International Microsimulation Association

RESEARCH ARTICLE

Dynamic Microsimulation Modelling: A Survey and Critical Assessment IV

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Abstract The sub-field of dynamic microsimulation modelling, the inter-temporal simulation of micro units over time, was one of the original areas of microsimulation. A number of surveys have documented progress in the field at approximately 7 year intervals over time. Reviewing developments over the decade 2013-2023, we find that progress in the field is accelerating, as nearly half the papers published in the field have been published since the last survey article. It is timely therefore to provide a more recent survey and critical assessment of the direction of the field. This paper reviews the evolution of dominant methodological choices. However given the increased scale of the sub-field, we make use of bibliometric tools to assist in the analysis of the field. There has been a clear change in direction over the past 8 years. Previous research could be classified in two clusters, largely divided into closed, aligned, discrete time and open, non-aligned continuous time frameworks, both with family units of analysis. However, the dominant current direction in the field has been the introduction of more parsimonious model particularly in the health sphere. These papers typically use an individual unit of analysis, are non-aligned and have simpler behavioural and simulation structures, with a greater focus on the particular health policy application.

JEL classification: C51, C61, C63

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1. Introduction

The sub-field of dynamic microsimulation modelling, the inter-temporal simulation of micro units over time, was one of the original areas of microsimulation (***Orcutt, 1957***) together with spatial microsimulation (***Hägerstrand, 1957***). It has evolved, initially relatively slowly, from the preserve of large-scale projects with super-computers to the realm of PhD students and being a day to day tool for policy analysts.

While there have been many reviews of microsimulation in general (***Merz, 1991***; ***Bourguignon and Spadaro, 2006***), there have been a series focusing on the sub-field of dynamic microsimulation. Reviews of dynamic microsimulation modelling have been undertaken at approximately 7 year intervals over time (***O'Donoghue, 2001***; ***Spielauer, 2007***; ***Li and O'Donoghue, 2013*** and see ***Figure 1***).[1] These reviews have focused on describing uses and applications of models and to categorise methodological choices made by modellers. Historically, methodological choices of interest were

- choice of the sample being based on cross-section or a synthetic cohort,
- whether the model was open or closed,
- whether models were aligned to external data sources,
- whether there were endogenous behaviours in the model,
- type of base data,
- whether discrete time or continuous time was used or

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1. ***Zaidi and Rake (2001)*** did a review of a subset of models, while ***Harding (2007)*** presented a plenary conference paper on challenges and opportunities of dynamic microsimulation modelling.

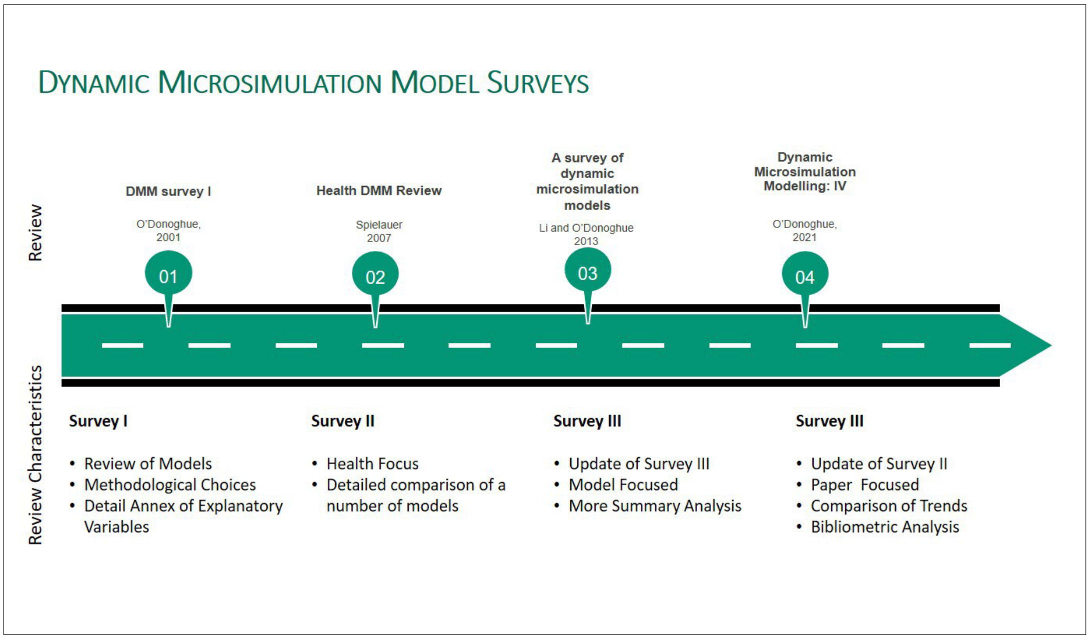

Figure 1. Dynamic microsimulation surveys.

whether they were linked with macro models.

In a review of papers (***Figure 1***) at an early stage of the field and given the size of the field, ***O'Donoghue (2001)*** was able to review almost every paper in the field, with a particular focus on methodological choices, including detailed sub-module characteristics. ***Spielauer (2007)*** paper had a slightly different format, taking a greater focus on the use of dynamic microsimulation models used in a health setting and undertook a detailed comparison of a number of models. ***Li and O'Donoghue (2013)*** and the related paper ***Li et al. (2014)*** in the Handbook of Microsimulation, given the later expansion of the field, focused on summary statistics of the structure of the field and methodological choices made by papers in the field.

The sub-field remains a relatively important part of the microsimulation community with 22% of papers at the 2019 World Congress of the International Microsimulation Association held at the National University of Ireland, Galway. Progress in the field is accelerating. As nearly half the papers published in the field of dynamic microsimulation have been published since the last survey article, it is timely to provide a more recent survey and critical assessment of the direction of the sub-field (***Table 1***). The number of publications per 5 year period rose rapidly to 2012, with the rate of growth slowly at this point at a historically high level. Globally microsimulation is used in many more disparate areas, reflecting a decline in papers published in this sub-field accounting from 7.5% a decade ago to 3.5% of all papers that reference microsimulation in the past 5 years.

Given the scale of publication since 2013, there is a merit in reviewing the literature again. It is particularly interesting to assess changes in use and methodological choices made since the last survey nearly a decade ago. We continue the structure of previous surveys, reviewing the evolution of dominant methodological choices, but make use of bibliometric tools to assist in the analysis of the larger field.

Table 1. Citation score from google search for dynamic microsimulation.

Period	Citations
2022-2023	380
2017-2021	900
2013-2016	718
2008-2012	761
2003-2007	514
1998-2002	319
1993-1997	146
1988-1992	30
1983-1987	8
1978-1982	4
1973-1977	1

Section 2 describe the theoretical framework used to underpin the bibliometric analysis. Section 3 describes briefly the methodological choice taken in reviewing the bibliometric data. In section 4, we analyse the data, with conclusions and future research directions reported in section 5.

2. Theoretical framework

Dynamic microsimulation models primarily help us to understand policy, economic and social change using simulation at the micro level via the complexity dimensions of population, policy, behaviour and time (***O'Donoghue, 2014***).

A number of publications have tried to present dynamic microsimulation models in mathematical form such as ***Klevmarken (1997)*** and ***O'Donoghue (2021)***. The broadest household level dynamic microsimulation model simulates the presence $I(\dashv)$ and levels $Y(\dashv)$ over time t for different incomes sources S, and for different factors such as health, wellbeing, consumption, care requirements, environmental impact Z for individuals I nested within families F within the household H. As an intertemporal simulation model the explanatory factors X also need to be simulated:

$$Y_t^H = \sum_F \sum_I \sum_S Y\left(BX + u_i + v_{it}\right).I\left(GZ + \varepsilon_{it}\right)$$

Where u_i is an individual fixed or random effect, v_{it} is a time varying component for the $Y(\dashv)$ model and ε_{it} the time varying component for the $I(\dashv)$ model.

