than SD is afflicted with severe flaws. Although there have been some attempts of unprejudiced comparisons of both modeling approaches (e.g., [28, 29, 31, 33, 41, 42], "the present situation is such that nonadversaries, i.e., neutral observers, find it difficult to assess the value of system dynamics (and competing methodologies) to them" [32, p. 23]. Nevertheless, at least two agreements seem to have emerged:

In the field of dynamic socioeconomic modeling and simulation econometrics and system dynamics are the most important competitors (microanalytical simulation left aside).

This competition has to be carried out on a general methodological and not on a model-specific level because criticisms against certain models (right or wrong) never

MANFRED SOMMER is Assistant Professor (Hochschulassistent) at the University of Bielefeld, Federal Republic of Germany. He holds a Dr. rer. pol. from the Technical University of Berlin. His research and teaching activities concentrate on issues in the economics of education, labour economics, and on general methodological aspects of socioeconomic modeling.

Address reprint requests to Dr. Manfred Sommer, Universität Bielefeld, Universitätsstr 25, D-4800 Bielefeld, Germany.

refute or corroborate the approach as such: model-specific objections can only illustrate approach-general objections.

There seem to be two advantages in starting with a comparison of the SD and EC methodologies rather than with a SD and EC model. First, comparing a SD and an EC model, e.g., of the labor market, leaves one with the trouble to decide whether the differences in results are due to the underlying modeling philosophies or to different problem definitions, conceptualizations of the research questions, theories and data employed (*problem of attribution*). Only if all these latter factors influencing the specification of comparable SD and EC models could be held constant—a kind of *ceteris paribus* clause—would the comparison of specific models allow for inferences about the methodologies. Second, similarities, as well as distinctions between certain SD and EC models may solely rest upon these two models and may not be found in others (*problem of generalization*). On the other hand, the knowledge obtained from a general confrontation of modeling approaches should render valuable guidelines for further comparisons of specific models.

Comparison of Model Features

Let us begin with an indication of some common basic beliefs of EC and SD. Both conceive the reality of modern socioeconomic systems to be so highly complex that mathematical models are held to be far superior devices for predictions and decisions than verbal or mental models. They also share the preoccupation with dynamic phenomena of these systems. It should further be recognized that both EC and SD are macroanalytical in the sense that they do not perceive real systems at the level of their elements (individuals, households), tracing changes of certain characteristics of these elements over time and aggregating them in order to describe the changes in system behavior (microanalytical approach). Instead, they model systems by variables that describe the characteristics of a sum of elements belonging to the same class [22 pp. 30–39]. These common characteristics seem to be the rationale for the SD-EC-rivalry that does not exist between much more distinct modeling approaches like SD or EC on one side and input–output analysis or event-oriented simulation methodologies on the other side. These differences in intensity of competition are also reflected in Donella Meadow's "Unavoidable A Priori," where four modeling methods are exposed (SD, EC, Input–Output Analysis, Optimization) but only SD and EC are seen to be involved in a "paradigm conflict" [41 pp. 222–236].

These similarities should not be overlooked while stressing the differences between EC and SD. Due to limited space, we cannot comment on all model features found to be relevant and presented in Table 1. Because some authors have lately recommended partial modifications of SD, we have introduced the distinction between Classical System Dynamics (CSD), as advocated by Forrester since "Industrial Dynamics" [11], and Modified System Dynamics concepts (MSD). Since it is impossible to reproduce our in-depth assessment of these model characteristics and of the justifications advanced by EC and SD—see [54] for a detailed treatment—we have to confine ourselves to an exemplary short-cut exposition.

SOURCES OF INFORMATION

It is well known that CSD heavily relies on expert opinion, intuition, and personal acquaintance with the real system as information base for model specification, while EC favors economic theory and available data. Nevertheless, both seem to mutually move towards each other: while SD—especially as applied in macroeconomic modeling [2, 33, 37, 39]—gives more scope for economic theory and data considerations, EC modelers

TABLE 1
Comparison of Econometric and System Dynamics Model Features

Model Features	Econometrics	System Dynamics	
	EC	CSD	MSD
1. Sources of information			
a. socioeconomic theory	<i>d</i>	<i>p</i>	<i>p</i>
b. expert experience etc.	<i>p</i>	<i>d</i>	<i>p</i>
c. data	<i>n</i>	<i>p</i>	<i>n</i>
2. Degree of hardness			
a. quantitative variables	<i>d</i>	<i>p</i>	<i>p</i>
b. qualitative variables	<i>p</i>	<i>p</i>	<i>p</i>
c. observable variables	<i>n</i>	<i>p</i>	<i>n</i>
d. nonobservable variables	<i>p</i>	<i>p</i>	<i>p</i>
3. Types of variables			
a. physical variables	—	<i>n</i>	—
b. informational variables	—	<i>n</i>	—
c. stock variables	<i>p</i>	<i>n</i>	<i>p</i>
d. flow variables	<i>d</i>	<i>n</i>	<i>n</i>
4. Types of equations			
a. behavioral equations	<i>n</i>	<i>n</i>	<i>n</i>
b. definitional identities, e.g.,	<i>p</i>	<i>n</i>	<i>n</i>
ba. stock-flow identities	<i>p</i>	<i>n</i>	<i>d</i>
bb. national accounting identities	<i>d</i>	<i>p</i>	<i>p</i>
5. Types of behavioral equations			
a. deterministic	—	<i>d</i>	<i>p</i>
b. stochastic	<i>n</i>	<i>p</i>	<i>p</i>
6. Functional forms			
a. linear in parameters and variables	<i>d</i>	(<i>p</i>)	<i>p</i>
b. nonlinear in parameters	(<i>p</i>)	<i>p</i>	<i>p</i>
c. nonlinear in variables	<i>p</i>	<i>p</i>	<i>p</i>
d. nonlinear in parameters and variables	—	<i>d</i>	—
7. Time interval			
a. statistic model	—	—	—
b. dynamic model	<i>n</i>	<i>n</i>	<i>n</i>
ba. discrete model	<i>d</i>	<i>p</i>	<i>d</i>
bb. quasicontinuous model	—	<i>d</i>	—
bc. continuous model	(<i>p</i>)	—	—
8. Lags			
a. fixed-time lags	<i>d</i>	<i>p</i>	<i>p</i>
b. distributed lags	<i>p</i>	<i>d</i>	<i>p</i>
ba. finite distributed lags	<i>p</i>	—	<i>p</i>
bb. infinite distributed lags	<i>p</i>	<i>d</i>	<i>p</i>
9. Model boundary			
a. closed model	<i>p</i>	<i>n</i>	<i>p</i>
b. open model	<i>d</i>	—	<i>p</i>
10. Causal ordering			
a. recursive model	(<i>p</i>)	<i>n</i>	<i>d</i>
b. block-recursive model	<i>d</i>	—	<i>p</i>
c. interdependent model	<i>p</i>	—	<i>p</i>
11. Feedback structure			
a. output-closed	<i>d</i>	<i>d</i>	<i>d</i>
b. output-open	<i>p</i>	—	<i>p</i>
12. Parameter estimation			
a. ad hoc	—	<i>n</i>	<i>p</i>
b. econometric methods	<i>n</i>	—	<i>p</i>

