Orcutt's Vision, 50 years on

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Abstract

Fifty years have passed since the seminal contribution of Guy Orcutt [Orcutt, 1957], which gave birth to the field of Microsimulation. We survey, from a methodological perspective, the literature that followed, highlighting its relevance, its pros and cons *vis-à-vis* other methodologies and pointing out the main open issues.

KeyWords: Microsimulation, Computational Economics, Agent Based Modeling.

1 Introduction

Fifty years have passed since the seminal contribution of Guy Orcutt [Orcutt, 1957], which originated the field of Microsimulation.

This paper aims to give an overview of the discipline´s development over these fifty years, and to provide a survey of microsimulation which focuses on methodological issues rather than on specific model applications that have been developed to date. In so doing, we wish to provide a sort of "beginners' guide" to microsimulation, explaining how microsimulation models (MSMs) can be classified, what are the main differences between different types of MSMs, and for what analytical purpose each type is most appropriate, with examples taken from the literature.

Broadly defined, microsimulation is a methodology used in a large variety of scientific fields to simulate the states and behaviors of different *units* - e.g. individuals, households, firms - as they evolve in a given *environment* - a market, a state, an institution. Very often it is motivated by a policy interest, so that narrower definitions are generally provided. For instance, [Martini and Trivellato, 1997] define microsimulation models as

> computer programs that simulate aggregate and distributional effects of a policy, by implementing the provisions of the policy on a representative sample of individuals and families, and then summing up the results across individual units (p. 85).

MSM can answer relevant policy questions by handling simultaneously a large number of data, and calculating both individual and aggregate outcomes emerging from the *complex interaction* of several explanatory levels: the macro level, including e.g. demographic or labor market trends, the institutional level, including e.g. the tax and benefit system or a certain normative environment, and the micro level, including e.g. the characteristics, choices and actions of basic behavioral units such as households or firms.

In particular, by allowing to quantify some of the policies' effects at the micro level, MSMs are an integral part of the so-called *evidence based* policy making, and a valuable instrument for politicians. Compared to other methodologies based on representative agents or aggregate level analysis, e.g. computable general equilibrium or macroeconomic models, the main strength of MSMs is indeed to simulate how a certain policy change may differently affect heterogeneous individuals (or other entities). Furthermore, modeling at the micro level allows macro phenomena to emerge “from the bottom up” without the aggregation bias deriving from the use of statistical averages. In addition, MSMs allow to compare outcomes of alternative reform scenarios down to a high level of disaggregation, e.g. distinguishing among different interest groups, thus providing a useful ground from which to justify subsequent policy decisions to the electorate. What is more, since MSMs keep track of all individual data, the level of disaggregation of the analysis can be chosen *ex post*, i.e. after the model has been constructed.

To emphasize their widespread utility, it is worth stressing the a large number of MSMs are currently used across the world by various government departments (or research institutes). Some of these models are as old as 30 years (DYNASIM in the U.S.), some other are still being developed to cope with specific policy areas (PENSIM II in the UK) as new issues have come to the forefront of the policy debate and request more detailed attention. In essence, the number of MSMs is growing as the necessity to produce evidence-based policy making is becoming stronger.

All this said, it seems to us that Orcutt’s vision has only partially come true. On the one hand, undeniably MSMs are more and more commonly used by governments before making policy decisions ranging, e.g., from tax or pension policies reforms, to urban planning or budget forecasts; they are also increasingly developed by research institutions more generally concerned with answering questions such as: what are the future efficiency and / or redistributive outcomes of a certain public action? What will be its financial costs? Who will gain and who will loose? What incentives or disincentives will it create in terms of behaviors of those affected by it?

On the other hand however, at an academic level microsimulation remains mostly confined within a niche of dedicated practitioners and specialized journals [1]. Works on MSMs still find it relatively hard to get published elsewhere. An EconLit search of the word “microsimulation” and its variants [2] returned 259 hits among journal articles [3]. This must be compared with more than 500 articles on Computable General Equilibrium (CGE), and over 1,250 articles employing Overlapping Generations (OLG) models. One reason lies in the fact that MSMs are often too complicated models to be fully described in one journal article. As a consequence, they are generally confined in dedicated volumes: the same EconLit search returned 143 hits among books and collective volumes, *vis-à-vis* 96 hits for CGE models and 136 hits for OLG models. Another more fundamental reason might lie in the general perception that MSMs often are not grounded in a very solid theoretical framework.

Regardless of why, this rather poor publication record might discourage researchers - who should be somewhat rational actors - from devoting time and resources to microsimulation.

With this survey we thus hope to convey that microsimulation deserves greater attention, and to suggest that MSMs can indeed match sound theory with solid empirical analysis.

After a short historical presentation of microsimulation development (section 2), we will review the essential technical features of MSMs (section 3), on the basis of which they are classified. In particular we will focus on the differences between static (section 4) and dynamic (section 5) MSMs. Some examples of how such models can or have been applied to different research questions will be provided. Finally, some methodological issues concerning estimation and validation will be discussed (section 6). Section 7 concludes.

2 Brief history

The field of microsimulation originates from a 1957 paper by Guy Orcutt, "A new type of socio-economic system" [Orcutt, 1957]. In Orcutt' s words,

> [t]his paper represents a first step in meeting the need for a new type of model of a socio-economic system designed to capitalize on our growing knowledge about decision-making units.

The paper remains an essential reading today in explaining what MSMs are, how they work and why they should be used. Orcutt was concerned that macroeconomic models of his time had little to say about the impact of government policy on things like income distribution or poverty; this is because these models were predicting highly aggregated outputs while lacking sufficiently detailed information of the underlying micro relationships, e.g. in terms of the behavior and interaction of the elemental decision-making units. However, if a non-linear relationship exists between an output Y and inputs X (as it is often the case in socio-economic relationships), the aggregate value of Y will indeed depend on the distribution of X, not on the total value of X only. Orcutt' s revolutionary contribution therefore consisted in his advocacy for a new type of modeling which is micro based, *i.e.* it uses as inputs representative *distributions* of individuals, households or firms, and puts emphasis on their heterogeneous decision making, as in the real world. Moreover, in so doing the entire distribution of Y and not only its aggregate value is recovered. As Klevmarken [Klevmarken, 2001] puts it,

> In microsimulation modeling there is no need to make assumptions about the average economic man. Although unpractical, we can in principle model every man.

Again, in Orcutt´s words,

> this new type of model consists of various sorts of interacting units which receive inputs and generate outputs. The outputs of each unit are, in part, functionally related to prior events and, in part, the result of a series of random drawings from discrete probability distributions.

These distributions specify the probabilities associated with the possible outputs of the unit, and are responsible for generating outcome variation over time. Indeed, these probabilities may vary over time as the system develops or as external conditions change. Orcutt also gave normative recommendations on how a model should be set up; for instance, units of each particular type in the model should be set as closely as possible to the numbers of corresponding units in the real world.

Orcutt was deeply convinced that this new type of modeling would open the way for several new uses, e.g. by facilitating and improving prediction of socio-economic phenomena, as well as testing of hypotheses.

The 1970s were an era of large scale microsimulation development, particularly in the United States where the government provided significant funding. This period marks essentially the beginning of dynamic microsimulation, as Orcutt himself and collaborators developed DYNASIM [Wertheimer et al., 1986], subsequently evolved by Steven Caldwell into CORSIM [Caldwell and Morrison, 2000].

