CHAPTER 10

Dynamic Models

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10.1. Introduction

A dynamic microsimulation model is a model that simulates the behaviour of micro-units over time. Orcutt, Greenberger, Kobel, and Rivlin (1961) described the first dynamic microsimulation model following the inspiration of Orcutt's (1957) article. Most dynamic microsimulation models that have developed in following decades trace a direct or indirect link back to this model. Urban planners use microsimulation techniques to estimate traffic flows, while in the field of economics and social science, microsimulation is often used to analyse the social economic policies. In this chapter, we shall review how dynamic microsimulation in social science has developed, with main focuses on the economic models developed in the past decade.

Micro-level data, such as data obtained from a household survey, is often chosen as the basis for social economic research. In order to evaluate certain impacts of public policies, for example the redistributive impact over the course of a lifetime, it is necessary to utilise a long panel dataset. In general, such datasets are not available, either because the analysis relates to the future, as in the case of pension forecasts, or because collected datasets do not cover sufficiently long time periods; therefore, analysts use dynamic microsimulation models to assist in their analysis, a concept which was first suggested by Orcutt in 1957. Essentially, microsimulation is a tool to generate synthetic micro-unit based data, which can then be used to answer many 'what-if' questions that, otherwise, cannot be answered.

Microsimulation models, as in the field of policy modelling, are usually categorised as 'static' or 'dynamic'. Static models, for example

CONTRIBUTIONS TO ECONOMIC ANALYSIS
VOLUME 293 ISSN: 0573-8555
DOI:10.1108/S0573-855520140000293009

EUROMOD (Mantovani, Papadopoulos, Sutherland, & Tsakloglou, 2006), are often used to evaluate the immediate distributional impact of policy changes upon individuals and households, without reference to the time dimension and extensive behavioural adjustment. Some more recent static models, for example IZAΨMOD (Peichl, Schneider, & Siegloch, 2010), improved the traditional model by incorporating certain behaviour responses assuming the market adjusts to the new steady state overnight. Dynamic models, for example DESTINIE, PENSIM, and SESIM (Bardaji, Sédillot, & Walraet, 2003; Curry, 1996; Flood, 2007), extend the static model by allowing individuals to change their characteristics due to endogenous factors within the model (O'Donoghue, 2001) and let individual units progress over time. Because of the integrated long-term projections and time dependent behaviour simulations, dynamic microsimulation models could offer further insights in theory.

More than ten years ago, O'Donoghue (2001) surveyed the dynamic microsimulation models that had been developed up to that point. However the 2000s have seen many of the barriers that existed for model development until that point overcome. Data collection projects such as the European Community Household Panel (ECHP) and the increased availability of longitudinal administrative data such as the Lifetime Labour Market Database in the United Kingdom or the GSOEP in Germany have eliminated to some degree data constraints. A number of new model were developed in the past decade, for instance Pensim2 (Emmerson, Reed, & Shephard, 2004), IFS Model (Brewer et al., 2007) and SAGE (Zaidi & Rake, 2001) models in the United Kingdom, APPSIM in Australia (Harding, 2007a) and DESTINIE2 (Blanchet, Crenner, & Minez, 2009) in France, MIDAS (Dekkers et al., 2010) in Belgium, etc. Meanwhile, a few generic microsimulation programmes have emerged, such as ModGen (Wolfson & Rowe, 1998), UMDBS (Sauerbier, 2002), Genesis (Edwards, 2004) and LIAM (O'Donoghue, Lennon, & Hynes, 2009), eliminating the need to create a model from scratch. It has allowed an internationalisation of the models with developments in Belgium (Dekkers & Belloni, 2009), Italy (Dekkers et al., 2010), Canada (Spielauer, 2009) and the United Kingdom (Emmerson et al., 2004). Nevertheless, the decade has seen the demise of several models such as DYNACAN in Canada, CORSIM in the United States, NEDYMAS (Dekkers, Nelissen, & Verbon, 1993) in the Netherlands, the Belgian model (Joyeux, Plasman, & Scholtus, 1996) and MIDAS in New Zealand. The micro-econometric and micro-economic understandings of the processes that make up a dynamic microsimulation model have also greatly improved over this period. It is therefore worth considering the progress made by the discipline over the past decade.

In this chapter, we shall describe the models developed, irrespective of whether they are still in use or not, their uses and data issues, and some of the methodological choices faced. We then review the progress made by the discipline since the earliest models and suggest some directions for future development. It draws on earlier work by two of the authors (Li & O'Donoghue, 2013), but is not intended for specialists in the field and aims to give an introductory birds-eye view on the field of dynamic microsimulation in the social sciences.

10.2. Uses and applications

Dynamic microsimulation models can have many uses and this section provides an overview of the principle uses. Table 10.1 summarises many of the existing dynamic microsimulation models in terms of their main purpose, which covers projection, evaluating or designing public policies, inter-temporal behaviour studies, etc. Given the most accessible micro datasets for social scientists are household or individual level information, most models do not incorporate information on business establishments, with a few exceptions for models like MOSES in Sweden (Eliasson, 1977), NEDYMAS in the Netherlands, where business behaviours are incorporated through market equilibriums in the models. There are only a few firm-level microsimulation models, for example DIECOFIS (Parisi, 2003), and they are mostly static.

Following the introduction of the time dimension into dynamic microsimulation, these models can provide useful projections for the trend of socio-economic development under current policies. DYNASIM2/3 (Favreault & Smith, 2004; Wertheimer, Zedlewski, Anderson, & Moore, 1986), APPSIM (Harding, 2007a), the SfB3 population model (Galler & Wagner, 1986), DYNAMITE (Ando et al., 2000), SADNAP (Van Sonsbeek, 2009) and DESTINIE1/2 (Blanchet et al., 2009; Bonnet & Mahieu, 2000) have all been used for these purposes. In some cases, dynamic microsimulation models have been used as an input for macro-models as in the case of the MOSART (Andreassen & Solli, 2000), DYNASIM2 and DARMSTADT models.

Table 10.1. Uses of dynamic microsimulation models

Pensions	34
Inequality and redistribution	13
Intergenerational	6
General ageing	4
Demographic	10
Health and LT care	3
Education	4
Spatial	5
Labour market	1
Benefit forecasting	1
Savings, wealth and macro	5

Source: Li and O'Donoghue (2013).

Dynamic microsimulation models can also be used to evaluate the future performance of various long-term programmes such as pensions, educational financing, and health and long-term care, by analysing simulated future cross-sectional data. The governmental models such as DYNACAN (Morrison, 2000), POLISIM (McKay, 2003), PENSIM2 (Emmerson et al., 2004), the Sfb3 models (Galler & Wagner, 1986), MOSART (Andreassen, Fredriksen, & Ljones, 1996), PENMOD (Shiraishi, 2008) and SESIM (Ericson & Hussenius, 1999; Klevmarken & Lindgren, 2008) have been extensively used for this purpose. The existence of baseline projections allows the design of a new public policy by simulating the effect of potential reforms. Models such as LIAM (O'Donoghue et al., 2009), PRISM (Kennell & Sheils, 1990), the Belgian dynamic model (Joyeux et al., 1996), the SfB3 population model (Galler & Wagner, 1986), LIFEMOD (Falkingham & Johnson, 1995), SESIM (Klevmarken et al., 2007) and Belgium MIDAS (Dekkers, 2010; Dekkers, Desmet, Fasquelle, & Weemaes, 2013) have all been used to look at pension reform. A number of models such as DYNAMOD (Antcliff, 1993), the SfB3 cohort model (Hain & Helberger, 1986), LIFEMOD (Harding, 1993), SAGE (Zaidi & Scott, 2001) and GAMEO (Courtioux, Gregoir, & Houeto, 2009) have been used to examine changes to education finance, whereby education costs are to be paid for over an individual's lifetime. Fölster (2001) used a microsimulation model to examine reforms to social insurance utilising personal savings accounts.

