WHAT IS DYNAMIC SOCIAL SCIENCE MICROSIMULATION?

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"Perhaps consciousness arises when the brain's simulation of the world becomes so complete that it must include a model of itself."
Richard Dawkins - The Selfish Gene

Introduction

Although the idea to study and project the socio-economic and demographic development of a society by simulating a large sample of individuals and their actions and interactions was already expressed in the 1950s, dynamic microsimulation still has yet to find its way into the methodological toolbox of mainstream social scientists. To simulate a society realistically requires detailed data, complicated models, fast computers and extensive testing. The more complex that models get, the more difficult it becomes to understand their operations and to assess their predictive power. One might speculate that microsimulation is too demanding, or that microsimulation models are niche products or dubious black box models, applicable only with caution where other methods are not available. Here, however, we will present an alternative point of view to such speculations.

First, microsimulation is a powerful tool that has already demonstrated its strength in applications of moderate complexity for which other modeling approaches exist--but those other approaches cannot compete in flexibility with the microsimulation approach.

Second, we increasingly face (or recognize) socio-economic challenges for which microsimulation is the only available study tool. Furthermore, microsimulation is an approach that follows naturally from modern research paradigms; it is a complement to detailed data analysis.

Third, microsimulation is an approach whose time has come. More than half a century after the introduction of microsimulation into the social sciences, the main obstacles to this approach have almost disappeared. Computer power has increased exponentially, the collection of individual longitudinal data has become routine, social scientists are trained in longitudinal research, and research itself has moved from a macro to a micro approach and is on the way towards a multilevel integration. The life course perspective has become a dominant paradigm and many of the most pressing problems we face are of a nature which makes dynamic microsimulation the most suitable study approach.

There is also one other former obstacle that has now disappeared. Programming languages, such as Modgen, currently enable researchers with only moderate programming skills – comparable to those needed for statistical software packages – to implement their models.

This chapter gives an introduction to microsimulation and presents the main underlying ideas as well as the strengths and drawbacks of this approach. It is organized in three parts:

– first, we start with a definition of dynamic social science microsimulation and a sketch of its history

– second, we explore three major situations for which microsimulation is an appropriate approach

– finally, we highlight the main strengths and drawbacks of microsimulation. With respect to its strengths, we distinguish its theoretical strengths from a life course perspective, its practical strengths from a policy makers' perspective, and its technical strengths. When confronting drawbacks and limitations, we distinguish between intrinsic limitations imposed by randomness and rather transitory limitations imposed by the high demand for data. We also touch briefly on computational and other technical issues, although their corresponding costs are decreasing over time.

1 Defining dynamic social science microsimulation

1.1 What is microsimulation?

A useful way of defining simulation in the social sciences is to think of it as the purposeful use of a model. Therefore, going back one step, social science simulation is both a modeling exercise and the exercise to 'run the model', or to 'play' or 'experiment' with it. The range of purposes is as broad as are the reasons for doing research: solving problems, finding explanations, building theory, predicting the future, and raising consciousness. From a more practical view, we can also add training to this list. Pilots are trained on flight simulators. Why should policy makers not be trained to improve their awareness by computer simulations of policy effects? And why should voters not have tools to study the effects of proposed policy measures? Social science simulation enables such visions.

Dynamic simulation includes time. How did we get where we are now, what changes can we expect for the future, what drives those changes, and how can we influence these processes? Most informed statements about the future are based on dynamic simulations of some kind. Some require complex computer simulations; others are the result of thought experiments. The exploration of future scenarios and how the future is shaped by our individual action is a core achievement of our human brain closely linked to consciousness itself. Being able to predict the future state of a system improves the planning of our actions, both those influencing the outcome of the system, and those affected by it. For example, weather forecasts are produced using complex computer simulations—and we have both fairly adequate forecasting models for the weather tomorrow (which we cannot influence) and much more controversial simulation models for long-term climate change (which we can influence). Dynamic simulation raises the public awareness of potential future problems, be it the storm tomorrow or the effect of CO_2 emissions over time. The same potential to raise awareness and improve the planning of our actions holds true in the social sciences for issues such as population aging, concentration of wealth or sustainability of social security systems.

