NATSEM
UNIVERSITY OF CANBERRA

MICROSIMULATION, MACROSIMULATION:

MODEL VALIDATION, LINKAGE AND ALIGNMENT

PREPARED BY

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About NATSEM

The National Centre for Social and Economic Modelling was established on 1 January 1993, and supports its activities through research grants, commissioned research and longer term contracts for model maintenance and development.

NATSEM aims to be a key contributor to social and economic policy debate and analysis by developing models of the highest quality, undertaking independent and impartial research, and supplying valued consultancy services.

Policy changes often have to be made without sufficient information about either the current environment or the consequences of change. NATSEM specialises in analysing data and producing models so that decision makers have the best possible quantitative information on which to base their decisions.

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It must be emphasised that NATSEM does not have views on policy. All opinions are the authors' own and are not necessarily shared by NATSEM.

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GENERAL CAVEAT

NATSEM research findings are generally based on estimated characteristics of the population. Such estimates are usually derived from the application of microsimulation modelling techniques to microdata based on sample surveys.

These estimates may be different from the actual characteristics of the population because of sampling and nonsampling errors in the microdata and because of the assumptions underlying the modelling techniques.

The microdata do not contain any information that enables identification of the individuals or families to which they refer.

SUMMARY

This paper explores the consequences of shortcomings in microsimulation models and the importance of purpose built macrosimulation models using techniques of model validation, data calibration and alignment.
The paper addresses issues of the long-run dynamics of microsimulation models.
In particular, the short-term trends revealed by micro-data are often not sufficient to capture long-term behavioural changes. The fact that micro-data may come from a range of sources further complicates the process. The paper proposes that appropriate micro-data calibration and parameter estimation, model validation against highly disaggregated macrosimulation modules and the use of alignment techniques dynamically linked to the macrosimulation modules can mitigate the unstable dynamic behaviour often produced by dynamic microsimulation models. The paper demonstrates how these proposals with some family formation modelling examples.

Key words

Microsimulation, macrosimulation, long-run, data calibration, validation, alignment.

1 INTRODUCTION

> "One of the first objectives in dynamic microsimulation models is to generate a synthetic population to which various modules can be added as needed to study phenomena of interest. Credibility of the model depends crucially on its ability to reproduce past history and/or benchmark measures……" (Chénard 2000, p.?)

1.1 BACKGROUND

The Australian Population and Policy Simulation Model (APPSIM) –is a Dynamic Microsimulation Model to provide Australian policy makers with tools to assess, plan and manage the current and future distributional consequences of required changes in social and fiscal policy as a result of Australia's ageing population.

Dynamic microsimulation models like APPSIM simulate individuals, families and households through time, to project the distributional consequences of social and fiscal policy in the framework of a consistent macro[1] or aggregate environment.

The objectives of the APPSIM model are to:

- Allow users to input alternative policies and examine the projected distributional outcomes up to 50 years into the future;
- Provide a model that is reliable, useable, understood and adaptable to changing conditions; and
- Produce outcomes that are timely and valid.

The acceptance of a Dynamic Microsimulation Model by policy makers depends on many factors and, in particular, on its ability to track historic data and produce projections that are consistent with other related official and non-official projections.

Based on these objectives, this paper develops some ideas for dynamic microsimulation model validation and looks critically at the use of macrosimulation model projections and their relationship to dynamic microsimulation models.

This paper was prompted by the question:

> "How does one construct a plausible and defensible log-run dynamic microsimulation model to analyse policy options?"

[1] Macro does not in general mean macro-economic

In summary the paper makes the propositions that:

- To develop a reliable microsimulation model that is credible over a 50 year time horizon, each of the key modules within the model should ideally have a purpose-built macrosimulation model
- Long-run assumptions should operate through the macrosimulation models
- Microsimulation models should be aligned to consistent macrosimulation models, which provide the long-run dynamics
- Processes to validate the model, calibrate the underlying databases, and link the microsimulation modules to the macrosimulation models should be explicit and well documented

1.2 THE IDEAL MICROSIMULATION MODEL

> "Dynamic microsimulation is a modeling technique that incrementally ages a population while projecting individual demographic and economic events such as marriage, fertility, employment, savings, divorce, retirement, and finally, mortality. Because dynamic microsimulation models produce longitudinal projections that contain detailed micro-level demographic and employment histories, they are excellent tools for analyzing the distribution of future retirement income and for estimating the impact of prospective Social Security reforms. A comprehensive dynamic microsimulation model consists of many modules that are responsible for projecting each of the included economic and demographic processes." (Perese, 2002, p. ?)

The ideal dynamic microsimulation model would be estimated and simulated using a well-specified model against an up-to-date, long-run, longitudinal microdatabase of the full population. Full Information Maximum Likelihood techniques would be employed to estimate all module parameters as a simultaneous system. From this ideal scenario we would model all appropriate underlying dynamics and long-run behaviour as captured and revealed by the historic data.

Sadly, in the real world, our data and models are often a long way from this ideal. To begin with, all modelling is only a representation of reality, often expressing the model-builder's view of how the world works. It is assumed that the model-builders have, to varying degrees, an underlying theoretical model, representing both the historic outcomes and a sufficiently rich dynamic structure to capture likely outcomes in the future. The utility of this model, however, critically depends on the availability of sufficient, reliable and useful data to support the estimation and simulation of the model.

Socio/economic behaviour at the micro level is very complex, both in terms of appropriate micro theory, the underlying dynamic behaviour and the variables that enter into these dynamics. Alas, appropriate micro theory is extremely limited and the scope and range of reliable data can be restrictive. Under these conditions, the likelihood of a misspecified model is high. Of course model misspecification is an issue for all modelling tasks and much effort is spent on finding appropriate models and methods to minimise its effects.