However, the large macro models of the 1960s and 1970s did not live up to their expectations as a tool to provide fast and reliable estimates of the effects of different policies [4].

MSMs were criticized primarily because of heavy programming, computing and data requirements. In particular, the lack of comprehensive representative micro data was possibly the major problem, and a huge amount of resources in those early days of microsimulation was devoted to overcome the paucity of public available datasets (as witnessed for instance by [Pechman and Okner, 1974]).

These shortcomings led to the development of more compact, less ambitious, static models in the 1980s. As we shall explain below, static models are primarily accounting models, with no or limited behavioral responses (*i.e.* changes in behaviors as a response to a change in policy). They do not take into consideration that the composition of the population itself might change, e.g. because some people die and some others have children, or because some people might decide to move in or out, possibly also as a consequence of the policy under examination. Moreover, they abstract from all the feedbacks between different aspects of individual behavior (e.g. the change in labor supply originated by a change in the tax system), and focus only on the direct, *ceteris paribus*, effects of a policy change (e.g. the immediate change in disposable income).

Rapidly reducing computing costs and improved access to data in the late 1980s have seen the field expand again, removing some of the obstacles for the development of large-scale dynamic models. Moreover, many of the early models were developed in isolation and had to learn lessons of model construction independently. Although the issue of re-usability remains, in the last few years there has been a welcome increase in cross-model co-operation. One example is provided by EUROMOD, a Europe-wide static tax-benefit model developed by a consortium of researchers from 15 EU member states. Another example involves the transfer of code and expertise from the CORSIM project to new models in Canada and Sweden.

While the majority of these models remain within the domain of academic institutions, public institutions are becoming increasingly interested in taking over the construction of such models themselves (e.g. DYNACAN [Caldwell and Morrison, 2000], PENSIM II [Curry, 1996], MOSART [Andreassen et al., 1996], SESIM [Economic Policy and Analysis Department, 2001], DESTINIE [Bonnet and Mahieu, 2000].

Today, we find MSMs in almost every developed country, with some models (mostly static) also in emerging or developing countries (e.g. Russia, Pakistan, Brazil) — see figure 1 for an (incomplete) map. Examples of applications together with general discussions on microsimulation modeling can be found in [Harding and Gupta, 2007, Mitton et al., 2000, Harding, 1996, C.F.Citro and Hanushek, 1991, C.F.Citro and E.A.Hanushek, 1991].

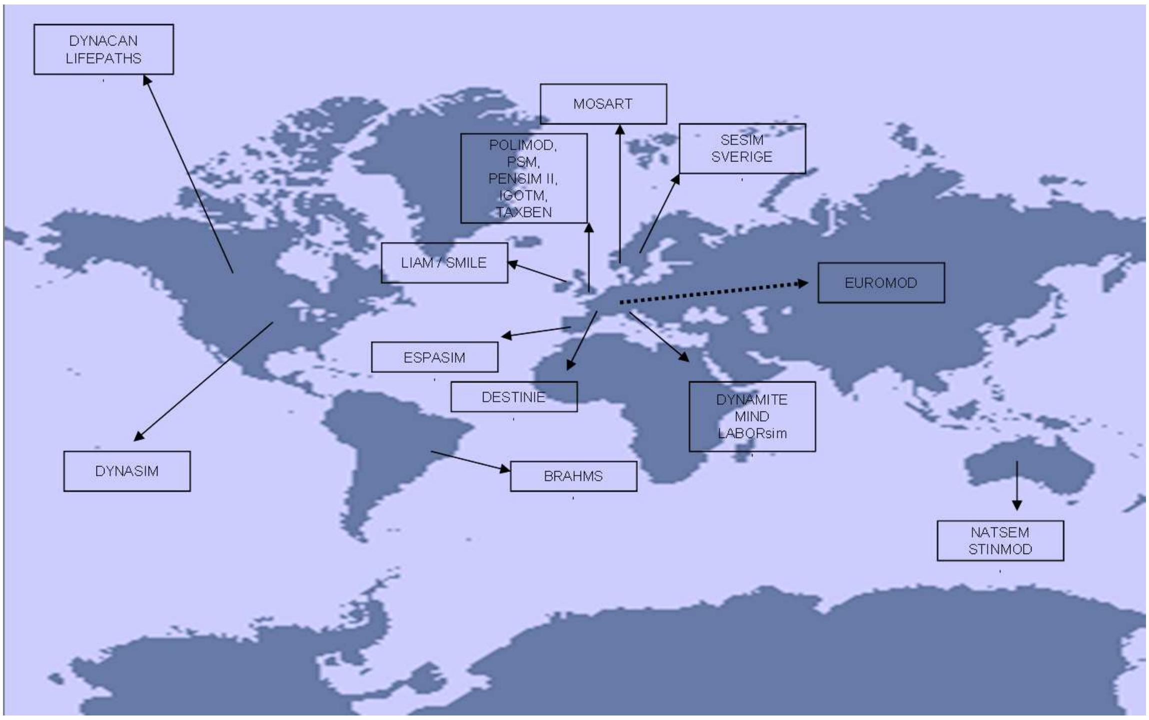

Figure 1: An (incomplete) map of microsimulation models

3 Key features

3.1 Differences with other methodologies

Before discussing the key features that characterize MSMs, we begin by looking at the key differences which distinguish these models from other tools of analysis which have been frequently used as alternatives [Dupont et al., 2003]. In particular, we focus on cell-based models, that being particularly easy to construct are often used to provide simple and quick projections.

3.1.1 Cell-based models

Cell-based models work on exogenous assumptions about future demographic trends and other scenario hypothesis and work out how the aggregate statistics of interest (e.g. the fiscal balance, or the employment rate) will change without explicitly modeling changes in individual behavior and without considering individual heterogeneity within each cell. The aggregate statistics of interest, Y, is analyzed in terms of the composition of the same statistics computed in smaller subgroups of the population,

$$Y_t = \sum_i p_{i,t} y_{i,t} \tag{1}$$

where p_i is the relative frequency of each subgroup (each cell): $\sum_i p_{i,t} = 1$. As an example, think of Y as the overall employment rate, which is a weighted average of gender and age-class specific employment rates. External demographic projections suggest changes in the p_is over time, while the behavior y_i is kept constant. Sometimes, specific scenarios are constructed, which assume changes in the behavior (e.g. convergence of the employment rates by age class and gender to the OECD average).

Note that (i) in cell-based models the dynamics of Y_t is entirely driven by exogenous assumptions, and (ii) these models do not provide an assessment of the likelihood of the different scenarios. Conversely, MSMs provide the micro-foundations for the different scenarios, while being able to take into account in more detail individual heterogeneity. While conditioning the transition rates on more variables is almost costless in an MSM, it increases the number of cells in a cell-based model geometrically: for instance, having 3 binary variables and 2 variables that can take 3 values implies having $3^2 * 2^3 = 72$ cells.

Alternatively, instead of keeping constant (or changing exogenously) the statistics $y_{i,t}$, models can be constructed where the transition rates in and out of the specific state y is kept constant within each cell. These are often labeled *cohort models*, although this definition looks somewhat ill-conceived, as it will soon become clear [5]. The name originates from the fact that these models should be able to account for cohort effects, *i.e.* gradual changes not explained by observable characteristics, which cause two otherwise identical individuals of the same age, but one born in period t and the other born in period s to behave differently. This has an effect on the aggregate statistics Y as individuals of any age in the population are gradually replaced with individuals of the same age who are born later, and hence behave differently.

