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A Brief Survey of Behavioral Modeling in Micro Simulation Models

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Since the start of microsimulation in economics with Orcutt's seminal 1957 article (***Orcutt, 1957***), and the first dynamic microsimulation model in the United States (***Orcutt, 1961***), this approach has in the past almost 40 years been both successful and met with a great degree of skepticism. Successful to the extent that static microsimulation models have become a standard tool for policy evaluation in most Western governments, but at the same time less accepted among academic economists, who sometimes find unacceptable the compromises between theoretical and methodological rigor and what is feasible given insufficient data and resources. They have not seen a microsimulation model as a useful tool in developing and testing theory.

Nonetheless, there is a rather impressive list of micro simulation models as shown by recent surveys, for instance, ***Merz (1991)***, ***Mot (1992)***, the ***OECD (1988)*** and ***Sutherland (1995)***, and by a number of conference volumes, for instance, ***Bergman et al. (1980)***, ***Orcutt et al. (1986)*** and ***Harding (1996)***. Many microsimulation models are static without behavioral relations, and this is in particular true for models run by government agencies, international organizations and consulting firms. Behavioral modeling is still to a large extent an academic exercise. ***Tables 1–3*** list models which at least include some behavioral relation. These tables have been put together using primary as well as secondary sources, for instance the survey articles mentioned above, which implies that a few models could well have become misclassified. What defines a behavioral relation is not crystal clear. A matrix of transition probabilities differentiated by age and sex is a simple behavioral relation in the sense that behavior is differentiated by age and sex. Some models include relations derived from economic theory but this is not a requirement for a model to become classified as behavioral. For instance, demographic models of transition matrix type have been included. Although these models include behavioral heterogeneity in a broad sense many of them do not capture any behavioral response to policy changes. Their behavioral relations do not include the relevant policy parameters.

There is also another type of behavioral modeling applied to micro simulation models where behavior is modeled at an aggregate level. The aggregate implications are then subsequently disaggregated in a micro simulation model. An example is ***Meagher (1996)***. A dynamic general equilibrium model of the Australian economy is used to compute growth rates in the (factor) incomes of selected groups. These income changes are then fed into a static micro simulation model, which produces simulations of the after-tax income distribution. A similar application is also given in ***Baekgaard and Robinson (1997)***. In the following we will not pursue further the linkage with the macro economy.

Table 1 includes static MSM with behavioral relations. One may note that among the most common behavioral relations are those of labor supply but there are also models which include expenditure functions to simulate the effects and changes in indirect taxation. The early models were designed in the United States while the Europeans caught up in the 1980s and now seem to dominate the work with static behavioral models.

Table 2 lists general dynamic models with behavioral relations. "General" here means two things. The model is not specialized for a very limited purpose or limited to a small group of individuals or households, and it contains more than a single or just a few behavioral relations. Most of these models are large and cover the whole household sector in a country and include modules which age their populations as well as modules which are more central to the general purpose of the models, for instance, labor supply relations which capture behavioral adjustments in the labor market to tax

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Table 1. Static models with behavioral modeling

Model	References	Country	Behavior
STATS	Bridges and Johnston (1976)	USA	Program participation
MATH	Beebout (1977) Kidd (1979) Doyle and Whitmore (1982) Beebout (1986)	USA	Demographics and labor supply, Program participation
KGB	Betson et al. (1982) O'Reilly (1977)	USA	Labor supply Program participation
TRIM	Webb (1979) Webb and Chow (1978)	USA	
TAXSIM	Feldstein (1983)	USA	Labor supply, demand for housing, charitable giving
Sfb3	Galler and Wagner (1986)	FRG	
Sfb3	Merz (1985); ; Merz (1986)	FRG	
MICSIM	Merz (1989a); Merz (1989b); Merz (1990); Merz (1989b); Merz and Buxmann (1990) Merz and Buxmann (1990)	FRG	Labor supply
	Bekkering et al. (1986); Grift et al. (1991)	NE	Labor supply
	Chernick et al. (1987)	USA	Health insurance and demand for medical services
	van Soest (1989)	NE	Labor supply
	Kapteyn et al. (1989)	NE	Labor supply
	Grift et al. (1991)	NE	Labor supply
TAXBEN/ SPAIN	Giles and McCrae (1995) Johnson et al. (1990) Duncan (1991)	UK	Labor supply
CNAF	Grignon and Pennec (1998)	F	Fertility, housing
INDICE	Patrizii and Rossi (1991)	I	Household expenditures - indirect taxes
INDIMOD	Baldini (1995)	I	Household expenditures - indirect taxes
ASTER	Decoster et al. (1994)	B	Household expenditures- indirect taxes
POLIMOD	Redmond et al. (1995); Sutherland (1995)	UK	Labor supply

