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The evaluation of health policies through microsimulation methods

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Abstract

This paper presents an overview of microsimulation as a method to evaluate health and health care policies and interventions. After presenting a brief survey of microsimulation models and applications we describe the main features of the approach and how these are implemented in practice. We pay particular attention to the innovative features of dynamic microsimulation as a method of ex-ante policy evaluation. The final section describes two leading microsimulation models, POHEM and FEM used to simulate lifecycle health trajectories and associated health care costs under competing policy scenarios to illustrate the power of microsimulation as a valid and relevant tool for policy evaluation.

Key words: microsimulation methods, policy evaluation, health, public health interventions.

JEL classification: C15 C21 C53 I10 J11

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1. Introduction

Establishing the effectiveness of health policies is central to understanding their value in improving health and reducing inequalities in health. However, there exists a substantial gap between the evidence base and the formulation of health policies, particularly in fields such as public health (Wanless, 2004; Allin et al., 2007) where methodological and practical challenges often restrict the ability to undertake robust policy evaluation (Petticrew et al., 2004). Accounting for issues such as population heterogeneity, multiple outcomes, spillovers and externalities and the capacity to capture the long-run effects of an intervention pose substantial challenges for the identification of the effects of a policy that hamper traditional methods for policy evaluation.

The literature on methods for policy evaluation is dominated by ex-post techniques which by definition are used to evaluate the impact of interventions and programmes following their implementation. In order to measure a treatment effect, commonly employed techniques such as matching, instrumental variables, control functions, regression discontinuity designs and difference-in-differences require the availability of data on individuals in a control and treated group and often both before and after the implementation of the policy under scrutiny. A fundamental requirement of all ex-post evaluation techniques is however that the policy has been implemented. In contrast, ex-ante policy evaluation methods, such as microsimulation (Bourguignon and Spadaro, 2006) and structural modelling (Todd and Wolpin, 2006a; Wolpin, 2007) attempt to overcome the requirement to collect data post-implementation by simulating the response. The simulated response under the policy can then be compared to the simulated response assuming either no change or a competing policy to evaluate the impact under alternative relevant scenarios. The flexibility afforded by the simulation approach broadens the scope of the evaluation problem beyond the identification of quantities such as an average treatment effect when assessing the impact of an intervention on a specific outcome of interest.

The literature has identified three main advantages of ex-ante policy evaluation techniques over ex-post methods (Todd and Wolpin, 2006b). First, ex-ante evaluation has the ability to predict the potential impact of a series of policies as well as the

impact of a specific policy under different scenarios. Second, an ex-ante appraisal can identify ineffective programmes before they are rolled-out and hence avoid the potentially high cost of implementation and subsequent withdrawal. Third, by providing evidence on the likely impacts of a policy, ex-ante evaluation can complement and inform subsequent ex-post evaluation of the same programme. For these reasons ex-ante evaluation offers an important tool to inform the design of policies, their implementation and subsequent refinement.

Microsimulation is an established method for the ex-ante evaluation of public policies (Creedy and Duncan, 2002; Creedy and Kalb, 2005; Spadaro, 2005; Bourguignon and Spadaro, 2006). The application of these techniques has, however, largely focused on simulating tax-benefit and pension systems and extensions to the evaluation of health and health-related policies is still limited (Spielauer, 2007). Microsimulation techniques simulate individual behavioural responses at a micro-level of policies yet to be implemented. The method attempts to mimic a natural experiment with the major difference that instead of outcomes being observed following a policy shock, they are simulated or imputed on the basis of a set of assumptions about the behavioural reactions of individuals following changes in the economic environment brought about by the introduction of a policy. Accordingly, a fundamental consideration is the quality of the model used to predict behavioural responses. One of the main advantages offered by the approach is the ability to account for the widest heterogeneity possible within the population of interest together with a focus of analysis at an individual level allowing the identification of both the mean and distributional impact of a reform. Moreover, dynamic microsimulation techniques are capable of measuring the effects of a policy across a number of time-horizons allowing for both short-run and long-run effects to be assessed.

The aim of this paper is to present a review of microsimulation methods for the ex-ante evaluation of health and health care policies. The following section describes the fundamentals of the approach using a taxonomy of models covering arithmetic and behavioural and static and dynamic microsimulation. We pay particular attention to the use of dynamic microsimulation models as an innovative method for the evaluation of policy interventions and discuss the implementation of this method in practical situations. Section 3 presents a brief review of existing microsimulation

models which incorporate a health component. This is complemented with a more detailed overview of two of the most comprehensive microsimulation models involving health, Population Health Model (POHEM) and the Future Elderly Model (FEM). These models illustrate well the scope and use of microsimulation in evaluating health and health related policies. Section 5 concludes.

2. Fundamentals of microsimulation

2.1 Origin and current use

Microsimulation was first introduced in the seminal work of Orcutt (1957; 1960). In his pioneering paper “A new type of socioeconomic system” (1957), Orcutt identified the need for models that could provide better long-term predictions about the effects of alternative governmental actions. In order to facilitate and improve model predictions, he underlined the necessity to correctly characterise the behaviour and interactions of the elemental decision-making units (individuals, households or firms) within the socioeconomic system represented. Further, in describing the mechanics of this new type of approach, he suggested the recursive and discrete-time structure that still represents the benchmark for the majority of current dynamic microsimulation models. Despite its heritage, however, the method has gained popularity only recently in accordance with increasing computing power and the availability of micro-data.

Microsimulation is regarded as a powerful tool for the analysis of the impact of public policies and has become a widely accepted instrument to shape and support government policy making. Prominent examples of microsimulation models employed by government departments to simulate the impact of policies include STINMOD (Australia), CBOLT, GEMINI and PENSIM (USA) and IGOTM (UK). STINMOD (Static Incomes Model) is a microsimulation model of Australia’s income tax and transfer system developed by NATSEM (the Australian National Center for Social and Economic Modelling).¹ This model is currently used by a number of Australian government departments to analyse the distributional impact of different

¹ This is a very partial list of existing government-used microsimulation models. For a comprehensive overview of microsimulation models and their users, see the website of the International Microsimulation Association, <http://www.microsimulation.org/>.

fiscal and income support programmes.² The Congressional Budget Office Long-Term (CBOLT) dynamic microsimulation model is used by the U.S. Budget Office to analyse the distributional effects of the American Social Security programme and other federal policies. GEMINI and PENSIM are two dynamic microsimulation models built and maintained by the Policy Simulation Group (U.S. Department of Labor) employed mainly to analyse the effects of different social security and retirement policies. Among other institutions, the U.S. Government Accountability Office (GAO) has used these models since 2001 to produce pension and social security reports.³ Finally, the Inter Government Tax-Benefit model (IGOTM) is a static microsimulation model that projects income and population distributions using data from a variety of U.K. national surveys. IGOTM is currently employed by HM Treasury, HM Revenue and Customs and by the Office for National Statistics to provide policy advice on the impact of tax-benefit reforms on UK households.⁴

For the purpose of policy evaluation, microsimulation aims to simulate changes in individual behaviour following the introduction of a policy. At their core, microsimulation models consist of two main components: a micro-dataset and a model that informs behavioural change under both current (or a default) and counterfactual policy scenarios. Although microsimulation models differ widely due to the structure and characteristics of the model used to represent individual behaviour (e.g. whether based on a behavioural structural model and a dynamic or static framework), the key feature embedded in all microsimulation models is the ability to *generate* individual-level data under different policy scenarios. For example, behavioural microsimulation models of labour supply, used to evaluate the impact of fiscal policies on individuals' employment transitions, incorporate arithmetical tax-benefit models that produce net incomes for different tax-benefit regimes. In contrast, dynamic microsimulation models project population samples over time, modelling life course events (such as household formation and dissolution, education, health and labour market status, etc.) under various policy rules.