However as the field moves beyond income related outcomes to other outcomes such as consumption, environmental, time (for caring) and in particular health outcomes, the ultimate dependent variable is often not an income variable, but rather a different outcome Z:

$Z_t^H = f\left(Y_t^H, X_t^H\right)$ However, in most cases the structure is simpler than this as complexity comes with a cost and so very few models utilise a household units of analysis due to difficulties in maintaining the coherence of intra unit correlations, while long-run dynamics are very challenging within shorter panels. More typically, the most income focused models aggregated unit of analysis is the family:

$$Y_t^F = \sum_I \sum_S Y\left(BX + u_i + v_{it}\right).I\left(GZ + \varepsilon_{it}\right)$$

However, although occasional utilised in the past, the individual as the unit of analysis is growing:

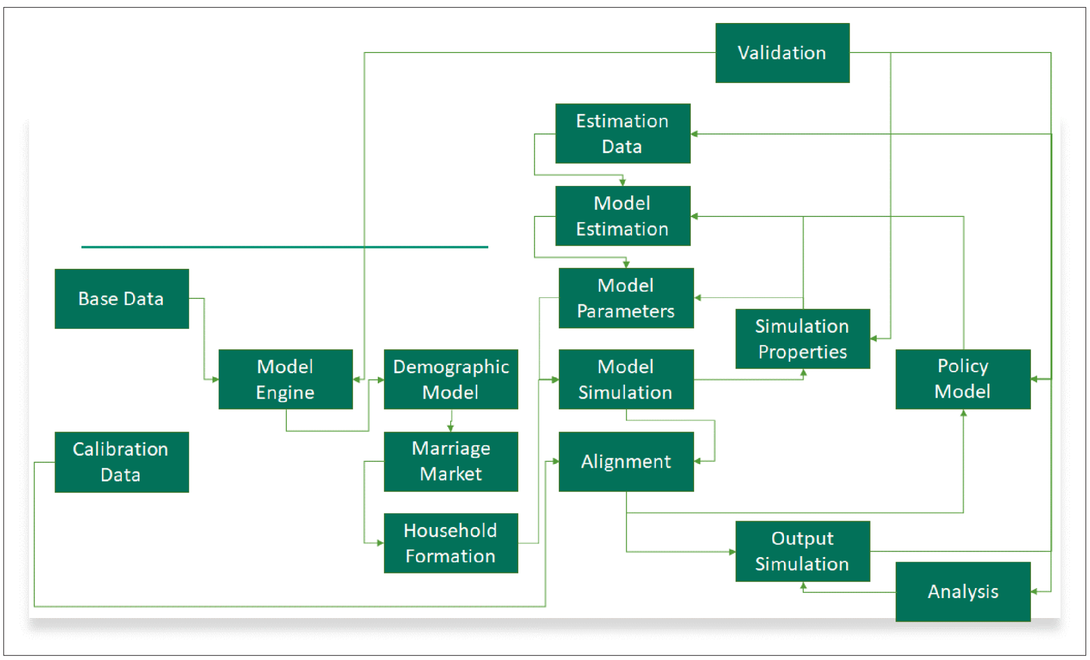

Figure 2 Components of a traditional, maximal, dynamic microsimulation model.

$$Y_t^I = \sum_S Y\left(BX + u_i + v_{it}\right).I\left(GZ + \varepsilon_{it}\right)$$

Particularly for models with a health related focus:

$$Z_t^I = f\left(Y_t^I, X_t^I\right)$$

In addition, the use of dynamic microsimulation type models for nowcasting, where the time trend of the distribution is more important that the longitudinal trajectory of individuals have become important in understanding the impacts of economic and health crises in near to real time (***Navicke et al., 2014***; ***O'Donoghue et al., 2020***):

$$Y_t^H = \sum_F \sum_I \sum_S Y\left(BX + v_i\right).I\left(GZ + \varepsilon_i\right)$$

Figure 2 defines the main components of a traditional maximal dynamic microsimulation model, however not necessarily all components are in every model. This to some extent was the focus of many large-scale modelling projects such sfb3 model (***Orcutt et al., 1986***), the CORSIM and DYNCAN models (***Caldwell and Morrison, 2000***), APPSIM (***Cassells et al., 2006***), LIAM2 ***(De Menten et al., 2014***). However as we will find later in the results section, the field is moving radically away from this perspective, even if it remains the dominant focus of dynamic microsimulation model papers in the IMA World Congresses.

As a micro model, it starts with a base dataset of micro units such as families or individuals. These are taken from either actual data such as a census, survey or administrative data in the case of a population mode

l or as hypothetical data in the case of a cohort model. There is a simulation modelling framework that manages the data handling and processing, either using a specific software system such as LIAM2 (***De Menten et al., 2014***), JASMINE (***Mannion et al., 2012***), neworder (***Smith, 2021***) or MODGEN (***Spielauer, 2009***), a bespoke programmed engine in for example C++ or using statistical software or other off the shelf tools. (***O'Donoghue, 2021***) provides a textbook on how to develop a dynamic microsimulation model in a statistical package.

Simulation modules are broadly broken up into demographic modules (which typically occur before the other modules relevant for the application, and policy modules. Demographic modules utilise tools such as life-tables for mortality, marriage markets for partner selection and statistical methods such as transition matrices or logistic regressions for transitions such as emigration, leaving the family home or fertility and family formation decisions (***Bouffard et al., 2001***; ***Rephann and Holm, 2004***; ***O'Donoghue et al., 2010***; ***Lomax and Smith, 2017***). Modelling immigration involves another bespoke process. The extent of the household formation processes (***Richiardi and Poggi, 2014***) depend upon the unit of analysis, which are often the individual or the family. It is rare to have the household as the unit of analysis, which involve household membership decisions by other adults.

Given the diversity of the model application, the Module Simulation component is broadening. Traditionally these dimension, would mainly have consisted of labour market modules, however increasingly, they include processes like education (***Smith, 2021***), long temr care (***Atella et al., 2017***) land use (***Ryan and O'Donoghue, 2019***) and particularly health care processes (***de Oliveira et al., 2023***). Many models use alignment or calibration. Typically unaligned characteristics are simulated using micro-equations, with results adjusted or aligned to external calibration totals.

There is greater homogeneity in regression models involving the estimation of of the relevant status (e.g. labour market or health etc) and potentially income variables using estimation data and then simulating them on the dynamic microsimulation dataset (***Nelissen, 1993***). In most dynamic microsimulation models, the equations are reduced form statistical models instead of structural behavioural models (***Klevmarken, 1997***). However occasionally decisions such as labour supply or retirement are endogenous to policy (***Garibay, 2023***).