changes. The behavioral relations of all models, however, are not specified such that behavior directly depends on the policy instruments, some are more of a demographic type. Also, in dynamic modeling the Americans were pioneers. In Europe German scientists would seem to have worked relatively early with dynamic microsimulation models.

Table 3 shows microsimulation models with a more specialized aim and limited scope. Labor market behavior is dominating among these models as well, but here is a greater variety of coverage: consumption behavior, housing demand, demand for energy, childcare, telephone services and non-market time. Most of these models are probably more closely based on economic models and econometric testing and estimation than the big general dynamic models.

1. Behavioral modeling for three purposes

A Behavioral model can serve at least three purposes in a microsimulation model. First it could be used to impute missing data as an alternative to statistical matching (see ***Klevmarken, 1983***).[1] Suppose there are X_1 data in the data set used for simulation, but X_2 data are missing, and that there is another data set with both X_1 and X_2 data. If X_2 can be related to X_1 by way of a behavioral model then the model can be estimated from the second, external data set and used in the micro simulation model to simulate X_2. Such a relation need not be based on theory about behavior, what is needed is a good predictive relation, but if it is delivered from good theory, one would probably have more confidence in its predictive ability.

Table 2. General dynamic models with behavioral relations

Model	References	Country
DYNASIM	Orcutt et al. (1976)	USA
DYNASIM II	Johnson and Zedlewski (1982); Johnson et al. (1983); Zedlewski (1990) Wertheimer et al. (1986)	USA
MICROSIM	McKay (1978)	USA
MICROSIM/MASS	Orcutt and Smith (1979)	USA
Sfb3-MSM	Helberger (1982) Hain and Helberger (1986) Galler and Wagner (1986) Galler (1989)	FRG
CORSIM	Caldwell (1988); Caldwell (1993)	USA
HARDING	Harding (1990); Harding (1993)	UK, AUS
DEMOGEN	Wolfson (1990)	CAN
LIFEMOD	Falkingham and Lessof (1991); Falkingham and Lessof (1992)	UK
MOSART	Andreassen et al. (1992); Andreassen (1993); Andreassen et al. (1993); Andreassen et al. (1994)	N
MICROHUS	Klevmarken et al. (1992) Klevmarken and Olovsson (1996)	S
DYNAMOD	Antcliff (1993)	AUS
NEDYMAS	Nelissen (1994)	NE

Behavioral models can also be used to age the simulation population (sample). This is usually done by introducing mortality tables, relations for the birth of new individuals, marriages, separations etc. Similarly, behavioral relations could update other characteristics of the population like the labor force participation, unemployment, hours of work, wage rates, housing, childcare etc. As long as the purpose is limited to updating, behavioral relations are only needed to the extent that they yield more stable and precise predictive relations compared to alternative ways of updating the population. In practice many models use matrices of transition probabilities estimated separately for a few subgroups of the population, for instance, by age and sex, but with no strong connection to theory.

The third and perhaps most interesting application of behavioral relations is to capture behavioral adjustments to policy changes. A necessary requirement of a behavioral model to satisfy this purpose