Quite apart from any possible mis-specification, a second issue is that structural relationships may have changed since the microdata used to estimate the behaviour of individuals were collected – or may change over the projection period. King et al outlined this dilemma very clearly, when discussing why there was a need for alignment of fertility processes in the earlier Australian DYNAMOD-2 dynamic microsimulation model:

> "Consider, for example, the relationship between a woman's employment status and her fertility. The survival functions used in DYNAMOD-2 specify markedly lower fertility rates for those women who are employed than those who are not. The nature of this relationship may, however, have changed since the 1970s and early 1980s, as women's labour force participation has continued to rise and there has been a considerable expansion in child care services and subsidies. If so, the model will capture women's increasing employment rate, but may exaggerate the dampening effect on fertility. Another example of a structural change not captured by the survival functions is the associated phenomenon of delayed fertility. An alignment procedure is thus useful not only to construct future scenarios, but also to allow calibration with observed outcomes — a response to the limitations of the estimation data." (1999, p. 17)

A third issue is that there may well be sampling and other error in the microdata used to estimate the various transition equations in dynamic microsimulation models. In the current Australian context, for example, the most obvious longitudinal data source for estimating the probabilities of transitions is the HILDA survey (Goode and al, 2007). But the HILDA sample size is relatively modest (about 8,000 households??) and only six waves of data have so far been collected with significant attrition of respondents from the survey . This means that for relatively rare events, or for events where behaviour ten years earlier has a bearing on current outcomes, it can be difficult to accurately capture in equations the relationships and characteristics that need to be replicated in dynamic microsimulation models.

Ideally, a well specified and estimated model should track historical aggregates and hopefully carry appropriate dynamics into the projection period. Unfortunately, for the types of reasons outlined above, the simulation outcomes of most dynamic microsimulation models around the world usually drift quickly away from historical aggregates if no action is taken to align the micro outcomes to the aggregate numbers. That is, the models often do not accurately replicate history and it can be rightly assumed that if they fail to get history right, they are unlikely to get the future right.

2 Long Run Dynamic Microsimulation Models

> "Micro-simulation is an approach to analyze the impact of economic and social policy on the distribution of target variables, not just on the means. It easily includes the true policy instruments and handles highly nonlinear relations. Most models currently used in policy analysis are static and they do not include behavioral response to policy changes, just their first order effects. There is, however, an increasing demand for dynamic models including behavioral responses." (Klevmarken, 1997, p.??)

2.1 Dynamics

The term dynamic microsimulation model implies the modelling and simulation over time of the behaviour of the micro-units. They are statistical models, in the sense that they use Monte-Carlo simulation of estimated transition rates like birth, death, marriage, divorce or leaving home. These transition rates dynamically update the characteristics of individuals, as well as adding or removing individuals via births and death.

Capturing appropriate dynamics is essential to the success of any dynamic microsimulation model. To fully capture the dynamics, one must have relevant variables in the database that permit modelling of the underlying dynamics. Most, if not all, behaviour changes with time – particularly over the time horizon envisaged by APPSIM. This necessitates that the model parameters be estimated in dynamic form which permits both the parameters and their interactions to vary over time as appropriate.

It is often the case that the available microdata do not permit the specification of the full dynamic structure. By way of example, consider the following statement on mortality modelling:

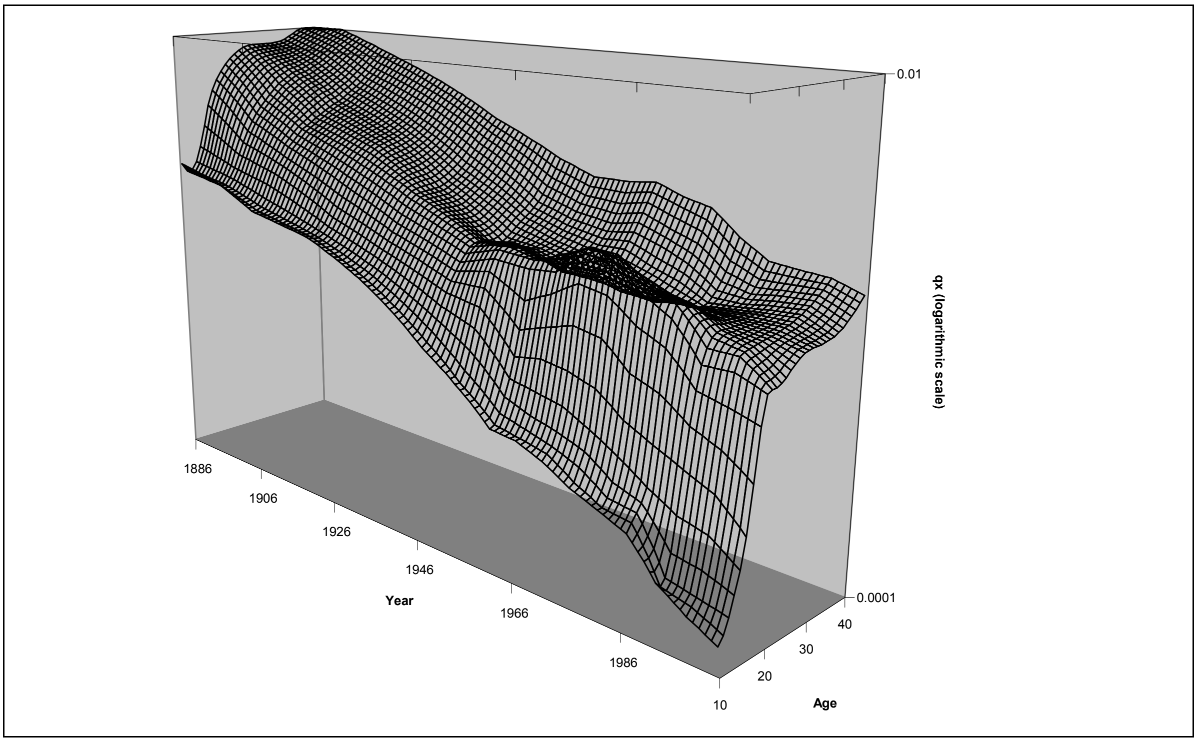
> "In Australia …. the statistics available on mortality are fairly limited, so that the only explanatory variables which can be reliably included in predicting mortality rates are year of birth, age and sex. Neither date of birth nor sex will change over an individual's lifetime and the probability function for survival can therefore be fully specified at the beginning of the simulation." (Antcliff, 1997, p.?)

