CeMPA Working Paper Series

CeMPA WP 08/23

Back to the future: Agent-based modelling and dynamic microsimulation

Matteo Richiardi

Justin van de Ven

Patryk Bronka

December 2023

Centre for Microsimulation and Policy Analysis

Back to the future: Agent-based modelling and dynamic microsimulation

Matteo Richiardi, Justin van de Ven, Patryk Bronka *

* Centre for Microsimulation and Policy Analysis, University of Essex

Revised version June 2024

Abstract

In this chapter we focus on the commonalities and differences between agent-based and dynamic microsimulation analytical approaches. Starting from a shared history, we discuss how the two literatures quickly diverged. Discussion concludes with evidence of some recent convergence between agent-based and dynamic microsimulation methods, and emerging opportunities for mutual reinforcement of the two methodologies.

1. Introduction

Agent-based models (ABMs) have become standard tools for research in Complexity Economics. At the same time, increasing availability of survey microdata and computational power has prompted interest in the related field of dynamic microsimulation modelling (DMM), particularly in relation to economics, health care, urban planning, and environmental studies.[1] Nevertheless, practitioners of both fields are often only vaguely aware of related work conducted in their apposing field. Furthermore, when work beyond a practitioner's specific field is discussed, it is sometimes regarded with interest, sometimes with suspicion, often with a focus on perceived methodological deficiencies. In this chapter, we focus on the relationship between agent-based and microsimulation approaches, point to the seminal dynamic microsimulation work of the 1960s as a precursor to agent-based models, and suggest that mutual knowledge and convergence has the potential to strengthen the Complexity Economics approach.

More specifically, we advance several claims:

Claim 1: Mathematically, the two methodologies are the same.

Claim 2: Historically, they have evolved separately, even though some of the first examples of agent-based models in the 1960s and 1970s, now largely forgotten, were developed as "microsimulations".

Claim 3: The microsimulation literature offers important insights for advancing agent-based studies, particularly in relation to:

[1] In this chapter, we use the acronym ABM for 'agent-based modelling', and ABMs for 'agent-based models'. Similarly, DMM refers to the methodology ('dynamic microsimulation modelling'), and DMMs to the applications ('dynamic microsimulation models').

i. introducing greater realism through empirical descriptions of agent-specific heterogeneity founded on survey micro-data;
ii. stylised approaches for obtaining realistic descriptions of the effects of complex real-world systems, including (e.g.) tax and benefit entitlements;
iii. approaches to improve alignment between models and survey observations;
iv. consideration of statistical uncertainty associated with model projections.

Claim 4: The agent-based literature, in turn, offers important insights for advancing microsimulation studies, particularly in relation to:

i. agent interactions and decision making
ii. macro-to-micro interactions

Claim 5: The time is ripe for a convergence between agent-based and microsimulation literatures, with some novel developments such as data assimilation techniques and integration of multiple data sources into realistic synthetic populations being at the forefront of research in both communities

The chapter is structured as follows. Section 2 presents a stylised description of ABMs and DMMs, forming the basis for Claim 1. Section 3 investigates the historical development of the two methodologies, leading to Claim 2. Section 4 discusses ongoing trends that outline a convergence between ABMs and DMMs and elaborates on the opportunities that this convergence opens (Claims 3-5). Section 5 concludes.

2. Modelling approaches

Readers of this chapter might be more familiar with ABMs than DMMs. As is well known, ABMs are composed by many entities, or agents, acting and interacting with each other and the environment (Axtell and Farmer, 2022). DMMs are very similar.[2] The field of microsimulation originates from work conducted by Guy Orcutt in the late 1950s (Orcutt, 1957, 1960, 1962). The 1950s saw intense research interest in the development of econometric models of the macro-economy, following the seminal work of Tinbergen (e.g. Solow, 2004). Orcutt was motivated by the observation that non-linearities in individual behaviour and the effects of policy on micro-units complicate macro-economic projections framed upon "representative" micro-agents; in this case valid macro-economic forecasts require the distribution of micro-agents to be taken into account.

Orcutt's revolutionary contribution was his advocacy for a new type of modelling approach that uses as inputs representative distributions of individuals, households, or firms, and puts emphasis on their heterogeneous decision making, as observed in the real world. In so doing, not only economy-wide averages can be correctly computed, but its entire distribution can be analysed.

[2] For reviews of dynamic microsimulation models, see O'Donoghue (2001), Li and O'Donoghue (2013), O'Donoghue (2014), and O'Donoghue and Dekkers (2018). A burgeoning area of application is health modelling (Schofield et al., 2018). Dynamic microsimulation models study changes in populations of agents over time. By contrast, static models (e.g. tax-benefit models) look at the short- to medium term effects of policy changes – or more generally changes in the environment, and are of less interest here.

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" (Orcutt et al., 1961). Klevmarken (2022) puts it in a way that will be familiar to any agent-based modeller: "[i]n micro simulation modeling there is no need to make assumptions about the average economic man. Although unpractical, we can in principle model every man".

Two key methodological stances are common to ABMs and DMMs: a focus on the role of individual specific heterogeneity underlying dynamic projections, and use of recursion in the computational approach to model solution. Other features of ABMs and DMMs generally emphasised in the literature, as a focus on interaction for ABMs, and on policies for DMMs, are to be understood more as distinctive flavours, not altering the underlying common analytical architecture.