Table 3. Specialized models with behavioral relations

Model	References	Country	Behavior
RFV-ATP	Eriksen (1973); Klevmarken (1973),	S	Life cycle earnings demographic transitions
Mikropolis	Bekkering et al. (1989)	NE	Labor supply labor demand
PRISIM	Kennel and Sheils (1986); Kennel and Sheils (1990)	USA	Decision to retire and accept pension benefits
	Atherton et al. (1990)	USA	Local residential telephone demand
SPEND	Baker (1991)	UK	Energy demand
SPIT	Baker and Symons (1991)	UK	Household consumption - indirect taxation
	Erksoy (1992a); Erksoy (1992b); Erksoy (1994)	CAN	Unemployment
	Baekgaard (1993)	DK	Demand for child care
	Merz (1993)	FRG	Market and nonmarket labor supply
	Bekkering (1995)	NE	Labor market (demographic and educational transitions by constant probabilities)
	Symons and Warren (1996)	AUS	Household consumption behavior
TOPSIM I	Holm et al. (1996)	S	Regional demography
	Fransson (1997)	S	Household formation and housing market

is that the policy parameters directly or indirectly enter the model. This is normally not the case in the simple transition matrixes used for aging and updating. For instance, in a study of the distributional effects of income tax changes the labor supply function should be such that labor supply depends on the tax rates (and virtual income). A second requirement is that the behavioral relation is stable such that its parameters do not change as a result of policy changes. This is an issue much discussed, for instance, in relation to the recent major tax reforms in many countries. Can labor supply relations estimated on data collected before the reforms be used to predict or evaluate the effects of the reforms? Are the parameter estimates stable in spite of the large tax changes in some countries? The same kind of concern could be raised when microsimulation models are used to simulate processes of long duration, for instance changes in pension systems. Is it possible to extrapolate long into the future earnings and labor supply relations estimated from short time spans of data?

2. Behavioral modeling in static micro simulation models

To emphasize the policy evaluation application of micro simulation models and make behavioral adjustments explicit assume there are three kinds of variables: Policy variables X_p, target variables Y and all other variables X_{np}. For instance, one could think of X_p as tax rates and tax bases, Y as taxes paid and after tax income, while X_{np} would include variables needed to compute taxes like labor incomes and nonlabor incomes, and group indices like sex, marital status, nationality, region, etc. In a conventional nonbehavioral static tax-benefit model policy variables are related to the target variables through the tax and benefit system conditional on X_{np}. For a single individual we could write this relation as,

$$Y = T(X_p,\ X_{np}) \tag{3}$$

In a microsimulation application of this model we compare the distributions of

$$Y_1 = T(X_{p1},\ X_{np0}) \tag{4a}$$

and

$$Y_2 = T(X_{p2},\ X_{np0}). \tag{4b}$$

for two different policy regimes X_{p1} and X_{p2} and a given set of population characteristics $X_{np\ 0}$. Replicated static microsimulation actually approximates the distribution,

$$f(Y_1,\ Y_2,|X_{p1},\ X_{p2},\ X_{np0}). \tag{5}$$

from which we can compute the marginal distributions by simple summation,

$$f(Y_1|X_{p1}) = \int f(Y_1|X_{p1},\ X_{np0})f(X_{np0})dX_{np0} \tag{6a}$$

and

$$f(Y_2|X_{p2}) = \int f(Y_2|X_{p2},\ X_{np0})f(X_{np0})dX_{np0} \tag{6b}$$

and various distributions conditional on subsets of X_{np0}, for instance on gender, type of family, region, etc. It is here assumed that the empirical distribution of X_{np0} in the microsimulation model closely approximates the true distribution of X_{np0}, which for instance would be the case if the sample used for micro simulation is a simple random sample from the target population. (If the sample is drawn with unequal sampling probabilities one would have to compensate for this by using appropriate sampling weights.)

If the model T(..) is just a nonstochastic tax-benefit model the distribution (5) could be a degenerate one-point distribution. It is of course still possible to compute the marginal distributions (6a) and (6b) and various conditional distributions. If T(..) is a stochastic model and the simulation is only done once we might not get a good approximation of the distribution (5), depending on how frequently X_{np0} is replicated in the simulated population. The reason is of course that we will only get one observation (Y_1, Y_2) for each individual. However, we can still compute good approximations of the marginal distributions (6a) and (6b) and various interesting conditional distributions.

The marginal distribution f(Y_1, Y_2| X_{p1}, X_{p2}) is of particular interest, because it tells us, for instance, about the after tax income mobility. What share of the population move from one after tax income decile to another as a result of the change in policy? Although X_{np0} has been integrated out f(Y_1, Y_2| X_{p1}, X_{p2}) is only valid for a population with the characteristics X_{np0}. Please also note that nothing is said and nothing can be said about the individual trajectories through time which result from a policy change. Nor do we say anything about changes through time in the distribution of Y or when a certain share of the population has moved from one decil to another.