In the case of mortality, casual inspection of the mortality rates in Figure 1 would not support the hypothesis that the survival curves are constant and that the dynamics are a function of age and sex only. The question is what models and data are available to capture the changing, but different, accident humps for males and females and the improvements in childhood mortality.

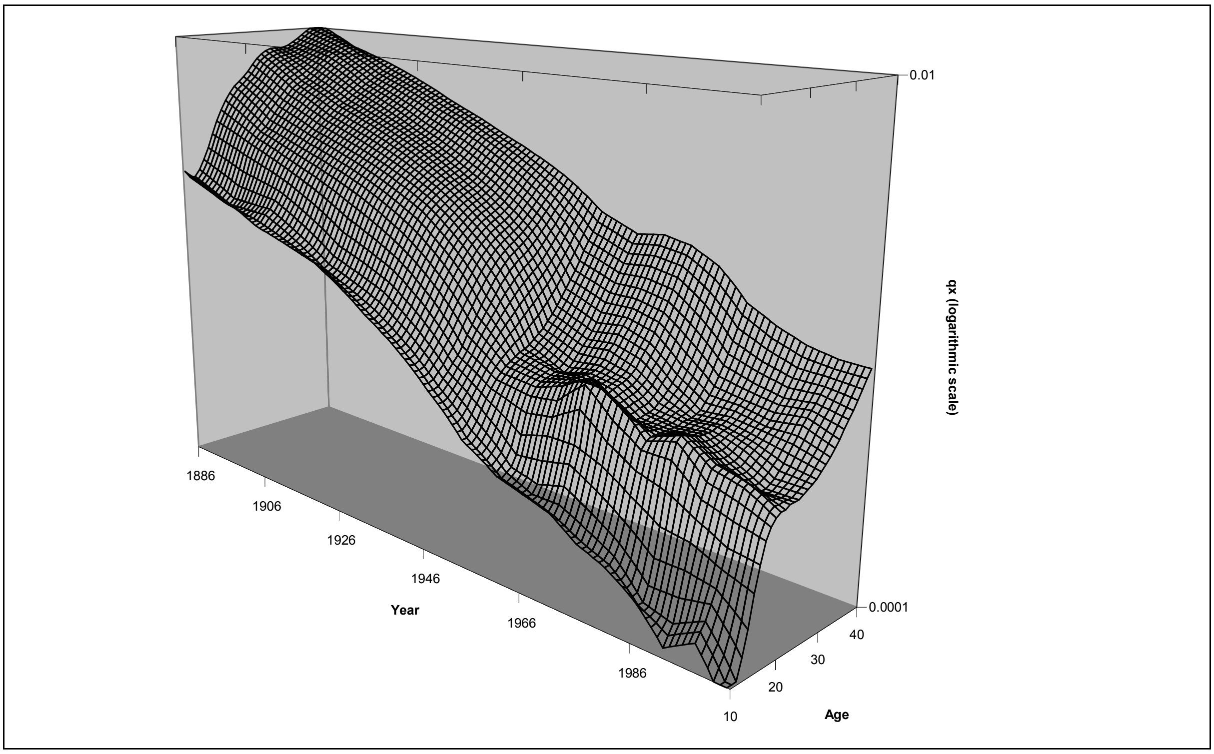
Figure 1. Smoothed mortality rates from 1886-2000 at ages 10 to 40

MALES

Is it possible to make the graphs axis labels bigger bruce???



FEMALES



Source: AGA, 2004

Clearly the macro data charted in Figure 1 do reflect these dynamics and it is appropriate to ask how these dynamics might be captured from the macro data and incorporated into the microsimulation model.

Before addressing this question it is useful to remember that the full dynamics of a microsimulation model may come from a number of interacting, but not necessarily mutually exclusive, sources:

- Dynamics from population change,
- Dynamic parameter estimates,
- Covariates (either endogenous or exogenous),
- Variables capturing nonlinear time trends,
- Dynamics captured in the alignment process,
- Dynamics from other modules either current or lagged, and
- Dynamics from policy instruments.

Unravelling, capturing and modelling these complex dynamics is fundamental to producing a useful and credible model.

2.2 THE LONG-TERM

> "Once a model has been validated, there is no reason to expect that the input assumptions will continue to hold indefinitely into the future. Indeed, a better assumption is that they would not. It will undoubtedly prove necessary to update the input assumptions during the life of the Centre" (Bracher, 1993, p23)

All forecast/projection techniques use trends in the historical data to estimate future outcomes. These trends may be mental models of how society works, based on years of casual observations, through to sophisticated statistical analysis that reveals multivariate relationships in the historic data that may be used to forecast.

Even when a stable trend or set of multivariate regression parameters have been identified in the historic data, the question remains as to whether these trends will persist into the projection period. In the short-term, this may a defensible and a testable proposition. However, in the long-term, the persistence is problematic since it is not feasibly 'testable'. Often, as in the case of simple linear extrapolation, the forecast of a linear trend is clearly not tenable in the long-term and the method can be disregarded for long-term projection use. In other cases long-term properties or limits must be imposed as an **assumption** of the modeller or user to provide acceptable, likely or plausible long-term projections. These assumptions usually take the form of some asymptotic constraint or steady state property either placed upon the parameter estimates or embedded directly in the model. Many techniques are used such as nonlinear extrapolation, functional data analysis, nonparametric analysis, transition rate analysis or structural econometric models, which all attempt to capture the underlying trends in the variables or trends in the relationships between the variables.