Since at each moment in time the three variables “cohort” (e.g. year of birth), “age” and “time” are collinear, it is not possible to estimate cohort effects unless observations on more than 1 period are available. This allows to observe individuals of the same age but born in different periods. Supporters claim that cohort models can overcome this difficulty, by including dynamic elements estimated on as little as 2 periods, e.g. on a simple cross-section of data with retrospective information. What they actually due is to introduce a spurious dynamic, linked to the true cohort effect in an unclear and unsystematic way.

As an example, think of the activity rate. Denote the number of inactive people of age i at time t as $A_{0,i}$ (the time index is omitted), while the number of active people is $A_{1,i}$. Some transition rates into the labor force ($r_{i,t}^{in}$) and out of the labor force ($r_{i,t}^{out}$) are observed for each age group i at time t. At time $t+1$ — abstracting from new entries and exits in the population — the projected activity rate of people aged $i+1$ will be $(A_{0,i}r_{i,t}^{in}+(1-r_{i,t}^{out})A_{1,i})/(A_{0,i}+A_{1,i})$. Thus, if more people are entering or exiting the state at a given age i, this will have repercussions s periods into the future by increasing the statistics $y_{i+s,t+s}$, as the entry and exit rates (observed in period t and kept constant) for the subsequent age groups will be applied to a population (the cell consistencies) that is dynamically computed and is in general different from that of period t.

A numerical example could be of value. Suppose there is a true process with entry rates into a state that differ with age, but homogeneously increase for all ages at, say, an annual pace of 2%. The entry rates would thus look as those of table 1. However, with only one cross-section of data (for instance referring to year 2004) only some combinations of age and cohort are observed — the bold numbers in the table. To simplify matters, suppose further that the exit rates are 0 for all age groups, with no trend.

	cohort						
age	1980	1981	1982	1983	1984	1985	1986
20	0.5	0.52	0.54	0.56	**0.58**	0.6	...
21	0.4	0.42	0.44	**0.46**	0.48	0.5	...
22	0.3	0.32	**0.34**	0.36	0.38	0.4	...
23	0.2	**0.22**	0.24	0.26	0.28	0.3	...
24	**0.1**	0.12	0.14	0.16	0.18	0.2	...

Table 1: "True" entry rates of an imaginary process. Bold numbers refer to values that would have been observable in 2004

Let's now consider a population of N individuals, homogeneously distributed by age. Assuming the process described above, table 2 compare the projections that an observer looking at the 2004 data would have made based on the assumption of constant entry rates (the bold numbers in table 1), with the true rates. Column 1 contains the "observed" cell frequencies for being in the state in 2004, while column 2 contains the projected rates for 2008 and column 3 the "true" rates for 2008. Finally, the rates that would be observed in 2008 should the trend toward increasing entry rate have stopped in 2004, the last observable year, are reported in column 4. The 2004 values are consistent with the entry rates given above: the share of people aged 20 in the state is .58, equal to the entry rate for those born in 1984; the share of people aged 21 in the state is $.56 + (1 - .56) * .46 = .762$, since among those born in 1983 56% entered the status at age 20 in 2003, while 46% of those who did not enter the status in 2003 did so one year later, aged 21; and so on. Incidentally, note that if the *frequency* of the status rather than the entry and exit rates are supposed to be constant within cells, as in the simpler cell-based models described above, column 1 would also give the projections for any period ahead. Assuming no population change, the overall frequency of the status would be predicted to remain constant.

Here however we are considering the case when the observed entry rates in 2004 (the bold numbers in table 1) are supposed to remain constant. The resulting projections for 2008 are anyway quite off the track, as a comparison of columns 2 and 3 shows. Neither this forecasting methodology implicitly makes the assumption that the trend toward increasing entry rates stops when last observed (in 2004) — this would have produced the values reported in column 4. Hence, we can conclude that cohort models introduce some sort of dynamics in the projections, but this dynamics is only loosely connected with any true cohort effect. More in general, the lesson is that cohort effects are impossible to estimate with observations referring to only 1 time period, and very imprecise to estimate with only a few time periods of observations available.

	col.1	col.2	col.3	col.4
	2004 obs.	2008 true	2008 proj.	2008 (*)
age			%	
20	58.0	66.0	58.0	58.0
21	76.2	83.4	77.3	78.2
22	83.0	89.4	85.0	86.5
23	85.2	91.6	88.3	90.3
24	84.9	92.0	89.5	92.0

(*) "true" values with trend stopped in 2004

Table 2: Observed and future ("true" and projected) frequencies of the state

Moreover, it may happen that the dynamics implicit in the entry and exit rates observed in period t are the result of more than one trend. For instance, suppose younger cohorts are less attached to the labor market because they go to school more, but that — after controlling for education — there is also an increasing trend toward higher labor market participation at all ages. When looking at the entry and exit rates in one specific period we observe only the net effect of the two trends, which — for the younger cohorts — is likely to be negative. A simple cohort model will project forward this negative trend and extend it to older ages, thus projecting an overall decrease in the activity rates! For this reason, cohort models are sometimes complemented by *ad hoc correction mechanisms*, thus introducing further "hidden" assumptions.

On the contrary, MSMs can directly model any cohort effect: allowing a separate treatment of every process they do not force to consider only net effects.

3.1.2 Other forecasting methodologies

Many other approaches to forecasting exist. Among the most popular, we have:

- **Representative types models**: a few representative "types" of relevant units, e.g. different household compositions or individuals with different career paths, are depicted and the effects of a given policy are simulated and compared between these stylized types. However these representative cases are inadequate in a dynamic context wherein agents actually move between different "types", and the composition of "types" in the population changes over time. In terms of equation 1, the focus is on the behavior of the different types, as characterized by a different vector of individual characteristics $\mathbf{x}_i$, generally as a deterministic function of some policy variables $\mathbf{P}$ (e.g. the tax and benefit system), while the distribution of p is not investigated.

$$y_i = f(\mathbf{x}_i, \mathbf{P}) \tag{2}$$

- **Behavioral microeconometrics model**: these are models where individual behavior, possibly conditional on specific policies of interest, is estimated in the data and then used for short-term projections and policy evaluation, the composition of the population and the distribution of individual characteristics being held constant. These models can be expressed either in a structural or in a reduced form, and may involve multiple simultaneous equations, as in the case of the joint determination of labor supply and child bearing. At a micro level (that is, within narrow cells that describe units with the same characteristics), the variable of interest y_i is analyzed in terms of individual variables $\mathbf{x} = \{\mathbf{x}_i, \mathbf{x}_{-i}\}$ (which may also contain lagged values), of policy variables $\mathbf{P}$ and of coefficients β, which are estimated in the data:

$$y_{i,t} = f(\mathbf{x}, \mathbf{P}, \beta) \tag{3}$$

- **Computable general equilibrium models**: these models look simultaneously at representatives cohorts and sectors of the economy (households, enterprises and the public sector), and aim to work out an (intertemporal) general equilibrium given full rationality, full information and optimal behavior of all the decision makers. Individual outcomes are connected to the overall macroeconomic dynamic through price adjustments and public intervention.

$$Y_e = f(\mathbf{X}_{1,0}, \mathbf{X}_{2,0}, \ldots \mathbf{X}_{n,0}, \alpha, \mathbf{P}) \tag{4}$$

where Y_e is the statistics of interest in equilibrium and the vectors $\mathbf{X}$ contain the (aggregate) state variables of the n different sectors, cohorts, *etc.*, whose initial values, together with the structural parameters α, determine the outcome. However, these models are highly theoretical (*i.e.* simplified), rely on a restrictive number of assumptions, are often hard to solve analytically (hence the need to recur to computational analysis) and lack empirical content (apart from some calibration) and verification.