Building on Grazzini and Richiardi (2015), we can formalise ABMs as composed of many entities, or agents, acting and interacting with each other and the environment. Agents can be of different types $j = 1, \dots, J$ (e.g. workers, firms, banks…), where each agent i at time t is described by a set of state variables $\boldsymbol{x}^j_{i,t}$. Then the evolution over (discrete) time of the state variables of agent i can be described by the law of motion:

$$\boldsymbol{x}^j_{i,t+1} = f_j(\boldsymbol{x}^j_{i,t}, \boldsymbol{X}^j_{-i,t}, \boldsymbol{X}^{-j}_t, \boldsymbol{\xi}^j_{i,t}, \boldsymbol{\theta}_t, \boldsymbol{P}_t) \quad (1)$$

where $\boldsymbol{X}^j_{-i,t}$ refers to the state of agents other than i of the type j at time t, $\boldsymbol{X}^{-j}_t$ refers to the state of all agents of types other than j, $\boldsymbol{\xi}$ are random draws that represent innovations beyond the explicit scope of the model, $\boldsymbol{\theta}$ are (possibly time variant) behavioural parameters, and $\boldsymbol{P}$ are (possibly time variant) environmental parameters, including public policies. The phase line f_j can be time-dependent, although this is rarely the case.

The same structure for the data generating process holds for DMMs. The emphasis however is different. In DMMs, there are generally fewer agent types (j), and their interaction $\left(\boldsymbol{X}^j_{-i,t}, \boldsymbol{X}^{-j}_t\right)$ is more limited than in an agent-based setting.[3] Furthermore, the number of parameters governing agents' behaviour ($\boldsymbol{\theta}$) is often larger in DMMs, and policies ($\boldsymbol{P}$) are spelled out in greater detail. The initial configuration of states ($\boldsymbol{D}^j_0$) are also often synthetically generated in ABMs, whereas they are typically drawn from survey data for DMMs.

Another frequently cited distinction between ABMs and DMMs is that the ABMs typically feature two-way interactions between the macro-environment and micro-agents, while DMMs focus more on the micro-to-macro direction of causality.[4] The micro-macro interplay

[3] For instance, in the state-of the art SimPaths modelling framework of Bronka et al. (2023), individuals form partnerships based on assortative mating (i.e. the probability of forming a partnership depends on the joint distribution of the characteristics of each pair of possible partners). Once partnered, individual trajectories depend on the partner's characteristics, and couples make joint decisions over some domains (e.g. labour supply), alongside individual decisions of the partners over other domains.

[4] Eq. 1 allows the evolution of each agent to depend upon the state of all other agents, hence upon the aggregate state of the system.

defines the property of *reflexivity,* where individual actions change the environment in which the same individuals operate. Complex reflexive systems lie at the far end of the complexity spectrum (Beinhocker, 2013), but they are indeed common when it comes to social interaction. However, not all ABMs target complex reflexive systems: in many cases, they are motivated "simply" by a desire to understand the aggregate implications of given micro behaviour, or to uncover what micro behaviour can possibly generate given macro phenomena of interest. An example is crowd dynamics, where the environment in which agents operate remains the same.[5] Similarly, while many DMMs do not exhibit reflexivity, some do – see the next Section. There is nothing *a priori* that limits ABMs to complex reflexive systems, and DMMs to non-complex, non-reflexive ones. Drawing a distinction between the two approaches based on the complexity of the system under investigation is akin to confusing the proverbial hammer with the nail.

Another false dichotomy refers to the partial vs. complete nature of the models. For example, a dynamic microsimulation might include detailed household behaviour, but abstract from the production side of the economy. In this context, the model might project the supply of labour and demand for consumption goods, treating wages and prices as exogenous.[6] This focus on sub-systems is commonly referred to as a "partial equilibrium" in the economics literature. In contrast, many ABMs are specifically designed to explore the dynamic feedback between different sub-systems; in the above example this would imply accounting for the dynamic interactions between agents in the domestic and production sectors that underly market prices. The economics literature commonly refers to this type of analysis as a 'general equilibrium'; given the focus of ABMs on non-equilibrium dynamics (see chapters 3 and 4, we prefer the term 'system closure'.[7]

A common source of confusion is the term "non-equilibrium" itself, which in agent-based modelling refers to temporal dynamics of the evolving economic environment (outside a fixed-point solution), rather than the absence of market-clearing regularities at any point in time. This is ultimately related to the nature of ABMs as dynamic systems, something that eq. 1 is designed to reflect. In microsimulation, there is less interest in the long-run properties of models, given the strict mapping between the initial conditions of the system and the populations of interest: the temporal horizon is usually restricted to the time-span of interest for policy purposes. This may be taken to reflect the empirical, policy-driven orientation of DMMs, relative to the more theoretical orientation of ABMs.

The differences above have implications in terms of the estimation strategy. DMMs are typically estimated piecewise on micro data, one component of $\boldsymbol{x}^j_{i,t+1}$ at a time, controlling for the lagged values of the other state variables of each individual agent. By contrast, ABMs

[5] See for instance Makinoshima and Oishi (2022).