² For a detailed description of this model, see NATSEM's STINMOD page at http://www.canberra.edu.au/centres/natsem/research-models/projects_and_models/stinmod

³ For more information on the U.S. based Policy Simulation Group (a research group based at the U.S. Department of Labor), their sponsors, models as well as their users, see <http://www.polsim.com/index.html>.

⁴ See *e-business strategy*, HM Treasury, October 2000 (p.30). Web-link: <http://archive.treasury.gov.uk/pdf/2000/ebusiness050101.pdf>

A number of authors have proposed a useful taxonomy of microsimulation models which broadly consist of arithmetical versus behavioural models and static versus dynamic models and the reader is referred to these for further information (Anderson, 1997; Klevmarken, 1997; O'Donoghue, 2001; Zaidi and Rake, 2001; Bourguignon and Spadaro, 2006). In the next section, we follow this classification to highlight and illustrate the main features of microsimulation models encountered in the applied literature.

2.2 Arithmetical versus behavioural models

Arithmetical microsimulation

Arithmetical microsimulation models (sometimes referred to as “micro-accounting models”, Cogneau et al., 2003) ignore individual’s behavioural responses to the policy under scrutiny. In the case of a tax-benefit model, arithmetical microsimulation simply simulates the change in real disposable income of individuals, following the introduction of a tax reform under the assumption that individual behaviour is unchanged (i.e. individual behaviour is exogenous to the tax-benefit system). Although based on this restrictive assumption, arithmetical microsimulation models are useful in illuminating the first-round effects of a reform and identifying the gainers and losers together with their characteristics. This will provide an approximation of the impact of the reform on individuals’ welfare. Information at the individual level can be aggregated and compared between policy-relevant social groups and analysed using social welfare indicators such as inequality and poverty indices (Atkinson et al., 2002). Further, Bourguignon and Spadaro (2006) show that the arithmetic evaluation approach, when used with the purpose of measuring changes in individual and social welfare and under certain conditions (when a reform causes marginal changes only to individuals’ budget constraints and individuals are optimising exclusively on the basis of their budget constraint) is consistent with the presence of behavioural responses. Arithmetical models have been used to examine indirect taxes and tax reforms both in developed and developing countries (Creedy, 1999; Sahn, 2003); to estimate the incidence of public spending in education and health (Demery, 2003) and to test and compare the effects of fiscal policies in different countries of the European Union (Atkinson et al., 1998, 2002; Callan and Sutherland, 1997; De Lathouwer, 1996). A number of governmental and research institutions

currently use arithmetical microsimulation models to estimate the budgetary and distributional impacts of a range of hypothetical and actual policy changes (within the UK these include, the HM Treasury Inter-Governmental Tax Model, *IGOTM*, the Pension Policy Simulation, *PPS*, model of the Department for Work and Pensions and the tax-benefit model of the Institute for Fiscal Studies, *TAXBEN*).

Behavioural microsimulation

In contrast to arithmetical models, behavioural microsimulation accounts for the behavioural response of agents to a policy reform. This means that changes to institutional, market or individual characteristics affect directly the *behaviour* of the micro-units within the model. A distinctive characteristic of such models is that the behavioural responses are grounded on economic theory and commonly involve the estimation of structural econometric models. Tax-benefit models that incorporate labour supply responses are typical examples of behavioural microsimulation models (Creedy and Duncan, 2002). For such models, changes in the tax-benefit system directly affect an individual's budget constraint which in turn may lead to a change in labour supplied. The purpose of these models is to provide an exact prediction of the change in labour supply under alternative tax-benefit scenarios, and the characteristics of the individuals impacted by the policy. To illustrate the characteristics of a behavioural microsimulation model we use labour supply as an example.

In order to illustrate the mechanics of a representative behavioural microsimulation model of labour supply, we follow broadly Creedy and Duncan (2002) and Bourguignon and Spadaro (2006). For a standard continuous model of labour supply, an individual i maximises her own utility $U(\cdot)$ subject to a budget constraint that includes the tax-benefit system $t(\cdot)$. According to this general framework, individuals derive utility from consumption, c_i , and leisure, L_i , defined in terms of the difference between an individual's time endowment T_i and the level of hours worked H_i , $L_i = T_i - H_i$. The optimisation problem can be defined as:

$$\text{Max } U(c_i, L_i; X_i, \beta, \varepsilon_i) \text{ s.t. } c_i \leq I_i + w_i H_i + t(H_i, w_i H_i, I_i; X_i; \gamma) \quad (1)$$

where X_i represent individual socio-demographic characteristics, β is a common preference parameter and ε_i , in the simplest stochastic utility structure, is an idiosyncratic term that represents the optimising error.⁵ In the budget constraint, I_i is the (exogenous) household non-labour income, w_i is the wage rate and $t(\cdot)$ represents the tax-benefit system. $t(\cdot)$ depends on labour supply H_i , labour income, $w_i H_i$, household non-labour income together with individual socio-demographic characteristics. The term γ represents the parameters of the tax-benefit system (i.e. the various taxes and transfers). Through this framework it is possible to simulate individuals' employment responses to alternative tax-benefit regimes by simply modifying the set of parameters of the tax-benefit system (γ) and comparing the estimated levels of labour supply provided by individuals before and after the change.

In this partial equilibrium setting, the change in labour supply is thus defined by the following difference:

$$H_i^R - H_i = F(w_i, I_i; X_i; \hat{\beta}, \hat{\varepsilon}_i; \gamma^R) - F(w_i, I_i; X_i; \hat{\beta}, \hat{\varepsilon}_i; \gamma) \quad (2)$$

where H_i^R and H_i are the level of hours worked derived from the labour supply functions estimated for the reformed and baseline tax-benefit system, respectively. The change in disposable income can be computed accordingly:

$$C_i^R - C_i = w_i(H_i^R - H_i) + t(H_i^R, w_i H_i^R, I_i; X_i; \gamma^R) - t(H_i, w_i H_i, I_i; X_i; \gamma) \quad (3)$$

Given the difficulties related to the estimation of this type of continuous model in the presence of non-linearity and non-convexities in complex tax-benefit schedules, the literature has tended to favour a discrete-choice approach to behavioural microsimulation modelling of labour supply (Callan and Van Soest, 1996; Bingley and Walker, 1997; Keane and Moffitt, 1997; Duncan and Harris, 2002; Andrén, 2003;

⁵ More sophisticated models distinguish between an optimizing error and random preference heterogeneity. In this type of model, optimising errors are simply regarded as errors in perception of the alternative utilities or as unobserved alternative-specific utility factors whereas random preference heterogeneity is intended to reflect random preferences derived from unobserved individual characteristics. For a brief discussion, see Brewer et al., 2005.

Brewer et al., 2006; Labeaga et al., 2008). Under this approach, an individuals' labour supply is approximated through a discrete-choice variable that can assume only a finite number of values within a set of hours worked. Each hour band corresponds to a given level of utility as defined by the budget constraint. While this method resolves part of the difficulties related to nonlinear tax schedules, rounding errors in the definition of hour levels can be introduced and it is good practice to undertake sensitivity analysis (Duncan and Harris, 2002).