Assume now that in addition to the tax-benefit model some of the variables X_{np} also depend on the policy regime. To mark their changed status call them Y_p , and keep the old notation X_{np} for variables which are truly exogenous. A static model with behavioral adjustments could be written as,

$$Y = T(X_p, Y_p, X_{np}) \tag{7a}$$

$$Y_p = C(X_p, X_{np}) \tag{7b}$$

Where C is a function which relates the policy variables to individual behavior of relevance for the target variables. One could, for instance think of C as a labor supply model which determines hours of work (Y_p) as a function of the tax rates, deductions and thresholds (X_p) and wage rates and nonlabor incomes (X_{np}). All these variables thus jointly determine disposable income.

Microsimulation of this model will, for instance, involve a comparison of the following two distributions,

$$f(Y_1, Y_{p1}|X_{p1}, X_{np0}) \text{ and } f(Y_2, Y_{p2}|X_{p2}, X_{np0}) \tag{8}$$

and the corresponding pairs of marginal distributions,

$$f(Y_1|X_{p1}, X_{np0}) \text{ and } f(Y_2|X_{p2}, X_{np0}) \tag{9}$$

and

$$f(Y_1|X_{p1}) \text{ and } f(Y_2|X_{p2}) \tag{10}$$

Again, there is no time dimension in this model. Although it is possible to compute the distribution f(Y_1, Y_2, Y_{p1}, Y_{p2} | X_{p1}, X_{p2}), which, for instance could tell us what share of the unemployed became employed as a result of the policy change, it does not tell us when. Depending on how the model is designed and estimated and the simulations done this distribution might also vastly overestimate mobility. If C(..) is a stochastic model such that the implicit individual random error is drawn independently for each policy regime then the model neglects any unobserved individual heterogeneity and it would simulate too much mobility. Although such a model could not be used to evaluate the "true" distribution f(Y_1, Y_2, Y_{p1}, Y_{p2} | X_{p1}, X_{p2}) it might still simulate well the marginal distributions (8), (9) and (10).

Suppose, for instance, that C is a static labor supply model of the Hausman type and Y_p is hours of work, and that this model is simulated for two different tax regimes. If the random "optimization errors" of the Hausman model are IID, and independent sets of errors are drawn for the two tax regimes, then mobility in hours will most certainly become exaggerated. This excess mobility will then transmit to disposable income. In this example the simulated joint distribution of disposable income and hours of work for the two policy regimes F(Y_1, Y_2, Y_{p1}, Y_{p2}| X_{p1}, X_{p2}) is the product of the marginal distributions f(Y_t, Y_{pt}| X_{pt}), t=1,2. Although this is believed to be unrealistic it does not exclude that each of the simulated marginal distributions are good approximations.

One way to reduce mobility is to use the same seed when the two sets of "optimizing errors" are drawn. Each individual will then have the same error in both tax regimes. However, there is no guarantee this approach will give a realistic representation of mobility. It might well create too little mobility. The simulation procedure should be based on empirical studies of mobility, and then a static model is not a good framework.

An alternative explanation to a smaller mobility compared to a purely random process is the presence of state dependence.[2] Assume, for instance, that,

$$Y_p = C(X_p,\ X_{p0},\ Y_0,\ Y_{p0},\ X_{np}). \tag{11}$$

In this model behavior does not only depend on the policy X_p chosen and the exogenous characteristics X_{np}, but also on a reference "level" of policy X_{p0}, target variables Y_0 and behavioral response variables Y_{p0}. For instance, the effect of a tax change on labor supply might depend on the level of unemployment when the tax change is implemented. It might also depend on the nature of the tax system used immediately before the tax change. The behavioral response to a change in the marginal tax rate may depend on whether the rate was higher or lower prior to the change.

3. Families of behavioral models

Only human imagination, data availability and computer resources limit the structures and forms behavioral models could take, and it is certainly possible to group existing models in many different ways. The following classification indicates the variety of approaches and functional forms used, many of which can usually be found within one and the same micro simulation model.