Lastly dynamic microsimulation models involving the simulation over time of households can generate prodigious amounts of data, meaning that dynamic microsimulation models often have bespoke analytical tools to analyse model results and to calculate specific life-cycle statistics. Given the potential complexity, validation tools are important to minimise error (***Caldwell and Morrison,***

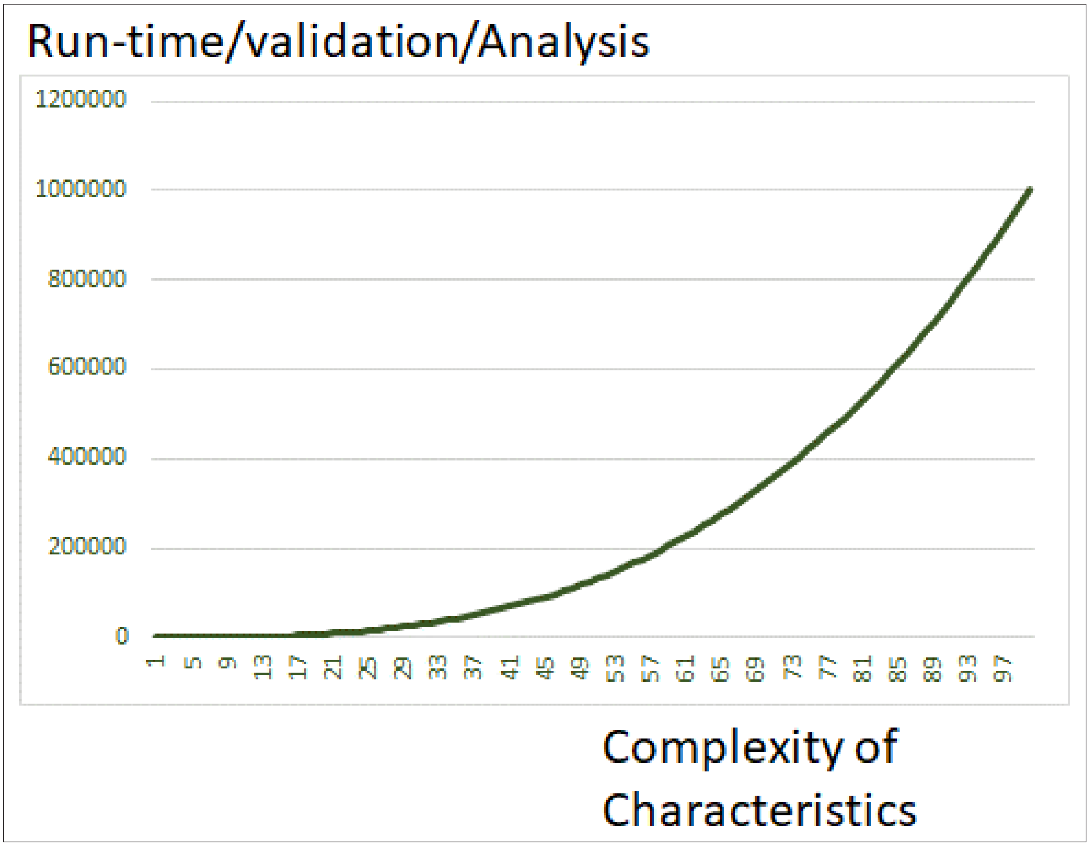

Figure 3 Non-linear relationship between complexity and development & run-time.

2000) at all levels of the model from the model engine to simulation properties of modules to policy analytical tools to output totals.

2.1. Complexity

The balance between model comprehensiveness and parsimony is a constant tension. In life-cycle simulations, much of the explanatory variables themselves change, requiring these variables also to be simulated. Attempts to improve the captured heterogeneity of models can lead to an increase in explanatory variables, further increasing complexity. A desire to model units of analysis beyond the individual such as the family further increase complexity.

Complexity comes with a cost, however. While each of these choices are justifiable in their own right in improving the explanatory power of a model, cumulatively additional complexity increases in a non-linear way, the challenges in running a microsimulation model (***Figure 3***). As the complexity of a model increases, the cost in terms of development run-time, validation, analysis time and consequential sources of error increase at a faster non-linear rate. More complex models are thus more costly, time consuming, harder to interpret. This is certainly my experience in microsimulation model development. It would be useful to quantitatively assess these trade-offs. Although minimising complexity is common sense, it is not always common practice. The choice of minimising complexity does not necessarily mean that we avoid complex problems. Rather the solution may be in developing multiple tools, each of which is less complex and thus much easier to validate, rather than developing a large-scale multi-purpose model.

Thinking about complexity and microsimulation models reminds us of what models are; road maps of reality, to enhance our understanding of reality not to replicate reality. An economic model is thus a simplified description of reality. To paraphrase George Box, the aim is not to be right but to be useful. A model should therefore be as it as complex as it needs to be.

A parsimonious model can be defined as simple models with great explanatory predictive power. They explain data with a minimum number of parameters, or predictor variables as possible.[2] On the other hand, the goodness of fit of a statistical model describes how well it fits a set of observations. Parsimony is based upon Occam's razor, or "the law of briefness" in that you should use no more "things" (or parameters) as necessary; with parsimonious models having just the right number of predictors needed to explain the model well. Parsimony can be compared to goodness of fit in that the former attempts to simulate new data well, while the latter attempts to describe the estimation data well. These can be conflicting goals with parsimonious models have a lower goodness of fit, while a higher goodness of fit model may contain more explanatory variables with poorer simulation properties. The focus on model efficiency such as the Akaike's Information Criterion (AIC) or the Bayesian Information Criterion (BIC) are tools used by statisticians to examine model efficiency. Parsimony is a much-ignored virtue, especially by reviewers! The peer review process often magnifies this process with helpful reviewers encouraging additional complexity or tweaks to enhance a model. I can count on one hand how many times reviewers have asked the opposite, to reduce the complexity of the model and increase parsimony.

2.2. Main modelling choices

The modelling choices in relation to open/closed, alignment and modelling time-period, within dynamic microsimulation models are well discussed in the literature (***Harding, 2007***; ***Harding and Slottje, 1995***). Here we discuss some of the implications. We do not discuss one of the other main choices relating to cohort versus population models as although having different analytical dimensions they have limited implications in terms of other modelling choices (***Harding, 1993***).

The choice to align or not to align is a debate has existed since the start of the field and is a fundamental choice (***Li and O'Donoghue, 2014***). Alignment often calibrates equations to external control totals because it has been challenging to use historical data to project coherent future scenarios. There is an argument that calibration or alignment is wrong, that needing to align a model means that the under-lying system of equations are "wrong" and that this can be resolved by improving the simulation performance of these equations. The question however, is it worth even trying to find this "Holy Grail"? Particularly for complex models, can we ever hope to predict the future well? Given the impossibility of forecasting at the resolution contained in a dynamic microsimulation model, is it more effective to consider a useful but simpler objective, such as scenario analysis or foresight analysis?

The choice of discrete or continuous time as the period of analysis is another choice (***Galler, 1997***). Continuous time is relatively more challenging in an alignment situation, albeit giving better a temporal resolution and better able to capture temporal inter-dependencies than discrete time.

It is more challenging to model for a number of reasons

- It is possible to align hazard model but loses much of the continuous nature as much of the calibration data is discrete
- Behavioural models such as labour supply have moved to discrete choice state space, reflecting the lumpy non-continuous nature of choices and corresponding more realistically with reality.

However, there are some specific needs for continuous models such as in demographic event timings or intra year labour market characteristics such as short unemployment spells. In addition, when models are not aligned in discrete time, they may not be more intrinsically more complex. To some extent, however this modelling choice is an ad hoc decision depending upon the specific modelling need and the availability of appropriate data.

The choice between whether a model is open or closed is the less complex (***Mannion et al., 2012***). A closed model means essentially partners, in mate selection, are found within a model, while in an open model partners are imported when required. Most models are open for births and migration however. Open models have the advantage of being more easily adopted for parallel processing, as there fewer interactions between units. It is more difficult to align open models.