By using longitudinal information created from dynamic microsimulation models, researchers can study the inter-temporal processes and behaviours at both the aggregate and individual levels. For example, CORSIM (Keister, 2000), DYNAMOD (Baekgaard, 1998), the New Zealand MIDAS model (Stroombergen, Rose, & Miller, 1995) and more recently CAPP_DYN (Tedeschi, Pisano, Mazzaferro, & Morciano, 2013) have all been used to look at wealth accumulation. Creedy and Van de Ven (2001), Nelissen (1996) and others have used dynamic microsimulation models to explore lifetime earning redistributions. Models such as DESTINIE1/2, LIAM, LifePaths, and IFSIM have been used to examine intergenerational transfers (Baroni, Žamac, & Öberg, 2009; Blanchet et al., 2009; Bonnet & Mahieu, 2000; O'Donoghue et al., 2009; Rowe & Wolfson, 2000), whilst FAMSIM (Lutz, 1997) has been used to study the demographic behaviour of women, and MICROHUS (Klevmarken & Olovsson, 1996) examined the impact of a tax-benefit system on labour market mobility. Légaré and Décarie (2011) looked at disability status amongst the elderly. Models that simulate these processes can be used to design policies to combat these problems, for example DYNASIM was used to study the effect of teenage childbearing, while CORSIM has been used to look at dental health within the US population (Brown, Caldwell, & Eklund, 1992). The models FEM and POHEM were designed to evaluate the evolution of the population's health status and its budget implications for the United States and Canada (Will, Berthelot, Nobrega, Flanagan, & Evans, 2001; Zucchelli, Jones, & Rice, 2012), whilst the LifePaths modelling framework has been used in Canada to examine time use issues (Wolfson & Rowe, 1998).

By combining spatial information with dynamic microsimulation models, the model can then be used to predict the geographical trend of certain social economic activities. This type of model is usually referred to as a dynamic spatial microsimulation model, for example MOSES (Wu, Birkin, & Rees, 2008). There are a number of models that attempt to analyse policy changes at the national level. For instance, the SVERIGE model simulates a number of demographic processes for policy analysis in Sweden (Holm, Holme, Mäkilä, Mattsson-Kauppi, & Mörtvik, 2006; Vencatasawmy et al., 1999), whilst the SMILE model (Ballas, Clarke, & Wiemers, 2005; O'Donoghue, Loughrey, & Morrissey, 2011) analyses the impact of policy change and economic development on rural areas in Ireland. Besides modelling economic policy, SimBritain (Ballas, Clarke, Dorling, et al., 2005) looks at the evolution of health while models such as HouseMod (Phillips & Kelly, 2006) and SustainCity (Morand, Toulemon, Pennec, Baggio, & Billari, 2010) focus on the housing issues with a time dimension.

Dynamic microsimulation models typically project samples of the population over time. If a full cross-section of the population is projected, then one can, for example, examine future income distributions under different economic and demographic scenarios. DYNASIM2/3 (Favreault & Smith, 2004; Wertheimer et al., 1986), APPSIM (Harding, 2007a), the SfB3 population model (Galler & Wagner, 1986), DYNAMITE (Ando et al., 2000), SESIM (Klevmarken & Lindgren, 2008), SADNAP (Van Sonsbeek, 2009), DESTINIE1/2 (Blanchet et al., 2009; Bonnet & Mahieu, 2000) and MIDAS (Dekkers et al., 2010) have been used for these purposes. These models typically utilise macro-models or forecasts to align their own projections. However, occasionally the opposite has occurred, where dynamic microsimulation models have been used as input into macro-models as in the case of MOSART (Andreassen & Solli, 2000), DYNASIM2 and the DARMSTADT models.

A full list of models and their broad characteristics is presented by Li and O'Donoghue (2013); this chapter uses some derived data from their paper to sketch the field in broader lines. Although Table 10.1 tries to cover many known models irrespective of whether they are in use today, it is nearly impossible to list all models as new ones are being developed every year. In addition, the list focuses more on the dynamic microsimulation models that are mainly used for social economic analyses. Certain regional dynamic spatial models and transportation models are not included.

One can also track the development of models through a number of lineages. The original Orcutt Socio-economic System (Orcutt et al., 1961) led to DYNASIM described above, which in turn led to CORSIM which led to POLISIM, DYNACAN and SVERIGE models. In parallel, large modelling developments in the 1970s took place in Sweden and Germany with current antecedents, while the LSE welfare state programme of the 1980s have spawned the LIFEMOD, PENSIM, PENSIM2 and SAGEMOD models in the United Kingdom as well as the HARDING model in Australia and LIAM model in Ireland. Subsequently the HARDIING model led within the creation of NATSEM to a range of models in Australia, while the LIAM model has influenced a number of European models including the LIAM2 modelling framework. Separately to these largely related developments, Statistics Canada has developed a series of LifePath/MODGEN based models based upon the original DEMOGEN.

All these powerful dynamic microsimulation models come with the cost of high complexity. Compared with static microsimulation, dynamic microsimulation is much more costly to develop and has more methodological challenges. This chapter intends to discuss some of the methodological issues related to the construction of a dynamic microsimulation model, surveying current practice in the field around the world.

10.3. Methodological characteristics and choices

This section continues to discuss methodological issues faced in constructing dynamic microsimulation models but focuses on the technical implementation and choices made in a model. Dekkers and Belloni (2009, p. 5) discern simulation characteristics[1] of a model from its technical characteristics. The present discussion will merely be on the latter, although consequences of technical choices on simulation characteristics will be discussed as well. Table 10.2 provides an overview of the technical choices covered in this section.

10.3.1. Base dataset selection

Base dataset selection is important in a microsimulation model as the quality of the input data determines the quality of the output. However,

[1] 'Simulation characteristics' are defined as those characteristics of a model that have consequences for the actual or potential research problems that can be covered by a model, as well as the implicit or explicit assumptions that a model makes when handling a specific research problem. For example, if the use of a model is to assess inference aspects of a certain potential policy measure, then the choice of model should be consider whether a model can simulate distributional effects. This feature then is a simulation characteristic. Whether the model is developed in C++, Fortran is a technical characteristic that is – in this case – of less relevance.

Table 10.2. An overview of the technical choices made by dynamic microsimulation models

Characteristic	Category	Share of models (%)
Base population	Cross	75.9
	Cohort	24.1
Type of time modelling	Discrete	88.9
	Continuous	16.7
Open or closed model	Open	14.8
	Closed	75.9
Use of alignment algorithms		68.5
Use of behavioural equations		29.6

Source: Li and O'Donoghue (2013).

Table 10.3. Base dataset selection of dynamic microsimulation models

Data source	Share
Survey	43.8
Census	23.4
Synthetic	15.6
Admin	17.2

Source: Li and O'Donoghue (2013).

selection of a base dataset is not an easy task as hardly any micro dataset contains all the information required by a dynamic population microsimulation model. The difficulties of picking a base dataset have been discussed by Zaidi and Scott (2001), Cassells, Harding, and Kelly (2006), Klevmarken and Lindgren (2008) and many other papers. Table 10.3 describes the types of base datasets used by different dynamic microsimulation models, including detailing of the data source and sample size. Typically, a dynamic microsimulation model starts with one or several of the following types of dataset according to their sources:

- Administrative Data
- Census Data
- Household Survey Data
- Synthetic Dataset

Administrative data often contains extensive information on taxable earnings and basic (tax-related) social economic variables and the data is often collected for the most part of the population, with a much bigger sample size compared with survey data. Because the data is often collected for taxations or law enforcement purpose, the data could be accurate for core variables, for example employee earnings, but limited or less specific for peripheral variables such as education levels. In addition, some specific information that is relevant to social economic research may be missing or available only for certain sub-groups. This is often the case for the educational attainment level of the individuals. Self-reported information, for example on household wealth, may be misleading. For these reasons, models using administrative data often seek to supplement information from external sources. Both SESIM in Sweden and MIDAS in Belgium imputed a few variables on survey datasets.