1. Models of transitions between different states: To this class belong models of transition probabilities like Markov-models, probit, logit, multinomial logit and ordered probit models to mention a few. It also includes event history (hazard rate) models.
2. Count data models: Count data models like for instance Poisson regression have been used to model the number of occurrences of an event in an a priori specified time span or the number of time periods an individual belongs to a certain state, for instance, the number of months of unemployment in a year or the number of weeks reported absent from work due to sickness in a year. These models have been used when event history data were not available, one only knew for how many weeks a person had been in a state, for instance sick, but not if these weeks formed one or more spells of sickness.
3. Continuous data models: To this group belong conventional linear and nonlinear regression models, equation systems etc. In micro simulation models for earnings functions, models for work hours and expenditure functions are examples of this model type.
4. Random assignment schemes (statistical matching): The models of the first three classes above belong to the conventional econometric paradigm of estimating an average structure from which there are only random deviations. In the first two cases one estimates (average) probabilities conditional on certain individual characteristics and the deviation from the most probable outcome is accomplished by chance, by throwing a ”loaded dice”. In the third case we simulate deviations from the average by adding random disturbances to the ”systematic” part of the model. In random assignment schemes like statistical matching, the model structure is implied and never estimated. It is only defined by the variables which define ”closeness”. The idea is to find a donor of data among the observations in the population which in some sense is similar or close to the receiving unit. Suppose for instance, that the original data set includes observations on income for two consecutive years for each individual. A simulated income distribution for a third year could be obtained by defining closeness between the donor's income in the first year and the receiver's income in the second year perhaps also between other variables like age and sex and then randomly select a donor among those who have the (approximately) same age, sex and income as the receiver. The donor's income for the second year is then used as a prediction of the receiver's income in year three. The implicit model assumption is of course that income transitions remain unchanged. With a similar but somewhat more elaborate approach ***Hussenius and Selén (1994)*** linked short panels of income data to life-cycle income paths to analyze how like-cycle incomes were influenced by tax and transfer changes. In the MICROHUS model (***Klevmarken et al., 1992***; ***Klevmarken and Olovsson, 1996***) the technique was used to simulate the properties of the house a family was predicted to buy (size, tax assessed value, size of mortgage and interest paid).

   Advantages with the random assignment technique are thus that no assumptions of functional forms or distribution families are needed, if preserves the variation and (most of) the correlation already present in the original data, and it is nonparametric so there is no estimation

2. In empirical work it might not always be easy to distinguish state dependence from individual heterogeneity.

of unknown parameters. The choice of variables and the measure used to define closeness can be tested by goodness of fit. A disadvantage though is that the statistical properties of the resulting "predictions" are incompletely known. Results from the imputation literature might be relevant. Another practical disadvantage is that the random assignment technique can never predict beyond the range of values already present in the original sample.

With exception of the random assignment technique the more traditional approaches to modeling invites the model builder to become excessively parsimonious with the number of estimated parameters and the models thus tend to become of the type average behavior with random variation. The possibility to permit people to behave fundamentally differently and to study the interaction between people with different aims which is feasible within the micro simulation approach, is usually not taken advantage of. For instance, with panel data, only a few observations for each individual are needed to estimate a utility function for each individual and allow everyone to maximize her own utility. One could also think of models when some individuals maximize their utility while the behavior of others are guided by something else than utility maximization!

4. The time unit in dynamic models

Continuous time models have the attraction to accommodate any time span one might like to use and also to permit different time spans for different purposes and in different sub models. However, a continuous time model which would permit the complexity and interaction between individuals which is necessary in most micro simulation models would become exceedingly difficult to estimate and simulate. It is thus probably not practical to have the entire microsimulation model formulated in continuous time. Continuous time might, however, be useful in certain sub models.