Thus, there are computational merits in being open. However, there needs to be a parallel set of processes for characteristics of spouse at the point of importing in keeping for example, the

2. https://www.statisticshowto.com/parsimonious-model/

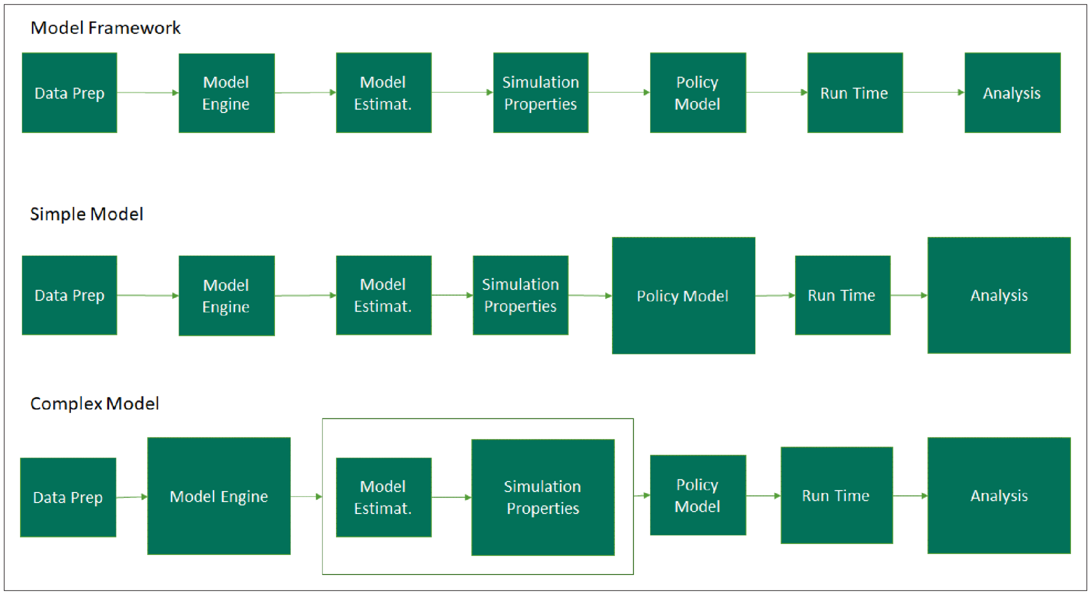

Figure 4 Model complexity and modelling time.

employment rate of imported spouse equivalent to similar people in the simulation. It can be challenging to ensure consistency with the rest of the simulation. Simplification may however, not lose much.

2.3. Two broad philosophies

From a structural point of view, traditional microsimulation modelling choices broadly clustered around two distinct modelling philosophies.

- Closed-Aligned-Discrete
- Open-Not Aligned-Continuous

The first cluster incorporates models and model frameworks such as DYNASIM, MIDAS/LIAM2, DYNACAN and APPSIM. They are closed with a marriage market within the model, but open for new births and immigrants. They use alignment with external control totals and run in discrete time, with transitions typically of a year. The second cluster contain models and model framework such as Lifepaths, MODGEN etc. developed by Wolfson, and Spielauer amongst others. They are open with partners "imported" into the sample, are non-aligned in continuous time with systems of equations explaining transitions. In this paper, we will consider whether the rapidly growing literature has maintained this clustering or whether new clusters have evolved.

2.4. Efficiency gains in microsimulation models

Figure 4 describes a model of the development and modelling time for different parts of a model. Summarising for convenience ***Figure 2***, the aspects that take time consist of:

- Data Preparation
- Model Engine
- Model Estimation
- Simulation Properties
- Policy Model
- Run Time
- Analysis

The figure is divided into a simple model and a complex model. The size of the blocks represent the likely time of engagement for a particular component.

In a simple policy focused model (say with a focus on health outcomes), more effort will be put into the policy simulation and analysis, with simpler dynamic simulation components. The creation of the policy model during the development phase and the repetition of analysis as the model is run will take the most time relative to other components, with run-time, the validation of simulation components and the development of the model engine due to the lower burden on infrastructure.

In a more complex framework (as in the case of a pensions model), with more simulated components, the data and process handling becomes more important and analysis remains important. In a more complex model, run-time becomes more important. However, it is likely to be less important than analysis in terms of time. A policy framework is deterministic in nature and so will be relatively less time consuming than stochastic components as the simulation properties of a complex system becomes increasingly important.

Model tools have been created to assist in the development of policy models as in the case of the EUROMOD modelling framework, which contains libraries of policy modules. A lot of work has been undertaken for dynamic micro-simulation model engines as in the case of MODGEN, LIAM2, JASMINE etc. The landscape is much better now than it used to be where earlier models had to "reinvent the wheel" in developing new models. Run-time has improved through the better programming in the generalised frameworks resulting in much faster runs than in the "amateur" model frameworks from earlier (***De Menten et al., 2014***). In reality however, the analysis time is likely to be longer than the simulation run-time as it can take a lot of time to interpret and validate results. Analysis also typically involves more interactive engagement with the data, while simulations can take place in the background. So in essence, the analytical time is more expensive from the researcher's point of view. There are opportunities for more off the shelf analytic tools for dynamic microsimulation analysis, however the bulk of the time spent in analysis is in the human interaction, rather than defining the calculations. In addition, most analyses are relatively idiosyncratic, meaning that it can be difficult define in advance.

The last source of time cost is the estimation and evaluation of the simulation properties of the modules within a dynamic microsimulation model. Returning to our parsimony discussion, producing a system of equations that result in realistic simulations is challenging, whether it be plausible heterogeneity, inter-temporal volatility or inertia, particularly when short panels are used in their estimation. Small errors in a single year iteration in inter-temporal simulation can blow up into large errors over the length of a simulation. It is surprising therefore how little effort there has been in sharing this part of the simulation process. In other words, it might be possible to utilise statistical equations from one country in the development of a model for another country. For models that are aligned, and for countries with a similar social and economic structure it is likely that simply varying calibration totals, while using another country's estimated equations will not lose too much power. This was the approach when the DYNACAN (***Morrison, 1997***) team started to use the CORSIM (***Caldwell et al., 1999***) modelling framework, starting initially with US equations and gradually moving to Canadian specific equations over time.

Note the Size of the boxes represent the relative importance of different parts of each model type. They are based upon expert judgement rather empirical investigation.

3. Methodology

As the volume of published information has expanded, there has been a greater need to systematise the review and synthesis of findings across the literature. While I was able to read almost every paper in the field when I undertook a literature review as part of my PhD and published in the first survey (***O'Donoghue, 2001***), it is now impossible to review in detail the field, given the number of publications.

Synthesising medium and large literatures requires analytical tools of their own, analysing bibliometric data with less detailed reading of the material. Building upon systematic reviews of clinical trial data in the health literature, systematic reviews are now commonly used to synthesise information in published research papers (***Gough et al., 2017***). They differ from meta-analysis which is a statistical tool to summarise often quantitative results of these papers.

Li and O'Donoghue (2013) attempted to some statistical analysis of bibliometric information. In this paper, we undertake a more formal assessment of the bibliometric data for more recent years and undertake a comparison with the data in the previous paper.

We have performed an analysis using a variant PRISMA approach (Preferred Reporting Items for Systematic reviews and Meta-Analyses) Statements methodology, comprising five steps: (1) data

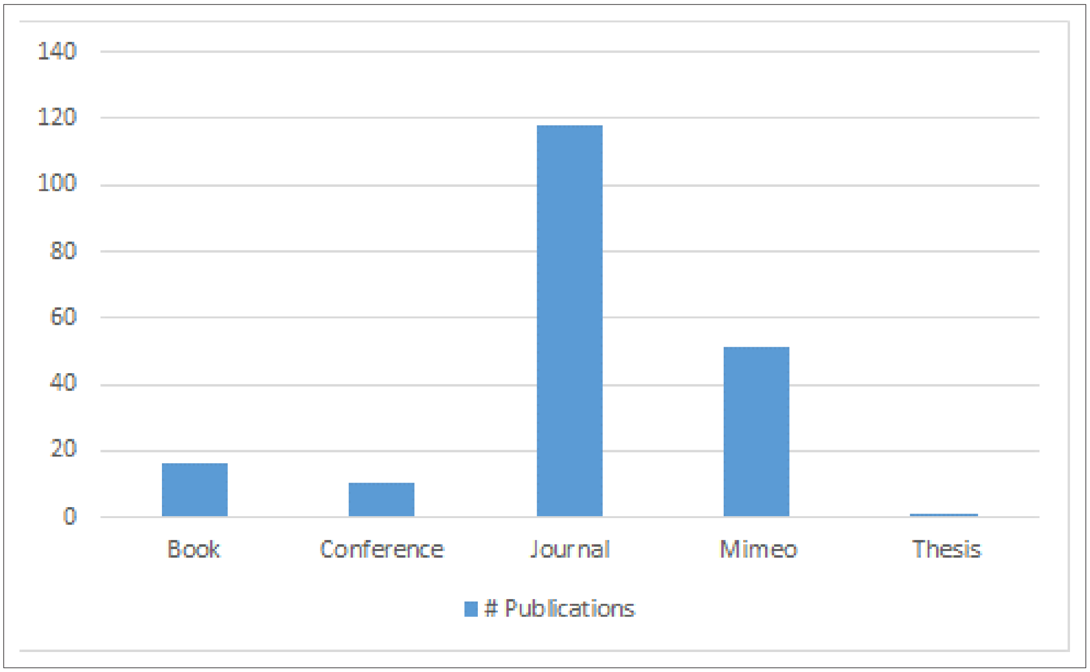

Figure 5 Number of publications.