- **Macroeconometric models**: these are models based on studying the interaction, at the aggregate level, between supply and demand, which together determine the value of key aggregate statistics of interest. Given a certain shock, prices typically adjust with a lag, and the path back to the equilibrium is studied in relation to aggregate variables through time series econometrics.

$$Y_t = f(\mathbf{X}_t, \mathbf{X}_{\tau<t}, \mathbf{P}, \beta) \tag{5}$$

More generally, we distinguish two fundamental approaches in the analysis of policy effects, one micro and one macro. As we have already mentioned, the *micro approach* relies on the availability of real or fictional individual units which represent the characteristics of the population; in this case, the models can help in deriving a heterogeneous set of life paths (e.g. in terms of consumption, income, savings etc) more or less consistent with economic theory. Usually, the micro approach uses exogenous assumptions about the macro context and does not include the monetary side.

The *macro approach* instead focuses on including all aggregate forces which play together in determining a certain economic equilibrium (e.g. the supply and demand of labor and capital) through a system of prices. The macro context is thus endogenized in that it results from the interaction of the various markets present in the model and their predicted behaviors. Indeed, macro models tend to be micro based in the sense that they model behaviors of each representative sector, or cohort, based on rigorous micro theory; however they tend to lack strong empirical foundations. They usually calibrate against observed aggregates hence they might get the micro behaviors wrong without means of verifying this.

The ideal model would aim to integrate the micro and macro sides, although this encounters a number of challenges (indeed, such attempts exist, see e.g. [Davies, 2004]). In essence, the two approaches are complementary and a choice should be made depending on the type of specific questions that need to be answered.

MSMs fall typically within the microeconomics approach, and are rather akin to behavioral econometrics models, which often are indeed built in as parts of a larger MSM (particularly dynamic MSMs, as we will see). A key feature distinguishing MSMs is indeed the degree of "structural" econometric modeling, *i.e.* the extent to which the included behavioral equations are modeled according to a predefined economic theory or whether instead they are simply *ad hoc*, or "reduced form".

MSMs are generally comprised of a number of partial equilibrium sub-models, or *modules*. These modules can be thought of as watertight compartments, or as compartments connected by simplified causal relationships. Indeed, there might be feedbacks between different modules, but these feedbacks are never simultaneous: if at time t the outcome of module A (e.g. education) affects the outcome of module B (e.g. employment), it cannot be the case that at the same time t the outcome of A depends on the outcome of B. This explains the main difference between MSMs and general equilibrium models, where the system is modeled as a set of simultaneous, possibly dynamical, equations. Of course, it is possible that the outcome of module B affects the outcome of module A in subsequent periods (e.g. the choice to attend education might depend on whether the individual was employed in the previous period). [6] Also, some modules may deal with simultaneous processes, e.g. fertility and work decisions, which are jointly estimated in the data.

Having placed microsimulation within a more general framework of analytical tools, we can now move on to the specific features which characterize this methodology. Under the label of microsimulation, there is in reality a vast range of different models which are somewhat unique in their design due to their specific purpose or data. There is however a key structure common to all MSMs which provides the underlying link between a model's inputs and its outputs. This structure is meant to draw some statistically valid inference about a population, given some carefully sampled data.

3.2 Basic elements of MSMs

Basically, MSMs are constructed around a micro database, which at time $t = 0$ is generally a sample from some real population — the so-called *initial population*. Each unit is represented by a record containing a unique identifier and a set of associated attributes, e.g. a list of persons characterized by a given age, sex, education, household composition, employment

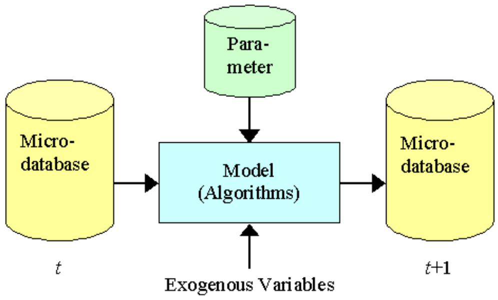

Figure 2: A microsimulation model. Source: [Sauerbier, 2002].

status, wealth, income, *etc.* A set of rules are then applied to these units leading to *simulated* changes in state and behavior. These rules may be mere *accounting rules*, *i.e.* instructions that reproduce, for each unit, the provisions of existing or hypothetical institutional features (e.g. taxes and transfers), or *behavioral relationships*. The latter might be either *deterministic*, as in the case of compulsory education for people aged less than a threshold, or *stochastic* (transition probabilities), as for the probability, given the individual characteristics, to extend education beyond this age.

The basic structure of a MSM is depicted in figure 2.

3.3 Data requirements

[Martini and Trivellato, 1997] analyze in details the issue of data requirements for MSMs. When estimation of the transition probabilities is needed, it can be performed either in the initial population, or using some other dataset . In the latter case, it is clearly necessary that all the variables used for the estimation of the transition probabilities are also present in the initial population, so that it can be evolved according to these probabilities. If some of them are missing, they must be imputed by a "donor" dataset, possibly the same used for estimation.

The dataset used for estimation can be a *cross-section*, a *time-series of cross-sections* or a *panel data*. Cross-sections contain information about a number of surveyed units at one point in time. When different cross-sections are collected over a number of time periods, possibly surveying different individuals, we have a time-series of cross-sections. Finally, when we have multiple observations of the same individuals over time we have a panel.

Both a time-series of cross-sections and a panel allow to establish whether a given relationship is constant over time or whether it is just valid for the particular period when the data is collected. If the latter is the case, individuals of the same age but of different year of birth exhibit a different behavior (the so-called time or *cohort effect*). In a cross-section all individuals of the same age are born in the same year: this is why it is not possible to identify a cohort effect — see the discussion on cell-based models.

Moreover, panel data allow to take into account also individual effects, *i.e.* the fact that some individuals might be characterized by unobserved characteristics (e.g. ability) that do not vary over time. Neglecting this individual fixed effect might induce to underestimate or overestimate the effect of some other variable that happens to be correlated with the individual effect (e.g. education).

Note that the initial population is, by definition, a cross-section, while the outcome of the MSM has in principle a panel structure (having at least one initial and one final period). Thus, if cohort-effects are included in the model specification, the estimation cannot be performed on the initial population alone.

3.4 Computing platforms

Furthermore, an MSM requires a computing platform to handle the simultaneous processing of individual data, exogenous variables and transition rules, and store the outputs (usually these platforms are written in C++, Fortran, Java or similar programming languages). This processing is repeated over time by the model for the desired length of forward simulations.