In long-term dynamic microsimulation models, the behaviour of micro-units is modelled through time over the lifetime of one or more generations. The short-term trends revealed by microdata are often not sufficient to capture long-term behavioural changes. Macro models can then be used in tandem with the micro model to provide or impose the long-term assumptions.

In the end, the long-term forecasters may simply be looking for plausible, consistent and defensible projections. Clearly any model system would need to provide users with input control over these long-term assumptions.

2.3 MACROSIMULATION MODELS

> "MicMac offers a bridge between aggregate projections of cohorts (Mac) and projections of the life courses of individual cohort members (Mic). Both Mic and Mac are multistate models with transition rates as parameters. Mac focuses on transitions among functional states by age and sex. The output of Mac consists of *cohort biographies*." (van der Gaag, 2005, p.?)

Recent research in demography, as exemplified by MICMAC, argues for the development of population forecasting models which explicitly link microsimulation models to macrosimulation models (hence the name MICMAC).[2]

> "In an ageing population, the demand for adequate health care services, pension systems and other social protection systems is paramount. The sustainability of high-quality health care and pension systems is influenced to a considerable extent by demographic change and by the way people live their lives (lifestyle and life course). Therefore, an adequate monitoring and forecasting of demographic change and of the lifestyle and life course of the population are a conditio sine qua non for the provision of health and social security to the people of Europe. This requires a methodology that moves beyond conventional projections of the population by age and sex. What is needed is a methodology that complements the demographic projections with projections of the way people live their lives. The objective of MicMac is to develop this methodology."
>
> http://www.nidi.knaw.nl/en/micmac/introduction

The innovation in MicMac is the bridge between aggregate projections of cohorts, extending the traditional cohort-component model (using macrosimulation), and the projection of the life courses of individual cohort members (using microsimulation). Tthe idea of developing a concordance and linkage between macro models and micro models is very applicable to the requirements of APPSIM.

As noted above, most dynamic microsimulation models align the micro model to external and exogenous macro aggregates. These macro aggregates usually have a historical component plus a projection component. The historical component comes from available historical statistics which may or may not have the same statistical basis as that used in the micro model (for example, if the macro data comes from administrative data and the micro

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[2] It is worth explicitly noting that we are not referring here *to macroeconomic* models, as modellers sometimes build bridges between microsimulation models and macro-economic or economy-wide economic models. The MAC used here instead refers to macro (or aggregate) socio-demographic outcomes or estimates.

data from a longitudinal database). Projected macro aggregates usually come from some official projection framework such that they:

- May not have the same conceptual or statistical basis;
- Are exogenous to the model and hence fixed, thus not permitting policy change analysis via macro variables;
- May not be the latest available projections and hence are not current; and
- Do not provide the possibility of two way linkage between the macro numbers and the micro numbers.

Clearly, because of the importance of the macro aggregates for providing the 'stabilising hand' to the microsimulation projections, it would appear that the development of consistent macro models that are integral to the microsimulation process is desirable.

Most dynamic microsimulation models already have macro models associated with their models but not necessarily recognised as such. For example, all cohort models, such as population projection cohort models, are macro models. Yet even when the model contains a cohort model, alignment is often done to static official projections, instead of linking the macro-micro models (even if they are able to reproduce the official numbers).

It is instructive at this point to ask what is the statistical relationship between macrosimulation models and microsimulation models? Just why are macrosimulation models required?

Firstly, they play different but equally important roles. The above quote from MicMac illustrates the point. Mac focuses on transitions among functional states by age and sex and provides the long run story —whereas Mic addresses micro events and other life transitions at the individual level and provides the distributional story. Mic and Mac are designed to work in tandem. Mac concentrates on the cohort level, whereas Mic concentrates on individual cohort members.

Secondly, as pointed out above, dynamic microsimulation models are usually estimated on data over a limited time span and consequently capture short-term dynamics but may miss completely the long-term dynamics. On the other hand, macrosimulation models are usually built using long time series which may reveal the underlying long-term movements of stable, but nonlinear relationships. These nonlinear trends often have embedded in them the slowly evolving behavioural changes which cannot be captured by micro model estimation.

Thirdly, because of the richness of the data used to estimate the microsimulation model, the micro model has access to variables not available to the macrosimulation model — and, similarly, the macrosimulation model has access to long-run variables not seen by the microsimulation model.

For an illustration of the macro/micro framework as applied to family formation see Bacon and Pennec 2007.

The above discussion shows how microsimulation and macrosimulation models can complement one other. It is how to estimate, integrate and utilise this complementarity that provides some interesting research questions. The following discussion on variance reduction and alignment picks up this point.

3 VALIDATION

> "Caldwell (1996, p515-7) lists reasons why the output from a dynamic microsimulation model run over a historical period may show discrepancies with empirical macro data from the same period. These include problems of determining an accurate model specification, sampling variation in the base data, and Monte Carlo variation in the model processes. In particular, when a model includes a large number of interacting processes, small errors in the model specification may produce quite large deviations in the output." (Scott 2001)

Validation[3] is the process of testing modules and the whole model against historical aggregate statistics and possibly against the macrosimulation model projections and is designed to ensure that the model is reasonable and credible. As Caldwell and Morrison note: "Model validation attempts to address the fundamental questions of:

- Is the model working?
- Is it working well enough?
- How do we tell?" …..

[3] The validation process can be used to identify computer code errors. However, code correctness is a separate issue to that being discussed here.