Legal and privacy reasons may also prevent administrative data from being accessible. Models such as CORSIM, DYNACAN and DYNAMOD use census data and while census data typically have better coverage than household surveys, they often contain less information and have to be supplemented with imputed information from other sources.

Household survey data, for example the LII survey utilised in the LIAM model, are also frequently used as the base dataset because it is rich in variables of interest and offers information on the dynamics of behaviours. However, household survey datasets may have the issues of smaller sample size and weights adjustment. The use of weights in a dynamic model adds complexity to many areas and can result in individuals being given different weightings at different points in their lives. As microsimulation aims at inference to a finite population, one potential solution, as implemented in MIDAS, the DYNAMITE and ANAC, is to replicate household population according to their frequency weights, so that each household would have the same basic weight. Another type of base dataset is synthetic data. These are selected when either a longitudinal model is used, as in the case of DEMOGEN, HARDING, LIFEMOD, LIAM and BALDINI (O'Donoghue, 2001), or where no data exists, as in the case of the NEDYMAS model, where a synthetic initial sample representative of the Dutch population in 1947 was generated. Synthetic datasets are artificially created with all required variables populated based on some known macro statistics and distributional assumptions. It is often used to understand theoretical implications of a single policy in depth. However, significant adjustments and justifications are required before inferring the policy effects in the actual population.

For microsimulation models analysing the dynamics of elderly earnings or pensions, the dataset requirement is usually higher than average microsimulation models as it requires historical variables that can affect the evolution of the elderly social economic status. This necessity implies that either retrospective information or a long panel dataset containing rich demographic, employment, and pension data is essential. Most researchers unfortunately do not have access to datasets that can fulfil this requirement. Instead, hybrid sources of datasets are often used where a combination of datasets from various sources, statistical matching and simulation techniques are used. For example, DYNASIM3 (Favreault &

Smith, 2004) matches two survey datasets, namely, Survey of Income and Program Participation (SIPP) and Panel Study of Income Dynamics (PSID) to construct its base dataset. CBOLT (Oharra, Sabelhaus, & Simpson, 2004) uses a similar approach to complement its main dataset with SIPP, PSID and data from the Current Population Survey (CPS). A recent model T-dymm (Tedeschi, 2011) intends to match administrative records with the European Union Statistics on Income and Living Conditions (EU-SILC) dataset. For researchers without access to the required data, simulation is used to impute the longitudinal history. The CORSIM model simulates part of the longitudinal profile based on a historical cross-sectional dataset and matches the model output to historical aggregate information such as fertility and mortality rates (Caldwell, 1996). LIAM also simulates historical profiles by exploiting retrospective variables, previous census information and other survey data (Li & O'Donoghue, 2012).

Each of data matching and imputation methods has its pros and cons. The method is often tailor-made to the specific datasets and projects. Statistical matching can be used when there are sufficient matching variables in a comparable dataset. This method has the desirable feature of having a 'real-world' value, although the quality of matching may vary substantially depending on the quality and quantity of matching variables. Synthetic simulation has the advantage of being flexible but longitudinal consistency may be an issue due to limited benchmark information. Additionally, it is also common to extract behavioural relations from a dataset other than the one used by the simulation. In this case, however, one may want to consider the comparability and consistency issues carefully due to the survey design and variable definitions.

Another issue in the base dataset selection is the sample size. The larger the sample size, the more the sub-groups of the population can be considered. Many dynamic models have a baseline dataset with more than 100,000 observations (Table 10.4). Sample sizes are particularly important for inter-temporal analysis because similar individuals in a cross-sectional sample may have taken different paths to reach the same state. Regardless the source of the dataset, panel data is usually preferred as it records changes over time. Sample size also has an impact on the model run time, where larger datasets will take longer to simulate, although it is less of an issue with faster computers.

Table 10.4. Sample size distribution

Base data size	Share
≤15,000	37.3
15,000–100,000	18.6
100,000+	44.1

Source: Li and O'Donoghue (2013).

10.3.2. Cohort model or population model

One issue that is closely related to the base dataset selection is the type of data structure that a model uses. Harding (1993) and others have categorised inter-temporal dynamic models into two types: cohort models that simulate a single cohort over a relative long time period (usually lifetime), and population models that simulate a population cross-section over a defined period of time. In addition, some models focus only on adults (i.e. ignore children) and thus they do not represent the entire age spectrum, although these models may contain a cross-section of the population.

From a model design perspective, the distinction between cohort and population model may be a simulation property rather than a technical characteristic. The distinction made in the literature from a historical viewpoint has more to do with the computational capacities and data constraints rather than any major methodological differences. Cohort models were typically used because the computing costs required to simulate whole lifetimes for cross-sections with sufficient sample sizes for cohort examinations were too high. The method typically features less micro-units interactions as compared with a full-fledged population model. Both types of models can be simulated in the same modelling environment: a cohort model is simply a model that ages a sample of individuals in a particular age group, while a population model ages a sample of individuals of different ages. Both samples are passed through ageing procedures, to produce life event histories over the modelled period.

It is also possible to model both types using the same computing platform. The potentially larger size of the cohort modelled in dynamic cohort models allows life time income patterns for smaller population groups such as recipients of disability benefits or lone parents to be studied. Some cross-section models such as MOSART combine both types of modelling technique as they may use a very large dataset. With increasing computation and modelling capacities, newer models tend to use be population models as one may get more information and draw inference to the population directly. Furthermore, cohort models by definition are less useful for the simulation of households and their income. This means that many indicators that use household-level information, including the at-risk-of-poverty rate, the low-work-intensity-rate and the Gini, can be simulated. For this reason, population models can be more useful for applied research.

10.3.3. Ageing method in dynamic microsimulation

Ageing within a microsimulation context may be defined as the process of updating a database to represent current conditions or of projecting a database for one or more years to represent expected future conditions. There are two types of ageing processes: static ageing and dynamic ageing.

Static ageing involves adjusting the weights of the observations so that the simulated population distribution matches the macro-aggregates. For example, in order to simulate an ageing society, the weighting of young people gradually decreases over time while the weighting of elderly people would increase; however, there is no change to the attributes of these individuals. Dynamic ageing in contrast changes the attributes of the individuals instead of altering their weights. In the same example of simulating an ageing society, models with dynamic ageing will update the age and other related attributes of individuals over time instead of changing their weights. The method can be referred as *cross-sectional dynamic ageing* if all individuals are updated before a model moves on to the next time period in a dynamic ageing process, or *longitudinal dynamic ageing* if a model simulates all time periods for one individual before repeating the same process for the next one in the population. The difference is far from trivial, because cross-sectional ageing allows for the matching and interactions between individuals in the dataset, whereas longitudinal ageing needs to resort to creating artificial individuals for the sole purpose of forming a partnership. Thus, modellers who want to simulate household characteristics in population models will resort to cross-sectional ageing in almost all cases. Generally speaking, dynamic ageing is more popular and may sometimes be used as the criteria to judge whether a model belongs to the camp of dynamic microsimulation models.[2]

While static ageing can ideally produce the same population representative cross-sectionals as models with dynamic ageing (Dekkers & van Camp, 2011), it works in a different way as it does not update social economic variables. In many cases, the only variable that needs to be changed over time is the weight of the observations. This might be attractive for modellers who already have a static microsimulation model. However, static ageing also has a number of disadvantages. Klevmarken (1997) highlighted that whereas static ageing may avoid some problems of drift in the projected cross-section associated with dynamic ageing because of misspecification in dynamic equations, it cannot account for mobility between states. In addition, he pointed out that it is inefficient not to use all available historical information to project into the future. A consequence of not modelling the mobility of individuals between points in time is that it reduces the type of analyses that can be undertaken by a microsimulation model, for example, it is not possible to conduct analyses that require life event histories such as the simulation of pensions.