3.5 Schedule of the simulation

Within a single period, an order (*schedule*) of events, *i.e.* the sequence of application of the different transition rules, must be specified. This schedule determines the order at which the different modules are called. Note that a module (e.g. education) might involve a multitude of events (e.g. whether an individual goes to school and whether — conditional on going to school — she gets her diploma. Also, the same module might specify different events for different individuals (e.g. education might refer to high school or university, depending on previous educational level).

In the following sections we describe the key differences between two types of MSMs: static and dynamic MSMs.

4 Static microsimulation

Static models examine the immediate impact of a policy change (so called *first round* effect) usually without any attempt to incorporate how that change might affect subsequent behaviors, or what effects it might have once the demographic or economic foundations change (although some static models can include a behavioral module, usually a labor supply module). For this reason, static models are often considered to be merely an accounting effort.

In essence a static MSM, aims at recovering the distribution $f_Y(Y|\mathbf{X}, \mathbf{P})$ of some endogenous variable Y, conditional on exogenous variables $\mathbf{X}$ and the institutional environment $\mathbf{P}$.

In an illustrative tax and benefit MSM, the model contains all the eligibility rules and amounts governing the tax and benefit system and affecting a household' disposable income (*i.e.* income tax, property tax, capital tax, unemployment subsidy, child benefits, pensions, housing allowances *etc.*) at a given time t. The model applies these rules to each household in the sample (given the characteristics $\mathbf{X}$ available in the survey) and computes the taxes and benefits that each household is entitled to or liable for (by law).

In reality, static models might involve some degree of statistical inference (beyond deterministic rules and simple accounting): for instance, a common issue with static model is slightly "dated" input data (representing a population sampled maybe a few years back relative to the year of interest). In such cases, before the model is run, a process of "re-weighting" is performed on the old data so that they become better representative of the current population. The sample weights are adjusted such that a standard inference will reproduce the observed distribution of certain variables in the present population.

In some cases, static models are used to make short term forecasts (one or two years ahead for instance), under the assumption that only small changes to the fundamental structure of the population, of the economy or of individual behaviors would occur within such a short time span. In these cases, static models are made to go through a process of so called *static* *aging*: this entails a purely deterministic re-weighting of the individuals in the simulation and an updating of some external parameters to account for exogenously forecast changes e.g. in the demographic structure of the population, in the sectoral composition of the economy, in the value of the benefits, in the level of inflation *etc.*

Sometimes different weights have to be used, when the MSM involves different level of analysis (e.g. individuals and families). This is generally referred to as *grossing*, i.e.

> a procedure to adjust the sample [already weighted, with the sum of the weights equal to the size of the population] to external data [on total population values of relevant variables, e.g. families, welfare recipients, *etc.*], by changing the weights of the sample units [Gomulka, 1992]

Put differently, in static models both the number of simulated individuals and their underlying characteristics do not change. However, some individuals become more important than others to account for changes occurring at the population level and maintain the statistical "representativeness" of each individual relative to the whole population.

What are the advantages of static models? For a start, they are rather simple to create and can offer a cost efficient tool for certain types of policy analysis. Static MSMs, for instance, can be used to analyze at the individual level the effects of different reform proposals, say on disposable income. At the aggregate level the policy maker will be able to compute the total costs of each reform proposal, and to identify the winners and losers.

Note that the effects of the application of a given rule are considered to be quasi immediate. The model answers the question: what would be the variation in variable x for household h at time $t + 1$ if policy rules R were applied, everything else remaining the same? The reference to time $t+1$ should literally be interpreted as a very close time frame, in order for the assumption of constant behaviors to hold [7]. This is of course one of the major limitations of static models.

Examples of static microsimulation models include PSM (Policy Simulation Model, developed at the UK Department of Work and Pensions), TAXBEN [Giles and McCrae, 1995], POLIMOD [Mitton and Sutherland, 1999]in the UK, or EUROMOD [Sutherland, 2001] in the EU.

5 Dynamic microsimulation

A dynamic MSM takes micro level units and synthetically generates a hypothetical future panel data, *i.e.* a simulated life trajectory for each one of the initial units (what is often called *dynamic aging* of the initial population), as well as creating new individuals and their history. Hence, births, deaths and migrations can take place in these models. It is important to stress again that this technique has found a large number of applications not only in economics or demography, but also in other disciplines ranging from epidemiology, to physics, to logistics and even personnel or financial management.

Contrarily to static modeling, in dynamic micro simulation agents change their characteristics as a result of endogenous factors within the model. There are in fact two often mixed up ways of interpreting the meaning of "dynamic". The first refers to behavioral traits which include active "responses" to changes in the surrounded environments (e.g. feedbacks). This implies that the set of exogenous variables $\mathbf{X}$ are made endogenous in response to institutional characteristics $\mathbf{P}$:

$$f_{X,Y}(Y, \mathbf{X}|\mathbf{P}) = f_{Y|X}(Y|\mathbf{X}, \mathbf{P}_1) f_X(\mathbf{X}|\mathbf{P}_2) \tag{6}$$

where $\mathbf{P}_1$ is the subset of the institutional environment that have only a *direct* effect on Y, while $\mathbf{P}_2$ is the subset of the institutional environment that have also an *indirect* effect on Y, since it affects the distribution of $\mathbf{X}$ (see [O'Donoghue, 2001]). Examples include models where labor supply responds to changes in government policy. The other form of dynamic process is where a dynamic model projects a sample over time, modeling life course events such as demographic changes like marriage and birth, educational attainment or labor market movements. In this case, the dynamics relate to the fact that characteristics in time t, Y_t depend on characteristics in time $t - j$ Y_{t-j} and exogenous characteristics $\mathbf{X}$.

Note however that if the microsimulation model includes only reduced form estimates, and the institutional feature or lack of adequate data do not allow to include policy parameters among the explanatory variables of individual behavior, it is not possible to use it to predict what would happen under some policy change. In other words, if the model structure is not autonomous to policy changes (within ranges of interest), it is not possible to use it for policy evaluation. This is the well-known Lucas' critique (see [Lucas, 1976], and also [Haavelmo, 1944]), and it is not peculiar to MSMs.

The most standard processes included in dynamic models used for economic policy evaluation are: (i) demographic changes due to fertility, mortality or migration (ii) marriage and household formation (this is very important as it establishes links between people which are often necessary for the calculation of incomes, or social benefits) (iii) educational path (iv) health status, including whether an individual might fall into long term sickness or disability (v) labor market status, including whether in work, unemployed or retired (e.g. retired), if employed, in what type of work, earnings and other related characteristics (e.g. working hours), (vi) taxes and benefits, (vii) savings and wealth. All these modules jointly determine, at any given point in time, each individual or household´ s disposable income, and since this will change under different policies affecting individual behaviors, the model will allow comparisons e.g. in intergenerational redistribution under different scenarios. Note that the focus in this example is on labor supply, while production and the demand for labor are not investigated, as are not considered inflation and the monetary side of the economy. This exemplifies the partial equilibrium nature of MSMs. Macro assumptions are therefore usually imported from external sources, using steady state assumptions about future economic conditions, or actual projections if available (e.g. labor demand and inflation).