Validation seeks to assess whether the model's outputs are reasonable for their intended purposes"(Caldwelll, 2000, p. 202-03)[4]

However, it is worth noting here that when it comes to the future, to say that the results are reasonable or not depends on whether the aggregate projections one is comparing against are themselves reasonable or not. Further, the aggregate projections are just one of a many possible aggregates one might want to compare against. In other words, one can compare the microsimulation results against macrosimulation projections, but this is a different form of validation.

Nonetheless, if the validation process reveals that the module/model is not working well enough, it is useful to ask:

- How do we identify the source of the validation discrepancy?, and
- Can we eliminate the discrepancy?

As noted above, validation discrepancies can, and will, arise from problems of determining an accurate model specification. Validation and model re-specification is an iterative process throughout the model development cycle. However, there are a number of other possible sources of validation discrepancy which should be addressed. These include: sampling variation in the base data, weighting issues of the data, data inconsistencies between the modelling and simulation databases and Monte Carlo variation in the model output.

In passing, we note that although errors in the model code may be revealed by the validation process, debugging is not the primary function of validation.

3.1 Estimation Issues

Even if we had a well specified model, unlimited data and unbiased and consistent (FIML) estimates of the model parameters, the logit/probit models used in dynamic microsimulation models would not guarantee unbiased forecasts.

[4] The paper by Caldwell and Morrison provides a excellent review of validation principles and objectives. They also make the extremely important point that once the micro results have been 'aligned', by forcing them to match, for example, group-level fertility rates, then one can no longer 'validate' the fertility module by comparing the group-level fertility rates produced by the model with vital statistics data on group-level fertility rates (p. 208). Thus, extensive alignment raises some challenges for validation of the model's results.

> "even in functionally well-specified models, the predictive performance is poor, particularly where some states are relatively densely or sparsely represented in the data."(Duncan and Weeks, 2000, p.?)

O'Donoghue notes that "the maximum likelihood estimator is not chosen to maximise a fitting criterion based on prediction of y, as it is in the classical regression (which maximises R^2). It is chosen to maximise the joint density of the observed dependent variable" and hence will not necessarily produce the most likely forecasts (2000, p.).

3.2 DATA CALIBRATION

APPSIM draws data from a range of sources. In particular it uses Census data as the core data to establish the base micro database, HILDA to estimate transition probabilities, and a macro database, constructed primarily on ABS data, for validation, alignment and macrosimulation model development.

Data inconsistency is a significant source of validation discrepancy and can be significant in model misspecification. Making the databases consistent is a process we call **data calibration.**

3.2.1 Benchmark Data

APPSIM uses data from the "Australian Demographic Statistics" (ABS 3101.0) as the base benchmark data for all modules. This highly aggregated data is released quarterly, and is the most up to date demographic data available. All APPSIM demographic data is calibrated to be consistent with the base benchmark data and will be recalibrated as necessary when new or revised data is published.

3.2.2 Macro database

Macro data is available by single year of age by sex by marital status for a range of demographic statistics. Both stock and flow data are constructed to be internally consistent and calibrated against 3101.0. As further sources of macro data are constructed, this process will be repeated to ensure that all data on the macro database are consistent and up to date.

3.2.3 Base Micro Database

As noted above, APPSIM uses a base database constructed from the 1% Census sample file of Australia 2001 with weights of 100 for each individual on the file.

The 2001 Census is used to provide the relevant Census information, as it is time consistent with the HILDA survey.

Even though the 1% file is a random sample of the full Census, in some dimensions it may not adequately reflect aggregates from the full Census. Calibration against the full Census may be required.

3.2.4 The Synthetic Micro Database

The 2001 base period is used as the jump off point to generate future life events of individuals, families and households. These projections can be calibrated to the benchmarks via model alignment to produce a consistent synthetic micro database.

All future runs of the model would then use the latest period in the synthetic micro database as the jump off point.

Some models, including CORSIM, DYNACAN and DYNAMOD, begin simulation several decades in the past to:

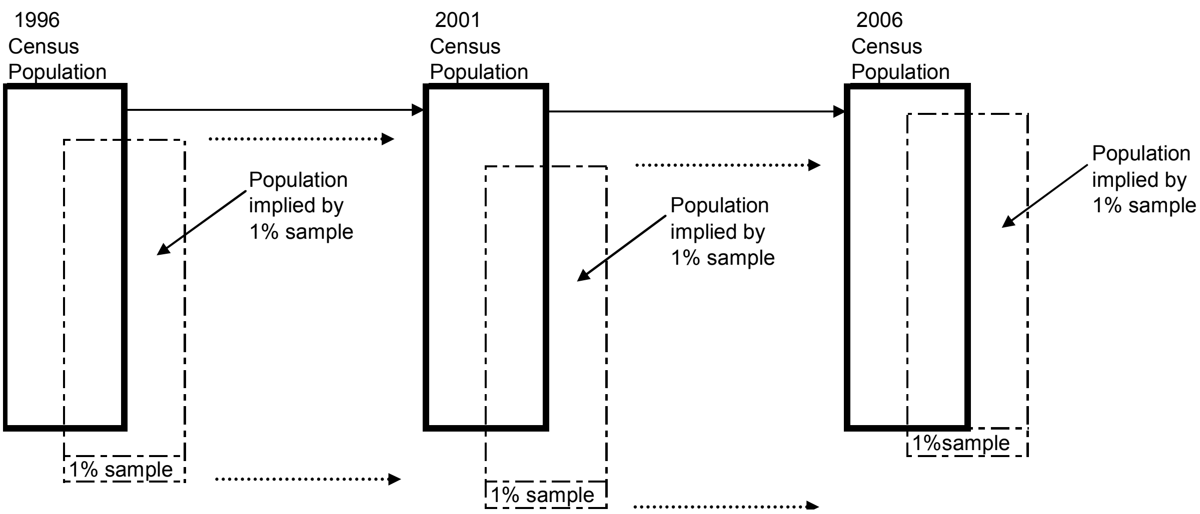
- Increase the period over which model validation can be assessed, and to

- Build up the necessary life histories that are required for some modules before projections are begun.