[2] This chapter uses a broad definition of dynamic microsimulation, where the main difference between static models and dynamic models is the inclusion of the time horizon. Some of the methodological discussions such as estimations and behavioural responses only apply to a dynamically aged microsimulation model.

Furthermore, future weights are needed to age a dataset. Although macro-models or other forecasting devices can be used, they may not forecast weights at the level of detail required. Besides, the weight calculation may be further complicated when the target is multi-dimensional.[3] Buddelmeyer, Hérault, Kalb, and van Zijll de Jong (2009) and De Blander, Schockaert, Decoster, and Deboosere (2013) have discussed some recent applications of static ageing. Generally speaking, static ageing cannot be used when there is no individual in the sample in a particular state (Dekkers & Van Camp, 2011). If there are a small number of cases in a particular household category, a very high weight may have to be applied, resulting in unstable predictions. As a result, static ageing procedures are mostly used in short to medium term forecasts, where it can be expected that large changes have not occurred in the underlying population. However, it may be more difficult to use static ageing over longer periods of time due to changing characteristics of the population.

Dynamic ageing aims to reflect the ageing process in real life though it could make a model very complicated and computational expensive. Cross-sectional dynamic ageing is the most common method while longitudinal ageing is sometimes used in cohort models. Dynamic ageing can consistently estimate characteristics of future income distributions under ideal circumstances in which all transition probabilities and state specific expectations can themselves be estimated consistently. This may be possible in a simple model with a small number of processes, but in a fully dynamic model of work and life histories, many more processes need to be jointly estimated, a formidable requirement given the available data. Therefore, it is necessary to make some assumptions to make estimation feasible, for example education choice happens before labour participation choice, etc. In addition, one may sometimes need to assume independent error terms and some other arbitrary assumptions in order to simplify the estimation. Although these assumptions are common in practice, they may lead to theoretical pitfalls and biased results when excessively used without proper testing. In addition, projections over time at the micro-level are particularly susceptible to assumptions on the stability of the panel data, the absence of structural breaks as well as misspecification error, as modelling at this level involves more details than in macro-models. Additionally, current knowledge regarding micro-behaviour is not good enough to specify a fully dynamic model. As a result, dynamic ageing often combines with an alignment (calibration) mechanism to keep aggregate outputs in line with predictions from macro-models. The method allows individual transitions to be simulated while ensuring that

[3] For some examples of the multi-dimensional reweight algorithm, see Deville, Sarndal, and Sautory (1993), Tanton, Vidyattama, Nepal, and McNamara (2011).

aggregate outputs track macro forecasts (see, for example, Chénard, 2000a, 2000b).

10.3.4. Discrete or continuous time modelling

Another choice in the development of dynamic microsimulation models is the treatment of time. Discrete time models simulate which individuals experience particular events in given time intervals while continuous time models treat time as a continuous variable and determine the exact time that an event occurs (Willekens, 2006).

Discrete time microsimulation models changes individual attributes once per time period. Take demography for example, demographic modules in dynamic models are often constructed using annual transition probability matrices. Individuals are passed through a collection of transition matrices in each time period of the simulation (usually a year) to determine their simulated life paths, for example death. This method often assumes a sequential order of life events, even if they may be interdependent in real life. As in the example given above, the order in which the transition matrices are applied is very important. If the marriage pattern is determined first, the potential fertility rate will change. Similarly, a premarital pregnancy will increase the probability of getting married. Galler (1997) discussed a number of options in this situation including the procedure of random ordering as used by the DARMSTADT (Heike, Hellwig, & Kaufmann, 1987) and Hungarian models (Csicsman & Pappne, 1987).

There are a number of problems with this type of approach. Firstly transitions are assumed to take place at a single point in each time period and the duration of the event must last at least one time period (typically a year, but may be of shorter duration). For example if the time period is a year, this approach rules out transitions in and out of unemployment over the course of a year. This is unrealistic, as many people will have unemployment transitions for periods of less than one year as in the case of seasonal workers. Therefore, the discrete time transitions simulate net transitions (see Galler, 1997) at discrete points in time, ignoring the transition path taken to reach the end state. Some models, for example MICROHUS and SESIM, therefore developed a workaround where the end state is stimulated together with an extra variable describing the transition. Take unemployment as an example, the method simulates both the employment status (end state) and the length of unemployment, which can be used to partially describe the transition with greater details.

Continuous time microsimulation models, on the other hand, usually use survival models to simulate the time of events. Rather than simulating annual transition probabilities, survival functions model the length of time an individual will face in his or her current state, for example DYNAMOD and SOCSIM (Hammel, 1990). The method was extensively discussed by Willekens (2006). Once a referencing event such as marriage has occurred, an individual is passed through each survival function that they are eligible for on condition of the current state. For example, once an individual is married, they become eligible for divorce. This process is continuously repeated until the end state, for example death, of the simulated individual.

While the continuous time model has some theoretical advantages as it pinpoints the time of events, it also has considerable practical limitations. The estimation of competing risks and survival functions place very high requirements on the data that are rarely matched by the actual data available (Zaidi & Rake, 2001). Given that most base datasets were collected yearly and many taxation procedures are reviewed annually, it is easier to incorporate a discrete time framework. Although a continuous time model could simulate the sequence of event occurrences, it still faces the estimation problems of interdependent processes and correlated error terms. In addition, the potential interdependence of transitions for members (e.g. family) further raises the complexity of implementation. See Zinn (2012) for a discussion of this issue in the case of the matching of individuals in partnership. Alignment for continuous models is more difficult as cross-sectional adjustments would erode the advantages of duration models, and the potential computation cost of alignment is much higher in continuous time models.

10.3.5. Open versus closed model

A decision dynamic microsimulation model builder has to consider whether the model should be open, closed or a mixture of the two. A model is often considered as 'closed' if, except in the case of new born and migrants, the model only uses a fixed set of individuals to create and maintain social links. Thus, if an individual is selected to be married, their spouse is selected within the existing population of the model. Similarly, a baby is always attached to a family within the sample. In contrast, an open model starts with a base population and new individuals are generated exogenously if spouses are required. This has the advantage that simulations for individuals (and their immediate families) can be independent of other individuals, thus allowing the model to run in parallel on different computer processors to reduce the run time.

Open models, for instance, PENSIM and LifePaths, have the advantage of having simpler interaction models, for example a newly married partner can be created artificially to fit the social economic characteristics of an individual. However, an open model is more difficult for matching external macro-aggregates, as the sample may not stay representative of the population as new individuals are created. Although possible, it is a non-trivial task to align a varying population with macro-aggregates, as the weights would require constant dynamic reweighting and in the case of heavy alignments, the benefits of running the model in parallel might be lost. Furthermore, the individuals created in an open model may not replicate the variations among actual individuals. Thus, a closed model approach is preferable when the model is used to simulate household-level variables, including equivalent household income and its derived variables such as the Gini or the at-risk-of-poverty rate. As a result, most dynamic population models in use utilise a closed model method in a cross-sectional ageing framework, whereas cohort models are often open and use longitudinal ageing method.