Dynamic microsimulation is a specific type of dynamic simulation. Unfortunately microsimulation itself can be a confusing word because, despite the 'micro' prefix, we are nevertheless still simulating a 'macro' system. The 'micro' prefix essentially corresponds to *how* we simulate that system. Many systems are made up of smaller level units. Liquids consist of particles which change behaviour when heated, traffic systems are made up of cars driven on a network of roads, and societies and economies consist of people, households, firms, etc. All these systems have one feature in common--macro level changes result from the actions and interactions of the micro units. The idea of microsimulation is that the best way to simulate such a system is often to model and simulate the actions and interactions of its smaller scale units and to obtain macro outcomes by aggregation.

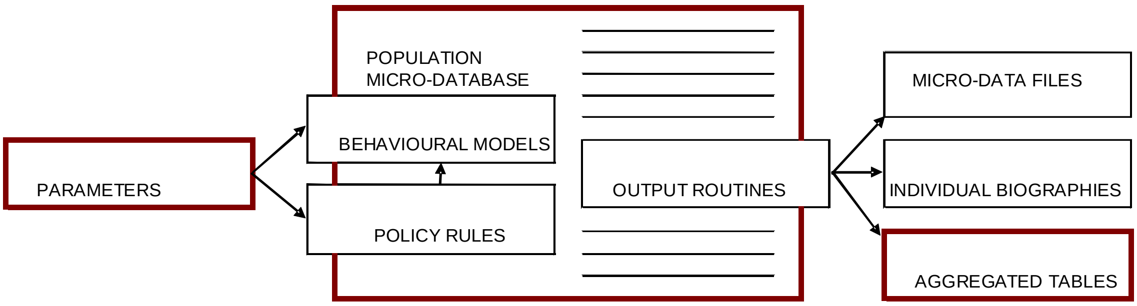
Dynamic social science microsimulation can be perceived as experimenting with a virtual society of thousands - or millions – of individuals who are created and whose life courses unfold in a computer. Depending on the purpose of the model, actors make education and career choices, form unions, give birth, work, pay taxes, receive benefits, get divorced, migrate, retire, receive pensions, and eventually die. Creating such a 'scientific computer game' involves various steps, the first being the modeling of individual behaviour. The dominant micro model types in microsimulation are statistical and econometric models. While the literature is rich in statistical micro data analysis, most research stops after the estimation of models of individual processes. With a microsimulation model, we go one step further: microsimulation adds synthesis to analysis. Accordingly, the second step of microsimulation, after the modeling of individual behaviour, is the programming of the various behavioural models to enable us to run simulations of the whole system. Microsimulation can help us to understand the effect of different processes and changes in processes on the total outcome. The larger the number of interdependent processes that have to be considered, the more difficult it gets to identify and understand the contribution of individual factors on the macro outcome. However, microsimulation provides the tool to study such systems.

Modeling at the micro level facilitates policy simulations. Tax, benefit, and social security regulations are defined on the individual or family level which makes microsimulation a natural modeling approach, allowing their simulation at any level of detail. As such rules are usually complex and depend in a nonlinear way on various characteristics like family composition or income (e.g. progressive taxes), microsimulation is often the only way for studying the distributional impact and long-term sustainability of such systems. In policy analysis, parts of the power of the microsimulation approach already unfold in so-called static microsimulation models. These are models designed to study the cross-sectional effect of policy change, e.g. by identifying immediate winners and losers of policy reform. Dynamic microsimulation adds a whole new dimension in policy analysis, however, since it allows individuals to be followed over their entire life course.