Clearly APPSIM can use previous Census files to construct the life histories in the synthetic data base. However, since the 1% sample file from 1996 will not necessarily reflect the 1% sample file from 2001, data matching techniques may also be required to calibrate the data across Census (see figure 2).

The recently released 2006 Census data could be used to re-calibrated the synthetic data base and bring it up-to-date. This possible approach is shown schematically in Figure 2.

Figure 2. Creation of synthetic micro database from consecutive Censuses

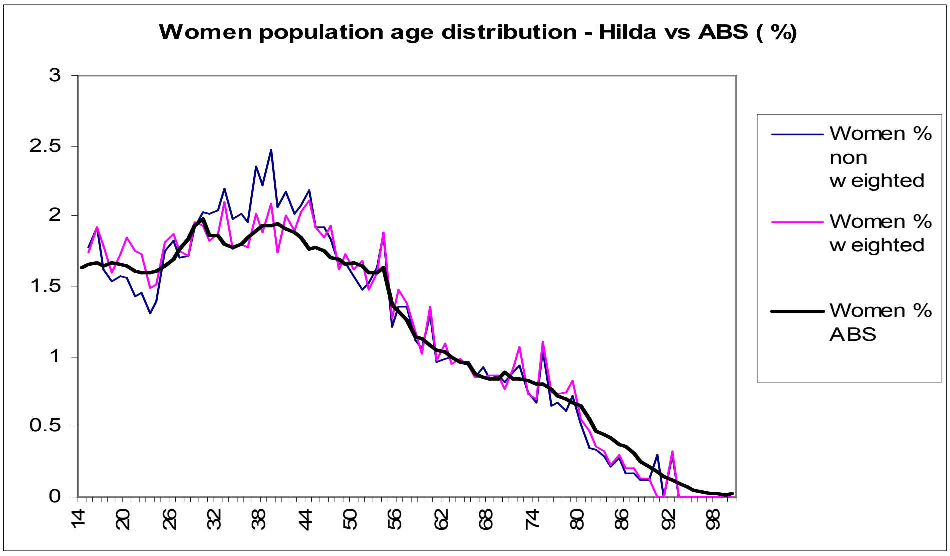


3.2.5 Estimation Data

Dynamic microsimulation studies in Australia are restricted by the quality and limited temporal coverage of micro data on which the model might be estimated. The lack of data restricts the range of models that might be investigated and the richness of the dynamic behaviour that might be captured.

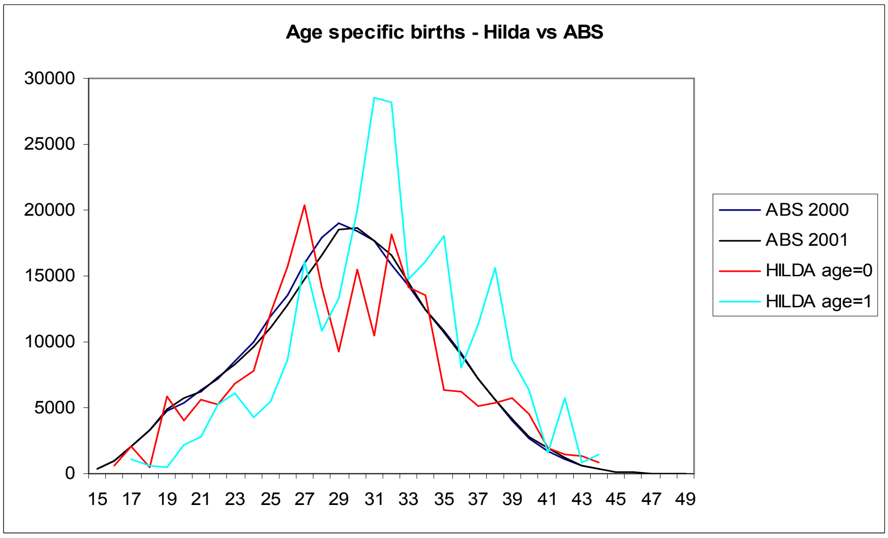
To illustrate the issues, Figure 3 charts the age profile of women from the ABS data (which is the benchmark) against HILDA, using the weighted and unweighted data. It is clear that the weighted data from HILDA approaches the ABS profile but is still biased at certain age groups (particularly women aged 80 to 90).

Figure 3.



The problem is compounded when we look at measures of fertility, as shown in Figure 4. Here we chart the number of children aged 0 and 1 by mother's age, against ABS births for 2000 and 2001.[5] We note firstly that there are too many one year olds and too few 0 year olds. Further, the age profiles are skewed (in different directions).

Figure 4.



The question therefore is: can the HILDA data be used with confidence to estimate a transition rate model of fertility? This raises some interesting statistical questions. As a first

[5] Because of death and migration, these statistics are not directly comparable and comparison of these statistics is only indicative.

level adjustment, it might be desirable to apply a reweighting scheme to calibrate the data towards the benchmark data before estimation, to ensure that the estimates best reflect reality. In theory, the incorrect estimation of parameters from distorted data should not be simply left for correction by alignment processes — although, obviously, a judgement will need to be made about when the longitudinal data are sufficiently distorted that they require reweighting.

3.3 VARIANCE REDUCTION

> "Micro-simulation is an approach to analyze the impact of economic and social policy on the distribution of target variables, not just on the means." (Klevmarken, 1997, p.)