Examples of dynamic MSMs include the already cited DYNACAN (Canada), DYNASYM and PENSIM (US) PENSIM II (UK), MOSART (Norway), DESTINIE (France), SESIM (Sweden), but also MIND [Vagliasindi et al., 2004], LABORsim [Leombruni and Richiardi, 2006] and DYNAMITE [Ando et al., 1999] in Italy, LIAM [O´Donoghue, 2002] and SMILE [Ballars et al., 2005] in Ireland, MIDAS [Goulias, 1992] in New Zealand, MICROHUS [Harding, 1996] and SVERIGE [Winder and Zhou, 1999] in Sweden, just to name a few. Some models have been used just to look at future income distributions under different economic or demographic scenarios, usually linking up to macro models or forecasts to align their own simulations (e.g. DYNASIM in the U.S., DYNAMITE in Italy); others have been used to evaluate the long term effects of policies and programs such as pensions, health and long term care, or educational financing (e.g. DYNACAN, PENSIM II, MOSART, SESIM, MIND). In addition, the existence of baseline projections also allows one to design new policies by simulating the effects of different proposed reforms, e.g. in the area of pension reform (e.g. LIAM in Ireland, LIFEMOD in UK, LABORsim in Italy). Finally, some models have been used specifically to study intertemporal processes and behavioral issues such as wealth accumulation, fertility or labor market mobility(e.g. CORSIM in the US, MIDAS in New Zealand; MICROHUS in Sweden). Other uses have been carried out in the sphere of health status over the life cycle, dental health or even spatial mobility or regional development (e.g. SMILE in Ireland, SVERIGE in Sweden).

Surveys of dynamic MSMs can be found in [O'Donoghue, 2001, Zaidi and Rake, 2001, Dupont et al., 2003].

The main advantages of dynamic MSMs, beside the use of individual representative micro data allowing to model individual decisions common in part also to static MSMs, are that they allow to simulate inter-temporal issues requiring historical information (e.g. the simulation of pensions requires knowledge of the full working history), as well as to include future behavioral adjustments of the population to either policy reforms or to changing economic, demographic or social scenarios. The disadvantages of dynamic MSMs include however insufficient knowledge of social, demographic or economic behaviors, leading most models to rely on reduced form estimations given the available data, large data requirements, large building and maintenance costs, and lack of an agreed validation methodology. In particular, incorporating behavioral feedback loops is generally quite a complex task, sometimes involving the need to link to outside models e.g. general equilibrium models; data requirements for behavioral estimations (e.g. on life cycle saving and consumption patterns) are also limited in most countries, unless register information is available. These disadvantages have meant that many newer models have actually tried to focus on specific processes or events (e.g. pensions) rather than attempting to be omni-comprehensive.

5.1 Classification

In principle, dynamic MSMs can be divided between *population* or *cohort* models (not to be confused with the cell-based cohort models described in section 3.1.1). The latter project forward only one cohort in time so as to simulate that cohort´ s entire life cycle (hence cohort models are used particularly to investigate life-course redistribution issues in given tax and benefit systems); while the former (population models) are able to simulate forward life histories for all age groups making up the entire population, including the reproduction of new individuals, to allow for the simulation to be carried out very many years into the future.

Microsimulations can be cast in *continuous* or in *discrete* time. Discrete time means that the system is sampled at periodical intervals (e.g. every simulated year), when all the individual state variables are in turn updated. Some variable will then change (if a transition has occurred), while some others will not. The order in which the update process takes place, *i.e.* the order of the events through which individuals pass, is exogenously chosen. For instance, in labor supply MSMs it is common to have the call to the education module before the call to the labor market participation module. Thus, labor market participation influence schooling only in later periods, while schooling influence labor market participation in the same period. Joint processes can also be simulated, but this does not change the fact that when separate processes take place within the same simulation period, an order must be specified.

Conversely, in continuous time microsimulation each process determines a waiting time for the corresponding transition to take place [Galler, 1997]. Thus, events can occur at any arbitrary moment. In addition, multiple events may occur during a discrete time interval, and their order is endogenously determined according to the theory of competing risks. The system is updated only when a transition occurs. However, when a transition occurs new waiting times need to be calculated for all the processes, based on the updated values of that variable. Appealing as this might seem, only few continuous time microsimulations exist (see [Willekens, 2007] for additional references and discussion). One reason is that the need to sample at regular intervals the simulated population cannot be totally dispensed with, if the simulation results are to be communicated.

Another distinction often found in the literature is between *case-based* and *time-based* microsimulations. Case-based MSMs involve the simulation of the different life paths one at a time, *i.e.* each history is fully simulated from the moment when the artificial person first appears (this may be at the beginning of the simulation if the individual belongs to the initial population, or in subsequent periods if new entries are allowed) up to either the end year of the simulation or the period when the simulated person exits the simulation (e.g because of migration, death or retirement), before moving on to the next history.

Conversely, in time-based microsimulation all individual histories are simulated in parallel.

In discrete-time microsimulations this involves one or more calls to each agent in each simulation period. For instance, all individuals are first asked to decide whether they go to school; then, graduation is determined for every student; then all individuals are asked to decide whether they are willing to participate in the labor market; finally, employment is determined for every active individual.

5.2 Transitions

A dynamic MSM is essentially meant to study complex stochastic systems, *i.e.* systems characterized by non-linear interactions and uncertain outcomes, either discrete or continuous. Thus, the model is able to predict the likelihood that each individual, given her current characteristics, will make a given *transition*, *i.e.* a change in her current status. Some transitions can be deterministic (e.g. age), but most are indeed stochastic, *i.e.* they incorporate random processes, and therefore require the application of statistical tools. Some stochastic methods reproduce the observed underlying relationships and features of the population indefinitely into the future (e.g. reduced form estimations or transition matrices); some others instead attempt to update the evolution of social and economic relationships by actually including behavioral responses (*i.e.* some variation in the future distribution which is actually determined by a change in the structural parameters governing the behaviors of simulated agents, resulting in different aggregate patterns with respect to the original sample).

A very common estimation process in dynamic *discrete-time* MSMs is related to discrete events e.g. whether someone is in work ($Y = 1$) or not ($Y = 0$), known as *reduced form discrete choice estimation modeling*: in essence, the probability that a certain event Y happens, at time $t + 1$ is a function of input variables at time t or before:

$$Pr\left(Y_{t+1} = 1\right) \equiv p = f\left(\mathbf{X}_t, \beta|\mathbf{P}\right) \tag{7}$$

$$Pr\left(Y_{t+1} = 0\right) = 1 - p \tag{8}$$

The simplest specification for these transition probabilities is unconditional observed transition rates. More elaborate models control for more variables $\mathbf{X}$ (e.g. age, sex, lagged status, *etc.*).

In a continuous-time microsimulation the same event, e.g. the transition to or out of work, is modeled with a duration model, where the variable of interest is the (waiting) time to event, T. The cumulative distribution function of T is $F(t) = Prob(T \leq t)$, *i.e.* the probability that the time to the transition is less than or equal to t, or that the transition occurs in the interval from 0 to t.

To determine whether (in discrete time) or when (in continuous time) the transition occurs, Monte Carlo techniques (also known as *random simulation*) are employed.

In discrete time the estimated probability p is simply compared to a uniformly generated random number u, and the transition is assigned if the probability for a given individual happens to be above that number. This is equivalent to extrapolating the estimates into the future with no constraints.

$$Pr\left(s_{t+1} = 1\right) = Pr\left(u_i < p_i\right) \tag{9}$$

In continuous time the timing of the transitions is determined by drawing a random waiting time from the waiting time distribution F, which is generally assumed to be exponential, Gompertz, or Weibull. The expected waiting time for individual i is therefore simply $G(u_i)$, where u_i is, as before, a random draw from a uniform distribution, and G is the inverse distribution function of T, $G(\alpha) = F^{-1}(t)$ (see [Willekens, 2007] for more details). Again, this is equivalent to extrapolating the estimates (of waiting times) into the future with no constraints.