In the social sciences, dynamic microsimulation goes back to Guy Orcutt's (1957) idea about mimicking natural experiments in economics. His proposed modeling approach corresponds to what can be labelled as the empirical or data-driven stream of dynamic microsimulation models, i.e. models designed and used operatively for forecasting and policy recommendations (Klevmarken 1997). Associated with this type of microsimulation are micro-econometric and statistical models as well as accounting routines. In contrast to this empirical stream is the theoretical stream or tradition of agent based simulation (ABS). While constituting microsimulation models under our broad definition, ABS is frequently considered as a separate branch of simulation different from microsimulation. This view is mostly based on the different purpose of ABS modeling (mainly to explore theories) and the different approaches used by ABS in the modeling of micro behaviour (rules based on theory and artificial intelligence). Unless otherwise stated, however, this discussion will only be concerned with the data-driven stream of dynamic microsimulation models[1].

The following graph (Figure 1) summarizes the main components of a typical data-driven microsimulation model. In its centre is a population micro-database storing the characteristics of all members of the population[2]. This database is dynamically updated in a simulation run according to micro models of behaviour and policy rules (such as contribution and benefit rules in a pension model). All these models can be parameterized by the user. Simulation results consist of aggregated tables produced by output routines. Additionally, output can consist of micro-data files which can be analyzed by statistical software. Some models (such as all of those generated with Modgen) also allow the graphing of individual biographies.

Figure 1: Components of a typical data-driven microsimulation model



1.2 Orcutt's vision and today's reality

Dynamic microsimulation was first introduced into the social sciences in 1957 by Guy Orcutt's landmark paper 'A new type of socio-economic system', a proposal for a new model type mainly based on the frustration about existing macroeconomic projection models. In this paper, Orcutt addresses various shortcomings of macroeconomic models which can be overcome by using microsimulation. The first is the "limited predictive usefulness" of macro

[1] It should be noted, however, that the Modgen language has also successfully been used for ABS, as documented in Wolfson (1999)

[2] From a more object-oriented perspective, the population database can also be viewed and implemented as decentralized individual 'brains' with actors possessing methods to report their states to a virtual statistician responsible for data collection and presentation.

models especially related to the effects of governmental action, since macro models are too abstract to allow for fine-grained policy simulations. The second is the focus on aggregates and the ignorance of distributional aspects in macroeconomic studies and projections. Third, he stresses that macro models fail to capitalize on the available knowledge about elemental decision-making units. In contrast, microsimulation is not bound by restrictive assumptions of “absurdly simple relationships about elemental decision-making units” in order to be able to aggregate. Modeling on the level on which decisions are taken makes models not only more understandable, but also, in the presence of nonlinear relationships, “stable relationships at the micro level are quite consistent with the absence of stable relationships at the aggregate level”.

While these observations still hold true after half a century, some of his other observations are a good illustration of how computers have altered research. In fact, a considerable part of his paper is dedicated to the justification of using expensive computer power for simulations – doing something that was widely thought of as the domain of mathematicians and analytic solutions derivable on paper. As one of its advantages, Orcutt notes that microsimulation “… is intelligible to people of only modest mathematical sophistication”.

While this proposed modeling approach was in fact visionary in 1957, due to the lack of sufficient computer power and data availability at that time, Orcutt soon afterwards was in charge of the development of the first large-scale American microsimulation model Dynasim. He later contributed to its offspring Corsim, which also served as a template for the Canadian Cansim and Swedish Sverige models. In the meantime, dozens of large-scale general purpose models and countless specialized smaller models can now be found around the world, (for a list, see e.g. Spielauer 2007). Nevertheless, microsimulation still faces the continued resistance of the mainstream economic profession “imbued with physics envy and ascribing the highest status to mathematical elegance rather than realism and usefulness” (Wolfson 2007). This front is increasingly broken up by the demands of policy makers concerned with distributional questions and facing problems of sustainability of policies in the context of demographic change. This holds especially true for pension models which constitute a showcase for the new demands of policy makers faced with population aging and questions of sustainability and intergenerational fairness, as well as for the power of microsimulation in addressing such issues. As individual pension benefits depend on individual contribution histories as well as family characteristics (e.g. survivor pensions), pension models require very detailed demographic and economic simulations. On one hand, this can make the models very complex, but on the other, it enables them to serve very distinct and separate purposes. Many models are designed as general purpose models capable of studying various behaviours and policies, such as educational dynamics, the distributional impact of tax-benefit systems, and health care needs and arrangements. It is the increasing demand of policy makers for more detailed projections necessary for planning purposes, together with advances in data collection and processing, which have triggered this development.