(continued)

TABLE 1 (continued)
Comparison of Econometric and System Dynamics Model Features

Model Features	Econometrics	System Dynamics	
	EC	CSD	MSD
13. Evaluation strategies			
a. non-predictive evaluation	<i>p</i>	—	<i>p</i>
b. predictive evaluation			
ba. deterministic simulation			
baa. ex post (explanation)			
baaa. static	<i>p</i>	—	<i>p</i>
baab. dynamic	<i>p</i>	—	<i>p</i>
bab. ex ante (prediction)			
baba. static	(<i>p</i>)	—	(<i>p</i>)
babb. dynamic	<i>d</i>	—	<i>d</i>
bb. endogenous simulation	<i>p</i>	<i>d</i>	<i>p</i>
bc. stochastic simulation	<i>p</i>	<i>p</i>	<i>p</i>
bd. backward simulation	—	—	(<i>p</i>)
c. policy evaluation			
ca. ex post (explanation)	<i>p</i>	<i>p</i>	<i>p</i>
cb. ex ante (decision)	<i>d</i>	<i>d</i>	<i>d</i>
cc. change in instruments	<i>d</i>	<i>p</i>	<i>p</i>
cd. change in specifications	<i>p</i>	<i>d</i>	<i>p</i>
ce. optimization	<i>p</i>	—	<i>p</i>
14. Time horizon			
a. short-/middle-term	<i>d</i>	(<i>p</i>)	<i>p</i>
b. long-term	<i>p</i>	<i>d</i>	<i>p</i>
15. Degree of accuracy			
a. high	<i>d</i>	—	<i>p</i>
b. low	—	<i>d</i>	<i>p</i>
16. Main model purpose			
a. obtaining knowledge of parameter magnitudes (elasticities, propensities, multipliers)	<i>p</i>	—	<i>p</i>
b. testing economic theories	<i>p</i>	<i>p</i>	<i>p</i>
c. precise prediction of variables	<i>d</i>	—	<i>p</i>
d. general understanding of dynamic behavior	<i>p</i>	<i>d</i>	<i>p</i>
e. improvement of model (and real system) behavior	<i>p</i>	<i>p</i>	<i>p</i>

CSD = Classical System Dynamics; MSD = Modified System Dynamics concepts; *n* = necessary; *d* = dominant; *p* = possible; (*p*) = possible, but seldom used; — = unimportant or impossible.

currently admittedly employ subjective expert judgement to adjust constants and coefficients in order to improve their forecasts [8, 24 p. 520]. There remains the difference, though, that EC models require timeseries data mainly for variables—for all variables in the parameter estimation phase and especially for the exogenous variables in ex-post simulations—while SD models need data primarily for initial level values and for parameter measurement, as far as they are directly observable.

DEGREE OF HARDNESS

The above comments on data requirements in connection with the aspired degree of accuracy (see Table 1, 15.) already indicate why the the emphasis of EC is on quantitative and observable variables, although not strictly excluding qualitative (dummies) or unobservable variables (e.g., proxies). The more liberal usage of unobservable variables in SD allows for an easier incorporation of “planned” or “desired” variables thus facilitating the modeling of disequilibrium mechanism [51]. Here again we observe signs of reduced differences between EC and SD as within the former the “soft modeling approach” gains ground [2].

TYPES OF EQUATIONS

Both EC and SD models consist of behavioral equations and definitional identities. Differences in the structure of behavioral equations are reflected in features 5–8 of Table 1. In SD models, definitions appear mainly in the form of stock-flow identities (level equations), which is justified by the importance of the principle of conservation [12, 38], while in EC models, they are mostly national income identities, relating flows to flows. We think that these differences are not primarily rooted in contradictory “world views” about conservation or nonconservation of flows in real systems but can rather be traced back to other model characteristics. Economic and social statistics generally contain more and better data on flows than on stocks that are often unobservable and, therefore, excluded from EC models (see Table 1, 2.). On the other hand, the importance of stock variables for the dynamic behavior of a model increases with the length of the time horizon to be simulated. This is another reason that EC models do not lay as much stress on stocks as SD models normally do (see Table 1, 14.). Furthermore, it must be recognized that some macroeconomic SD models are themselves not immune from lack of stock variables (e.g., [33, 49]).