10.3.6. Link between micro- and macro-models

Microsimulation models increasingly interact with macro economy through either an alignment process or the computational general equilibrium (CGE) feedback. Alignment, as discussed earlier, offers a simple but limited way to enforce the aggregate statistics within a simulation. However, it is usually limited to very specific variables and does not change based on the feedback from simulated micro-data. Besides alignment, it is also possible to use CGE models to link macro, meso and micro models (see Ahmed & O'Donoghue, 2007; Davies, 2004). CGE models offer a potential opportunity to allow macro-models to interact with micro models via prices in different markets, which is particularly useful for analysing large scale macroeconomic shock. For instance, IFSIM links a microsimulation model with a simple CGE model with a single sector economy.

There are a few papers discussing the potential methods of linking a microsimulation model and a CGE model. Cockburn (2001) used an integrated approach to link a survey dataset within a CGE framework, where the main concept was to replace the traditional unit of analysis in CGE, representative household, with a real household. Another approach is to separate macro and micro components while allowing the result of the micro or macro-models is fed into the other models. Depending on the direction of the output feeding and the number of iterations, this approach was further subcategorised into 'Top-Down', 'Bottom-Up', 'Top-Down Bottom-Up' and 'Iterated Top-Down Bottom-Up' approaches (Baekgaard, 1995; Galler, 1990; Savard, 2003). Colombo (2010) compared several CGE microsimulation linkage methods and suggested the 'Iterated Top-Down Bottom-Up' as the currently most complete approach. However, with only few exceptions like NEDYMAS (Dekkers et al., 1993) which used the iterated approach, most macro-micro linking attempts in dynamic microsimulation models are limited to one-way only.

The integration of CGE with microsimulation is still limited at the current stage (Ahmed & O'Donoghue, 2007). This might be the result of several factors, including modelling complexity, data issues, model stability and computational costs. Robilliard and Robinson (2003) indicated that current approaches in linking micro-macro might still need to be refined before addressing distributional issues. In addition, linking with CGE requires decent quality of household income and expenditure data, which is not widely available. Furthermore, the integration between CGE and dynamic microsimulation could potentially exaggerate the uncertainty introduced in results due to the complexities in interactions of different social economic variables and a greatly increased computation time.

Given the complexity in incorporating a complete CGE model in microsimulation, it might be more feasible to incorporate a partial equilibrium into the model. A static microsimulation model, IZAΨMOD, allows feedback from a computed labour market equilibrium model to refine the labour supply behavioural responses. In a spatial microsimulation model, one may consider to model the feedback from the housing market. This type of single market equilibrium implementation can sometimes avoid the complexities introduced by the social accounting matrix and inaccurate expenditure data.

10.3.7. Links and integrations with agent based models

Although this chapter mostly focuses on the development of dynamic microsimulation models, it is also worth to note that microsimulation is closely related to two other individual level modelling approaches, cellular automata and agent based models (ABMs) (Williamson, 2007). In particular, ABMs are also used in social science to analyse macro level phenomena gathered from micro-units. An ABM typically consists of a set of autonomous decision-making entities (agents), a set of agent relationships and methods of interaction, and the agents' environment (Macal & North, 2010). It is often used to show how macro level properties such as spatial patterns and levels of co-operation emerge from adaptive behaviours of individuals.

Traditionally, ABMs are highly abstract and theoretical without many direct empirical applications (Boero & Squazzoni, 2005; Janssen & Ostrom, 2006). In recent years, however, there is a growing interest in ABM literature of injecting empirical data in an attempt to simulate some real-world phenomenon (Hassan, Pavon, & Gilbert, 2008; Parker, Manson, Janssen, Hoffmann, & Deadman, 2003). From a practical point of view, when ABMs add more socio-economic attributes to the agents, and when microsimulation models add more behaviour rules and interactions, they are moving toward to a common ground (Williamson, 2007). Some papers, for example Eliasson (1991), Baroni et al. (2009), etc., use the words interchangeably when behavioural models are included in microsimulation.

ABMs cover an important aspect of social economic modelling. For example, network effects, which have long been discussed by sociologists and economists, hardly exist in microsimulation models beyond the spouse matching. Microsimulation modellers often implicitly assume that the effects of social pressures and peer effects are already embedded in the existing distribution and they are likely to keep constant, that is there is no need to update the model as time passes. While this assumption might be acceptable for some research, such as tax reform analysis, it might be too strong for some other types of research, for example evaluating alternative health intervention policy. ABMs, on the other hand, often explicitly model these interactions and allow certain social factors to change as the population evolves.

With a growing number of social networking data, it is now possible to integrate empirically tested adaptive behaviours from ABM into microsimulation models to produce a more realistic model. The potential introduction of network effects could benefit a set of microsimulation models, for example health simulation models, in which the social factors may play a role. In addition, peer effects may also help to model the evolution of marriage and fertility patterns, the formations and dissolutions of neighbourhoods, which have been extensively discussed by Richiardi (2014).

It should also be noted that this potential integration may also bring some disadvantages. The implementations of micro interactions would greatly increase the computational cost and complexity, thus makes the model more difficult to understand and validate. Besides, the current base datasets of the microsimulation models are often standard surveys or census data that do not cover extensive network attributes. At the current stage, the implementation of extensive interactions like ABM in microsimulation models is still at its infancy, and the existing attempts are limited to the introduction of simple behaviour rules, for example copying consumption habits as in Lawson (2011).

10.3.8. Modelling transitions and behaviours

Microsimulation models could use structural behavioural models, reduced form statistical model or as simple transition matrix to simulate changes. Behavioural models are grounded in economic theory, in the sense that changes in institutional or market characteristics cause changes in the individual behaviours through an optimisation process. In contrast, reduced form statistical models aim to model the probabilities using relevant variables. It aims to reproduce observed distributional characteristics in sample surveys without explicit considerations on policies. Reduced form models usually do not respond to external market and institutional characteristics and implicitly assume a stable policy environment. Transition matrix is often a time-homogeneous Markov chain with limited number of states (e.g. age group, gender). It is the easiest way to model potential changes with least theoretical considerations.

Reduced form models and transition matrices are often used to simulate mortality, fertility, family formation, labour market transitions, etc. As these models usually do not depend on policy parameters, they are often restricted to simulating status quo, and are not suitable for reform analysis. The method is often used in static tax-benefit microsimulation models as well as the demographic components of dynamic microsimulation models.

In a structural behavioural model, policy parameters have a direct or indirect impact on the individual behaviours. An example could be a labour supply model that responds to changes in the tax-benefit system. Klevmarken (1997) outlined three criteria for choosing behavioural equations in a microsimulation model:

(1) They should be relevant for the objectives of the model.
(2) There should be major behavioural adjustments to the policy that the model is built to analyse.
(3) Behaviour that influences the fiscal balance should be included.

Examples of behavioural responses that fit these requirements include labour supply, retirement decisions, the effect of income and price changes on consumption, fertility and marital decisions, the take-up of social benefits and many others. In the case of labour supply models, structural behaviour simulation models typically consist of three subcomponents: an arithmetic tax-benefit model to estimate budget constraints, a quantifiable behaviour model using variables that can be simulated and a mechanism to predict the labour supply under a new policy environment (Creedy, Duncan, Harris, & Scutella, 2002).