2 When is dynamic microsimulation the appropriate simulation approach?

Whenever we study the dynamics of a system made up of smaller scale units, microsimulation is a possible simulation approach – but when is it worth the trouble creating thousands or millions of micro units? In this section we give three answers to this question, the first focusing on population heterogeneity, the second on the difficulty to aggregate behavioural relations, and the third on individual histories.

2.1 Population heterogeneity

Microsimulation is the preferred modeling choice if individuals are different, if differences matter, and if there are too many possible combinations of considered characteristics to split the population into a manageable number of groups.

Most of classical macroeconomic theory is based on the assumption that the household sector can be represented by one representative agent. Individuals are assumed to be identical or, in the case of overlapping generation models, to differ only by age. (Each cohort is represented by one representative agent). Such an approach is not applicable whenever finer grained distributions matter. Imagine we are interested in studying the sustainability and distributional impact of a tax-benefit system. If there is only one representative individual and the tax-benefit system is balanced, this average person will receive in benefits and services what she pays for through taxes and social insurance contributions (with some of her work hours spent to administer the system). To model tax revenues, we have to account for the heterogeneity in the population--if income taxes are progressive, tax revenues depend not only on total income but also its distribution. When designing tax reform, we usually aim at distributing burdens differently. We have to represent the heterogeneity of the population in the model to identify the winners and losers of reform.

Microsimulation is not the only modeling choice when dealing with heterogeneity. The alternative is to group people by combinations of relevant characteristics instead of representing each person individually. This is done in cell-based models. The two approaches have a direct analogy in how data are stored: a set of individual records versus a cross-classification table in which each cell corresponds to a combination of characteristics. A population census can serve as an example. If we were only interested in age and sex breakdowns, a census could be conducted by counting the individuals with each combination of characteristics. The whole census could be displayed in a single table stored as a spreadsheet. However, if we were to add characteristics to our description beyond age and sex, the number of table cells would grow exponentially, making this approach increasingly impractical. For example, 12 variables or characteristics with 6 levels each would force us to group our population into more than 2 billion cells ($6^{\wedge}12$= 2,176,782,336). We would quickly end up with more cells than people. In the presence of continuous variables (e.g. income) the grouping approach becomes impossible altogether without losing information, since we would have to group data (e.g. defining income levels). The solution is to keep the characteristics of each person in an individual record – the questionnaire – and eventually a database row.

These two types of data representation (cross-classification table versus a set of individual records) correspond to the two types of dynamic simulation. In cell-based models, we update a table; in microsimulation models, we change the characteristics of every single record (and create a new record at each birth event). In the first case we have to find formulas on how the occupancy of each cell changes over time; in the second we have to model individual changes over time. Both approaches aim at modeling the same processes but on different levels. Modeling on the macro level might save us a lot of work but is only possible under restrictive conditions since the individual behavioural relations themselves need to be aggregated, which is not always possible. Otherwise no formulas will exist on how the occupancy of each cell changes over time.