3.3.1 Variance introduced by the use of a sample and not the full population

The ideal microsimulation model would use a longitudinal microdatabase of the full population and it is this full population, along with its statistical properties, that the model is attempting to replicate and project. Dynamic microsimulation models use Monte Carlo techniques, often called stochastic drawing, to solve the model. In its simplest form the model determines if an event occurs by drawing a random number. The uncertainty associated with this stochastic drawing shows up as statistical variance in the resulting population, in addition to the natural variance found in the actual full population.

3.3.2 Variance introduced by the use of Monte Carlo techniques

As Caldwell and Morrison note: 'Different runs of the model, with identical parameters but using different random number seeds, give different answers. Decision-makers, however, dislike such variation." (2000, p. 203). Thus, this stochastic variations is unwanted in policy analysis and methods have been devised to reduce their effect. In this case, one can average multiple runs with different seeds to ensure that the result fall fairly close to the central tendency with reduced variance.

These variance reduction techniques (see Bekkering, 1995) impose restrictions on the aggregate number of events (which is exactly the objective of the alignment techniques to be discussed in the next section). Van Inhoff (1998) reinforces the importance of macrosimulation when he notes, "… these methods combine properties of microsimulation with macrosimulation: a macro step calculates a total number of events as its expected value, a micro step (involving Monte Carlo experiments) assigns this number of events to individual data records."

4 ALIGNMENT

> "Our limited capacity as model builders, the difficulties to get good comprehensive data from which the model parameters can be estimated, the piece meal approach usually adopted, in practice, to estimate the model sub-model by sub-model, all contribute to deviations of simulated values and distributions from observed data." (Klevmarken, 2002, p.)

4.1 ALIGNMENT ISSUES

As noted above, the paucity of Australian data may mean that we only have cross-sectional data or a limited span of longitudinal data to estimate parameters for most modules of the model. These parameter estimates might not capture critical dynamics which, in turn, may significantly bias projections. To address this and other problems discussed earlier, in dynamic microsimulation models calibration techniques are introduced to align the model outcomes to external aggregates.

> "Alignment… [is used] to bring them into closer agreement with exogenously provided average values." (Neufeld, 2000, p.)

and

"*Alignment* is a process of constraining model output to conform more closely to externally derived macro-data ('targets'). In addition to using the alignment results for historical periods as a means of model validation, alignment can also be performed when simulating future states, using projections of population characteristics derived from other simulations." (Scott 2001, p.)

Unfortunately, the term alignment has become associated with some form of 'after model run' ad-hoc adjustment towards the aggregates. Anderson, for example, states: "Aligning the micro values produced by dynamic models with known or projected macro aggregates usually involves some type of "tweaking" or modification of model estimates." (year, p.) Further these targets are sometimes incorrectly associated with only macroeconomic aggregates, which form only a small subset of possible macro aggregates.

There are a number of reasons for aligning microsimulation output to a corresponding macrosimulation model. Alignment may be used to:

- Capture missing information in the estimation database,
- Adjust for poor predictive performance of the micro model,
- Adjust for model misspecification,
- Reduce variance,
- Investigate alternate long-term trend assumptions embodied in the macrosimulation model, and
- Implement policy changes via the macrosimulation model.

Clearly alignment should not be used to hide model misspecification that can and should be identified and fixed. However, if after appropriate and exhaustive modelling, some model misspecification remains (which is most likely), alignment may be a valid procedure for removing its influence.

4.2 METHODOLOGY

> "Unfortunately, even in the face of considerable care and expertise in specifying and estimating equations, the average of the event probabilities for members of a group will only very rarely equal one's desired average probability for the event for the group" (Morrison, 2006, p.)

The simplest method used to calibrate micro models is transition probability adjustment. "This is used in order to modify the proportion of the population (or of population subgroups) in each category of a status variable after the transitions for that variable have been computed." (Scott, ibid)

This usually means that the model is run in 'one-step ahead' forecast mode, with the current adjustment factor calculated and applied to the adjusted outcome from the previous period. This commonly used alignment technique is often used for computational simplicity.

There are some important issues to be considered when adjusting transition probabilities:

- Should alignment be carried out on stock or flow variables?
- How does one ensure that the probabilities remain between 0 and 1?
- How to adjust the probabilities in the case of multinomial transition when there is no unique solution?

More elegant calibration methods embed the alignment technique directly into the simulation process in such a way that it permits some form of linkage between the microsimulation model and the macro aggregates or macrosimulation model producing the target aggregates.

4.3 STOCHASTIC DRAWING

4.3.1 "Many are called but few are chosen."

This section discusses how to embed the alignment process directly into the simulation process in such away that it permits linkage between the micro model and the macro model.

The principal method of embedding employs stochastic drawing where the probability of an event occurring is calculated for each individual.

If we consider the example of death then, in terms of the often employed logistic model, we have $p_i = logit^{-1}(\alpha + \beta X_i + \varepsilon_i)$, where p_i is the probability that an individuals dies, X_i are covariates and ε_i is the error process.

A simple decision process would be to assign a random number between 0 and 1 to all individuals within the model and then select to die all individuals whose probabilities of dying lie above this random number. However, the number of people who die will most likely not match the number projected by the macrosimulation model. Different methods can be used to align the result: most of them sort the individuals according to their probability of facing the event and selecting the top x% to die as specified by the macrosimulation model, or in order not to remove all the stochastic variation, sort by the probability altered by a random draw.