FUNCTIONAL FORMS

Although EC has never claimed that linear functions are the only true way of interrelating variables (see [25, 57, 26] for a very early controversy on this subject and [54, pp. 51–55 for a comment), there is no doubt that nonlinearities only played a minor part in first-generation EC models. After problems of estimating (see Table 1, 12.) and solving nonlinear EC models with simultaneous equations (see Table 1, 10.) had become easier to handle, the “world view” of EC shifted towards a fuller recognition of the relevance of nonlinear functions. Since the 1960s “neither we nor the practicing econometrics profession really believe that the economy can be adequately represented by a linear model” [30, p. 9]. This is very much in line with convictions held by CSD from the outset. In spite of this development of EC in the SD direction, there still remain two differences. First, the portion of nonlinear equations within EC models seems to be smaller than within SD models on the average. Second, the forms of the nonlinearities employed are not congruent. While SD models incorporate piecewise linear table functions (TABLE, TABHL) that render equations nonlinear in parameters, EC models overwhelmingly use nonlinear-in-variables formulations. Here again, however, we observe narrowing gaps. Today, DYNAMO offers a nonlinear-in-variables table function TABPL [47, pp. 34–35] for SD models, while EC has started to deal with varying-parameter models [4, 9, 36]. Another perspective of similar treatment of nonlinearities emerges with the incorporation of linear and cubic splines in EC models [46] as well as in MSD models [54, pp. 185–187, 380–382].

LAGS

Figure 1 demonstrates that SD delays can be regarded as a portion of the larger set of EC lag structures. Actually, SD delays are the quasicontinuous counterparts of the geometric and Pascal lag distributions. For $DT = 1$, both groups become equivalent [54, pp. 206–207]. Although it is often very plausible that the output of a certain process will be distributed over time relative to its input, there is no reason to neglect the existence of other kinds of dynamic processes with fixed-time lags. In the early days of SD (e.g., [11, p. 91]) they appeared as so-called pipeline delays and were represented in DYNAMO I as BOXLIN functions. Later, they were discarded from SD [12] as well as from DYNAMO II. Today, they are resurrected in DYNAMO III as SHIFTL functions but the SD methodology has not yet reestablished them. In EC models, these fixed-time lags

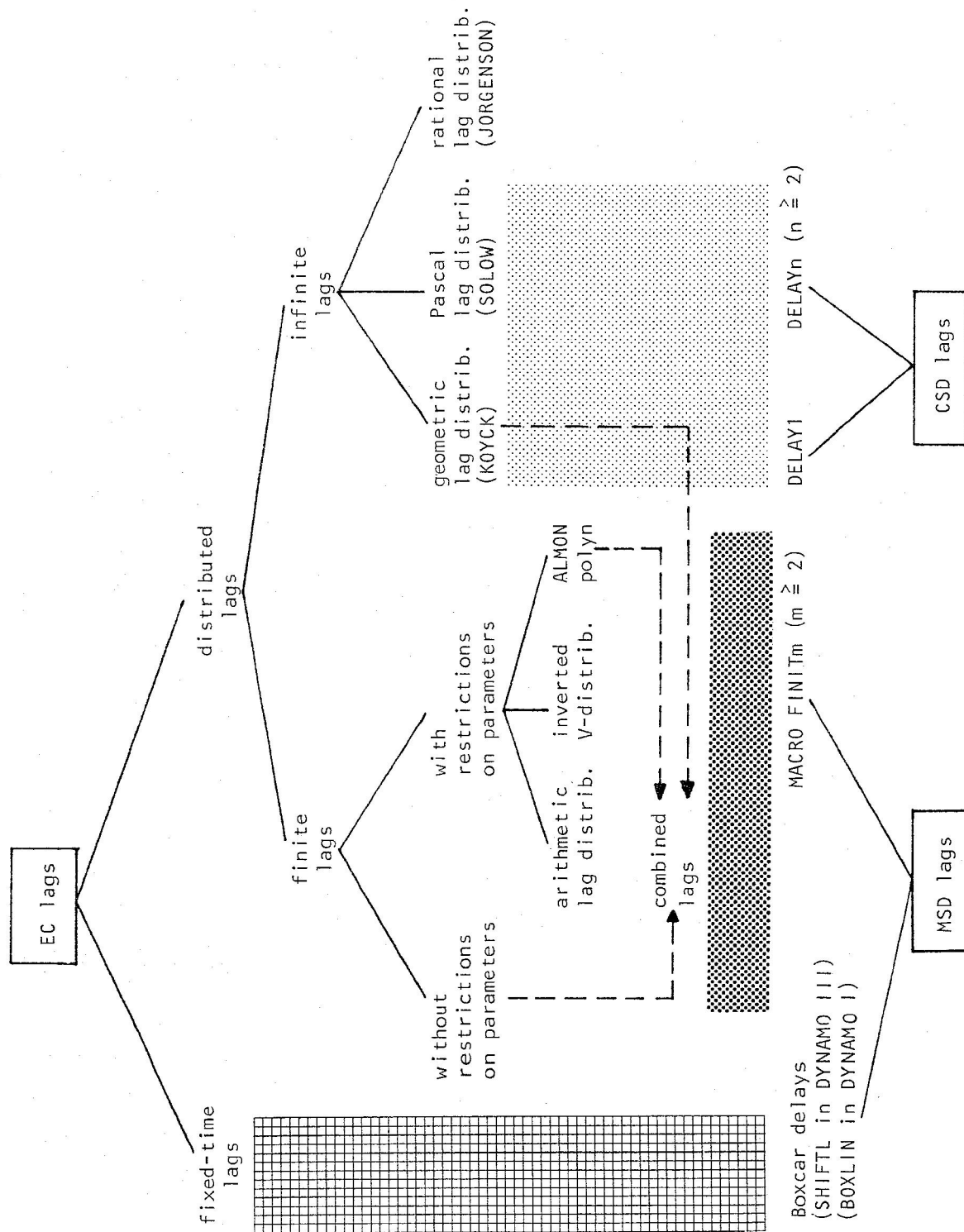


Fig. 1. Syntactical correspondence between EC and SD lag structures.