Contrasting microsimulation to cell-based models is fruitful for the understanding of the microsimulation approach. In the following we further develop this comparison using population projections as an example. With a cell-based approach, if we are only interested in total population numbers by age, updating an aggregated table (a population pyramid) only requires a few pieces of information: age-specific fertility rates, age-specific mortality rates, and the age distribution in the previous period. In the absence of migration, the population of age x in period t is the surviving population from age x-1 in the period t-1. For a given mortality assumption, we can directly calculate the expected future population size of age x. With a microsimulation approach, survival corresponds to an individual probability (or rate, if we model in continuous time). An assumption that 95% of an age group will be still alive in a year results in a stochastic process at the micro level--individuals can be either alive or dead. We draw a random number between 0 and 1--if it is below the .95 threshold, the simulated person survives. This exercise is called Monte Carlo simulation. Due to this random element, each simulation experiment will result in a slightly different aggregated outcome, converging to the expected value as we increase the simulated population size. This difference in aggregate results is called Monte Carlo variation which is a typical attribute of microsimulation.

2.2 The problem of aggregation

Microsimulation is the adequate modeling choice if behaviours are complex at the macro level but better understood at the micro level.

Many behaviours are modeled much more easily at the micro level, as this is where decisions are taken and tax rules are defined. In many cases, behaviours are also more stable at the micro level at which there is no interference from composition effects. Even complete stability at the micro level does not automatically correspond to stability at the macro level. For example, looking at educational attainment, one of the best predictors of educational decisions is parents' education. So if we observe an educational expansion – e.g. increasing graduation rates - at the population level, the reason is not necessarily a change of micro behaviour; it can lie entirely in the changing composition of the parents' generation.

Tax and social security regulations tie rules in a non-linear way to individual and family characteristics, impeding the aggregation of their operations. Again, there is no formula to directly calculate the effect of reform or the sustainability of a system, not even ignoring distributive issues. To calculate total tax revenues, we need to know the composition of the population by income (progressive taxes), family characteristics (dependent children and spouses) and all other characteristics which affect the calculation of the individual tax liability. Using microsimulation, we are able to model such a system at any level of detail at the micro level and to then aggregate individual taxes, contributions and benefits.

2.3 Individual histories

Microsimulation is the only modeling choice if individual histories matter, i.e. when processes possess memory.

School dropout is influenced by previous dropout experiences, mortality by smoking histories, old age pensions by individual contribution histories, and unemployment by previous unemployment spells and durations. Processes of interest in the social sciences are frequently of this type, i.e. they have a memory. For such processes, events that have occurred in the past can have a direct influence on what happens in the future. This impedes the use of cell-based models because once a cell is entered, all information on previous cell membership is lost. In such cases, microsimulation thus becomes the only available modeling option.

3 Strengths and drawbacks

The strengths of microsimulation unfold in three dimensions. Microsimulation is attractive from a theoretical point of view, as it supports innovative research embedded into modern research paradigms like the life course perspective. (In this respect, microsimulation is the logical next step following life course analysis.) Microsimulation is attractive from a practical point of view, as it can provide the tools for the study and projection of socio-demographic and socio-economic dynamics of high policy relevance. And microsimulation is attractive from a technical perspective, since it is not restricted with respect to variable and process types, as is the case with cell-based models.

3.1 Strengths of microsimulation from a theoretical perspective

The massive social and demographic change in the last decades went hand in hand with tremendous technological progress. The ability to process large amounts of data has boosted data collection and enabled new survey designs and methods of data analysis. These developments went hand in hand with a general paradigm shift in the social sciences, many of the changes pointing in the same direction as Orcutt's vision. Among them is the general shift from macro to micro, moving individuals within their context into the centre of research. Another change relates to the increasing emphasis on processes rather than static structures, bringing in the concepts of causality and time. While the microsimulation approach supports both of these new focuses of attention, it constitutes the main tool for a third trend in research: the move from analysis to synthesis (Willekens 1999). Microsimulation links multiple elementary processes in order to generate complex dynamics and to quantify what a given process contributes to the complex pattern of change.