Compared with earlier microsimulation models, more models today have incorporated behavioural responses into their design although these responses are often limited to labour market simulations. Models such as MICROHUS, PRISM, NEDYMAS, SAGE and LIAM all incorporate labour supply behavioural responses to the tax-benefit system, while SESIM, DYNAMITE, ANAC and SADNAP model retirement decisions depending on the social security system. However, there is still only limited implementation of life-cycle models in microsimulation and the study on the impact of prediction errors on simulation results is scarce.

10.3.9. Alignment with projections

As statistical models are typically estimated using historical datasets with specific characteristics and period effects, projections of the future may therefore contain errors or may not correspond to exogenous expectations of future events. In addition, the complexity of micro-behaviour modelling mean that simulation models may over or under predict the occurrence of a certain event, even in a well-specified model (Duncan & Weeks, 2000). Furthermore, behavioural models are often estimated on cross-sectional data or panel data of a very short time spans. The simulation results of these models over time may therefore become unrealistic, even though their results at any point in time are reasonable. Because of these issues, methods of calibration known as alignment have been developed to correct for issues related to the adequacy of micro projections. As a fortunate side effect, alignment allows for the use of dynamic microsimulation models for the policy assessment together with (and making use of) the simulation results of macroeconomic models (Dekkers, 2013).

Scott (2001) defines alignment as 'a process of constraining model output to conform more closely to externally derived macro-data ('targets').' Clearly, in an ideal world, a system of equations would be estimated that could replicate reality and give effective future projections without the need for alignment. However, as Winder (2000) stated, 'microsimulation models usually fail to simulate known time-series data. By aligning the model, goodness of fit to an observed time series can be guaranteed.' Some modellers suggest that alignment is an effective pragmatic solution for highly complex models (O'Donoghue et al., 2009), as it offers a connection between micro and macro-data.

Alignment also has its downsides, several being highlighted by Baekgaard (2002). Concerns raised regarding alignment include the issue of consistency within the estimates and the level of disaggregation at which this should occur. The implementation of alignment may twist the relations of key variables in an undesired way (Li & O'Donoghue, 2014). The existence of an alignment mechanism may constrain model outputs to always hit aggregate targets even if there has been an underlying behavioural or structural change. For example, if education levels rose, mortality rates would fall and the female labour force participation might increase. If the alignment mechanism for each process did not incorporate the impact of educational achievement, then an increase in the education level would have no effect on these aggregates. It has been suggested that equations should be reformulated rather than constrained *ex post*. Klevmarken (2002) demonstrated various potential methods in incorporating alignment information in estimations. Furthermore, changes of the individual states induced by alignment may be at odds with individual entry conditions. For example, in situations where the entry conditions into a state are based on retrospective data, alignment tables may not contain all variables required. It is for this reason that the so-called 'hard take and leave conditions' have been developed to be used jointly with alignment. These conditions a priori force or prevent individuals with predetermined characteristics to enter or leave a certain state and adapt the alignment tables to account for the sizes of these groups.

In most cases, alignment methods are only documented briefly as a minor technical part of the main model, and there is very limited number of studies analysing how projections and distributions change as a result of the use of different alignment methods. Despite the potential pitfall of its statistical properties, aligning the output of a microsimulation model to exogenous assumptions has become standard over the past decade. As Anderson (2001) noted, almost all existing dynamic microsimulation models are adjusted to align to external projections of aggregate or group variables when used for policy analysis. Continuous variables such as earnings are typically aligned with a fix ratio in order to meet the projected average or distribution, whilst binary variables, such as working status, are aligned with various methods, including multiplicative scaling, sidewalk and sorting based algorithms (see Morrison, 2006). Microsimulation models using historical datasets, for example CORSIM, align their output to historical data to create a more credible profile (SOA, 1997), while Models that work prospectively, for example APPSIM, also utilise the technique to align their simulations with external projections (Kelly & Percival, 2009).

10.3.10. Model complexity

To clarify the discussion, this section makes a difference between microsimulation models and partial models, where the former are included in the latter. Dynamic microsimulation is mostly built on the assumed parameters, estimated Markov chains and the conditional probability distributions estimated by various econometric methods. It usually involves many equations and parameters estimated or fixed by laws and regulations. Once the estimations and parameters are put in place, most microsimulation models follow a straightforward execution process without invoking computational complicated algorithms. The complexity of a microsimulation model, as a result, often comes from the constructions of the partial models and is mostly guided by the potential policy questions that the model is required to answer. Microsimulation models focusing on pension issues usually simulate detailed labour market behaviour for decades ahead, as a change in the pension system can only mature when the youngest cohort in the labour market retires. In contrast, short term tax policy models usually forward simulate 3–5 years and are typically limited to tax-related variables only. If a model is being used for a broad range of research questions, it usually needs to simulate more variables for a longer period of time, which involves greater complexities.

An ideal microsimulation model should have the capacity to simulate details of all possibly related variables. However, the costs of building large models, both in terms of model validity and management, need to be taken into consideration. Dynamic microsimulation models have the reputation of being complex and the potential to run 'out-of-spin' with regard to some aspects. This might be a particular concern when simulating policy reforms. Partial models, especially reduced form models, are often criticised for simulation purpose as the stability of the model structure is questionable when policies change. This argument is also known as

Lucas' critique. As a result, structural models are usually seen as a better choice. Since some part of the policies (e.g. tax) can be explicitly included in the structural model, the estimated utility parameters are perceived to be more stable (Klevmarken & Lindgren, 2008), although utility parameters can sometimes be very sensitive to even a small change in the model specification. Over fitting may also be a potential issue when the list of explanatory variables grows. Due to the number of partial models that one microsimulation model can invoke and the budget/time constraints, many microsimulation models are primarily constructed using reduced form partial models with some partial models of a structural nature in key components.

Complex structural models are much more difficult to validate and may often contain bugs in their implementation due to the increased complexity. In addition, the complexity of the processes often means long development time. Large general purpose microsimulation models are usually built by large teams with access to large and complex datasets. These models usually simulate a wide variety of economic and demographic processes and can therefore be used for many different applications. These forecasting models usually incorporate alignment systems in order to keep consistencies with external forecasts or macro-models. Models of this type include DYNASIM from the United States, the Canadian Pensions Program DYNACAN, SESIM in Sweden, MOSART in Norway, APPSIM in Australia, MIDAS in Belgium, and others.

10.3.11. Model validation

Given the increasing complexity of models, it is important to validate a model in order to maintain its credibility. Unfortunately, only limited effort has been placed on validation matters and there is no international consensus on validation procedures. Klevmarken and Lindgren (2008) suggest that validation should be put in the same context as estimation and testing and should involve the identification of all sources of errors and their properties. Given the size and structure of a large microsimulation model, bootstrapping and Monte Carlo exercises are likely to be more practical than the analytical deduction. In addition, sensitivity analysis on the models should also be part of the microsimulation validations (Klevmarken & Lindgren, 2008). In Morrison (2008)'s paper, DYNACAN published their method of the validation from a practical point of view. It lists several important components one should cover during a microsimulation validation process: context of validation, data/coefficient/parameter validation, programmers/algorithmic validation, module-specific validation, multi-module validation and policy impact validation.

Ex post analyses of previous periods can also be used to assess the reliability of a model, and this is also the reason why a number of the major microsimulation projects have taken historic datasets as their starting population base for simulations. For example, the CORSIM and POLISIM models are based on a sub-sample of the 1971 and 1960 US Censuses, respectively, and the DYNACAN model takes a sample of the 1970 Canadian Census as its base. By running the model forward to the present day, the model forecasts can be compared to what has actually happened (see for example Caldwell & Morrison, 2000; Morrison, 2000). However, these models invariably incorporate historical information such as macro-aggregates into the model and this may produce better forecasts compared with the results when the historical information is not available. One method to overcome this is to directly compare generated forecasts with what happened in reality, for example comparing forecasted labour participation rates with actual rates. Another method described by Caldwell (1996) is to use an indirect approach, known as a multiple module approach. An example cited by Caldwell is the case of validating the numbers of married persons with health insurance, when the directly simulated processes are marriage and medical insurance membership. Sources of error may result from errors in either or both direct processes, or because of mis-specified interactions.