always played a dominant role. Another major difference between EC and SD exists within the group of distributed lags. While SD only knows infinite lag distributions, EC also uses different types of finite lag distributions, partly with and partly without a priori restrictions on their parameters.

Two kinds of modifications of the CSD treatment of time lags have been suggested:

1. the use of econometric estimation techniques to determine the order and the average delay of SD delays [21]
2. the transfer of EC finite-distributed lag forms to SD [59].

With regard to the first point, two strategies are conceivable:

- 1a. estimation of the appropriate Koyck distribution (for a DELAY1) or Pascal distribution (for a DELAY of higher than first order)
- 1b. estimation of a finite lag distribution and afterwards approximation by an appropriate DELAY.

We have demonstrated that strategy 1b. can be successfully followed by estimating an arithmetic lag distribution as a basis for a DELAY1 and an Almon distribution with a polynomial of second degree for a DELAY_n ($n \geq 2$). Another interesting perspective is the estimation of an Almon distribution with a polynomial of fourth degree possibly leading to a bimodal lag distribution that can be approximated by a combination of different DELAYs [54, pp. 209–217].

If one is ready, however, to employ a finite lag distribution mainly to get an empirical estimate of the average delay DEL, it is worthwhile to consider a complete incorporation of the estimated Almon lag distribution in the model. An adequate DYNAMO-Macro has been formulated by Zwicker [59, p. 514]. One should recognize, though, that with the application of a varying time increment DT, the definition of the average delay DEL only holds for CSD exponential DELAYs. The transfer of fixed-time and finite-distributed lags into a MSD concept requires one to drop the DT-variability and, therefore, makes sense only together with another modification: the shift from quasicontinuous to discrete SD models (see Table 1, 7.).

MODEL BOUNDARY

One of the severest differences between EC and CSD models is their very dissimilar tolerance for exogenous variables. It would be misleading, though, to assert that these differences are mainly caused by the philosophical question of whether real systems are open or not. In fact, the “world views” are rather close together here. While CSD allows for exogenous variables only “where the external input is completely independent of and unaffected by any of the variables generated in the model” [11, p. 113], EC requires not complete but only approximate independence [27, p. 394]. The fact that CSD models are closed and EC models are usually open with different degrees [54, p. 223] is, above all, due to disagreement on the proper model purposes to be pursued (see Table 1, 16.). “System dynamicists are generally unconcerned with specific values of system variables in specific years. They are much more interested in general dynamic tendencies; whether the system as a whole is stable or unstable, oscillating, growing, declining or in equilibrium” [41, pp. 176–177]. The apparent trade-off between endogeneity and predictive capabilities of a dynamic model—already recognized in [11, p. 113]—leads EC models to treat those variables as exogenous that can be externally predicted with greater accuracy (see Table 1, 15.).

Two misunderstandings should be avoided though. The use of exogenous variables does not necessarily and exclusively imply that they are fed with their actual values [11, p. 113] but they may be—even ex post—and must be—ex ante—formulated as functions of time. It further follows that the internal dynamics of an open model can just as well be analyzed by endogenous simulations (see Table 1, 13bb.) as those of a closed model, if one holds the exogenous variables constant or treats them as simple functions of time. Finally, it should be mentioned that some departures from the CSD closed boundary concept can be observed. Some models, e.g., those developed by Lehmann [33] and Blackman [6] make use of exogenous variables. Two MSD concepts have suggested a general methodological shift in this respect: “Probalistic System Dynamics” [19] includes probalistic outside events while Zwicker’s “Feedback-oriented Open Level-Rate” modeling (FOLR) allows for exogenous variables more along traditional EC lines [59].

CAUSAL ORDERING

It is well known that circular causal relations in CSD models must always pass through a level implying a lag of length DT and thus prohibiting the occurrence of simultaneous interdependences between two variables. This has been justified by the “principle of independence of decisions” but the central motive probably was the easier computational handling of recursive than interdependent models [11, p. 70]. It is interesting to register that, although the alternative “interdependence versus recursiveness” has been one of the oldest methodological disputes within EC (see [34] for a survey), SD proponents have never drawn on the arguments that the advocates of recursive EC models had raised. “Our main conclusion, therefore, is that if the model is made sufficiently detailed and appropriately specified, and if the periods are sufficiently short, i.e., if we work with a basic model constructed on the principles of the “disequilibrium” method of the Stockholm-school, the model can always be made recursive, and, indeed, must always become recursive” [5, p. 160]. This fits very well with CSD views.