5.3 Alignment

Sometimes the simulated stock of those who do make the transitions is adjusted, with respect to what comes out of the Monte Carlo simulation. This is called alignment: the composition of the simulated population with respect to some characteristics (e.g. age and sex) is matched to the aggregates observed in the real data, or to external forecast (e.g. demographic projections by official statistical offices).

In discrete-time MSMs it is generally made by ranking the individual difference between the transition probability and a uniform random draw, and then assigning the event (the transition) to the proportion z of individuals in each group of interest with the highest ranked values, where z corresponds to the proportion observed or forecasted for that specific group (e.g. mortality rates by sex and age).

$$Pr\left(s_{t+1}=1\right)=Pr\left(u_i-p_i<z\right) \tag{10}$$

Alternatively, the individual transition probabilities (or waiting times in continuous-time MSMs) can be inflated or deflated until the external controls are met. In discrete time this can easily be done by re-drawing the event for randomly selected individuals who have not made the transition, if the statistics in the artificial population is below the target, or who have made the transition, if the statistics is above the target. For example, suppose that alignment is sought for the unemployment rate, and that random simulation implies a level of the unemployment rate that is too small, with respect to some external forecast. Then, the transition is drawn again for some (randomly selected) employed individuals. Some of these individuals will confirm their employment status, while some others will switch to unemployment. Hence, the overall unemployment rate will increase. The process is repeated until the target is met.

More specifically, we can identify two types of alignment, depending on what z represents: alignment of totals and alignment of flows. Alignment of totals refers to a methodology used to force the simulated micro aggregates to hit external control totals.

Alignment of transitions (or rates) is actually a complement to alignment of totals in that it aims not only to achieve a given aggregate total, but also to reproduce the flows which will generate that total (i.e. the model dynamics). If there are two possible states for an individual to be in, A and B, and eventually we know that at the population level x percent of people are in A state at a given time t, we want to make sure that we get the same x percent in our model by capturing the full dynamics occurring between time t and time $t-1$, namely the proportion of people who have moved from A to B plus the proportion of those who have moved from B to A, as well as those who have not moved states at all. Getting right these flows will be as important as hitting the final x percentage.

From an econometric point of view, estimating a process unconditionally and then aligning the resulting projections is equivalent to estimating the process subject to the constraint of satisfying the benchmarks [Klevmarken, 2007] [8]. But at first sight, alignment looks as an admission of defeat: wasn't the MSM built exactly for forecasting purposes? Does alignment means that the forecasts of the MSM are "wrong" (worse: known to be wrong in advance)? The point is that the dynamics of some variables might be influenced by factors that are purposely left out of the model. When a dynamic MSM lacks a macro model, a lot of macro level variables, which in reality do condition micro behaviors, will be unavailable, thus resulting in inaccurate predictions. For instance, dynamic MSMs of labor supply generally do not consider labor demand. The underlying assumption is that the labor supply decisions of individuals are independent of the demand side — this being of course a simplification, the level of the demand influencing the expectations of individuals concerning the probability of finding a job, and the associated wage. This assumption cannot be defended when it comes to analyzing the unemployment rate. However, unemployment differentials (by gender, age, education, *etc.*) can be considered to be less dependent on the level of the demand. Hence, alignment of totals will be used to guide the evolution of the (overall) unemployment rate, while the predictions of the MSM will redistribute the probability of being unemployed in the simulated population, taking into account individual characteristics.

Sometimes alignment is used to reduce sampling and Monte Carlo variation. In particular, Monte Carlo variation means that given the same characteristics, not all individuals in the sample will necessarily follow the same trajectory. This is good because it implies that the dynamic model is able to reproduce at every period an heterogeneous distribution of agents and events which is what characterize the evolution of real societies. But in some simulation runs pernicious combinations of many random variations might drive away the results from what is expected. The correct way to deal with this problem, however, is not to use alignment, but rather to have multiple runs of the simulation. This would allow not only to average out unfortunate runs, but will also provide accuracy measures (e.g. standard errors of the estimates).

Finally, alignment is definitely a bad practice when it is used to "correct" for abnormal projections that cannot be explained by random variation alone. If this is the case, the estimation procedure or the model structure itself should be reconsidered.

6 Estimation and Validation

In the case of static MSMs without behavioral adjustments, as conventional static tax-benefit models, all transitions are deterministic — hence there are no parameters to estimate and there is no need for validation, provided that the tax and benefit legislation has been translated into computer code with sufficient detail and care, and that the data are detailed and accurate enough. However, if the transitions are stochastic and the simulation model includes behavioral adjustments the need for estimation and validation arises.

To start with, estimates of the parameters of the different modules of an MSM are generally performed separately and independently from each other. However, this approach can be justified only if there is independence or lack of correlation between the modules, short of which it will lead to biased and inconsistent estimates (see [Klevmarken, 2001, 2002]). The correct way of estimating an MSM would be to specify a model-wide estimation criterion, and then derive the specific estimators to be used. This implies that some *target variables*, against which the model will be evaluated, must be specified. One possibility is then to use a least-square criterion: this will produce estimates such that the mean predictions minimize prediction errors. However, as discussed above, in developing an MSM we are generally interested in the whole distribution of the target variables, and not only in their mean. The following quote explains this in more detail [Klevmarken, 2001], p. 10:

> Given the purpose of microsimulation, the estimation criterion should not only penalize deviations from the mean but also deviations in terms of higher order moments. A natural candidate estimation principle then becomes the Generalized Method of Moments. The complexity and non-linearity of a microsimulation model, however, cause difficulties in evaluating the moment conditions. A potential solution to this problem is to use the fact that the model is built to simulate and thus replace GMM by the Simulated Method of Moments [Train, 2003].

The Simulated Method of Moments is just one of the Indirect Inference methods [Gourieroux and Monfort, 1997] that can be used to estimate jointly all the parameters of an MSM. However, such methods are computationally very intensive and often difficult to implement. Most MSMs then rely on piece-meal estimation, where each module is estimated from its own dataset and no model-wide estimation criterion is used. In this case, what is called a *multiple-module* validation should be provided. This requires testing the validity of a joint process which is not directly simulated in the model. For instance, let's consider the example of a model where marriage and health insurance decisions are estimated separately within an MSM. A multiple module validation would then require to test the accuracy of results of health insurance for all different groups (married couples and unmarried individuals). This example is examined by Caldwell in [Harding, 1996].

More generally, validation involves evaluating the model outcomes against some predefined criterion. A first issue then arises about the identification of the model outcomes. Often, microsimulation results are presented with a single estimate and do not typically show the degree of error attached to it. However, confidence intervals for microsimulation results should be provided, to account for errors associated with (i) stochastic effects, (ii) sampling variability, and (iii) parameter estimation (see [Harding, 1996], ch. 21).