In their most general representation, discrete-choice microsimulation models of labour supply can be defined as follows:

$$H_i = N_j \text{ if } U_i^j = f(w_i, c_i^j; X_i; \beta^j, \varepsilon_i^j) \geq U_i^k = f(w_i, c_i^k; X_i; \beta^k, \varepsilon_i^k) \text{ for } k \neq j \quad (4)$$

N_j is the number of hours worked corresponding to the j th alternative among the finite set of discrete hours choices; U_i^j is the level of utility provided by alternative j and c_i^j is the alternative-specific income defined by the following budget constraint:

$$c_i^j = I_i + w_i N_j + t(N_j, w_i N_j, I_i; X_i; \gamma) \quad (5)$$

Although different functional forms have been proposed to define individual preferences $f(\cdot)$, a direct quadratic utility function (i.e. usually containing additive linear and quadratic terms for income and hours worked) has gained wide popularity in the empirical literature and represents the benchmark for this type of model (Keane and Moffitt, 1998; Blundell et al., 2000). For estimation, the idiosyncratic term ε_i^j is often assumed to follow a Type I Extreme Value distribution. This leads to a conditional logit model, a model that nests the standard multinomial logit model. An alternative empirical specification that further accounts for work specific or institutional constraints in discrete labour supply models is the Dogit model (Gaundry and Dagenais, 1979). This model includes and parameterises what is termed the degree of "captivity" for each discrete outcome within the set of hours choices. The captivity parameter represents an hour band specific employment constraint that facilitates the modelling of employment responses to be extended beyond pure

preferences. Notwithstanding its flexibility, few empirical studies have adopted the Dogit model in the context of behavioural microsimulation modelling of labour supply (Harris and Duncan, 2003).

Reviews of applications of behavioural microsimulation models of labour supply can be found in Creedy and Duncan (2002) and in Creedy and Kalb (2005). Although behavioural microsimulation models have the advantage of being grounded in economic theory, they are usually policy-specific and thus require the estimation of a particular behavioural model that fits the policy to be evaluated. As a consequence, they are often not generalisable to the evaluation of other policies.

2.3 Static versus dynamic models

Static microsimulation models do not incorporate a time element in the analysis. The behavioural model of labour supply described in the previous section can be considered an example of a static microsimulation model as it considers an individual's employment response to a policy in the current period. In contrast dynamic models adopt a life-cycle perspective and project the population structure through time. This consists of the creation of a synthetic population through the simulation of individuals' life trajectories using what are termed static or dynamic ageing techniques. Static ageing produces projections of the population over time by simply re-weighting parts of the sample according to the future expected characteristics of the population with weights usually set using official population projections. The underlying demographic and socioeconomic characteristics of individuals remain constant over time with changes to the weight attached to each individual to produce the synthetic future population. In contrast, dynamic ageing is based on the creation of transition probabilities to update individual demographic and economic characteristics over time. Accordingly, the demographic and socioeconomic profile of the synthetic population is based on the assumptions implicit in the underlying transition probabilities. While static ageing simply brings a population sample into line with external estimates at a specific point in time, dynamic ageing is concerned with the underlying economic and social processes which generate changes within the population (Zaidi and Rake, 2001).

Dynamic ageing can be represented in discrete or continuous time and typically incorporates life-course events such as demographic changes (i.e. fertility, marriage formation and dissolution, mortality), educational attainment, labour market transitions and, more rarely, the evolution of individual health status (O'Donoghue, 2001). Microsimulation models based on ageing techniques incorporate Monte Carlo simulation methods to generate a stochastic process that determines individual transition probabilities. These are used to update the characteristics of individuals over time. The implementation of the Monte Carlo simulation will depend on whether the model is assumed to operate in discrete or continuous time. This is discussed in more details below.

2.3.1 Discrete-time dynamic microsimulation models

Markov chain models and Monte Carlo simulation methods

Discrete-time dynamic ageing is usually based on a first order Markov process. In the simplest representation of a first order Markov process, for any individual demographic or socioeconomic event E an individual transition probability from state e_k at time t to state e_j at time $t + 1$, depends only on their characteristics at time t :

$$P_{kj} = P(E_{t+1} = e_j \mid E_t = e_k) \quad (6)$$

The resulting transition matrix includes all possible transition probabilities between the set of states at time t and the set of states at $t+1$ and can be described as follows:

$$P_{m \times n} = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1j} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2j} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ p_{k1} & p_{k2} & \cdots & p_{kj} & \cdots & p_{kn} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mj} & \cdots & p_{mn} \end{pmatrix} \quad (7)$$

where the set of transitions from t to $t + 1$ is given by the m rows and the n columns of the matrix. Accordingly, the k -th row, $p_{k1} \ p_{k2} \dots \ p_{kj} \dots \ p_{kn}$, is a vector that contains the probabilities of all possible transitions from state e_k into any other state within the set of events at time $t + 1$ (Mazzaferro and Morciano, 2008). The resulting matrix, P , is a square positive matrix with the same number of states at t and $t + 1$. Hence,

$$0 \leq p_{kj} \leq 1, \forall k, j \text{ and } \sum_{j=1}^n p_{kj} = 1 \text{ for } k = 1,..m.$$

The occurrence of a transition between two states is established using Monte Carlo simulation. For the i -th observation and for each state, a random number r is drawn from a uniform distribution in the interval $[0,1]$ at every time interval t , r_{ijt} . A transition occurs if the generated random number is less than or equal to the probability of the event to occur: $r_{ijt} \leq P_{ijt}$. If the random draw from the distribution exceeds the probability, $r_{ijt} > P_{ijt}$, the individual remains in the state of origin.

There exist a variety of discrete-time dynamic microsimulation models built for a variety of purposes and using data specific to a wide range of countries. A leading example of discrete-time dynamic microsimulation modelling is *CORSIM* (Cornell Simulation Model). *CORSIM* (Strategic Forecasting, 2002) models a range of demographic events such as birth, death, marriage and divorce, immigration and emigration together with levels of education, work and earning patters and the accumulation of assets and debts using annual discrete-time simulations. *CORSIM* was used as a template by the Office of Chief Actuary (OCA) of the Canadian Government for the development of *DYNACAN* (Dussault, 2000), a dynamic microsimulation of the Canadian population, as well as by the Swedish Spatial Modelling Centre for the construction of *SVERIGE*, a spatial dynamic microsimulation model for Sweden. Comprehensive surveys of discrete-time dynamic microsimulation models can be found in O'Donoghue (2001), Zaidi and Rake, (2001) and Cassells et al. (2006).