search strategy, (2) data collection, (3) data screening and data cleaning, (4) quantitative and qualitative analysis of the publication output, and (5) interpretation (***Moher et al., 2009***). In my experience PRISMA is ideal when there is a clear narrow question to be considered. While for more open ended less clear approaches such as describing models is it less helpful. However at the same time the ad hoc approach of most previous survey articles in microsimulation is unsystematic and given the growing field not appropriate. The approach taken here is to draw upon the PRISMA approach in categorising the search using the approach defined, but allowing for both a combination of additional papers that are not picked up by the narrow search, but also to sample or exclude uncited grey literature to keep the sample manageable. One could interpret the approach as PRISMA Lite.

Fundamentally, the research question considered here relates to the use of dynamic microsimulation models during the period 2013-2023. We undertook a Google Scholar search and found 1998 items.

Some systematic reviews rely mainly on bibliometric data alone to undertake the analysis such as key words. However, for the purposes of our study, given our goal to consider methodological choices, there is a need for a deeper examination of the papers rather than merely quantitative bibliometric data. The approach is more of a hybrid one combining mixed quantitative and qualitative methods. In order to restrict the analysis to a manageable set for review, we limit our papers, mainly taking a non-random sample. Weighted by the more highly cited papers while ensuring a good representation of different areas, we selected 198 papers to be reviewed.

However, it should be noted that a random procedure would result in many papers that either working papers or papers that merely cite dynamic microsimulation models. Taking a non-random approach allows me to use my judgement, as a practitioner to select what I feel are the most important papers. As a test, I took a higher proportion of papers for the period 2022-2023 in supplementing an earlier collection effort for 2014-2021. There were no major differences in the overall qualitative conclusions from the analysis.

Figure 5 reports the types of publications reviewed in this systematic review. The dominant publication source are journal articles, with mimeo or in-house technical reports being the second most common. Unlike earlier periods, the number of papers published in books or conference proceedings are lower. A number of PhD theses are cited. Relative to other fields, the proportion of non-peer reviewed technical reports is relatively high, with a growing trend, particularly late in the period (2022-2023).

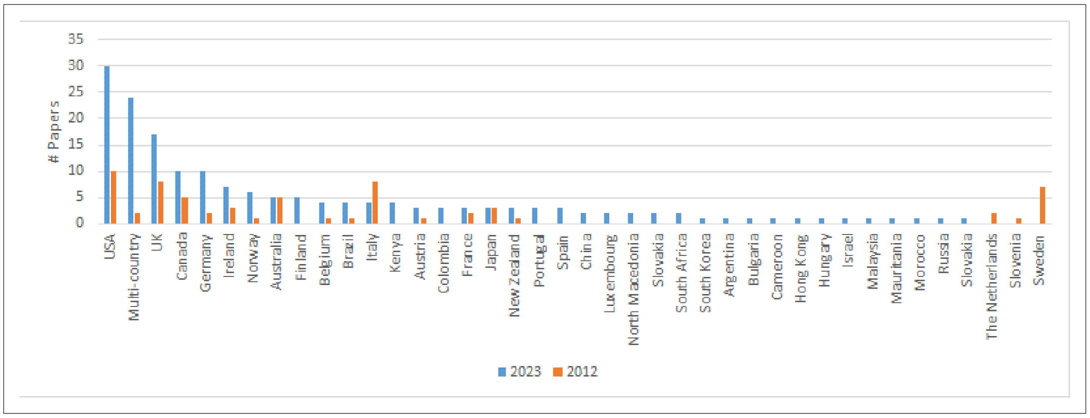

Figure 6 Geographical spread of dynamic microsimulation models.

4. Results

In the results section, we report tabulations of various paper characteristics and model choices made by the papers. Where possible we compare the tabulations for the period 2013-2021 with the previous period reviewed in ***Li and O'Donoghue (2013)***.

Figure 6 reports the geographic spread of dynamic microsimulation models and analysis comparing the post 2012 period with beforehand. What is very apparent is the increasing range of countries that undertake dynamic microsimulation modelling. Although the totals are not directly comparable the modal countries have more papers using the method. The USA, particularly with the growing interest of dynamic microsimulation of health professionals has the highest number of papers. There is a re-emergence of interest in an early leader in the field, Germany (***Nguyen et al., 2024***; ***Münnich et al., 2021***; ***Fischer and Hügle, 2020***). There are new papers from countries that have limited backgrounds in microsimulation such as Kenya (***Luong Nguyen et al., 2018***) or North Macedonia (***Petreski and Petreski, 2021***). However, there is an ebb and flow of countries as there are fewer analyses from early leaders in dynamic microsimulation such as Sweden, Netherlands and Italy.

One of the most significant trends is in the increased interest in multi-country comparative analyses (***Atella et al., 2017***; ***Dekkers et al., 2022***; ***Spielauer et al., 2020***; ***Rasella et al., 2021***). Comparative

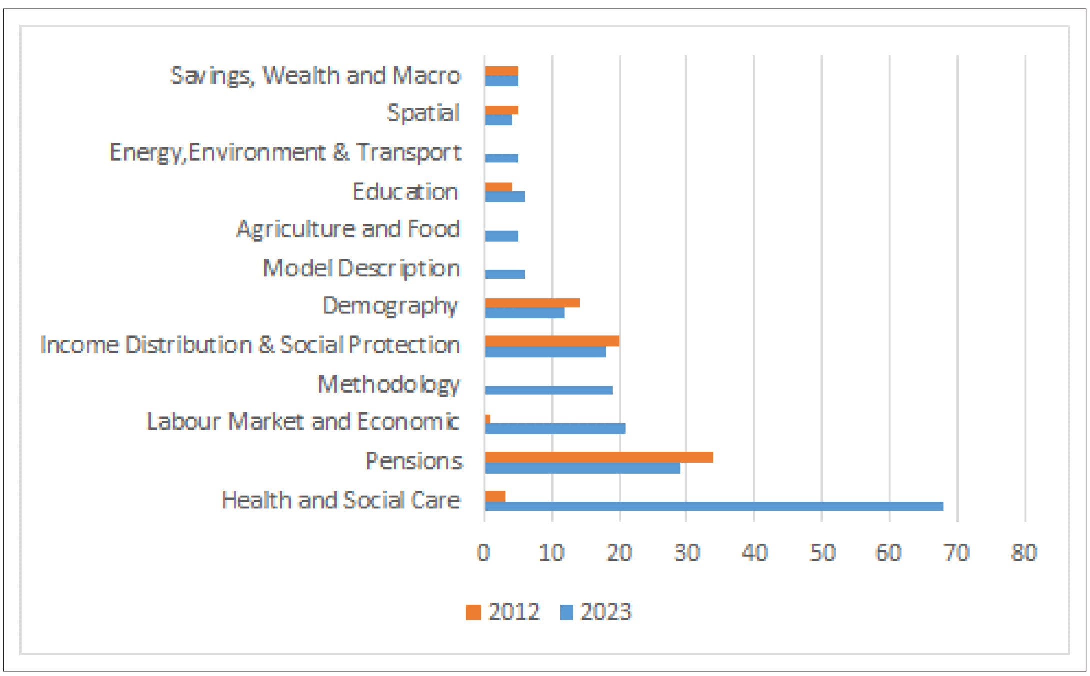

Figure 7 Subject areas of dynamic microsimulation models.