In micro simulation models which include income tax systems it is necessary to use the time unit of a year because income taxes are usually assessed annually. Some benefit systems, however, operate on shorter time spans. For instance, compensation for sickness and unemployment and social assistance might be given on a daily, weekly or monthly basis for the duration of the particular state. There is thus a need to use more than one time unit within a micro simulation model. This could be accomplished in several ways. One approach is to run simulation loops within a year for those sub models which operate on a shorter time unit, another approach is to use count models which simulate the number of days, weeks or months a person is sick, unemployed, etc in a year. A third approach is to use a continuous time model, for instance an event history model, to simulate the date when a person enters and leaves a certain state. The last approach has the advantage that it can accommodate a particular problem which sometimes occurs, namely that benefit rules are changed such that the change takes effect at a date other than the 1st of January.

5. Conclusions

After the dismal experiences with structural macro models we had the hope that modeling at the micro level and using large samples of micro data would yield estimated relations with some stability and scope. This hope has only been met to a limited extent (see for instance the discussion of models to capture work incentives in ***Atkinson and Mogensen, 1993***). It is hard to know if this is the result of the nonexistence of stable micro relations, that the behavior of economic agents changes as the result of new policies, new institutions and other external changes, or of insufficient data and inadequate research approaches in economics (for a discussion see ***Klevmarken, 1994***), or that the research process simply has to take more time. Behavioral modeling in the micro simulation context cannot be expected to go much beyond the state of art in economics. In each module of a large microsimulation model modeling meets with the same difficulties as in more conventional economic modeling, but in addition it has the difficulty of making the different modules fit together. There are obvious problems when modules have to be tested and estimated on different data sets, but there is also a requirement of an internal consistency of the model structure. For instance, if one module needs a particular explanatory variable, then another module is needed to simulate it such that the simulated values can be fed into the first module. To handle these problems the model builder needs a strategy as to the general model structure, as discussed above. A piecewise approach in which one starts with one module and then takes decisions about subsequent modules depending on the outcome of the research for the first is likely to lead to inconsistencies and to force the model builder to painful compromises for practical purposes.

It is also obvious that the availability of a rich data source of micro data will reduce the need to use supplementary data sets and thus greatly facilitate modeling. Depending on the purpose it would seem essential to have at least the key policy and effect variables included in the same data set. Assumptions of independence or conditional independence should be limited to relations which are of second order importance to the uses of the microsimulation model. If the dynamics of behavioral adjustments is important, which is almost always the case in policy simulations and evaluations, then panel data are needed. The large household panel data sets collected in several countries are thus essential for the construction of general microsimulation models of the household sector.

Modeling for regions larger than a country, EU for instance, would in principle require comparable data collected in all countries. Separate but comparable surveys in each country could be used to design comparable models for each country, which could be run one by one. Such an approach would make feasible an analysis of the same policy carried out in each country separately, but it would not permit the analysis of any interacting effects across boarders. If, for instance tax policies and social policies in one country are likely to attract or detract workers from another country, then a data collection design is needed which permits the survey people to follow respondents from one country to another to make feasible an analysis of the region wide policy effects mediated by migration.

Given that the above-mentioned difficulties can be handled in a satisfactory way microsimulation offers in principle opportunities to submit behavioral models to stronger tests than the usual diagnostic and specification testing done for each module separately. In addition to these tests a microsimulation model can be tested by comparing the simulated results with external data. Because simulated data can be aggregated, the data used to ”calibrate” against could either be micro data or aggregate data, for instance from the national accounts. It is a practical problem that these data need apply to the same population and observational units as the microsimulation model and they also need to comply with the same variable definitions.

The methodology for this ”calibration” is not fully developed. In particular there are a few issues which should be studied. First, the choice of criterion for a good model, second the inference theory needed to decide if the simulated (predicted) data lie within reasonable confidence bands from the observed data, and third, methods to evaluate the marginal influence of each parameter on the simulation results. It would be very useful to know which parameters have the most influence on the simulated results. A fourth issue is the estimation theory needed to incorporate new benchmark data.

Most of the modeling done in microsimulation is of the type ”average behavior with random deviations”. Conventional econometric models have been plugged into microsimulation models. As indicated above microsimulation offers opportunities to deviate from the paradigm of average behavior and allows for systematic differences in behavior, for instance, individual preference parameters estimated from panel data. One should probably also explore more the techniques to copy ”donors” by the random assignment approach, which avoids unnecessary restrictive assumptions about functional forms.

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