[6] In DMMs of households, wages are typically related to individual characteristics such as age and education; they can also follow some exogenously given macro trend (for instance related to productivity growth). The wage *structure* however, that is the premium that each individual characteristic commands, remains constant.

[7] A systematic application of the system closure approach requires *stock-flow* consistency, the requirement that all the monetary and physical flows in a model are properly accounted for by both originators and recipients – see for instance Caiani et al. (2016).

are often calibrated using various sources of micro and macro data, as in Poledna et al. (2023), or estimated via indirect inference on macro data (e.g. Platt, 2020; Dyer, 2022).[8]

The difference in methods employed for estimation however does not reflect a fundamental discriminant between the two approaches, but rather specific constraints coming from the data, given specific applications. In particular, recourse to indirect inference is necessary when some of the variables are not observable. Typically, in DMM all the state variables characterising individuals have a counterpart in survey data. Hence, standard estimation techniques can be used. In contrast, ABMs often include details which cannot be observed, such as the topology of interaction networks. The associated parameters must then be deduced by means of indirect inference. However, when datasets are available with the relevant information, they are used for direct parameterisation.[9]

2. Historical developments

A classic example of the ABM literature is the Schelling segregation model (Schelling, 1971). This toy model has two populations of agents distinguished by one characteristic: ethnicity. Individuals are characterised by two interdependent state variables: their location, and whether they are a minority ethnicity. Individuals possess one behavioural parameter: their tolerance for living in a minority ethnicity. Individuals make one choice each period: to stay or change location. This highly stylised model, characterised by limited heterogeneity and interaction brought about by a shared space, allows for interesting dynamics that lead to high levels of ethnic segregation, even when the tolerance for living in a minority is relatively high.[10]

It is interesting to contrast the Schelling segregation model with one of the longest running and actively used DMMs; MOSART (Andreassen et al., 2020). MOSART is a life course model based on administrative data for the entire Norwegian population, which projects birth, death, migration, marriage, divorce, educational activities, labour force participation, retirement, income and wealth based on estimated transition probabilities. The model is used by Statistics Norway and the Norwegian government for projections and policy analyses related to the pension system. MOSART features heterogeneity across a wide range of dimensions, but allows for limited interaction between agents and features no emergent properties[11].

While the pairwise comparison presented above captures the essence of traditional differences between the ABM and DMM literatures, such generalities break-down with

[8] Recent work employing a transformer-based, machine learning architecture to predict sequences of life events (Savcisens et al., 2023) is promising, but seems to rely upon “almost ideal” large scale administrative data.

[9] An example is the paper by Pangallo et al. (2024), where they use census, survey and mobility data to parameterise a granular model of the interplay between economic and health factors during the Covid-19 pandemic, in the New York metropolitan area. van de Ven (2017) is – on the other hand – an instance of a microsimulation model partially parameterised by means of indirect inference (method of simulated moments).

[10] “At home [...] I made a 16x16 checkerboard, located zincs and coppers at random with about a fifth of the spaces blank, got my twelve-year-old to sit across from me at the coffee table, and moved discontented zincs and coppers to where their demands for like or unlike neighbors were met. The dynamics were sufficiently intriguing to keep my twelve-year-old engaged.” (Schelling, 2006).

[11] Emergent properties refer to phenomena that result from interactions between agents.

respect to the scope of variation described by the contemporary literature. For example, the ABM literature includes increasing examples of large-scale, data driven models, as in the model of the UK housing market by Carro et al. (2023), and the model of the Austrian economy by Poledna et al. (2023). These models include diverse behavioural and policy parameters and are extensively calibrated and validated.

A cursory observer might now conclude that ABMs have expanded to *encamps* DMMs, presenting comparable functionality (rich heterogeneity, realistic behaviours, and policy details), with the addition of coherent assumptions concerning system closure. However, what is perhaps less well known is that early examples from the DMM literature feature the same emphasis on empirically founded interactions between agents and agent types underlying macro-phenomena as the most recent macroeconomic ABMs. Two striking examples in this regard are Barbara Bergmann's "U.S. Transactions" model (Bergmann, 1973; Bennet and Bergmann, 1986) and Gunnar Eliasson's "Model of the Swedish Economic System (MOSES)" (Eliasson, 1976; Eliasson, 1977).

In Bergmann's model, workers, firms[12], banks, financial intermediaries, the government and the central bank interact with one another to determine aggregate and distributional outcomes. The model is simulated on a weekly basis. Each period: firms make production plans based on past sales and inventory position; firms attempt to adjust the size of their workforce; wages are set and the government adjusts public employment; production occurs; firms adjust prices; firms compute profits, pay taxes and buy inputs for the next period; workers receive wages, government transfers, property income; workers pay taxes and make payments on outstanding loans; workers decide how much to consume and save, choose among different consumption goods and adjust their portfolios of assets; firms invest; the government purchases public procurement from firms; firms make decisions on seeking outside financing; the government issues public debt; banks and financial intermediaries buy or sell private and public bonds; the monetary authority buys or sells government bonds; and interest rates are set. In the labour market, firms offer jobs to particular workers, some of which are accepted; some vacancies remain unfilled, with the vacancy rate affecting the wage setting mechanism. The model could easily be described as an agent-based macro model *ante litteram*. However, Bergmann consistently referred to her work as a 'microsimulation'.