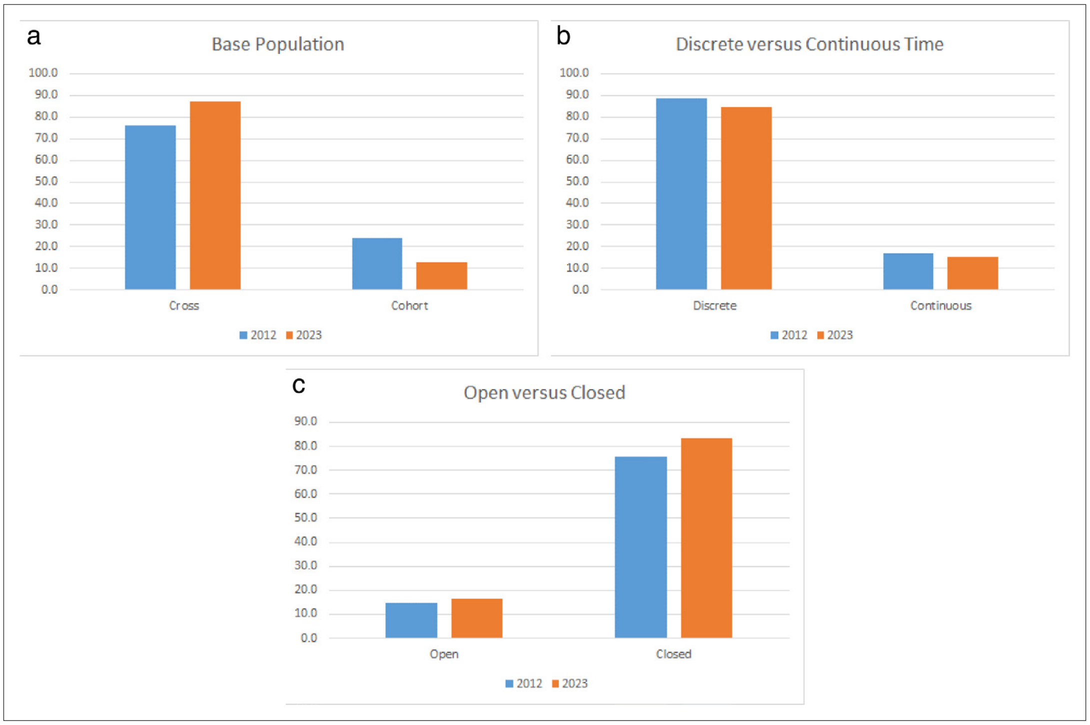

Figure 8 Methodological choices in dynamic microsimulation models.

analyses have spanned different sub-fields, including health, income distribution and pensions. The increase in comparative analysis has developed in a slightly different way to static microsimulation in that it did not evolve by more countries with national models agreeing that they wanted to do a comparative exercise and then developing a comparative framework like EUROMOD (***Sutherland and Figari, 2013***). Rather many of the comparative frameworks have evolved as distinct projects with an aim to do comparative research.

The period since 2013 has seen significant changes in use of dynamic microsimulation models (***Figure 7***). Like elsewhere in the field, health care modelling has been growing rapidly (***Mortari et al., 2020***; ***Pappas et al., 2018***). The COVID crisis has spurred a lot of interest (***Reddy et al., 2021***; ***O'Donoghue et al., 2020***; ***Spooner et al., 2021***). This is reflected in the share of papers at the World Congress of the International Microsimulation Association conducted face to face in 2019 and higher again with a record number of particularly high quality papers in 2023. Labour market analyses have also increased in importance (***Calcagno, 2017***; ***Harmon and Miller, 2018***; ***Horvath et al., 2020***). There is more interest also in the, environment, energy and agriculture (***Montaud et al., 2017***; ***O'Donoghue, 2017***; ***Ryan and O'Donoghue, 2017***). Traditional areas such as pensions, inequality and demography (***Andreassen et al., 2020***) remain important, but have declined since the ***Li and O'Donoghue (2013)*** paper, particularly given the longer sample period in this paper.

In relation to methodological choices, there has not been much change in the modelling choices over the 2013-2021 period (***Figure 8***). The field is primarily cross-sectional focused with a slightly higher share than before. Most of the analyses used closed models, but many do not utilise marriage markets, particularly the health models, so the point is less important. The majority of models utilise discrete time transitions, rather than continuous time transitions, with a minor reduction in the latter. In summary the modelling choices of microsimulation models has become simpler and more parsimonious with the increase in health sector modelling.

As health care models, which often focus on central projections of demographic characteristics, with a more detailed focus on health outcome modelling, alignment has decreased very substantially (***Figure 9***) in use (***Mortari et al., 2020***; ***Archer et al., 2021***). Also given the more parsimonious approach, behavioural feedback loops have decreased in dynamic microsimulation modelling over the two periods considered.

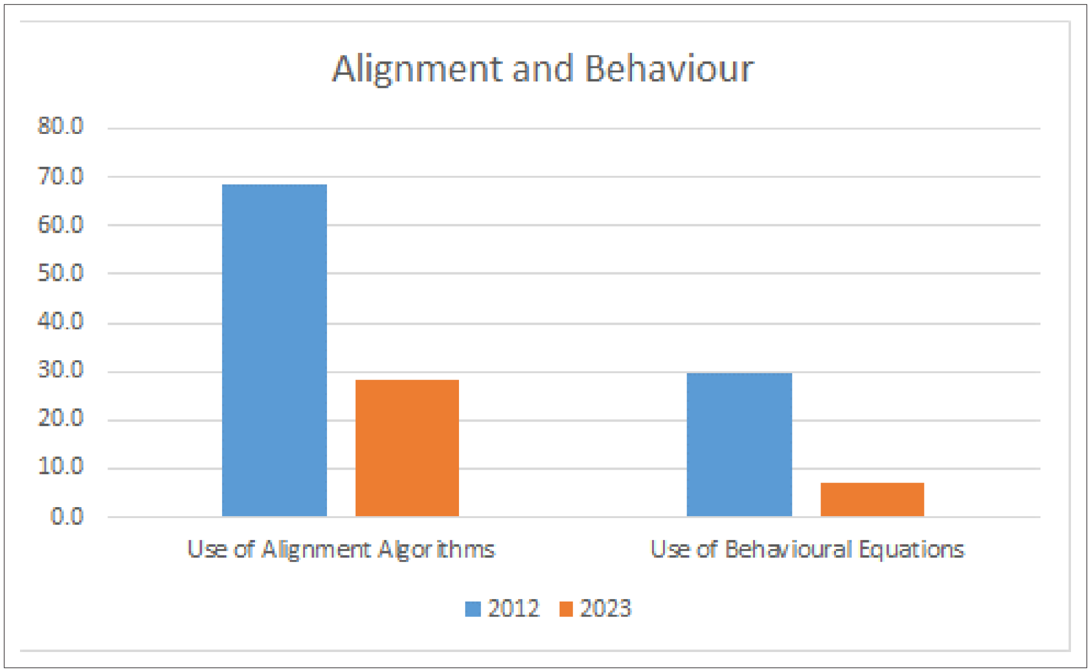

Figure 9 Alignment and behaviour.