An example for health

We illustrate the implementation of Monte Carlo simulation to compute transitions using health states as an example. Several methods have been proposed to estimate transition probabilities in discrete-state panel data Markov chain models (Singer and Spilerman, 1974; Tuma and Hannan, 1984; Laditka and Wolf, 1998) and for our purposes, we follow the approach proposed by Laditka and Wolf (1998) who consider a transition process between four states: three non absorbing states of functional health limitations and a fourth absorbing state, death. The non-absorbing states are unimpaired (or active), being moderately impaired (having one or two impairments in activities of daily living, ADL) and being severely impaired (having three to five ADL limitations). Accordingly, we have a multinomial variable of health limitation status, L that can assume four values: U (unimpaired), M (moderately impaired), S (severely impaired) and D (dead). Transition probabilities between two consecutive periods of time, t and $t+1$, can be expressed as:

$$P_{kj} = P(L_{t+1} = j | L_t = k; X_t) \quad (8)$$

For each individual the probability of being in a particular state in the next time period ($t+1$) depends on the state in the current period (t) together with current period socioeconomic characteristics, X_t (e.g. age, ethnicity, education, income, marital status, etc.). The transition probabilities can be arranged in a 4×4 matrix as follows:

$$P = \begin{pmatrix} P_{UU} & P_{UM} & P_{US} & P_{UD} \\ P_{MU} & P_{MM} & P_{MS} & P_{MD} \\ P_{SU} & P_{SM} & P_{SS} & P_{SD} \\ P_{DU} & P_{DM} & P_{DS} & P_{DD} \end{pmatrix} \quad (9)$$

where $P_{DU} = P_{DM} = P_{DS} = 0$ and $P_{DD} = 1$, due to the absorbing nature of death. To populate the remaining 12 transition probabilities, we estimate multinomial logit models with covariates representing individual socioeconomic characteristics and health limitation status. A separate model is estimated for each row of the transition matrix. Again, Monte Carlo simulation methods are used to establish the actual incidence of transitions between different health states in consecutive periods of times

by comparing the predicted probability for any transition, p , with a random number, r , drawn from a uniform distribution $U \sim U[0,1]$. The transition occurs if $r \leq p$, otherwise the individual remains in their current health state.

Implementation of a typical discrete-time dynamic microsimulation model

Discrete-time dynamic microsimulation models are typically structured on a modular basis where events are usually represented as a set of univariate processes that follow a hierarchical order. This structure is represented in Figure 1. The figure shows the starting point of a dynamic microsimulation model, the baseline dataset, the modules used to simulate individual events (in this stylised example, demographic, health and labour market modules) and the outcome produced by the simulation; here the difference in the trajectories between a baseline scenario and an alternative under evaluation.

(Figure 1 about here)

A fundamental component of any dynamic microsimulation model is its baseline dataset. This is usually composed of a main source, based on individual records taken from survey or administrative data, augmented with information imported from additional sources, using imputation or matching techniques. The rationale behind the use of multiple sources of data is often to fill information gaps in the primary data source or simply to integrate external information. Ultimately, the essential requirement for a baseline dataset is for it to be representative of the population relevant for the policy being simulated (Martini and Trivellato, 1997).

In a discrete-time setting, all individuals at a particular time period t are at risk of experiencing a series of events. The occurrence and timing of each event are established according to the Markov chain Monte Carlo rules outlined earlier. Depending on the focus of the model, modules and events may differ. However, the majority of discrete-time dynamic microsimulation models include demographic events (such as birth, mortality, household formation and dissolution and more rarely immigration), education and labour market-related events (e.g. modules that “attach” a degree to each individual and subsequently consider transitions into and out of as

well as within the labour market) and less commonly health events, usually in the form of a stylised health status (for example, a binary measure of individual health status, being in good health or ill-health). Richer dynamic models might also contain modules that compute labour earnings, non-labour income, expenditures as well as reproducing the tax and social security systems of a specific country.⁶ The baseline dataset modified by the transitions incurred by individuals at the end of a time period t becomes the input dataset for the following time period, $t + 1$. This is repeated until the entire dynamic simulation cycle is complete (i.e. until the last time period considered is reached).

An essential feature of a typical discrete-time dynamic microsimulation model is the hierarchical nature of the events represented. The sequence of events within each time period is established *a priori* by the model builder. Hence, the sequence of causal relationships between key events within an individual's life is pre-determined. Although this modelling strategy allows the researcher to control the consequence of changes within the chain of events, ignoring the potentially numerous endogeneity issues could seriously hamper the reliability of the model's results.

2.3.2 Continuous-time dynamic microsimulation models

Dynamic microsimulation can be implemented in continuous-time using duration models. In this framework, the variable of interest is the time to occurrence of an event (in this case, the time to a transition between an origin state and a destination state). Within this setting, a central mechanism that governs the timing of events is the concept of the inverse distribution function or *quantile function*. While a distribution function transforms a real number into a probability, the quantile function translates a probability into a real number (Willekens, 2006, 2009). In continuous-time dynamic microsimulation models, the quantile function is used to transform the probability of a transition from one state to another into a real number that represents the time to an event.

⁶ One of the most comprehensive discrete-time dynamic microsimulation models is the Australian Population and Policy Simulator (APPSIM) that is currently under development at NATSEM, University of Canberra. For a brief overview of the APPSIM simulation cycle, see http://www.canberra.edu.au/centres/natsem/research-models/projects_and_models/appsim

In continuous-time duration models, the time to an event T can be considered a random variable with the following cumulative distribution function (cdf):

$$F(t) = \Pr(T \leq t) \quad (10)$$

The cdf represents the probability that the duration spell length is less than t in the interval from 0 to t (i.e. the probability that the transition between two states occurs in the period between 0 and t). The probability that the duration equals or exceeds t is defined by the survivor function:

$$S(t) = \Pr(T > t) = 1 - F(t) \quad (11)$$

The concentration of events along the time axis is given by the density function that is the slope of the survivor function expressed as follows:

$$f(t) = \frac{\partial F(t)}{\partial t} = -\frac{\partial S(t)}{\partial t} \quad (12)$$

The instantaneous rate of leaving a state conditional on survival to time t is given by the hazard function that can be expressed by:

$$h(t) = \lim_{\Delta_t \rightarrow 0} \frac{F(t + \Delta_t) - F(t)}{\Delta_t} \cdot \frac{1}{1 - F(t)} = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)} \quad (13)$$

The cumulative hazard function (or integrated hazard function) can be obtained by integrating the hazard rate at each instant in time:

$$H(t) = \int_0^t h(u) du \quad (14)$$

The timing of the transition for an individual i is given by $G(r_i)$ where r_i is a random value drawn from a uniform distribution in the interval $[0,1]$ and G is the inverse distribution function of T , i.e. $G = F^{-1}(t)$. That is, the inverse distribution function or

quantile function is used to map the realisation of the random draw into a real number t which indicates the timing of the transition. Hence, in the context of continuous-time dynamic microsimulation, the decision rule that is used to set the timing of an event entails two stages. First, a random number r_i is drawn from a uniform distribution $U \sim U[0,1]$. Second, a quantile function of the probability distribution $F(t)$ is used to convert this number r_i into a real value of t .⁷

An example: simulating the time to transitions

As an example, we consider the simulation of the time to transition between different states produced using a Cox proportional hazard model, a widely used duration model (Bender et al., 2005). The Cox proportional hazard model can be defined through its hazard function:

$$h(t / X) = h_0 \exp(\phi' X) \quad (15)$$

where t is time, X is a vector containing a set of covariates that define a series of individual socioeconomic characteristics, ϕ is a vector of regression coefficients and h_0 is the baseline hazard function (i.e. the hazard function in the absence of covariates, $X=0$). The survival function of the Cox proportional hazard model can be written as follows:

$$S(t / x) = \exp[-H_0(t) \exp(\phi' X)] \quad (16)$$

where H_0 is the cumulative baseline hazard function. The distribution function of this model is:

$$F(t / X) = 1 - \exp[-H_0(t) \exp(\phi' X)] \quad (17)$$

⁷ In the majority of applications, the distribution $F(t)$ is assumed to be either exponential, Gompertz or Weibull. If the time to a transition event follows an exponential distribution, then transitions are assumed to occur at a constant rate. In case of a Gompertz distribution, the transition rate changes exponentially with duration while with a Weibull distribution the transition rate varies with duration following a power function of duration.