EC has, nevertheless, very much favored interdependent models. “While most builders of econometric models use an interdependent system and have, as a result, accumulated much empirical evidence; virtually all the debate has consisted of criticism of interdependent systems by proponents of recursiveness who bring to battle an imposing array of conceptual and theoretical arguments, but very little empirical evidence” [34, p. 119]. The above quoted statement by Bentzel and Hansen already indicates the circumstances which can lead to simultaneous interdependences in dynamic models:

1. aggregation over time due to a sampling period longer than the decision period
2. aggregation over individual decision units and over economic goods causing a loss of “sufficient detail”
3. static equilibrium conditions and definitional identities

The first point reflects the indirect influence of the primary decision whether the parameters should be estimated formally or not (see Table 1, 12.) on the causal ordering, because the sampling period of most economic time-series data is seldom shorter than a month (see Table 1, 7.). This implies that macroeconomic SD models with formally estimated parameters cannot per se rule out simultaneous interactions. An analogous argument can be put forward with respect to the second point. The relevance of the third point can be demonstrated by a quote from a report on a SD model of the German economy, “We used a smooothed average of GNP to compute the demand for intermediate inputs in order to avoid simultaneity between Equations 59 and 61” [33, p. 151]. All in all, we feel that the enforcement of *a priori* recursiveness would be hard to defend in

the case of discrete, macroeconomic MSD models. This does not contradict our opinion that recursiveness would be a desirable property even of discrete MSD models because it allows for better causal interpretation of the single equations. We are just skeptical that it can be achieved and therefore prefer to regard recursiveness as an heuristic principle rather than an obligation.

FEEDBACK STRUCTURE

While the causal ordering gives insights into the intraperiodic (inter-) dependences between the endogenous variables, the feedback structure reveals the interperiodic causal relations. By this criterion we define dynamic models as output-closed if all endogenous variables contribute to the explanation of at least one other variable; if one variable does not, we define the dynamic model as output-open. The main difference is not between ready-built EC and SD models, because almost all of their endogenous variables are part of dynamic feedback loops. The real distinction is of heuristic nature. While SD model building concentrates on the detection of feedback loops from the very beginning, EC model building starts with the specification of a variety of single equations and afterwards takes a look at the feedback loops that have resulted.

PARAMETER ESTIMATION

We have given relatively broader scope for the features concerning model specification because they have usually not gained as much attention as the highly controversial issues of parameter estimation and nonpredictive evaluation. We will refrain from commenting on these really complex topics and refer the reader to [54, pp. 244–291, 298–299, 55]. Only the two major logical connections to other characteristics should be mentioned here. CSD believed that statistical parameter estimation methods were superfluous because of

1. the qualitative insensitivity of model behavior to most parameter values that is understandable only on the grounds of the SD model purpose (see Table 1, 16d.)
2. the direct observability of parameters from the real system.

EC on the other hand wants (see Table 1, 16a.) and needs precise parameter values (see Table 1, 16c.) and assumes that variables are more likely to be observable than parameters (see Table 1, 2.). In the last years, the CSD aversion to statistical estimation and testing of parameters has sharpened considerably. Instead of regarding them as superfluous but harmless [11], they are now attributed to even render “major errors in estimates of parameters” and “misleading indications from internal measures of validity” [14]. This point of view is clearly contradictory to a cornerstone of the EC methodology.

Other system dynamicists have turned away from this antieconometric attitude and called for an adaption of EC parameter estimation techniques to SD models [33, 43]. A mutual advancement of EC and SD with respect to parameter estimation only dawns at the horizon with the integration of Kalman filtering techniques [45, 50].

EVALUATION

A general agreement existing between EC and SD is that evaluation is a purpose-oriented procedure aimed at the improvement of models (see Table 1, 16e.) Because, however, of differences in the model purpose itself, this unison should not be esteemed. This can be illustrated by confronting two typical statements. Forrester and Senge “take the view that the ultimate objective of validation in system dynamics is transferred confidence in a model’s soundness and usefulness as a policy tool” [17, p. 211]. A representative group of econometricians has taken a slightly different view emphasizing

predictive capability more than political usefulness, "Validation becomes a problem-dependent process, differing from case to case as the proposed use of the model under consideration changes Thus a model which accurately predicts the employment effects of alternative tax policies may be considered 'successful', even if its prediction of the composition of GNP is poor by the standards for other uses of a model" [10, p. 311].

SD-followers agree as to the relevance of a specific purpose the model should serve, but disagree on the more general aspect of the model purpose. EC favors accurate predictions of future system and states as a desirable goal of knowledge to be gained from modeling (see Table 1, 16c.); SD holds for prediction of global behavior characteristics in order to achieve system improvement (see Table 1, 16d.). This dissent on the proper model purpose is of overwhelming but often underrated importance, not only for understanding differences in model structures (e.g., the SD verdict against and the EC allowance for exogenous variables) but also for distinctions in the evaluation strategies.

Although both agree that validation should be a multistage process of successive nonpredictive and predictive procedures, there is strong disagreement on the kinds of nonpredictive procedures to be employed. While EC relies on a variety of economic, statistical, and econometric criteria, SD favors expert experience and descriptive literature. A careful comparison of section 4.7 on "Sources of Information for Constructing Models" and section 13.4 in the validation chapter of [11] substantiates that Forrester recommends the use of the same information for validating parameters and specification assumptions (structure) that have already been incorporated within the prior formulation of the model. "In the design and justification of a model, we need to call upon the full variety of knowledge that is available about the system." Since using the same information twice cannot yield any genuine insights, this strategy must be regarded as a spurious validation. Elsewhere, Forrester went even further, arguing that only poor models present insurmountable questions of validation, in other words: "good" models do not require validation, "bad" models cannot be exposed to validation [13, p. 164]. The whole validation topic, including Forrester's own treatment, is thus in danger of erosion and might in the end be regarded as a spurious problem.