These trends in social sciences are mirrored in the emergence of the life course paradigm which connects social change, social structure, and individual action (Giele and Elder 1998). Its multidimensional and dynamic view is reflected in longitudinal research and the collection of longitudinal data. Individual lives are described as a multitude of parallel and interacting careers like education, work, partnership, and parenthood. The states of each career are changed by events whose timing is collected in surveys and respectively simulated in microsimulation models. Various strengths of the microsimulation approach have a direct correspondence to key concepts of the life course perspective, making it the logical approach for the study and projection of social phenomena.

Microsimulation is well suited to simulate the interaction of careers, as it allows for both the modeling of processes that have a memory (i.e. individuals have a memory of past events of various career domains) and the modeling of various parallel careers with event probabilities or hazards of one career responding to state changes in other careers.

Besides the recognition of interactions between careers, the life course perspective emphasizes the interaction between individuals--the concept of linked lives. Microsimulation is a powerful tool to study and project these interactions. This includes changes in kinship networks (e.g. Wachter 1995), intergenerational transfers and transmission of characteristics like education (e.g. Spielauer 2004), and the transmission of diseases like AIDS.

According to the life course perspective, the current situation and decisions of a person can be seen as the consequence of past experiences and future expectations, and as an integration of individual motives and external constraints. In this way, human agency and individual goal orientation are part of the explanatory framework. One of the main mechanisms with which individuals confront the challenges of life is by the timing of life course events of parallel –

and often difficult to reconcile - careers like work and parenthood. Microsimulation supports the modeling of individual agency, as all decisions and events are modeled at the level where they take place and models can account for the individual context. Besides these intrinsic strengths of microsimulation, microsimulation also does not impose any restrictions of how decisions are modeled, i.e. it allows for any kind of behavioural models which can be expressed in computer code.

3.2 Strengths of microsimulation from a practical perspective

The ability to create models for the projection of policy effects lies at the core of Orcutt's vision. The attractiveness of dynamic microsimulation in policymaking is closely linked to the intrinsic strengths of this approach. It allows the modeling of policies at any level of detail, and it is prepared to address distributional issues as well as issues of long-term sustainability. A part of this power unfolds already in static tax-benefit microsimulation models, which have become a standard tool for policy analysis in most developed countries. These models resulted from the increased interest among policy makers in distributional studies, but are limited to cross-sectional studies by nature. While limited tax-benefit projections into the future are possible with static microsimulation models by re-weighting the individuals of an initial population to represent a future population (and by upgrading income and other variables), this approach lacks the longitudinal dimension, i.e. the individual life courses (and contribution histories) simulated in dynamic models. The importance of dynamics in policy applications was most prominently recognized in the design and modeling of pension systems, which are highly affected by population aging. Pension models are also good examples of applications where both individual (contribution) histories and the concept of linked lives (survivor pensions) matter. Another example is the planning of care institutions whose demand is driven by population aging as well as by changing kinship networks and labour market participation, i.e. the main factors affecting the availability of informal care.

Given the rapid rate of social and demographic change, the need for a longitudinal perspective has quickly been recognized in most other policy areas which benefit from detailed projections and the "virtual world" or test environment provided by dynamic microsimulation models. The longitudinal aspect of dynamic microsimulation is not only important for sustainability issues but also extends the scope of how the distributional impact of policies can be analyzed. Microsimulation can be used to analyze distributions on a lifetime basis and to address questions of intergenerational fairness. An example is the possibility to study and compare the distribution of rates of return of individual contribution and benefit histories over the whole individual lifespan.