This can be done with the aid of *bootstrapping*, *i.e.* running the MSM many times and (i) changing the random numbers governing the random processes in the simulation (this can be done by changing the random number generator), (ii) re-sampling the initial population, (iii) sampling the values of the parameters of the transition models from their estimated distribution (with mean equal to the estimate of the coefficient and variance equal to the estimate of the variance of the error term). For a survey of variance estimation methods see [C.F.Citro and Hanushek, 1991, C.F.Citro and E.A.Hanushek, 1991].

Hence, an entire distribution for each simulation output can be constructed, its variability becoming larger as the time horizon increases.

A second issue concerns the choice of an appropriate validation criterion, which must consider at leas some distributional measures.

Then, different validation exercises can then be performed. Abstracting from all other types of validation [Leombruni et al., 2005], we can mainly distinguish between:

- *in-sample validation*, which tests the predictive power of the model in describing the data on which it was estimated;
- *out-of-sample validation*, which requires to split the dataset(s) used for estimation in two parts, estimate the model parameters on the the first sub-sample (generally two-thirds of

the overall size of the dataset), and then test the validity of the model by comparing the simulation outcome with data of the second sub-sample (the test data). When the data is a time-series, it is natural to use older data for estimation and newer data for testing.

7 Conclusions

Fifty years from the publication's of Orcutt's 1957 paper, we present a short review of the developments of microsimulation modeling since those days. In our paper, we have hopefully shown that, under many accounts, the field of microsimulation has indeed developed in accordance to Orcutt' s vision; there remains nevertheless some aspects, especially at the methodological level, that will require further efforts by the scientific community if his vision has to come true.

Today, taking into account the enormous progress made by computer technology in terms of e.g. speed, power and large data handling capacity, we find countless MSMs models around the world developed by governments or research institutes (e.g. PENSIM in the UK's Department of Work and Pension; SESIM at the Swedish Ministry of Finance, to name just a few). As Orcutt had intended, they are indeed often used as policy making tools to e.g. help forecast and simulate the effects of an existing or proposed policy change on future public costs, poverty and inequality levels, as well as compare these effects under alternative policy scenarios, so as to choose the policy which fits better government's aims. Examples of policies which have been tested through MSMs include e.g. raising the retirement age, introducing new family benefits or changing social contributions. Furthermore MSMs are able to identify who will loose and who will gain from different policy scenarios, thanks to their reliance of micro data and ability to reproduce entire distributions of key variables. At a more theoretical level, MSMs models are increasingly being used in the social sciences to study inter-temporal processes and behaviors (e.g. LIAM in Ireland), in particular the complex interactions between demographic, economic, institutional and behavioral levels, resulting in multiple feedbacks which could not be easily quantified without the aid of such models.

MSMs can be divided into static and dynamic, depending on whether they include a time and / or behavioral dimension. Static models are generally limited to compute the quasi-simultaneous effects of an exogenous change on agents' incomes without accounting for secondary effects e.g. agents' responses or changes to the underlying population which might indeed occur over time (e.g. PSM in the UK). Dynamic MSMs models (e.g. DESTINIE in France or DYNACAN in Canada) try to simulate future life paths of each agents, thus the input characteristics themselves become endogenous overtime, given a certain policy environment. However these models require more challenging estimation and validation procedures than static ones.

In his seminal paper, Orcutt expresses a number of goals which MSMs should ideally fulfill. Orcutt wished first of all that MSMs would help overcome the "limited predictive usefulness" of previous (macro) models, both in the short and long run. Fifty years on, this goal has been in part accomplished, as it is proved e.g. by the wide acceptance of MSMs as predictive tools for policy making among governments and public institutions. In fact, in some cases, by taking into account behavioral responses such as labor supply, MSMs make substantially different predictions than traditional macro models (see for instance the results produced by the Italian model LABORsim, with respect to the economic consequences of population aging). Nevertheless, it is now accepted that predictive models, whether micro or macro based, need not be exclusive, but rather they can and should coexist for the best possible results and for stimulating comparison and mutual development. In this sense, compared to Orcutt's view, MSMs should nor replace but rather complement other existing methodologies such as cell-based or CGE macro models.

A similar argument applies to Orcutt' s goal of using MSMs for testing socio-economic behaviors. With hindsight, MSMs today are to a large extent able to reproduce empirical relationships which one observes in real data (e.g. fertility and education), so long as the input data are sufficiently detailed and cover a sufficiently long time dimension. The availability and quality of the input data however, together with intrinsic limits to the number of processes which can be simulated at any one time by such models, is still an issue.

However, in most developed countries there has been a tremendous development in the collection and public availability of micro-based panel data sets (including e.g. survey or even register-based data) — see for example the list of international data bases available for labor market research maintained with a rich set of meta-data by IZA (`http://metadata.iza.org/home.php`), almost all of which are micro-based (e.g. the European Community Household Panel, the

British Labor Force Survey, the British Household Panel Survey, the Luxemburg Income Study, the Health and Retirement Survey, the American Panel Study of Income Dynamics, the German Income and Retirement Survey, the Italian Panel of Work Histories etc.)

Overall, our knowledge of individual decision making has gone a long way since Orcutt' s days, and this has been reflected in MSMs which can handle a growing number of behavioral sub-modules (e.g. simulating life-cycle processes such as pension savings, or retirement choices, which depend, among others, on household level dynamics, spouse behavior, future expectations etc). Moreover, the specification of the micro-econometric modules of dynamic MSMs can accommodate simultaneous decision making processes, e.g. labor supply and fertility decisions.

In conclusion, although much has been achieved in MSM development over the past fifty years, this paper has hopefully identified some remaining weaknesses of MSMs which still need addressing. One of the main problems is that most MSMs in circulation lack model-wide output validation, often in favor of e.g. simpler piecemeal estimation and validation of each sub-module separately. This means that, short of a model-wide estimation criterion, the consistency of the model as a "holistic" predictive tool cannot really be tested. Different strategies, such as simulated method of moments, have been proposed at this regard. More generally, there is a lack of well defined validation criteria. Due to lack of adequate data, validation of model outputs is often done in relation to averages rather than to whole distributions. Furthermore, simulated outputs are not generally accompanied by confidence intervals and a related distribution. Bootstrapping methods should be used to this end.

Having identified these methodology shortcomings, as well as acknowledged the advancements taking place in areas such as micro data collection, with this paper we hope to have highlighted where future efforts in the micro simulation discipline could be concentrated, and to have identified a new agenda that luckily will be accomplished long before Orcutt's centenary anniversary paper.

Notes

[1]the International Microsimulation Association, which was established only in 2005, publishes the *International Journal of Microsimulation*

[2]"micro-simulation" and "micro simulation"

[3]as of June 30, 2007

[4]Douglass Lee, having in mind urban planning models, wrote in 1973 a "Requiem for Large-Scale Models" [Lee, 1973]

[5]a better name would be "chain" models, as they introduce a direct link between adjacent age cells. For examples of cohort models and references see [Carone, 2005], page 7

[6]This is called a block recursive structure. If the processes are recursive also in a statistical sense, they can be estimated independently. If not, the implied stochastic dependence must be accounted for [Klevmarken, 2007].

[7]individuals are characterized by different level of *inertia*, depending on the specific behavior considered. For instance, reactions to changes in the tax systems are generally quite rapid, while changes in the retirement behavior, following changes in the legislation, might take longer, sometimes even years [Axtell and Epstein, 1999]

[8][Klevmarken, 2007] however shows that the kind of proportional adjustment discussed above might not be efficient, in nonlinear models

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