Let r be a random number drawn from a uniform distribution $U \sim U[0,1]$. Then, the simulated time to transition T is produced using the inverse or quantile function of the Cox proportional hazard model that takes the following form:⁸

$$F^{-1}(t / X) = T = H_0^{-1}[-\log(r) \exp(-\phi' X)] \quad (18)$$

Accordingly, the simulated time to transition depends on a constant transition rate and a set of covariates. It should be noted that the Cox hazard model is not restricted to the exponential distribution and that a set of alternative survival time distributions can be used to generate simulated times to transition using Cox hazard models (for an overview, see Bender et al. 2005).

The individual life-cycle in continuous-time dynamic microsimulation modelling

In continuous time dynamic microsimulation the life-cycle of an individual can be modelled in two alternative ways (Willekens, 2009). One possibility is to simulate the entire life-cycle of an individual until the event death before starting the simulation of the life-cycle of another individual. For each individual separate time to transitions are simulated for competing events (e.g. demographic transitions, labour market transitions, transitions between different health states, etc.). The first state transition to occur is established by choosing the shortest time to transition.

An alternative is to employ discrete-time duration analysis and model segments of an individual life-cycle. The procedure consists of breaking down the continuous time frame into a series of discrete spells and considering the simulation of a set of events (transitions) within these spells. The length of the spells can vary according to the specific need of the modeller but most applications use spell lengths of one year (Willekens, 2009). In this framework, transitions from one state to another occur by comparing the simulated time to transition for each specific event with the length of the time spell. For example, if we consider spells of the length of n years and a simulated time to transition, t , the transition occurs during the first spell n if the simulated time to transitions is less than n , ($t < n$). This framework also accounts for repeatable events (i.e. events that can occur more than once such as child birth, labour

⁸ It should be highlighted that in equation (17), H_0 can be inverted if $h_0(t) > 0$ for all t .

market and health transitions). Assuming that an event is repeatable and its first occurrence is at t_1 if $t_1 < n$, the event occurs a second time during the same spell if a second draw of a random number from the uniform distribution $U \sim U[0,1]$ generates a simulated time to transition t_2 that is less than or equal to $n - t_1$ ($t_2 \leq n - t_1$). As a result, the event occurs at time $t_1 + t_2$.⁹

Modelling multiple transitions in continuous-time dynamic microsimulation

The majority of continuous-time dynamic microsimulation models aim to model multiple transitions among a number of states. This translates into extending the framework presented above into a multiple hazard setting (Cameron and Trivedi, 2005). In this context, the basic *competing risks model* (CRM) offers a suitable way of modelling the time to transition between one state of origin and one of a series of competing destination states.¹⁰ Competing risks models assume that a latent duration, t_j , exists for each possible destination state (or risk) j ($1, \dots, m$). In the absence of other risk factors that might cause the end of the spell to occur sooner, t_j can be interpreted as the spell duration for each possible destination j . In this setting, the observed duration T is the minimum (or shortest) duration t_j :

$$T = \min(t_1, \dots, t_m) = \min(t_j), \quad t_j > 0 \quad (19)$$

And the corresponding simulated destination state, r , is:

$$r = \arg \min_{j \in \{1, \dots, m\}} (t_j) \quad (20)$$

The distribution of t_j can be modelled through its hazard function, h_j , that defines the hazard rate of the j th type of failure (or transition into the destination state j). In the case of independent risks, the hazard function can be written as:

⁹ For an example, see Willekens (2009).

¹⁰ For a fuller explanation of competing risks models, see Chapter 19 pp.642-648 of Cameron and Trivedi (2005) and Mealli and Pudney (1996). In this section, we broadly follow these expositions.

$$h_j(t_j | X_j) = \lim_{\Delta_t \rightarrow 0} \frac{P[t_j \leq T \leq t_j + \Delta_t | T \geq t_j, X_j]}{\Delta_t} \quad (21)$$

where X_j is a destination-specific vector of exogenous covariates. Provided that the event transition into destination state j has not already occurred, the hazard rate is the product of the rate of transition in the interval Δ_t and the probability of transiting into destination j .

Willekens (2009) highlights two approaches to model time to transition and destination states in multiple state continuous-time dynamic microsimulation. The first method simulates the time to transitions for every possible destination state. The shortest time to transition determines the actual time to event to that destination. This method is applied in two models developed at Statistics Canada, *LifePaths*, a dynamic microsimulation model of Canadian individuals and households, and *POHEM* (Population Health Model), a dynamic microsimulation of diseases and risk factors within the Canadian population.¹¹ An alternative method employs two random draws, one to define the time to transition and the other to determine the destination state. The time to transition is simulated drawing a random number from an exponential distribution while the destination state is simulated using a draw from a uniform distribution in a fashion similar to that described earlier.

2.4 Validation

Predictions from dynamic microsimulation models must be considered credible in order to be accepted and used by both modellers and policy-makers. The credibility of a dynamic microsimulation model is based on its capacity to reproduce observed data or known benchmarks such as official population projections. Accordingly, an important aspect of dynamic microsimulation modelling is the validation of results produced by the simulation exercise. Interestingly, the applied literature has devoted little attention to validation procedures and the quantification of uncertainty around model predictions (Wolf, 2001; Klevmarken, 2002). Moreover, among practitioners

¹¹ For an overview of *LifePaths*, see <http://www.statcan.gc.ca/cgi-bin/af-fdr.cgi?l=eng&loc=http://www.statcan.gc.ca/microsimulation/pdf/lifePaths-overview-vuedensemble-eng.pdf&keng=310>

there is currently no apparent consensus on what constitutes best practice. In the majority of applications, discrepancies between simulation outputs and some external benchmark are often resolved using alignment techniques. In general, alignment consists of adjustment of the simulation output in order to reflect the expected proportion of certain events in a population. Alignment methods applied to dynamic microsimulation have significantly evolved in the past few years and vary widely (Morrison, 2006). In the case of a hierarchical or recursive model such as the one depicted in Figure 1 of section 2.3.1, a “piece-meal” validation procedure can be used (Klevmarken, 2002) where validation is performed separately for each sub-model. A comprehensive list of alignment methods can be found in Morrison (2006). For an illustration of the various validation methods applied to two different dynamic microsimulation models, *DYNACAN* and *APPSIM*, readers should refer to Morrison (2008) and Kelly and Percival (2009), respectively.

Pudney and Sutherland (1994) and Klevmarken (1998) identify three sources of uncertainty around the predictions produced by microsimulation models. These are classic sampling error, Monte Carlo errors and parameter uncertainty. Sampling error is simply the error linked to the use of a sample rather than the entire population to build the initial or base dataset. Monte Carlo errors are associated with the use of a particular set of random draws in the stochastic process that generates individual trajectories. Klevmarken (1998) suggests dealing with Monte Carlo variation by taking a high number of random draws and further proposes the use of bootstrapping techniques to account for parameter uncertainty.

3. Dynamic microsimulation and health

Existing dynamic microsimulation models have been extensively used to project populations over time, to design and evaluate public policies and to investigate income inequality and its distribution. Although a number of dynamic microsimulation models include health-related components, health is rarely the central focus of the analysis. Following O’Donoghue’s (2001) classification between multi-purposes versus special-purpose microsimulation models, we can distinguish between dynamic microsimulation models that are not specifically designed to represent

health-related aspects and models explicitly centred on health and health related policies.

3.1 Multi-purposes models

Within the multi-purposes dynamic microsimulation models, health-related aspects are often included in a fairly rudimentary way. Models account for health, usually defined through disability and mainly used to inform social security benefits, institutionalisation, or to determine the need for health care and, in some cases, to project health care expenditure and usage.