Some types of dynamic models, however, may have no comparable source of validation. For example, some theoretical models that solely look at a single cohort living in a steady state have nothing with which they can be validated through external data source as they do not attempt to mimic real life. These types of models, due to the lack of validations, are often restricted in their interpretations of policy impact. Additionally, countries that have only recently developed their micro-data resources may not have alternative sources of data with which to validate, although this problem will become progressively less with time.

Recent developments suggest an alternative validation method using a simplified model. Since no future data is available to validate a forecasting dynamic microsimulation model, Morrison (2008) suggests comparing a model's result to a trustworthy model's result. Dekkers (2013) argues that the general trend of certain indicators estimated by a simple model could be seen as a benchmark for more complicated microsimulation model as there is no black box in a simple model. The Belgium MIDAS model used this approach to validate against a 'simple stylised' model, which is essentially a representative household model with only demographic and pension indexation components. This approach, however, raises another question on the criteria of a 'trustworthy' model. It is difficult to say which model is correct when the output of a stylised benchmark model differs significantly from the result of a comprehensive population model. Without further analysis, the differences between model outputs may only be used as indicative validation tests rather than anything conclusive.

10.4. Summary and future directions

10.4.1. Progress of dynamic microsimulation modelling since 1970s

In reviewing progress made by the field, it is useful to consider an early model development, the DYNASIM model developed by Orcutt, Caldwell, and Wertheimer (1976) in the Urban Institute in the early 1960s to mid-1970s. In terms of our classification above, DYNASIM was a longitudinal closed model running a 10,000 person dataset. It contained:

- A demographic module, modelling leaving home, births, deaths partnership formation and dissolution, disability, education and broad location.
- A labour market module containing participation, hours, unemployment and labour income.
- A Tax-Transfer and Wealth module containing capital income and the main tax and transfer instruments.
- A marriage matching module.
- As well as a simple macroeconomic model and feedback loops linked with the microsimulation model via alignment.

Thus in terms of generic structure, this 1970s model incorporates much of what has been included in later dynamic microsimulation models, although each component has been largely improved by the newer models. Despite the progresses in 1970s and 1980s, early microsimulation modellers faced a number of challenges, which were summarised by Hoschka (1986):

(a) Many of the behavioural hypotheses in microsimulation models are of insufficient theoretical and/or empirical basis.
(b) Dynamic changes in the behaviour of the population are mostly not regarded by micro modellers.
(c) The problems of including more than the primary effects of a policy programme are still unresolved.
(d) Quality and accessibility of the data required by micro models often are restricted severely.
(e) The development of micro-models frequently needs too much time and its costs are accordingly high.
(f) Running micro models usually requires a lot of computer time.
(g) The prediction quality of micro-models has not yet been systematically evaluated and validated.
(h) Large microsimulation models are so complex that they are difficult to comprehend and control.

These challenges can be broadly categorised into five different areas: behaviour response modelling (a-c), micro-data quality (d), development cost (e), limited computation capacity (f) and model validation (g-h). Comparing with some recent discussions in issues of microsimulation

(Harding, 2007a; Wolfson, 2009), it is clear that most issues mentioned are still relevant and high on the list several decades later.

By comparing the DYNASIM model structure with today's dynamic microsimulation models, and the challenges faced by the modellers in 1980s and today, what we are seeing are gradual advancements in the methodologies rather than breakthrough in model designs and applications. Improved computer hardware has allowed both improved speed and larger databases. Good quality data and software packages with built-in micro-econometric techniques have improved the sophistication level in individual models (see O'Donoghue, 2001). There has been some improvement also in the incorporation of behavioural responses, which allows the assessment of policy changes in their social economic impact on individuals. In addition, today's microsimulation modellers have proposed several methods to systematically validate the simulation output (Morrison, 2008). Another major advancement in the past decades is the emergence of generic models or development packages, including Modgen (Wolfson & Rowe, 1998), UMDBS (Sauerbier, 2002), GENESIS (Edwards, 2004, 2010), LIAM (O'Donoghue et al., 2009) and LIAM2 (Bryon, Dekkers, & de Menten, 2011). These can greatly reduce the workload of new modellers by providing commonly used and thoroughly tested microsimulation routines.

10.4.2. Obstacles in the advancement of microsimulation, and some possible solutions

While the field of microsimulation has progressed greatly in many aspects since the original paper of Orcutt (1957), the rate of progress in dynamic microsimulation, nonetheless, is arguably slow given that we still share the same model design and face similar problems as early DYNASIM modellers did nearly 40 years ago. There are a number of reasons could be ascribed to this lack of progress, including knowledge transfer, model ownership, unrealistic expectations and funding.

This section will discuss these issues and some interesting developments that (potentially) provide a silver lining. One criticism of the knowledge transfer mechanisms within the field is that most of the transfer has been via tacit knowledge rather than codified knowledge. Much important knowledge and methodologies have mainly been codified as 'documentation,' with the main aim to facilitate other team members utilising the models. In addition, microsimulation models are mostly developed in governmental or policy institutions, where developing a literature on which a wider group of scientists could build has been a secondary objective at best. Furthermore, the documents are mainly spread with limited books and conference presentations, which may not be easily available for researchers outside of the network. Additionally, the framework of traditional academic publications may not be suitable for complex dynamic microsimulation models. For one, it relies on preparing papers of 5–10 thousand words, which may not be enough to describe a complex model in depth. Additionally, many journals do not allow for (long) pieces of code, while it remains difficult to publish the results of work on and with microsimulation models in applied scientific journals.

Thus a significant proportion of the extensive methods used in the field are not formally codified, meaning that to a large extent new models have had to reinvent the wheel and re-develop existing methods over and over again. There are however various reasons why there might be hope that the transfer of knowledge will improve in the (near) future. First of all, researchers these days are much more aware of the actual and potential benefits of collaboration and the exchange of information between teams. Thus, there are many ad-hoc meetings where teams compare their models, results, and general experience. Furthermore, through the use and development of generic platform such as ModGen and LIAM2, information that was previously tacit now becomes codified and broadly available. This has also allowed for the dissemination of pieces of code or even entire models. For example, using a series of European projects, the Belgian model MIDAS (whose first version was based on the Irish model LIAM), has been 'exported' to teams in Hungary and Luxembourg. This of course reduced the development costs of the latter groups, while increasing the 'return on investment' of the Belgian development team, and allowing them to invest further in the development of LIAM2. Finally, open access to the source code of a model allows the findings to be replicated and could help to locate errors that the development team overlooked. Hence, moving from 'black box' modelling to a 'glass box' modelling could ease many potential users' concerns and raise the method's scientific status (Wolfson, 2009). The availability of less closed model frameworks such as GENESIS, LIAM and LIAM2 can facilitate the development of new models.

Another reason for the lack of progress was the perceived 'failure' of the earlier models. However this failure to some extent can be attributed to failing to meet unachievably high expectations. Orcutt et al. (1961) focused on the capacity to undertake prediction at a micro-level to facilitate planning. Human behaviour is of such complexity and is endogenous to economic analysis that dynamic microsimulation models cannot hope to make highly accurate predictions. Even well-specified econometric model over or under predicts the outcomes (Duncan & Weeks, 1998) and the explanatory value of especially micro-level logistic models remains modest even in the best of cases. For example, a microsimulation model studying poverty rates may exaggerate the impact of changes or developments, when the policy environment is complex and many individuals in the dataset are close to the poverty threshold. As George Box once said, 'All models are wrong, some are useful' (Box & Draper, 1987). This might be true for models that dive beyond the aggregate and aim to shed light to the chaos of individual changes over time. In being useful we can hope, by using good theory, data and statistical and computational methods, dynamic microsimulation models can provide a consistent and reasonable framework with which to undertake policies analyses incorporating intertemporal events and the distribution of the population.