Relatedly, Bergmann also developed 'toy' simulation models that she used to investigate specific theoretical mechanisms of interest. These models are broadly comparable to those of Schelling, and when considered as such represent early examples of agent-based analyses that appear in high-grade economic journals (e.g. Bergmann, 1990). Importantly, Bergmann considered her article as providing "an introduction to microsimulation".

Meanwhile, Eliasson's model of the Swedish economy, MOSES (Eliasson, 1976, 1977), was rooted in the Wicksellian/Stockholm School of *ex ante* plans and *ex post* outcomes (Jonung, 1991), an intellectual tradition that agent-based modellers and the complexity economics literature should perhaps rediscover. MOSES featured a one-to-one mapping between the

[12] distinguished in six sectors: motor vehicles, other durables, nondurables, services and construction.

universe of Swedish firms and their simulated counterparts, endowed with real balance sheets (some synthetic firms were also introduced with calibrated balance sheets to match sector totals). In the model, operating on a quarterly basis, firms make production plans, invest, hire workers in advance, and set prices. They then review their choices based on realised profits, leading to endogenous growth dynamics. A monetary system, later integrated with a stock and financial derivatives market, and a rudimentary venture capital market, completed the description of the economy.

Echoing Bergmann, Eliasson described his model as a 'microsimulation', although in later work he referred to it as an 'agent-based macroeconomic model' (Eliasson, 2018). Indeed, Bergmann and Eliasson played an important role, together with Orcutt, in developing the microsimulation approach to economics. In the introduction to a jointly edited volume (Bergmann *et al.*, 1980), they discuss the role of microsimulation in "integrating theory and measurement": "Aspects of a theory that do not pass the test against observation are not allowed to survive in a true scientific environment. In a complex world one should consider it natural to live with many conflicting interpretations of economic reality; but in a world of scientific progress the interpretations should change, old erroneous doctrine should be unloaded and new theory allowed to enter. […] We believe that micro simulation opens up new possibilities for estimation and analysis based on direct access to the wealth of data that exists at the micro level" (Bergmann *et al.*, 1980, p. 11). This same research program resonates well with many modern macro-ABMs.

The above discussion suggests that microsimulation should not only be considered a closely related field to agent-based modelling, but one of its precursors – arguably its oldest – alongside evolutionary economics (Nelson and Winter, 1982) and complexity economics (Anderson et al., 1988).[13]

Notwithstanding their common roots, the DMM and ABM literatures have evolved along different trajectories. In this regard, it is of note that the Bergmann et al. (1980) volume cited above discusses three state-of-the-art DMMs of the time: Bergmann's (U.S. Transactions) model, Eliasson's (MOSES) model, and Orcutt's "Urban Institute – Yale" model. In contrast to the extensive agent interactions of the Bergmann and Eliasson models, Orcutt's model focusses primarily on behaviour in the household sector, including an auxiliary module to capture macro-trends that might affect households' decisions. History reveals that it is Orcutt's model that won the day, inspiring the majority of subsequent developmental work conducted by within the DMM literature.[14]

With hindsight, the models of Bergmann and Eliasson were ahead of their time. It is notable that it took Bergmann more than 15 years to complete her model, and Eliasson managed to complete his thanks to support from IBM, which offered "unlimited programming and computer support for two years" (Eliasson, 2018, p. 11). Unsurprisingly, these examples

[13] See Richiardi (2018) for a discussion.

[14] Orcutt's model evolved into DYNASIM (Orcutt et al., 1976), which remains under development at the Urban Institute (Favreault et al., 2015).

were not considered to offer a viable research avenue to the contemporary scientific community.

Simplification of the Bergmann-Eliasson examples was necessary in context of prevailing data, developmental, and computational limitations. In the case of the evolving DMM literature, empirical relevance was prioritised at the expense of the diversity of considered agent types and their interactions. Meanwhile, the ABM literature resolved the trade-off in the opposite direction, slowly adding realistic features to the first, simple cellular automata models (e.g. John Conway's Game of Life).

Differences between the DMM and ABM literatures that now exist can consequently be understood as the product of differences in researcher priorities, given the prevailing analytical trade-offs. In this regard it is notable that recent advances in computer power have supported the emergence of data-driven, empirically calibrated ABMs (Dawid and Delli Gatti, 2018).[15] This same increase in computational power may support a shift in DMMs back toward their origin. Seen from this perspective, the models of Bergmann and Eliasson can be understood as being illustrative of an approach, thereby providing a glimpse of a brighter modelling future that will take 50 years to develop. The re-convergence of ABM and DMM literatures presents exciting research opportunities, to which we now turn.

4. Convergence

As discussed previously, there is evidence of increasing realism in the empirical descriptions of agent-specific heterogeneity in recent ABM literature, which tends to reduce the disparity with DMMs. This shift involves estimation of transitional relationships that are well understood in the existing econometric literature and is facilitated by publicly available data sources and widely available statistical software. There are, nevertheless, several ways in which the development of associated ABMs could benefit by drawing on the contemporary DMM literature.