DYNAMOD, the Dynamic Microsimulation Model of the Australian population (King et al., 1999) and *CAPP_DYN*, the Italian dynamic microsimulation model developed by the Centre for Analysis of Public Policies (Mazzaferro and Morciano, 2008), include disability as a proxy for individual health status. *INAHSIM*, the Integrated Analytical Model for Household Simulation for the Japanese population (Inagaki, 2008) and *SAGE* (Simulating Social Policy in an Ageing Population), a dynamic microsimulation model for England (Evandrou et al., 2001) use health dichotomised into two categories: “good health” and “ill-health”.¹² *DYNASIM3* (the third version of the Dynamic Simulation of Income model for the US) includes individual health measured by the number of limitations on activities of daily life (ADLs) as well as by limitations on instrumental activities of daily living (IADLs). It also includes events such as the onset and recovery of disability and institutionalisation (Favreault and Smith, 2004). *MOSART*, the dynamic microsimulation model for Norway, includes a number of health events: moving in or out of old age care institutions, rehabilitation, disability and public disability pensions (Fredriksen, 2003). Further aspects of health are also included in the Cornell Dynamic Population Microsimulation model (*CORSIM*) for the US, including risk factors (smoking, alcohol and sugar consumption, diabetes), disability status, institutionalisation as well as disability insurance and dental conditions, services and expenditures (Strategic Forecasting, 2002). *SESIM* (Bolin et al., 2007), the dynamic microsimulation model of the Swedish

¹² The Economic and Social Research Council (ESRC) Research Group for Simulating Social Policy in an Ageing Society (SAGE) was established in November 1999 with funding from the ESRC. It was jointly located within the Social Policy Department at LSE, the Institute of Gerontology at King's College London and the School of Social Science at the University of Southampton.

Ministry of Finance, and *APPSIM* (Lymer, 2009), the Australian Population and Policy Simulator, focus on the consequences of ageing and model health status, health care expenditure and health service usage.¹³ The *HARDING* model for Australia, a cohort dynamic microsimulation model, also models health service usage as well as health expenditure (Harding et al., 2002). However, it does not model individual health status by itself.

3.2 Models focused on health

A limited but growing number of dynamic microsimulation models are centred on health. Among these models, the aspects of health considered and the methods used vary widely (Spielauer, 2007). A number of studies attempt to project and estimate long-term health care costs (Baldini et al., 2007), the costs of disability (Van Sonsbeek and Gradus, 2006) and the distributional effects of the pharmaceutical benefits scheme (Abello et al., 2008). The following section focuses on the description of two models, the Population Health Model (POHEM) and the Future Elderly Model (FEM) which represent leading examples of dynamic microsimulation models dedicated to health and health care expenditure.

3.2.1 Population Health Model

POHEM (Population Health Model) is a continuous-time dynamic microsimulation model designed to represent the lifecycle dynamics of the Canadian population.¹⁴ The model focuses on the evolution and interactions of a set of specific diseases and risk factors. *POHEM* also includes individual-level data on health care costs and utilisation together with a measure of health-related quality of life, the Health Utility Index Mark 3 (HUI3) (Grootendorst, 2000). Initially developed by Statistics Canada

¹³ The health module of the APPSIM model is currently under construction. The information on its main features is drawn from Lymer (2009).

¹⁴ A general overview of *POHEM* can be found in the *POHEM* page at the Statistics Canada website (<http://www.statcan.gc.ca/microsimulation/pohem/pohem-eng.htm>). The information contained in this section on structure, data and mechanics of *POHEM* was obtained combining a variety of sources: Evans et al. (1997), Berthelot et al. (2000), Will et al. (2001), Kopce et al. (2009), the *LifePaths* microsimulation model overview (<http://www.statcan.gc.ca/microsimulation/pdf/lifePaths-overview-vuedensemble-eng.pdf>) and a series of presentations on *POHEM* that are freely available at the website of the International Microsimulation Association (IMA) (http://www.microsimulation.org/IMA/Ottawa_2009.htm).

as a sub-model of the microsimulation model *Lifepaths*, *POHEM* integrates data from different sources on heart disease, diabetes, osteoarthritis, different types of cancer (lung, breast and colorectal cancer) and risk factors such as smoking, body mass index, cholesterol, blood pressure and mortality. Starting from this comprehensive baseline dataset, the model employs continuous-time dynamic microsimulation techniques to age the initial population forward in time and to model the onset and evolution of disease, co-morbidities and the influence of risk factors.

The baseline dataset: integrating different sources

The baseline dataset of *POHEM* combines data drawn from a multiplicity of sources. These include the Canadian Community Health Service (CCHS), the Statistics Canada's census projections, the National Population Health Survey (NPHS), the Canadian Heart Health Survey (CHHS), the Health Person Oriented Information (HPOI), the Registered Persons Database (RPDB) and the British Columbia Linked Hospital Database (BCLHD).¹⁵ Each source of data was employed for a specific purpose. The CCHS is a cross sectional survey started in 2000-2001 with an initial sample of 131,535 individuals, representative of the Canadian household population aged 12 and over. The survey was used to define the initial population that is projected forward in time by the simulation model. Statistics Canada's census projections were employed to inform the projections of new births and immigrants in the simulation. Data on Body Mass Index and cigarette consumption were integrated using information drawn from the NPHS, a longitudinal survey started in 1994-1995 with an initial sample of 17,276 Canadian individuals. Blood pressure, total cholesterol and high density lipid count were modelled using data contained in the Canadian Heart Health Survey (CHHS), a cross-sectional survey of 23,129 individuals conducted between 1986 and 1992. Statistics Canada's HPOI includes hospital morbidity records drawn from the Canadian Institute for Health Information's (CIHI) general records and was used both to improve the quality of the morbidity files and to derive rates of incidence of acute myocardial infarction. The RPDB dataset links the CIHI's morbidity records with the vital statistics for Ontario from 1988 to 2002 and was used to model survival times following different types of acute myocardial interventions. Finally, data on visits to health professionals and hospital admissions

¹⁵ This list of datasets includes only the main sources of data used in *POHEM* and is not meant to be comprehensive.

covered by the Medical Services Plan of British Columbia were included in the baseline data of the BCLHD.

Modelling approach: continuous-time dynamic microsimulation

In order to model the lifecycle dynamics of diseases and risk factors, *POHEM* makes use of continuous-time dynamic microsimulation modelling techniques. Microsimulation is employed to model the onset, progression and cessation of disease as well as the ageing process of the population. The time to incidence of each disease is established according to the general methodology depicted in section 2.3. In this case, random draws generated through Monte Carlo simulations are converted into time to transitions using the inverse function of piecewise Weibull proportional hazards models. Co-morbidities are modelled as multiple hazards where the shortest time to transition determines the first transition to occur. *POHEM* is organised on a modular basis and contains a sub-model for each disease and risk factor. Below, we provide further details for each sub-model.

Disease-specific sub-models

POHEM contains four disease sub-models: a heart diseases model, a diabetes model, an osteoarthritis model and a cancers model.¹⁶ The heart disease sub-model simulates the incidence of acute myocardial infarction (AMI) using data on socioeconomic characteristics and risk factors from various sources (the Canadian Community Health Service, the National Population Health Survey and The Canadian Heart Health Survey). The Framingham risk incidence function (Wilson et al., 1998) is used to predict the incidence of AMI according to individual sociodemographic characteristics such as age, gender, region of residence and risk factors such as total cholesterol, blood pressure, smoking and body weight. Once the initial prevalence of risk factors is established, the model projects individuals through time and produces projections for episodes of acute myocardial infarction for each individual until death. Data produced from this sub-model are subsequently used to inform the other sub-models of *POHEM*.