Within the aligned models, the nature of the alignment has changed with an increasing use of computable general equilibrium (CGE) models being used to calibrate micro data (***Njoya and Seetaram, 2018***). There is also an increased use of dynamic microsimulation methods to undertake nowcasting particularly during the COVID crisis focusing only on cross-sectional distributions, with or without dynamics (***Cassells et al., 2006***).

Another difference in trend is the changing unit of analysis used in different papers (***Figure 10***). There has been a shift towards models with an individual unit of analysis as health papers become

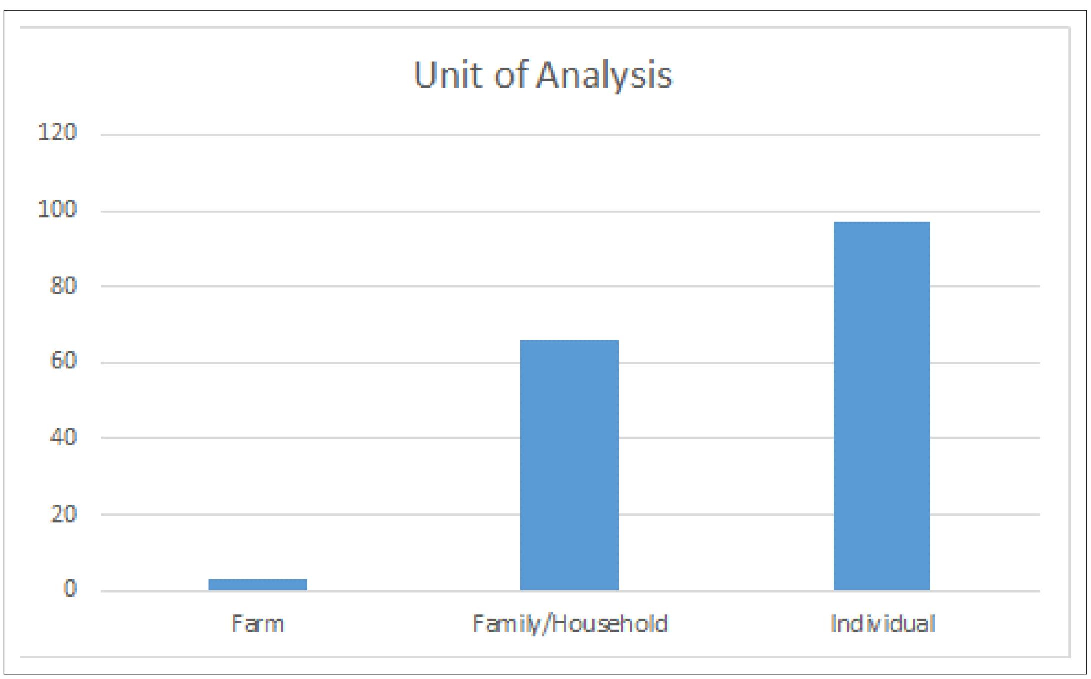

Figure 10 Unit of analysis.

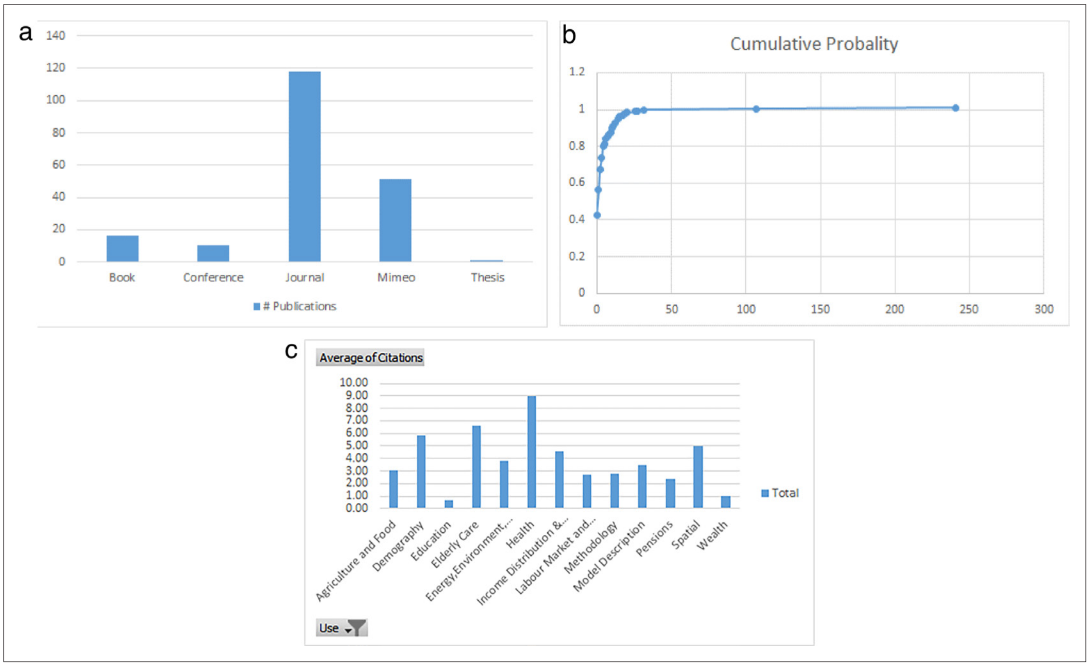

Figure 11 Citations analysis.

more important. The use of farms as a unit of analysis has also appeared as the methodology broadens into environmental and land use issues.

4.1. Impact - bibliometrics

We finish our results by undertaking a citations analysis (***Figure 11***). While there are a higher number of published papers and an increase in the number of journal articles, nevertheless, there are still a relatively large number of working papers and policy reports. Journal articles have the highest citation scores across publication types, with books and book chapters having the second highest citation score. A particular point to note is that the majority of journal articles on dynamic microsimulation models are occurring in main-stream health and social science journals with only 15 of the 118 journal articles considered in this review being published in a simulation journal. Worryingly the large number of technical reports and lesser number of conference papers have a lower citation record even than hard to access PhD these.

It is interesting to note that relationship between citations and publication type varies by application (***Table 2***). In most applications, the journal, non-journal dichotomy is very clear such as Health, Agriculture, Model Description and Income Distribution. However, for some areas such as Energy, Pensions, Elderly Care and Spatial this does not hold. There may be a time element in this result, given the increasing share of journal

Table 2. Tabulation of average citation rate decomposed by journal.

Application	Journal	Other	Total
Agriculture and Food	12.0	0.8	3.0
Demography	4.2	7.8	5.8
Education	0.5	1.0	0.7
Elderly Care	5.4	8.7	6.6
Energy,Environment, Transport and Land Use	3.3	4.5	3.8
Health	13.4	0.5	8.9
Income Distribution & Social Protection	10.8	0.8	4.6
Labour Market and Economic	3.5	1.1	2.7
Methodology	3.7	1.3	2.8
Model Description	20.0	0.2	3.5
Pensions	2.5	2.1	2.3
Spatial	1.5	8.5	5.0
Wealth		1.0	1.0

papers in some of these areas such as elderly care later in the period with lower citation levels given their recent publication. Some areas, such as pensions are more policy dominated with a consequentially lower citation rate on average, but with less difference between publication type.

5. Discussion and conclusions

In this paper, we have undertaken an updated review of dynamic microsimulation models covering the period 2013-2023. The sub-field has continued to expand, albeit at a lower rate than the wider field of microsimulation, in part be due to the relative technical difficulty of dynamic microsimulation. However, the broadening reach is very positive with many non-traditional countries for microsimulation, outside of the OECD, using the field.