The developmental overhead associated with implementing increasing statistical detail in an ABM can be mitigated by one of the generic software packages that have been developed within the DMM literature. There now exist several of these to choose from (openM++, JAS-mine, AnyLogic, LIAM2, MODGEN, GENESIS), each of which generally includes libraries that support common model building tasks.[16]

Another approach for mitigating model developmental costs in the DMM literature is to facilitate integration of results from specialist model structures. Consider, for example, attempts to obtain a realistic reflection of tax and benefit payments, which may reasonably be posited to influence labour decisions. Most OECD countries have tax and benefit systems

[15] Interestingly, the ASPEN model of the U.S. economy (Basu et al., 1998), heavily built on the Orcutt-Bergmann experience, was branded an "agent-based microeconomic simulation model", a sign that agent-based modelling was replacing microsimulation as "the new game in town".

[16] openM++: https://openmpp.org. JAS-mine: Richiardi and Richardson (2017). AnyLogic: https://www.anylogic.com. LIAM2: de Menten et al. (2014). MODGEN: https://www.statcan.gc.ca/en/microsimulation/modgen/modgen. GENESIS: Gillman (2017).

that are non-trivially complex and subject to constant revision. Capturing a realistic reflection of this dynamic complexity represents a substantial modelling challenge. It is consequently notable that there exist well-maintained static tax-benefit calculators that focus exclusively on encoding the variation of policy through time (e.g. TaxBEN maintained by the OECD, and EUROMOD maintained by the Joint Research Council).[17] Methods have been developed in the DMM literature to facilitate integration of results generated by these purpose-specific applications into more general DMMs/ABMs (e.g. van de Ven *et al*., 2022).

Integrating increased realism into a dynamic microsimulation by adding new agent-specific heterogeneity introduces a range of associated issues of concern. Many of these issues have been addressed in the DMM literature, presenting off-the-shelf solutions for related development in ABMs.

Consider, for example, the problem of empirically estimating model parameters. Ideally, all model parameters would be estimated endogenous to a model's structure. In the case of microsimulation models, however, this is often not computationally feasible. Hence, the equations governing temporal dynamics of individual specific characteristics are often estimated on external survey data, exogenous to a model's structure. Although this approach mitigates the computational burden of parameter estimation, it increases the likelihood of model mis-specification. Hence, even when multiple processes are estimated using a common data source, their combination within a DMM or ABM context can result in unrealistic projections.

Alignment methods have been devised within the DMM literature to mitigate model mis-specification attributable to exogenous estimation of parameters. These methods are typically divided into two broad categories, distinguishing methods that seek to (implicitly or explicitly) adjust model parameters, from those that seek to adjust *ex post* simulation projections given model parameters (e.g. Baekgaard, 2002, Li and O'Donoghue, 2014). An example of the former approach is logit scaling, which seeks to identify adjusted probabilities that match a model to external targets (e.g. Stephensen, 2016). An example of the latter approach is resampling, where the set of random draws used to project uncertain outcomes through time are re-drawn until a target is obtained. Most of the "generic software packages" referred to above also facilitate implementation of alignment methods (e.g. Richiardi and Richardson, 2017, Section 4.4).

Another issue associated with attempts to reflect greater statistical detail in ABMs concerns accompanying measures of uncertainty in projections. Coming from a more theoretical interest, ABMs have traditionally emphasised exploration of the possible behaviours of the models under alternative parameterisations, by means of sensitivity analysis of model outputs to model parameters (e.g. Lee et al., 2015). Empirically relevant ABMs on the other hand share with DMMs a focus on narrower parameterisations – those supported by the

[17] OECD (2022), Euromod: https://euromod-web.jrc.ec.europa.eu/).

data. Uncertainty regarding a model's projections arise for a variety of reasons (Bilcke et al., 2011; Creedy et al., 2007), including the representativeness of input data, a model's structure and parameterisation, and the random draws underlying a dynamic projection. Some of these are difficult or impossible to quantify (e.g. model structure), while others might reasonably be abstracted from (input data). Uncertainty stemming from model parameters and simulated random events, however, qualifies for neither of these potential exemptions State-of-the-art methods for uncertainty quantification in DMMs include bootstrapping of model parameters based on estimated variance-covariance matrixes(e.g. Bronka et al., 2023).

There are also methods and practices from the ABM literature that can be usefully imported into DMM, as models incorporate more agent types and increased interaction. In particular, use of simple heuristics in the decision making of at least some of the agents will help keep models manageable. Expectation formation is also another area where DMM can learn from ABM, either in a repeated decision context (Mu et al., 2022), or in a social learning environment (Nowak et al., 2017).

Recent developments highlight areas of common interest. Data assimilation techniques, initially developed in meteorology and the earth sciences, have started to be used in ABM (e.g. Ward et al., 2016). Data assimilation aims at a re-parameterisation of the models as new data becomes available, and provides a more general framework for "learning" from data than alignment. In particular, alignment puts an emphasis on hitting the (macro) targets more or less exactly, while in data assimilation the new information is weighted against previous information. Data assimilation is more relevant for high-frequency applications – e.g. finance or traffic models – but the increasing availability of big data updated almost in real time will spread its use to other areas where DMM has been more active, such as household behaviour.