¹⁶ The structure of the model is here illustrated in a simplified way. For more details on the main components of *POHEM*, the different sub-modules and their state of development see the “Overall person life flow” scheme contained in any of the *POHEM*-related presentations given at the second General Conference of the International Microsimulation Association (IMA) (http://www.microsimulation.org/IMA/Ottawa_2009.htm). Part of the overall *POHEM* structure is also illustrated in Kopec et al., 2009.

The diabetes sub-module is based on the Diabetes Population Risk Tool (DPORT), a diabetes risk incidence model developed using data from the National Population Health Survey, the Ontario Diabetes Database and the state of Ontario mortality rates. This model produces diabetes types II incidence rates according to a series of socioeconomic determinants (age, gender, education, income, ethnicity, geographical area) and risk factors (alcohol, smoking, blood pressure, obesity, physical activity). The sub-model also produces incidence rates of different diseases resulting from type II diabetes such as coronary heart disease, stroke, diabetic retinopathy, kidney diseases, etc. The incidence rates produced by the diabetes model are employed in the other sub-models.

The osteoarthritis model measures the prevalence and incidence of osteoarthritis using data from the Canadian Community Health Service and the National Health Population Survey (Kopec et al., 2009). This model includes the possibility of modelling changes in health-related quality of life using the Health Utility Index Mark 3(HUI3). Finally, the cancers sub-model produces the incidence and progression of lung, breast and colorectal cancers.

Risk factors sub-models

POHEM includes three risk factor sub-models: smoking, the evolution of body mass index (BMI) and blood-related risk factors (total cholesterol, high density lipid count (HDL) and blood pressure). Within the smoking sub-model, smoking status (being a regular smoker or former smoker who quit within the last year or alternatively being a non-smoker) and transitions between smoking states are modelled using data from National Population Health Survey (NPHS). Transitions are based on a fourth-order Markov process and are conditional on age, gender and previous smoking status. The evolution of individual BMI is informed by a series of linear regressions of self-reported BMI estimated on data drawn from the NPHS. The set of covariates used for the BMI regression models include age, gender, region of residence, income quartile, education and previous BMI. The blood-related risk factors sub-model estimates joint probabilities of changing total cholesterol levels (among low, low-medium, medium, medium-high and high quantity of total cholesterol) and blood pressure states (optimal, normal, high-normal, hypertensive stage I, Hypertensive stage II-IV). These probabilities are derived using data from the Canadian Heart Health Survey.

Outputs

POHEM can be used to evaluate the effects of alternative health programmes. To date, the model has been used mainly to evaluate the costs-effectiveness of a number of alternative interventions. Among the various applications, Evans et al. (1997) use *PHOEM* to evaluate the cost-effectiveness of different combined therapies on patients with non-small-cell lung cancer (NSCLC). Berthelot et al. (2000) employ the model to evaluate the cost-effectiveness of different chemotherapeutic treatments on patients with NSCLC. Will et al. (2001) use *POHEM* to analyse both the impact of reduced length of hospital stay following breast cancer surgery and the cost-effectiveness of the provision of preventive therapies for women at risk of developing breast cancer. Further, Kopec et al. (2009) employ *POHEM* to model and quantify the incidence of osteoarthritis and its effect on health-related quality of life. More generally, the model can be used to evaluate and project the long-run effects of interventions concerned with any of the diseases or risk factors included in the model.

3.2.2 Future elderly model

The Future Elderly Model (*FEM*) is a demographic and economic microsimulation model developed at RAND (Goldman et al., 2004). It focuses on predicting future health care expenditures and the health status of a population of older Americans drawn from the Medicare Current Beneficiary Survey (MCBS). The model consists of three main components: a model for health care costs, a model of health status transitions and a model that predicts health characteristics of new Medicare enrollees (termed the “rejuvenation” model). *FEM* is used for evaluating what-if scenarios of a variety of health care interventions.

Data

FEM makes use of individual records drawn from the MCBS (1992-1998), a nationally representative dataset of Medicare beneficiaries composed of individuals who are either over 65, disabled or institutionalised. Originally developed as a longitudinal survey, the first MCBS sample was collected in 1992 and included 10,584 individuals. Since 1996, the MCBS became a rotating panel and new samples of around 10,000 individuals were introduced each year until the end of the survey in 1998. The MCBS contains self-reported information on height, weight, general health

status, a set of specific health conditions (different types of cancers, heart disease, Alzheimer, stroke, diabetes, hypertension, lung-related conditions, arthritis), measures of physical limitations in performing Activities of Daily Living (ADL) and Instrumental Activities of Daily Living (IADL). The survey also includes variables on health care utilisation and expenditures obtained through self-reported information and the Medicare service use records.

Model structure

The Future Elderly Model comprises three main sub-modules. The first sub-module produces individual trajectories for a number of health conditions and disability status. A second sub-module (the rejuvenation module) ensures that the data remains representative of the population aged 65 years or over. A third sub-module projects future Medicare and total health care expenditures based on the demographic and health characteristics of the population.

Health transitions sub-module

In the first sub-module, transitions into mortality, cancers (breast, prostate, uterus, colon, bladder, lung, kidney, throat, head, brain), cardiovascular disease (angina pectoris, myocardial infarction), neurological disorder, diabetes, hypertension, ADL and facility residence (i.e. entry into a nursing home) are modelled using piecewise Gompertz proportional hazard models. Covariates include socio-demographic characteristics (age, gender, ethnicity, and education), co-morbidities and risk factors (smoking and obesity). Individual transition probabilities obtained from these models are compared with random numbers extracted from a uniform distribution [0,1]. Health transitions occur whenever the transition probabilities exceed the corresponding random draws. In *FEM*, all health conditions are treated as absorbing (i.e. permanent) states.

Rejuvenation sub-module

The second sub-module is designed to predict the health and disability status of the entering cohorts of Medicare patients between the years 2001 and 2030 using data on chronic disease from the National Health Interview Survey (NHIS) and information on cause-specific mortality profiles from the Vital Statistics of the United States. In this module, the prediction of the health status of the future cohorts entails three main

steps. First, age-specific prevalence rates are obtained for each chronic disease considered (heart disease, hypertension, cerebrovascular disease, Alzheimer, cancer, diabetes, chronic obstructive pulmonary disease) and disability status using data from the NHIS. Second, age-incidence trajectories are created combining information on successive disease prevalence and disease-specific death rates from the US Vital Statistics. Third, age-specific prevalence rates and disease-specific trajectories generated in the previous two steps are used to predict and adjust the health status of the incoming Medicare sample.¹⁷

Health expenditure sub-module

The health expenditure module aims to identify the determinants of health care expenditures among elderly Americans. In this module, Medicare reimbursements and total healthcare expenditures are predicted using OLS cost regression models. Explanatory variables include socio-demographic characteristics (age, gender, ethnicity, education, geographical area of residence), health measures (self-reported health, ADL, self-reported diseases such as cancer, heart disease, diabetes and neurological conditions as well as interactions with ADL categories and disease conditions), mortality, obesity, smoking and nursing home residency.