With respect to statistical and econometric criteria, a remarkable shift within the SD evaluation concept has occurred in the last years. While in "Industrial Dynamics" statistical tests were assumed to be an acceptable though mostly useless and only exceptionally necessary instrument for independently supporting faith in the parameter values and model structure, they are now judged as possibly dangerous because their internal validity criteria are supposed to provide incorrect inferences, "Although the literature of regression analysis and econometrics dominates the social sciences in describing the use of data for relating real life to models, much new light can be shed on the proper and possible uses of statistical methods by experiments such as Peter Senge is now conducting at MIT" [15, p. 31]. "The laboratory tests indicate that the generalized least-squares data analysis can give not only major errors in the estimates of parameters, but also misleading indications from the internal measures of validity" [14, p. 126]. We have demonstrated elsewhere [55, 55a] that these negative conclusions that Forrester and Senge [53] have drawn from their experiments are unjustified.

EC and SD not only differ as to the relevance and methods of nonpredictive evaluation of parameters and model specification, but also with respect to the kinds of simulations employed for predictive evaluation (see Table 1, 13b.). Finally, SD and EC put different emphasis on policy simulations. The former models try to achieve better long-run behavior modes by changes in the model structure (see Table 1, 13c d.) while the latter look for

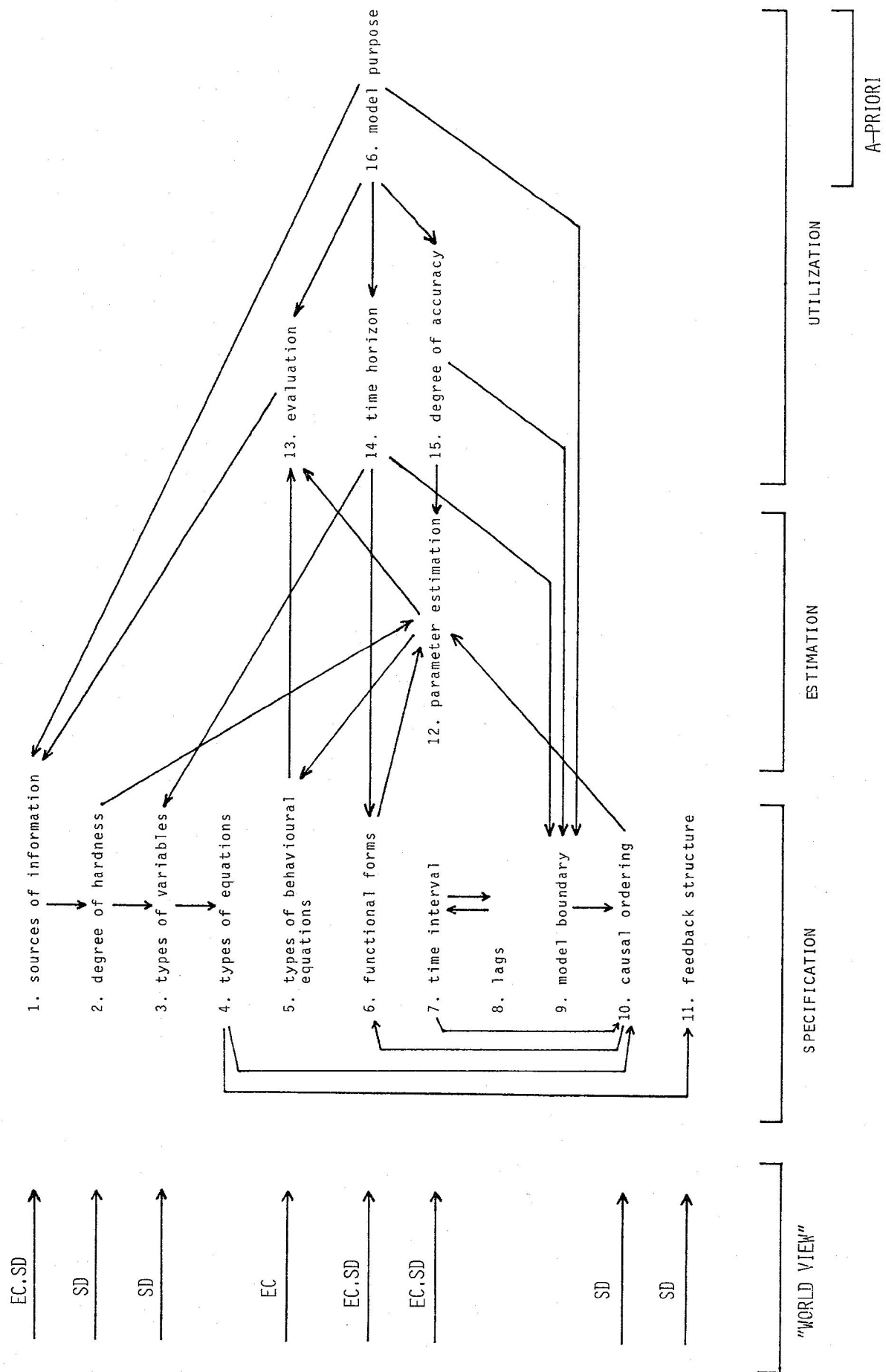


Fig. 2. A network of model features.

meeting certain quantified values of target variables by changing some instrumental parameters or variables (see Table 1, 13c c.).