The use of synthetic population is another area of convergence. Because ABMs evolved mostly with a theoretical rather than an applied interest, they tended to be based on artificial and rather abstract simulated populations (as in the Schelling segregation model). However, an increased attention to empirical relevance means that the synthetic populations of ABMs are becoming more sophisticated (e.g. Dyer et al., 2023). On the other hand, as discussed above, DMMs usually build their simulated populations from survey data. However, as DMMs grow in scope, they need to integrate information coming from multiple sources (such as wealth and asset holdings, and consumption or mobility patterns, all not generally available in household surveys) and disaggregate information at more fine-grained geographical levels. This is done through probabilistic (regression based or hot deck) imputation, and use of spatial microsimulation techniques (e.g. Wu et al., 2022). The usefulness of building simulations on synthetic populations is also connected to the ability of sharing the data, when privacy concerns can be overcome. This is increasingly relevant in a scientific environment emphasising open-source development, which is common to ABM and DMM.

Realism in model structure and parameterisation also calls for validation of model outputs against real data, a critical issue for both ABMs and DMMs. Approaches to model validation are quite well-established in the literature (see for instance National Research Council, 2012, and Alarid-Escudero et al., 2020), although no universal prescription for determining when a model passes the validity test exists.

5. Conclusions

The real world is a complex system. But complex systems are not necessarily realistic. Although a few visionaries had imagined microsimulation models which are at the same time complex and realistic, and had built working prototypes at a time when PCs did not even exist, computational and data limitations have until recently precluded a wide adoption of this research programme. Since the 1970s, ABMs and DMMs have taken the challenge of modelling a complex world from two different perspectives: ABMs emphasising complexity, at the detriment of realism; and DMMs emphasising realism, at the detriment of complexity. Advances in computational power and a wider availability of good quality micro data has changed this landscape, prompting ABMs to increase in realism, and DMMs to increase in complexity. A convergence in the two approaches is therefore under way, with the potential to finally realise the vision of Bergmann and Eliasson. Rarely has the phrase “back to the future” been more apt to describe the emergence of a new research paradigm.

References

Alarid-Escudero, F., Gulati, R., and Rutter, C.M. (2020); “Validation of Microsimulation Models Used for Population Health Policy”, in: Apostolopoulos, Y., Lemke, M.K., and Hassmiller Lich, K. (eds); “Complex Systems and Population Health”, Oxford University Press.

Anderson, P.W., Arrow, K., and Pines, D. (1988); “The Economy As An Evolving Complex System”; 1st ed.; CRC Press, Boca Raton.

Andreassen, L., Fredriksen, D., Gjefsen, H.M., Halvorsen, E., and Stølen, N.M. (2020); “The dynamic cross-sectional microsimulation model MOSART”; International Journal of Microsimulation; vol. 13(1); pp. 92-113; DOI: 10.34196/IJM.00214.

Axtell, R., and Farmer, J.D. (2022); “Agent-Based Modeling in Economics and Finance: Past, Present, and Future”; Journal of Economic Literature; forthcoming.

Baekgaard, H. (2002), “Micro-macro linkage and the alignment of transition processes: some issues, techniques and examples”. National Centre for Social and Economic Modelling (NATSEM) Technical paper 25.

Basu, N., Pryor, R., and Quint, T. (1998); “ASPEN: A Microsimulation Model of the Economy”; Computational Economics; vol. 12, pp. 223-241; DOI: 10.1023/A:1008691115079.

Beinhocker, E. (2013), "Reflexivity, Complexity, and the Nature of Social Science", Journal of Economic Methodology, 20(4): 330-342.

Bennett, R.L., and Bergmann, B.R. (1986); “A Microsimulated Transactions Model of the United States Economy”; John Hopkins University Press, Baltimore.

Bergmann, B.R. (1974); “A microsimulation of the macroeconomy with explicitely represented money flows”; Annals of Economic and Social Measurement; vol. 3(3); pp. 475–489.

Bergmann, B.R. (1990), “Micro-to-Macro Simulation: A Primer With a Labor Market Example”; The Journal of Economic Perspectives; vol. 4(1); pp. 99-116.

Bergmann, B.R., Eliasson, G., and Orcutt, G. (1980); “Micro Simulation – Models, Methods and Applications. Proceedings of a Symposium in Stockholm, Sept 19-22, 1977”; The Industrial Institute for Economic and Social Research; Stockholm.

Bilcke, J., Beutels, P., Brisson, M., and Jit, M. (2011); “Accounting for Methodological, Structural, and Parameter Uncertainty in Decision-Analytic Models: A Practical Guide”; Medical Decision Making 31(4): 675-692; DOI: 10.1177/0272989X11409240.

Brock, W.A., and Hommes, C.H. (1997); "A Rational Route to Randomness"; Econometrica; vol. 65(5); pp. 1059-1096; DOI: 10.2307/2171879.

Bronka, P., van de Ven, J., Kopasker, D., Katikireddi, S. V., & Richiardi, M.. (2023); “SimPaths: an open-source microsimulation model for life course analysis”; Centre for Microsimulation and Policy Analysis Working Paper Series, CEMPA6/23.

Caiani, A., Godin, A., Caverzasi, E., Gallegati, M., Kinsella, S., and Stiglitz, J.E. (2016); “Agent based-stock flow consistent macroeconomics: Towards a benchmark model”; Journal of Economic Dynamics and Control; vol. 69; pp. 375-408; DOI: 10.1016/j.jedc.2016.06.001.