There has been a clear change in direction over the past 10 years. Previous research could be classified in two clusters, largely divided into closed, aligned, discrete time and open, non-aligned continuous time frameworks, both with family units of analysis. However, the dominant current direction in the field has been the introduction of more parsimonious model particularly in the health sphere. These papers typically use an individual unit of analysis, are non-aligned and have simpler behavioural and simulation structures, with a greater focus on the particular health policy application. The nowcasting models have also adopted the strengths of the dynamic microsimulation approach, but simplifying to make them relevant during analysis of crises. To some extent the papers represented in the IMA World Congress to do not reflect the changed direction of the field, with a higher proportion of papers reflecting the traditional maximal model approach compared with the more parsimonious approach found in journal articles.

In practical terms, from the point of dynamic microsimulation models, what does this mean? In my experience, advising various teams and in doing my own work, there has been a tendency to build in complexity, so to consider what potential uses the model might have rather than what is sufficient now. Frequently models do not survive long enough to realise all of the potential gains from the model. Many of models and institutions that were prominent in the last systematic review prepared in 2013/4 are no longer there such as NATSEM, CORSIM and DYNACAN. As a result, inbuilt flexibility is not always exploited.

What we can see from the current literature is the increasing simplification of models in terms of focus on single applications, use of individual units of analysis rather than household units of analysis, treating more variables either as exogenous outside of the model system or modelling variables such as incomes in aggregate. There are some applications that require the disaggregation of individuals within households and disposable income into income components, such survivorship or gender gaps (***Kirn and Dekkers, 2023***). However the question needs to be asked, does every application require full flexibility and complexity.

There are clear lessons for the wider field in the approach of this new cluster. They focus on being complex enough, rather than trying to maximise the range and functionality of the model. As a result, of this parsimony, they are easier and quicker to develop. They are easier to link to other modelling frameworks such as CGE models. It strikes me that it might be more efficient to focus on outcome-focused models that more targeted than to develop the large comprehensive modelling framework, requiring large resources.

The advent of this new cluster has happened with large gaps remaining in the literature. The field is still light on defining and evaluating the methodologies used in the field. From alignment to information to support decisions in relation to the where efficiencies can be realised in development to demographic processes to policy endogenous behaviour to simulation properties, there are many unanswered questions. As a result, modelling decisions are often relatively ad hoc. While the new cluster is agile and impactful, the evaluation of the simulation properties of the models are very limited.

In starting this paper, I started with the familiar classification of dynamic microsimulation models into traditional characterisations. To some extent between pre-1990 and ***O'Donoghue (2001)*** and ***Li and O'Donoghue (2013)***, this classification remained appropriate. This traditional approach informed my priors in analysing the current trends. However, what is clear from the analysis of the published papers, particularly in the latter part of the decade, is that field is moving rapidly away from the traditional classification as the field has moved away from almost an exclusively household income distribution perspective. It is a reflection on the progress of the field, which had been a worry in ***Li and***

O'Donoghue (2013), that these priors no longer hold. If there were to be a further iterations of these systematic reviews, I think the focus of the review would change somewhat, what a much greater focus on time and less on the complexity assumed in at the outset of this work.

In terms of future development, my sense is that the trajectory the field is on what rapidly growing number of papers that look at dynamics and inter-temporal trends. There is a merit in more methodological work to be undertaken to support the volume of applications that test and analyse the simulation properties of these models.

The challenge of sustaining future retirement cohorts will grow as populations age. This enhances the demand for larger scale models. However, the costs remain large. The impact of issues such as housing costs will in fact add to the complexity required. Is there a way forward for teams and agencies without access to these large scale resources? It may however be that increasing use of static ageing techniques or calibrated cross-sections (as in nowcasting) combined with dynamic ageing to provide histories might help to reduce the computational complexity of dealing with these issues. Static ageing has been dismissed as a methodology for pensions analysis. There may be merits in assessing a combination of simpler individual focused career trajectories combined with static aged household structures as an intermediate solution to these diverging trends. An advantage of this approach, used in nowcasting is that scenario analyses or foresight type analyses can be undertaken without the overhead of doing longitudinal simulations of full cross-sections.

Finally, while there have been great strides made in the peer review of publications and publishing papers in internationally accessible formats, the volume of papers that are published without peer review remains a worry from the point of view of scientific quality control and also in relation to access. This has a major impact on average citation scores. The new cluster are much more likely to be published in journals, particularly health journals and have higher citation rates. There is a merit in finding a peer reviewed home with the International Journal of Microsimulation of many of these technical documents.

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Conflict of Interest

No competing interests reported.

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Appendix 1

Papers Considered for Bibliometric Exercise

The following papers are data points from the bibliometric analysis:

1. Abbasi, A., Nasiri Aghdam, A. 2024. Evaluating the impacts of retirement age reform on financial status of the Iranian Social Security Organization using a dynamic microsimulation model. *Social Welfare Quarterly*, (91), pp. 0–0.
2. Adepeju, M.O., Evans, A. 2018. A dynamic microsimulation framework for generating synthetic spatiotemporal crime patterns. *GISRUK 2018 Proceedings*, Leeds.
3. Aktas, A., Poblete-Cazenave, M., Pachauri, S. 2022. Quantifying the impacts of clean cooking transitions on future health-age trajectories in South Africa. *Environmental Research Letters*, 17(5), pp. 055001.
4. An, R., Zheng, J., Xiang, X. 2022. Projecting the influence of sugar-sweetened beverage warning labels and restaurant menu labeling regulations on energy intake, weight status, and health care expenditures in US adults: a microsimulation. *Journal of the Academy of Nutrition and Dietetics*, 122(2), pp. 334–344.
5. Andreassen, L., Fredriksen, D., Gjefsen, H.M., Halvorsen, E., Stølen, N.M. 2020. The dynamic cross-sectional microsimulation model MOSART. *International Journal of Microsimulation*, 13(1), pp. 97–119.
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9. Atella, V., Belotti, F., Carrino, L., Piano Mortari, A. 2017. The future of long-term care in Europe: An investigation using a dynamic microsimulation model. *CEIS Working Paper*, No. 405.
10. Atella, V., Belotti, F., Kim, D., Goldman, D., Gracner, T., Piano Mortari, A., Tysinger, B. 2020. The future of the elderly population health status: filling a knowledge gap. *Unpublished Manuscript*.
11. Azevedo, A.B., Moreira, A., Manso, L., Nicola, R. 2018. Demographic ageing and the Portuguese pension system: Evidence from a dynamic microsimulation model. *European Population Conference 2018*, EAPS.
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13. Baggett, T.P., Scott, J.A., Le, M.H., Shebl, F.M., Panella, C., Losina, E. Freedberg, K.A. 2020. Management strategies for people experiencing sheltered homelessness during the COVID-19 pandemic: clinical outcomes and costs. *JAMA Network Open*.
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15. Bastian, B., Smith, M., Cheong, B., Pineda, V., Stevenson, M., Hutchison, O., Kluth, S. 2017. Development of Treasury's new model of Australian retirement incomes and assets: MARIA. *Treasury Working Paper*, No. 2017-02.

16. Bavaro, M., Boscolo, S., Tedeschi, S. n.d. Simulating long-run wealth distribution and transmission: the role of inter-generational transfers in Italy. *Unpublished Manuscript*.
17. Bekalarczyk, P.S.D. n.d. On the prognosis of third generation migrants' occupational status in Germany – a dynamic microsimulation. *International Journal of Microsimulation Modelling*, pp. 95.
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33. Calcagno, L.E. 2017. Does the introduction of non-contributory social benefits discourage registered labour? Testing the impact of pension moratoriums on unregistered employment in Argentina (2003–2015). *Unpublished Manuscript*.
34. Cheng, W.H., Gaudette, É., Goldman, D.P. 2017. PCSK9 inhibitors show value for patients and the US health care system. *Value in Health*, 20(10), pp. 1270–1278.
35. Chhatwal, J., Chen, Q. 2019. An optimization tool for global hepatitis C elimination: A case for hepatitis C elimination in China. *Hepatology*, 70(S1).
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