One way to introduce this stochastic element, used by a number of microsimulation models, is to draw a random number u_i for each individual, then if p_i is greater than u_i. the event (death) occurs. One approach to accomplish this is to construct a ranking variable, $r_i = p*_i - u_i$ which is then used to rank individuals so that the top x% ranked individuals are selected.

$$r_i = \text{logit}^{-1}(\alpha + \beta X_i) - u_i = \frac{\exp(\alpha + \beta X_i)}{1 + \exp(\alpha + \beta X_i)} - u_i$$

The issue of using random numbers from a uniform distribution is again problematic. This issue is comprehensively addressed by O'Donoghue (2001) when he notes that the range of possible ranking values is not the same for each point. O'Donoghue suggests that the ranking variable should be

$$r_i = logit^{-1}(\alpha + \beta X_i + \varepsilon_i) = \frac{\exp(\alpha + \beta X_i + \varepsilon_i)}{1 + \exp(\alpha + \beta X_i + \varepsilon_i)}$$

with

$$\varepsilon_i = -logit(u_i) = -\ln(u_i / (1 - u_i)) \text{ or } u_i = \frac{\exp(-\varepsilon_i)}{1 + \exp(-\varepsilon_i)}.$$

He notes that the rank produced by the two ranking variables is not the same. The second method will be more likely to select cases at extreme points than the first, while first method will select more points with central values of $p*_i$.

A useful way of analysing alignment methods can be found in Kumar 2002.

4.4 MACROSIMULATION DISTRIBUTIONS

The methodological issues discussed in the example above are based around the simple object of aligning deaths to a single aggregate number. It does not, for instance, enforce alignment of deaths at each age and/or by marital status.

Clearly, for the alignment process to fully capture the distributional characteristics of the population, it must be stratified as much as possible. Practically this suggests that the macrosimulation model must be estimated at the greatest level of disaggregation possible with the alignment process designed to address each level of disaggregation. In the case of deaths we could model deaths by age and marital status in the macrosimulation model and align the microsimulation model by age (or age group) and marital status.

It is possible however that there will not be a sufficient number of individuals in each stratification to hit the target aggregate number. In this case processes are employed to find an appropriate individual in an adjacent stratification and correct for the adjustment in the next period or simply leave the missing individuals until the next period.

4.5 Stochastic Issues

We noted above that alignment has the effect of removing the randomness associated with each aligned variable. This means that in these dimensions the stochastic nature of microsimulation has been made deterministic. One can reintroduce stochastic properties on the microsimulation model outcomes by building stochastics into the macrosimulation model. That is, historic stochastics can be applied to the aggregate profiles that are being used for alignment or the macrosimulation model can be developed within in a stochastic framework.

However, even though alignment introduces some determinacy, the underlying stochastic drawing is still operating within the microsimulation model to provide stochastic projections to the life outcomes of each individual.

5 Policy analysis

One Australian policy department made the observation:

> "One of the most important reasons for having an alignment facility is to have the capacity to impose alternative macro scenarios on the projections (e.g. high fertility, low fertility)."

but went on to note that the model must be capable of addressing more complex policy questions.

> "For example, an increase in the level of government assistance for child care may lead to an increase in the labour force participation of married women and sole parents and also boost fertility rates in the long term."

We believe that attempting to adjust transition probabilities with the microsimulation framework is very difficult, particularly if the underlying models have been estimated with a range of covariates.

This paper suggests that by linking the microsimulation model to consistent long-run macrosimulation models (and even macro-economic models) the model will lend itself more easily to complex policy questions. And as we have noted, this will most likely be necessary for log-run analysis.

We do not underestimate the statistical and consistency issues raised by these linkages, but put the proposition forward as one way of addressing the use of microsimulation models as a tool in the complex policy environment.

Clearly, considerable more research and discussion is required.

6 CONCLUSIONS

> "microsimulation should be viewed as an exercise in *taking one's model seriously*. That is to say, any assumptions that are imposed during the specification and estimation steps must, as well, be imposed in the microsimulation algorithm. And, if the microsimulation output produces a finding that is sharply at odds with known facts, then it is not adequate to 'adjust' (or 'calibrate') the microsimulation; rather, one must return to the model, prepared to respecify it and to reestimate its parameters" (Wolf, 2001)

Dynamic microsimulation models allow construction of appropriate behavioural models at the level on which the relevant decisions are made. However, careful testing of the dynamics of the model and the underlying data are required. As noted by Wolf above, it is always important to run a dynamic microsimulation model in unaligned mode, so that the accuracy of the micro behavioural equations used within the model can be checked. However, it appears almost inevitable that microsimulation models will drift away from macro aggregates that we would like to track — such as official government population forecasts or forecasts of future labour force participation. In such cases, it may be desirable to force the model to align with these official benchmarks — or with our own macro estimates of, for example, how labour force participation and first marriage rates will evolve through time.

It is therefore proposed that a highly disaggregated macro database will be developed for many (if not all) of the modules in a Dynamic Microsimulation Model. The transitions for individuals predicted by the behavioural equations will be aligned each year to the targets within this macro database. However, there will be a facility to 'turn off' this alignment facility within each module, so that the analyst may choose within each run of the model whether to run some or all modules in 'aligned' or 'unaligned' mode. In this way comparison of the microsimulation modules and the corresponding macrosimulation models can be performed. Differeneces can then be used to investigate the predictive power of each model separately.

Further, this comparison process is important when modifying the modules to reflect alternate policy options. This process is one way users might investigate the most appropriate way to model alternate policy development.

While micro macro linkage is seen as potentially desirable, there are also some practical uncertainties and unanswered questions. One is that it is not yet clear whether multiple alignment processes will slow the run times for the model to such an extent that policy makers will prefer some or all module outcomes to be unaligned. Another is that if everything is aligned at a very disaggregated level (e.g. predicted first marriage rates by detailed age, gender and education groups), will this act to reduce the predictive usefulness of the dynamic model, by imposing upon the micro results pre-determined aggregate outcomes. We have noted above, however, that the underlying mechanism of stochastic drawing mitigates this view. Further research to explore the usefulness of and relationships between the microsimulation and macrosimulation models is called for.

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