INTERCONNECTIONS BETWEEN MODEL FEATURES

In the preceding sections we have used cross-references to illustrate that the option for a specific model property frequently depends on other model characteristics or, in turn, influences them. A detailed consideration of all the relevant links leads to a strongly interrelated network of model features that can be grouped into three categories, also well known as the major stages in the model building process (Figure 2):

specification
estimation
utilization

Figure 2 helps to clarify some points that have been widely debated. First, the variety of the interrelations together with the complexity of each model feature, which is rather simplified by Figure 2, prohibits any unilateral, deductive reasoning such as the following: the model purpose delimits the problem type and the problem type defines the proper modeling approach [31, pp. 254]. This criticism is not to deny the important role of the model purpose, but puts emphasis on the need for many other considerations along the model building process. Second, Figure 2 supports the opinion that the model purpose is the only true "Unavoidable *A Priori*" [41] because there is no other knot with only outwards directed arrows. Third, in SD, specification options are much more based on "external" beliefs about the "true" nature of social systems ("world views") than in EC. This characterizes SD as a mixtum compositum of a modeling method and a fragmentary theory of real world social systems.

Conceivable Relations Between Econometrics and System Dynamics

Referring to Table 1 and the above explanation we can now systematize the relations between EC and SD that have been put forward by different authors.

EQUIVALENCE

There is obviously no equivalence in the structure, specification and quantification of EC and SD models (see Table 1, 1–12). Some model builders speak of equivalence in a wider sense, expressing their conviction that qualified econometricians and system dynamicists should be able to tackle the same problem equally well. Looking at the different model purposes of EC and SD, we can hardly agree with this view.

DOMINANCE

A relation of dominance would exist if one approach would emerge to be superior for all possible uses of dynamic models in all conceivable fields of applications (*dominance by superiority*). This seems to be the more or less hidden persuasion of most EC as well as SD followers. The rigour of many EC criticisms of SD models like "Urban Dynamics" or "World Dynamics" apparently implies the inferiority of the SD methodology on the whole. Even economists who have taken a more refined stand are in danger of such a view. "... my main grievance with Forrester is the way, in which he has chosen to apply his methodology, rather than with the methodology per se" [44]. In spite of this, Naylor's suggestions for a sound world model would not lead to a "better" application of SD but rather to a typical econometric model. A systematic proof for the superiority of the EC over the SD methodology has to our knowledge not yet been presented.

System dynamicists, on the other hand, had proclaimed a hegemony of their approach simply because no other modeling approach was believed to be in sight, in spite of thirty years of applied econometrics (*dominance by lack of competition*). "Until recently, there has been no way to estimate the behavior of social systems except by contemplation, discussion, argument, and guesswork" [13, p. 212]. This attitude has changed in recent years, recognizing the existence and potential usefulness of EC models. "We believe there is an excellent chance that a comprehensive system-dynamics model . . . can complement other approaches and can fill in where other methods of analysis have been unable to answer important questions" [14, p. 125]. Nevertheless, this perspective of complementarity (see cooperation) remains vague as long as it is not made explicit under which conditions EC models would be preferable. From Forrester's catalogue of SD advantages, it may be concluded *ex negativo* that EC models are regarded to be superior for accurate, short-term predictions. However, even this partial superiority of EC models, which is a prerequisite for actual complementarity, is doubted by other SD authors. If one believes that forecasts without any model are better than EC predictions and that "naive models" do as well as EC models [48, p. 233], then there again remains no scope for this approach (*dominance by superfluity of the competing approach*). Here too, we think that the maintained dominance of SD has not yet been and probably will never be proven. The most convincing way to defend the dominance of either approach would be if one methodology could be shown to be the more general in structure and in range of applications. This seems to be doubtful.

CONVERGENCE

While we have dealt with equivalence and dominance as relations between mainstream EC, often referred to as EC in the Cowles Commission tradition, and CSD as founded by Forrester, it is also possible to confront EC and SD not in a static but in a dynamic way by including the internal developments, extensions, and modifications of both. We speak of a convergence, if these internal developments increase the intersection of common model features. The convergence will be called one-sided, if it only affects either EC or SD, and two-sided, if both are involved. We will further distinguish between a convergence with a tendency towards equivalence, if the approaches become very much alike, and of a convergence with a tendency towards dominance, if one of the approaches will be absorbed by the other. It is easy to imagine the numerous possibilities of isolated changes in certain model features. We have documented some of the proposed modifications of SD in the MSD column (Table 1). One has to pay attention to the interconnections between the model characteristics (Figure 2).

Two-Sided Convergence

An example for this variant of convergence is the research strategy pursued by a group that has built a model of HESSEN (a state of the FRG). The underlying philosophy stems from the recognition that the theoretical background and the amount of data available are very dissimilar for different socioeconomic subsystems [3]. The cornerstones of their merging of SD and EC ideas are the following:

- greater emphasis on theory and data than expert opinion and intuition as informational basis
- more nonobservables than usually employed in EC
- preference for nonlinearities in variables because of reluctance against SD table functions
- preference for a recursive causal ordering as applied in SD models

preference for a discrete rather than quasicontinuous model, especially because of
 a plea for least-squares estimation of parameters
 preference for EC validation strategies

One-Sided Convergence With Tendency Towards Equivalence

Zwicker's above mentioned FOLR-modeling concept [59, pp. 480–521] modifies CSD as to four central aspects:

substitution of the premise of infinitesimal time intervals by the discrete time hypothesis ($DT = 1$)
 incorporation of finite-distributed lags because of the principle of unconstrained hypothesis formulation
 suspension of the closed boundary concept and allowance for exogenous variables
 a plea for statistical parameter estimation and evaluation

Like all proposals of modified SD (or EC) methodologies, FOLR raises the question of what remains of the "hard core" of the original approach. Zwicker holds that the two retained elements of CSD, a revised level-rate concept and the feedback concept, are the most fruitful parts. He characterizes them as heuristically powerful procedures for hypothesis generation, guiding the modeling process up to the stages of a comparative causal diagram and finally to a level-rate structure. It should be recognized, though, that FOLR does not go beyond this rather modest heuristic view of the level-rate and the feedback concept and does neither require a strict alternation of levels and rates nor a feedback of every endogenous variable without exception. In this sense the feedback-oriented open level-rate concept must be interpreted as a major relaxation of the "System Dynamics Hypothesis" [56, p. 47].