Funding may also be a major issue facing many microsimulation modellers. Building and using large microsimulation models requires a team of researchers representing different disciplines and experiences. In addition, the scale of the model also suggests the need for long-term funding. These two requirements are almost routinely underestimated by semi-public research institutions, nor do they always fit well into a university department with its normal rotation of people and the three-year funding of research projects. As a consequence, most models are not actively maintained after the initial funding, which makes it difficult for people outside of the original team to utilise the model for other research purposes.

10.4.3. Future directions

The applications of microsimulation are widespread as suggested by the list of current and previous models outlined in Table 10.1. With the availability of better modelling tools and greater number of researchers from different fields engaging in microsimulation, the method is now applied in many fields other than the traditional welfare policy research. For instance, using microsimulation model as part of the tools to estimate impact of climate change (Buddelmeyer et al., 2009; Hynes, Morrissey, O'Donoghue, & Clarke, 2009), disease spread (Will et al., 2001), time use simulation (Anderson, Agostini, Laidoudi, Weston, & Zon, 2009), and even to assist personal financial planning (Avery & Morrison, 2011). The use of dynamic microsimulation models can be even further expanded as more micro-level data becomes available. With the better availability of the longitudinal data and administrative data, it is possible to better understand the consequence of ageing. In addition, the raise of the network data could help to model the disease spread and knowledge diffusion in a more realistic way.

While large dynamic models have their advantages for providing more comprehensive simulation outputs, the complexity also increases the difficulties in validation, model usages, management and funding. It might be also beneficial to develop some complementary, specialised simple dynamic models. Smaller models could be better validated and make it easier to publish the model details within the length limit of a journal article. These easy-to-validate smaller models could then be absorbed into a more complicated microsimulation model when the need for more complex interactions arises.

A problem that remains is how to deal with the sometimes unachievably high expectations, especially in semi-public research institutions where the outcomes of microsimulation models are used to assess the consequences of actual or potential policy measures. These expectations are often fuelled by the requirements for stable funding of enough researchers. A possible solution out of this deadlock might be researchers could focus more on scenario analyses instead of implicitly suggesting an accurate long run simulation. Assumptions are almost by definition more explicit in the former and there is less pressure to be a fortune teller. The changes in economic and politics climate also mean that all the simulations results may become obsolete in relative short time. Focusing on the scenario analyses could be more cost effective and relevant to the debate of contemporary issues.

Furthermore, academics might also use dynamic microsimulation to improve the understanding and modelling of inter-temporal behaviours. Traditionally, labour economists do not have access to the longitudinal data that covers the whole life-span of individuals. With the help of microsimulation, it is possible to generate budget constraints for use as input into life-cycle behaviour choice modelling, for example retirement choice as in Li and O'Donoghue (2011). The method would assist us to better understand the many inter-temporal processes, for example fertility decision, education choices, etc. The raising interest from the academic side would benefit the field development and ensures the sustainability of the knowledge.

In terms of the methodological development, a primary need is to codify the various methodologies that are currently being used in dynamic microsimulation models and to allow more countries than before access these techniques and models. There are many methods being used in microsimulation, most without any published description or evaluation. As noted above, this can impede the progress of the field. Formally documenting the methods used and publishing in a peer-reviewed journal could improve the knowledge diffusion and increase the public good returns by academics, providing incentive to innovate. Additionally, publications could preserve the knowledge that could have been lost due to the end of project funding. The *International Journal of Microsimulation* aims to be an important opportunity for citable peer-reviewed publications.

Another potentially important way in which information can be codified and distributed is by the dissemination of full models or modules and the further use and development of modelling frameworks like ModGen and LIAM2, both of which are freely available. This allows modellers to make use of previous work and methodologies developed by others at limited costs.

There remains room for improvement in understanding on the simulation properties of many algorithms used, including alignment, error term manipulation, complex reweighting and random numbers. In most models, each equation is estimated separately without considering the potential correlations in error terms. This may lead to undesired bias due to inconsistent assumptions when simulating some reforms. In addition, to improve the model credibility, it is worthwhile to pay attention to the testing and validation process of a simulation model. Additionally, papers using microsimulation model typically provide the result of only one-run although some papers, for example Pudney and Sutherland (1994, 1996) found that the microsimulation results could have a wide confidence interval. Dekkers (2000) argues that Monte Carlo approach can be used to assess the statistical significance of simulation results. Given the raising computing capacity available for researchers these days, modellers could potentially provide more information about the simulation, for example the confidence intervals of the result using Monte Carlo techniques.

Despite the discussions and the general consensus to improve validation process in microsimulation, there is still little guideline on how dynamic microsimulation models should be validated (Harding, 2007b). While DYNASIM documented many issues involved in the model validation, there are still many areas that need to be explored, such as behaviour responses validation, longitudinal consistency validation and module interactions. Besides the validation from the technical side, it is also worth considering to validate the simulation with historical data, from which we can learn what has been done right, how the simulation performs under different assumptions, etc.

10.5. Conclusion

This chapter has discussed some of main issues involved in constructing a dynamic microsimulation model and described some of the choices made by different models in use worldwide. The main issues discussed have covered some of the general model development issues, such as base dataset selection, cohort or population based model structure, programming environment and model validation. The chapter has also discussed some of the technical choices made in model implementation, such as whether the model should be open or closed, whether alignment algorithms should be used, whether the model should incorporate behavioural response to policy changes and links to the ABMs.

Over the past decades, microsimulation models have been applied to many different policy areas and a comparison of models as given in Table 10.1 illustrates the scope of application of past and current dynamic microsimulation models. Most dynamic microsimulation models listed can be categorised as discrete models using dynamic ageing approach. For newer models, alignment has become a standard component allowing interactions with macro-aggregates and more recently, simulation packages that are dedicated solely to microsimulation have become a viable option in model development. These packages, together with increased co-operation through meetings and code sharing, could significantly increase the development process.

The increasing use of microsimulation models has raised many technical challenges to meet the needs of more complex and accurate policy analyses. For instance, there is a growing interest in integrating CGE into microsimulation models, although the actual implementations of CGE microsimulation are at this stage restricted due to data and technical limitations. Behavioural responses in microsimulation could also be further improved and one should consider more life-cycle models when simulating inter-temporal choices. Microsimulation models could potentially implement some elements from ABM to allow dynamic behaviour interactions and adaptations. In addition, considering different unit of analysis, budget and political constraints, may also broaden the field of microsimulation applications. Furthermore, certain practices within the simulations, such as alignment for complex models, and error term simulation, should be more thoroughly studied.

Besides technical challenges, there are also some general issues in the field. The lack of documentations often forces new modellers need to reinvent the wheel; closed sourced models which slow down the knowledge transmission. The unrealistically high expectation in long run simulation may challenge the creditability of the model and make applying for funding more difficult in long run. Future modellers may help to address these issues by publishing model details in academic journals and be more open on the algorithm implementations. Newer modelling platforms attempt to be more open and transparent in the software source code, which would potentially benefit the field development and knowledge transmission. In addition, the field can also explore topics other than taxations and standard government policies. Topics like the impact of climate change, the social consequence of ageing, for instance, could also potentially gain benefits from microsimulation techniques.

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