Carro, A., Hinterschweiger, M., Uluc, A., and Farmer, J.D. (2023); “Heterogeneous effects and spillovers of macroprudential policy in an agent-based model of the UK housing market”; Industrial and Corporate Change; vol. 32(2); pp. 386-432; DOI: 10.1093/icc/dtac030.

Creedy, J., Kalb, G., and Kew, H. (2007); “Confidence intervals for policy reforms in behavioural tax microsimulation modelling”; Bulletin of Economic Research; vol. 59(1); pp. 37-65; DOI: 10.1111/j.0307-3378.2007.00250.x.

Dawid, H., and Delli Gatti, D. (2018); “Agent-Based Macroeconomics”; in: Hommes, C., and LeBaron, B., “Handbook of Computational Economics”; vol. 4; ch. 2; pp. 63-156; Elsevier; Amsterdam; DOI: 10.1016/bs.hescom.2018.02.006.

De Menten, G., Dekkers, G., Bryon, G., Liégeois, and O‘Donoghue, C. (2014); “LIAM2: a new open source development tool for discrete-time dynamic microsimulation models”; Journal of Artificial Societies and Social Simulation; vol. 17; DOI: 10.18564/jasss.2574.

Dyer, J., Cannon, P., Farmer, J.D., and Schmon, S.M. (2022); “Black-box Bayesian inference for economic agent-based models”; INET Oxford Working Paper No. 2022-05.

Dyer, J., Quera-Bofarull, A., Bishop, N., Farmer, J.D., Calinescu, A., and Wooldridge, M. (2023). “Population synthesis as scenario generation for simulation-based planning under uncertainty”, 23rd International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2024), forthcoming.

Eliasson, G. (1976); “A Micro-Macro Interactive Simulation Model of the Swedish Economy”; Economic Research Report B15, December 1976, Stockholm: Federation of Swedish Industries; reprinted in Eliasson, G. (2024); “A Micro-Macro Interactive Simulation Model of the Swedish Economy”; International Journal of Microsimulation; forthcoming.

Eliasson, G. (1977); “Competition and market processes in a simulation model of the Swedish economy”; The American Economic Review; vol. 67; pp. 277-281.

Eliasson, G. (2018); “Why complex, data demanding and difficult to estimate agent based models? Lessons from a decades long research program”; International Journal of Microsimulation; vol. 11(1); pp. 4-60; DOI: 10.34196/IJM.00173.

Favreault, M., Smith, K.E., and Johnson, R.W. (2015); “The Dynamic Simulation of Income Model (DYNASIM)”; Urban Institute research report; September.

Gillman, M.S. (2017); “GENESIS - The GENEric SImulation System for modelling state transitions”; Journal of Open Research Software; vol. 5; DOI: 10.5334/jors.179.

Grazzini, J., and Richiardi, M. (2015); “Estimation of ergodic agent-based models by simulated minimum distance”; Journal of Economic Dynamics and Control; vol. 51; pp. 148-165; DOI: 10.1016/j.jedc.2014.10.006.

Jonung, L. (1991); “The Stockholm School of Economics Revisited”; Historical Perspectives on Modern Economics; Cambridge University Press; Cambridge, UK.

Klevmarken, A. (2022); “Microsimulation. A Tool for Economic Analysis”; International Journal of Microsimulation; vol. 15(1); pp. 6-14; DOI: 10.34196/IJM.00246.

Lee, J.-S., Filatova, T., Ligmann-Zielinska, A., Hassani-Mahmooei, B., Stonedahl, F., Lorscheid, I., Voinov, A., Polhill, J.G., Sun, Z. and Parker, D.C. (2015); “The Complexities of Agent-Based Modeling Output Analysis”; Journal of Artificial Societies and Social Simulation, 18(4): 4.

Li J, O’Donoghue C (2014). “Evaluating Binary Alignment Methods in Microsimulation Models”. Journal of Artificial Societies and Social Simulation, 17(1): art. 15.

Li, J., and O’Donoghue, C. (2013); “A survey of dynamic microsimulation models: uses, model structure and methodology”; International Journal of Microsimulation; vol. 6(2); pp. 3-55; DOI: 10.34196/IJM.00082.

Makinoshima, F., and Oishi, Y. (2022); “Crowd flow forecasting via agent-based simulations with sequential latent parameter estimation from aggregate observation”; Scientific Reports 12: 11168.

Mu, T., Zheng, S., and Trott, A. (2022); “Modeling Bounded Rationality in Multi-Agent Simulations Using Rationally Inattentive Reinforcement Learning”; Transactions on Machine Learning Research; vol. 12; https://openreview.net/forum?id=DY1pMrmDkm.

National Research Council (2012); “Assessing the Reliability of Complex Models: Mathematical and Statistical Foundations of Verification, Validation, and Uncertainty Quantification”; The National Academies Press, Washington, DC.

Nelson, R.R., and Winter, S.G. (1982); “An Evolutionary Theory of Economic Change”; Harvard University Press; Cambridge, MA.

Nowak, S.A., Matthews, L.J., and Parker, A.M. (2017); “A General Agent-Based Model of Social Learning”; RAND Corporation; Santa Monica, CA; https://www.rand.org/pubs/research_reports/RR1768.html.

OEDC (2022); “TaxBEN: The OECD tax-benefit simulation model”; OECD; Paris.