3.3 Strengths of microsimulation from a technical perspective

From a technical point of view, the main strength of microsimulation is that it is not subject to the restrictions which are typical to other modeling approaches. Unlike cell-based models, microsimulation can handle any number of variables of any type. Compared to macro models, there is no need to aggregate behavioural relations which, in macro models, is only possible under restrictive assumptions. With microsimulation, there are no restrictions on how individual behaviours are modeled, as it is the behavioural outcomes which are aggregated. In other words, there are no restrictions on process types. Most importantly, microsimulation allows for Non-Markov processes, i.e. processes which possess a memory. Based on micro data, microsimulation allows flexible aggregation, as the information may be cross-tabulated in any form, while in aggregate approaches, the aggregation scheme is determined a priori. Simulation results can be displayed and accounted for simultaneously in various ways--in aggregate time series, cross-sectional joint distributions, and individual and family life paths.

3.4 What is the price? Drawbacks and limitations

Microsimulation has three types of drawbacks (and preconceptions) which are of a very different nature: aesthetics, the fundamental limitations inherent to all forecasting, and costs.

If beauty is to be found in simplicity and mathematical elegance (a view not uncommon in mainstream economics), microsimulation models violate all rules of aesthetics. Larger scale microsimulation models require countless parameters estimated from various data sources which are frequently not easy to reconcile. Policy simulation requires tiresome accounting, and due to their complexity, microsimulation models are always in danger of becoming hard-to-operate-and-understand black boxes. While there is clearly room for improvement in the documentation and user interface of microsimulation models (the latter clearly demonstrated by computer games), the sacrifice of elegance for usefulness will always apply to this modeling approach.

The second drawback is more fundamental. The central limitation of microsimulation lies in the fact that the degree of model detail does not go hand in hand with overall prediction power. The reason for this can be found in what is called randomness, partly caused by the stochastic nature of microsimulation models, and partly due to accumulated errors and biases of variable values. The trade-off between detail and possible bias is already present in the choice of data sources, since the sample size of surveys does not go hand in hand with the model's level of detail. There is a trade-off between the additional randomness introduced by additional variables and misspecification errors caused by models that are too simplified. This means that the feature that makes microsimulation especially attractive, namely the large number of variables that models can include, comes at the price of randomness and the resulting prediction power that weakens or decreases as the number of variables increases. This generates a trade-off between good aggregate predictions versus a good prediction regarding distributional issues in the long run, a fact that modellers have to be aware of. This trade-off problem is not specific to microsimulation, but as microsimulation is typically employed for detailed projections, the scope for randomness becomes accordingly large. Not surprisingly, in many large-scale models some processes are aligned or calibrated towards aggregated projections obtained by external means.

Besides the fundamental nature of this type of randomness, its extent also depends on data reliability or quality. In this respect we can observe and expect various improvements as more and more detailed data becomes available for research, not only in the form of survey data but also administrative data. The latter has boosted microsimulation, especially in the Nordic European countries.

Since microsimulation produces not expected values but instead random variables distributed around the expected values, it is subject to another type of randomness: Monte Carlo variability. Every simulation experiment will produce different aggregate results. While this was cumbersome in times of limited computer power, many repeated experiments and/or the simulation of large populations can eliminate this sort of randomness and deliver valuable information on the distribution of results in addition to point estimates.

The third type of drawback is related to development costs. Microsimulation models have a need for high-quality, longitudinal and sometimes highly specific types of data--and there are costs involved to acquire and compile such data. Note that such costs are not explicit costs associated with the actual microsimulation itself but represent the price to be paid for longitudinal research in general and informed policy making in particular.

Microsimulation models also usually require large investments with respect to both manpower and hardware. However, these costs can be expected to further decrease over time as hardware prices fall and more powerful and efficient computer languages become available. Still, many researchers perceive entry barriers to be high. While many do recognize the potential of microsimulation, they remain sceptical about the feasibility of its technical implementation within the framework of smaller research projects. We hope that the availability of the Modgen language lowers this perceived barrier and makes microsimulation more accessible in the research community. In the last couple of years, various smaller-scale microsimulation models have been developed alongside PhD projects or as part of single studies. Modgen can both speed up the programming of smaller applications and provide a tested and maintained modeling platform for large-scale models, such as Statistics Canada’s LifePaths and Pohem models.

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