Scenarios modelling

The *FEM* simulates a set of potential health care scenarios identified by a technical expert panel (TEP).¹⁸ These simulated scenarios include potential breakthrough technologies in areas such as disease prevention, early detection and improved treatments of certain diseases but also changes in the health care system and individuals' lifestyle. In order to evaluate the effectiveness of these health interventions, the model compares diseases prevalence rates and related costs across the baseline and simulated scenarios. Among the interventions that *FEM* is designed to model are the possibility of treating cancers using telomerase inhibitors¹⁹, the introduction of cancer vaccines and of new non-invasive diagnostic imaging

¹⁷ For a detailed description of the statistical models used in each of these phases, see Goldman et al. (2004), Chapter 7, pp. 72-83.

¹⁸ The panel was formed by social scientists and experts on cardiovascular diseases, biology of aging and cancer and neurological diseases. For a full list of members of this panel, see Goldman et al., (2004), Appendix B, p. 194, and Appendix C, pp.202-203.

¹⁹ Telomerase inhibitors are molecules that prevent the expression of telomerase, an enzyme that allows cancer cells to reproduce.

technologies to improve the detection of cardiovascular diseases, and diabetes prevention. Simulated scenarios also comprise changes in education (such as an increase in educational attainment of new Medicare enrollees), changes in the composition of the population (e.g. a rise in the Hispanic population) and lifestyle changes (decrease in smoking prevalence and obesity rates).

4. Conclusions

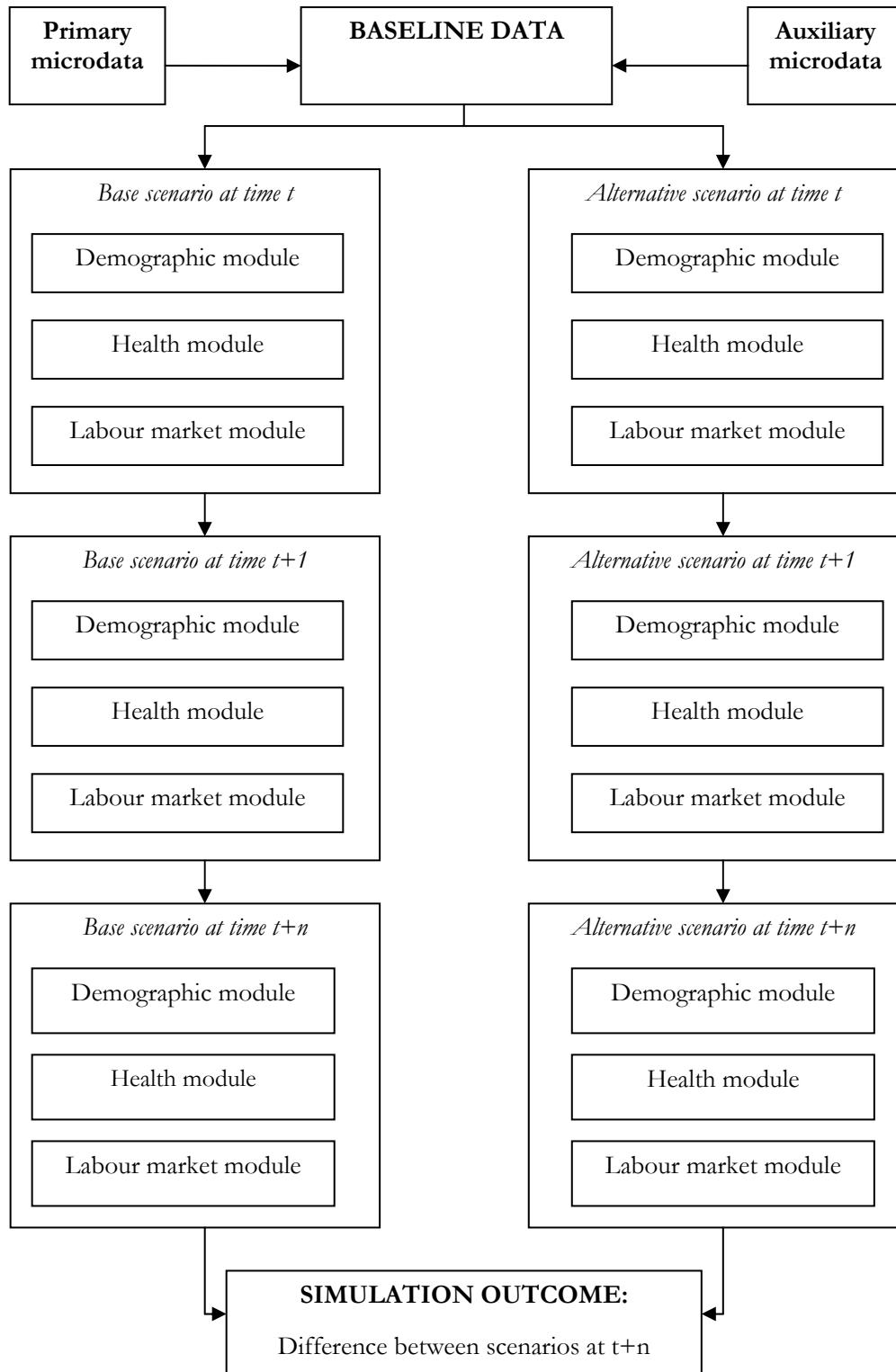
This paper has two core objectives. The first is to present an overview of microsimulation methods and applications that are relevant for the purpose of health policy evaluation. The second is to promote the use of dynamic microsimulation as a tool for the ex-ante evaluation of health policies, and particularly in the field of public health interventions where evaluations are often challenging and costly. Dynamic microsimulation offers a number of important advantages over more standard methods of ex-post policy evaluation. First, by simulating data under alternative scenarios, dynamic microsimulation allows for the evaluation of outcomes of interest prior to actual implementation of a policy. Second, by projecting individual socioeconomic and health trajectories over multiple periods of time, dynamic microsimulation techniques readily incorporate both heterogeneity in estimated treatment effects together with the long-run effects of treatment. Finally, dynamic microsimulation can additionally be used to identify better externalities and spillovers in treatment.

For the purpose of evaluating public health interventions, the main advantage in the use of dynamic microsimulation lies in the possibility of simulating the likely impact of alternative interventions and the capacity to evaluate the efficacy of a given intervention for different future health scenarios. This provides the opportunity to test the effectiveness of different policies as well as to assess the efficacy of different versions of the same policy, for example a phased implementation of a policy. Through the repetition and variation of the assessment exercise, microsimulation further allows for testing the robustness of the results produced by the simulation itself. Given the wealth of information offered by these methods, dynamic microsimulation should be considered an important tool for the evaluation and refinement of health policies.

It is important to underline that the output of any microsimulation model relies on a particular set of assumptions regarding the behaviour of the micro-units represented. These assumptions need to be credible for the outputs from a microsimulation exercise to have validity. Further, while estimates of behavioural microsimulation models have the advantage of being grounded on economic theory tend to be policy-specific and difficult to extend to alternative contexts. Dynamic microsimulation models that project the characteristics of a population over time usually include the simulation of a series of interacting micro-processes such as demographic, labour market and health dynamics. The way in which these processes interact with each other represents the core of a dynamic microsimulation model. These interactions are however rarely justified using structural models. That is, dynamic microsimulation models often include only very limited behavioural components. Accordingly, one of the challenges facing the future development of dynamic microsimulation model is the incorporation of credible structural microeconomic models capable of taking into account the various behavioural components of the simulation exercise.

Appendix – Tables and figures

Figure 1: Structure of a typical discrete-time dynamic microsimulation model*



* This graph is based on Graph 1 in Martini and Trivellato (1997).

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