Facing these major shifts from CSD to the FOLR-variant, a second question has to be answered: Are there still any differences between FOLR and EC modeling? The only key distinction seems to be the recursiveness of FOLR-models. This justifies our assertion that FOLR has a strong tendency towards equivalence with EC.

COEXISTENCE

The perspective of coexistence has been derived from a critical appraisal of SD-EC convergence. "I cannot imagine how the two basic philosophies can be mixed or merged in one model, although the tools that have shaped and been shaped by those philosophies might be exchanged. . . . Econometrics and system dynamics clearly fit different niches in the modeling policy-making environment. As long as both short-term predictions and long-term perspectives are needed, these two techniques can both be actively pursued, probably with continued mutual hostility, at least until a better competitor comes along" [41, pp. 235–236]. Although we doubt whether the distinction between "borrowings from each other's techniques" and "shifts in world view" is possible or helpful, the question of whether SD and EC could be merged leads to the essential point: should both modeling approaches really converge or would it not be preferable to accumulate knowledge on their specific merits and to strive for an active cooperation? A hostile coexistence seems rather fruitless and irrational.

COOPERATION

Cooperation does not aim at flattening the differences between EC and SD on a methodological meta-level (see convergence), but tries to make use of them in the development of specific models.

Rational Choice

This perspective follows directly from Donella Meadow's argument, but does not tend to externalize the choice to the policy-making environment (see also [48, p. 234]. It leaves the job of choosing between EC and SD with the model builder. "The rather obvious underlying thought (and conclusion) is that the choice will depend on the ultimate use to which the model will be put, It will be argued that the time horizon has significant implications of utilization and epistemology" [7, p. 27]. Although the time horizon is an important aspect of choice (see Table 1, 14.), it is certainly not the only one. Progress along the lines suggested by Dennis Meadows [42] would lead to a deeper understanding of the contribution of the different model features to the achievement of pursued goals.

Modular Linkage

While Chen argued "that the linkage of models will be successful and meaningful only to the extent that the models are epistemologically compatible" [7] the idea gained ground that different parts of a problem might be addressed most adequately by different modeling philosophies (see, e.g., [3]). Since we are more and more confronted with a vast amount of already existent models, it will become increasingly attractive to link them, in spite of or even because of their different methodological background. Software for such a linkage, like the "Modellbanksystem MBS" of the Gesellschaft für Mathematik und Datenverarbeitung, is in development [23].

Change Of Methodology

During a modeling project, it may become evident that the initial choice of a specific modeling approach was wrong or that the model purpose has shifted in the meanwhile, so that the choice was correct but is not anymore (*unplanned change*). Drawing on Zwicker's FOLR concept, it can also be argued that SD has a specific heuristic power in the initial phases of model specification while a change to an EC model may be recommendable during the development of a refined model (*planned change*). A similar view has been presented by Zahn [58].

Cross-Modeling

Finally, cross-modeling should be mentioned as a strategy to gain increased empirical evidence on the factors influencing the rational choice of modeling approaches. While "counter-modeling" [20, pp. 145–176] holds the methodological meta-assumptions constant and changes certain model-specific hypotheses, "cross-modeling" tries to keep the latter as much the same as possible while formulating models based on different modeling philosophies [18, 35, 42].

Some Final Epistemological Remarks

It would be very tempting to employ epistemological theories to further clarify the relations between EC and SD. Attempts in this direction have easily found the way to Kuhn's "Structure of Scientific Revolutions" and put EC and SD in a paradigm conflict [41, 56]. On the other hand, econometrics regards itself as an outstanding example for the success of Popper's falsificationist view in the social sciences, while the history of econometrics has not yet—to our knowledge—been interpreted in the light of Kuhn's paradigm theory. Neither has the content of the SD paradigm been convincingly revealed. The literature presents vague descriptions of SD as a "Hypothesis" consisting of applied fundamental attitudes and concepts [56, p. 47], as a bundle of three guidelines [52, p.

269], as a set of “meta-assumptions” [1, p. 246] or just as a profession [16, p. 7]. The scope of the SD reasoning stretches from general hypotheses about the nature of social systems (e.g., the possibility of counterintuitive behavior or the worse-before-better syndrome) to methodological rules about proper model building, to a collection of model tests [17], and to purely technical aspects such as the proper integration method. There still seems to be disagreement on what is part of the SD “hypothesis”, “paradigm”, or “hard core”, and what is not. The present situation is definitely such that “System dynamics needs a broader and deeper debate about its underlying philosophy, the contrast with alternative philosophies, the nature of knowledge, the role of subjective and observational information, and the criteria for judging validity” [16, p. 15]. Within these very necessary and challenging studies, the question deserves attention if a comparison of different modeling approaches like SD and EC benefits most from referring to Kuhn or to Popper. Why not try to apply Lakatos’ methodology of scientific research programmes or other epistemological theories? Or will we finish the whole debate with a Feyerabend conclusion that “anything goes”?

However, not only the growth of scientific knowledge in the area of dynamic, socioeconomic model building but also the improvement of applicable policy models is at stake. This is why Greenberger et al. have called for a better mutual understanding between econometricians and system dynamicists, “Despite appearances, bridges may gradually be built between these two methodologies. We believe that construction of such bridges, as well as the willingness by opposing sides to use them, could help make policy models more intelligible and useful to policymakers in future years” [20, p. 182].

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