O’Donoghue, C. (2001); “Dynamic Microsimulation: a methodological survey”; Brazilian Electronic Journal of Economics, vol. 4; p. 77.

O’Donoghue, C. (ed.) (2014); “Handbook of Microsimulation Modelling”, Contributions to Economic Analysis, Vol. 293; pp. 305-343; Emerald Group Publishing Limited, Leeds.

O’Donoghue, C., and Dekkers, G. (2018); “Increasing the impact of dynamic microsimulation modelling”; International Journal of Microsimulation; vol. 11(1); pp. 61-96; DOI: 10.34196/IJM.00174.

O’Donoghue, C., and Dekkers, G. (2014); “Dynamic microsimulation”; in: O’Donoghue, C. (ed.); “Handbook of Microsimulation Modelling”; Contributions to Economic Analysis, Vol. 293; pp. 305-343; Emerald Group Publishing Limited; Leeds. DOI: 10.1108/S0573-855520140000293009.

Orcutt, G. H. (1957); “A new type of socio-economic system”; The Review of Economics and Statistics; vol. 39; pp. 116–123.

Orcutt, G.H. (1960); “Simulation of Economic Systems”; American Economic Review, vol. 50(5); pp. 894-907.

Orcutt, G.H. (1962); “Microanalytic Models of the United States Economy: Need and Development”; American Economic Review, vol. 52(2), pp. 229-40.

Orcutt, G. H., Greenberger, M., Korbel, J., and Rivlin, A. M. (1961); “Microanalysis of Socioeconomic Systems. A Simulation Study”; Harper & Brothers.

Orcutt, G.H., Caldwell, S., and Wertheimer, R. (1976); Policy Exploration through Microanalytic Simulation”; Urban Institute, Washington, DC.

Pangallo, M., Aleta, A., del Rio-Chanona, R.M. et al. (2024); “The unequal effects of the health–economy trade-off during the COVID-19 pandemic; Nature Human Behavior 8: 264–275.

Platt, D. (2020); “A comparison of economic agent-based model calibration methods”; Journal of Economic Dynamics and Control; vol. 113; 103859; DOI: 10.1016/j.jedc.2020.103859.

Poledna, S., Miess, M.G., Hommes, C., and Rabitsch, K. (2023); “Economic forecasting with an agent-based model”; European Economic Review; vol. 151; 104306; DOI: 10.1016/j.euroecorev.2022.104306.

Richiardi, M. (2018); “Agent-Based Computational Economics: What, Why, When”; in: Delli Gatti, D., Fagiolo, G., Gallegati, M., Richiardi, M., and Russo, A. (eds); “Agent-Based Models in Economics; Cambridge University Press; Cambridge, UK.

Richiardi, M., and Richardson R.E. (2017); “JAS-mine: a new platform for microsimulation and agent-based modelling”; International Journal of Microsimulation; vol. 10; pp. 106-134; DOI: 10.34196/IJM.00151.

Savcisens, G., Eliassi-Rad, T., Hansen, L.K. et al. (2024); “Using sequences of life-events to predict human lives”. Nature Computational Science 4: 43–56.

Schelling, T.C .(1971); “Dynamic models of segregation”; The Journal of Mathematical Sociology; vol. 1 (2); pp. 143-186; DOI:10.1080/0022250x.1971.9989794.

Schelling, T.C. (2006); “Some Fun, Thirty-Five Years Ago”; Handbook of Computational Economics; in: Tesfatsion L., and Judd K.L. (ed.); Handbook of Computational Economics; 1st ed.; vol. 2; ch. 37; pp. 1639-1644; Elsevier.

Schofield, D.J., Zeppel, M.J.B., Tan, O., Lymer, S., Cunich, M.M., and Shrestha, R.N. (2018); “A brief, global history of microsimulation models in health: Past applications, lessons learned and future directions”; International Journal of Microsimulation; vol. 11(1); pp. 97-142; DOI: 10.34196/IJM.00175.

Solow, R.M. (2004), “Progress in economics since Tinbergen”; De Economist; vol. 152; pp. 159-160; DOI: 10.1023/B:ECOT.0000023252.86552.5b.

Stephensen, P. (2016); “Logit scaling: A general method for alignment in microsimulation models”; International Journal of Microsimulation, vol. 9, pp. 89-101; DOI: 10.34196/IJM.00144.

van de Ven, J. (2017); “Parameterising a detailed dynamic programming model of savings and labour supply using cross-sectional data”; International Journal of Microsimulation; vol. 10(1); pp. 135-166; DOI: 10.34196/IJM.00152.

van de Ven, J., Richiardi, M. and Bronka, P. (2022); “Dynamic simulation of taxes and welfare benefits by database imputation”; Centre for Microsimulation and Policy Analysis Working Paper Series, CEMPA3/22.

Ward, J.A.,Evans, A.J., and Malleson, N.S. (2016); “Dynamic calibration of agent-based models using data assimilation”; Royal Society Open Science 3: 150703.

Wu, G., Heppenstall, A., Meier, P., Purshouse, R., and Lomax, N. (2022); “A synthetic population dataset for estimating small area health and socio-economic outcomes in Great Britain”; Scientific Data, 9(1):19. doi: 10.1038/s41597-022-01124-9. PMID: 35058471;