Chapter 14

Employment Transitions and Earnings Dynamics in the SAGE Model

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1 Introduction

The SAGE dynamic microsimulation model is an analytical tool with which to make projections and inform the development of social policy in Britain for the twenty-first century. As in other such models, the principal purpose of this model is to study the implications of population ageing for pensions and issues regarding health and long-term care needs.[1] The model starts with a base population of individuals from a sample of the 1991 Census of Great Britain, and proceeds by updating each individual's status for every year in accordance with various life course transitions. The model specifies various demographic processes, education, employment, earnings, pension accumulation, health and disability and support networks.[2] This chapter describes the work undertaken in constructing the labour market module and highlights generic lessons that can be drawn from this work.[3]

1 Evandrou et al. (2001) provide the objectives and the work programme pursued in the ESRC-SAGE ("Simulating Social Policy for an Ageing Society") Research Group.

2 See Zaidi and Rake (2001) for a review of major dynamic microsimulation models; the same paper also discusses pros and cons of alternative empirical choices to be made in building a dynamic microsimulation model.

3 The chapter draws upon a number of technical papers prepared while documenting the work undertaken in the SAGE team. In particular, the work reported here makes use of the information available in Zaidi (2004a, 2004b), Zaidi and Scott (2001), Scott and Zaidi (2004), and Scott (2004). Authors are also grateful for the comments received from Paul Williamson and Marcia Keegan (NATSEM) on an earlier version of the chapter.

In modelling retirement incomes, it is necessary to generate for each individual a lifetime trajectory of labour market experience that is subsequently used to compute his/her accumulation of pension entitlements. The labour market module therefore simulates, for each year and for each individual, whether or not the individual will work, and how many weeks or months the individual will work in a single year. Subsequently, the module computes earnings generated from that work. The module also provides information about whether absences from the labour market are due to unemployment, inactivity due to studentship or inactivity of other kinds (principally, caring for children, caring for sick and disabled). Such distinctions between different forms of non-employment are critical inputs for the pension module: they determine whether and how individuals receive credits towards their pension entitlements.

Various factors are important in determining a credible simulation of a life course trajectory of employment and earnings. The requirements can be threefold:

1. Estimation of credible predictors of employment transitions and earnings dynamics from the existing datasets, including a plausible account of inter-cohort and intra-cohort differentials in lifetime labour force experiences;
2. Implementation of estimated employment and earnings equations on the base data, for simulation purposes, including undertaking all the imputations necessary in the base dataset to enable this implementation; and
3. The validation for logic and consistency of simulated results, and – if necessary – calibrations, so as to be able to reliably predict the impact of various policy scenarios for the future.

In line with these requirements, the main body of the chapter is organized into three sections. Section 2 describes the modelling of the labour force dynamics, covering both employment transitions and earnings dynamics. In Section 3, the implementation of the labour force event is discussed. Section 4 illustrates the methods adopted in testing the implementation of the labour force event – logic testing as well as statistical evaluation. Section 5 provides the conclusions.

2 Modelling labour force dynamics

In the SAGE model, individuals were subject to employment dynamics from the year after they leave education, at an age between 16 and 22, until the year they retire, at 65.[4] The employment transitions took place on a quarterly basis, as this modelling choice facilitated accounting for sub-annual changes in employment. However, for computational efficiency, the employment transitions were all computed in a single event in the last quarter of the model year, after the annual demographic transitions had taken place.[5]

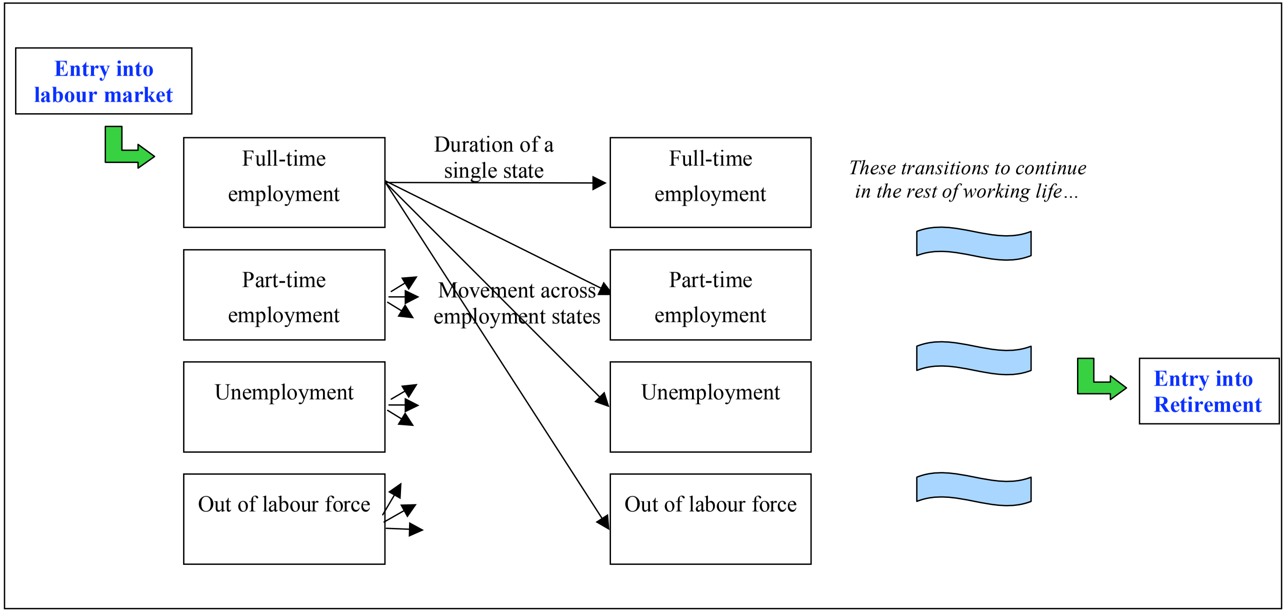
The labour force dynamics cover three aspects: in employment *status*; in the *level* (full-time / part-time), *type* (employee / self-employed), and *location* (sector, industry and occupation) of employment; and in earnings. Figures 1 and 2 display different processes and outcomes that are involved in these dynamics. They seek to illustrate all possible labour force transitions, and thus provide a framework within which to evaluate processes modelled in the SAGE model.

Figure 1 exhibits the employment status dynamics, starting with an entry into the labour market status and ending with retirement. Notably, it shows that the entry into the labour market may start with experiences of employment (full-time or part-time), unemployment or inactivity. The phenomenon of unemployment or inactivity right at the start of one's career is more frequently observed in recent times in Great Britain, and also serves as a strong predictor of labour market experience during the rest of the working life. From there onwards, individuals make transitions across other employment states or they maintain the same status as before. All transitions possible between the four alternative states of employment are shown at the bottom of Figure 1.

4 One of the guidelines adopted by the SAGE team is that no unnecessary effort will be expended on an accurate representation of characteristics that will have little or no effect on the simulated outcomes of interest. For this reason, we decided on a simple initial model in which education and working life are discrete phases of the life course (and there is no return to education after entering the labour market). An implicit assumption is that the part-time work among full-time students does not count towards pension accumulation and such work has no impact on future employment experiences. Such generalizations helped us to simplify the work of implementation and also keep the model "smaller" – easier to understand and faster to execute.

5 The impact of demographic changes on labour market transitions is relatively gradual (apart from the birth of a child), and it was considered unnecessary to tie employment transition probabilities to the demographic state at precisely the same time.

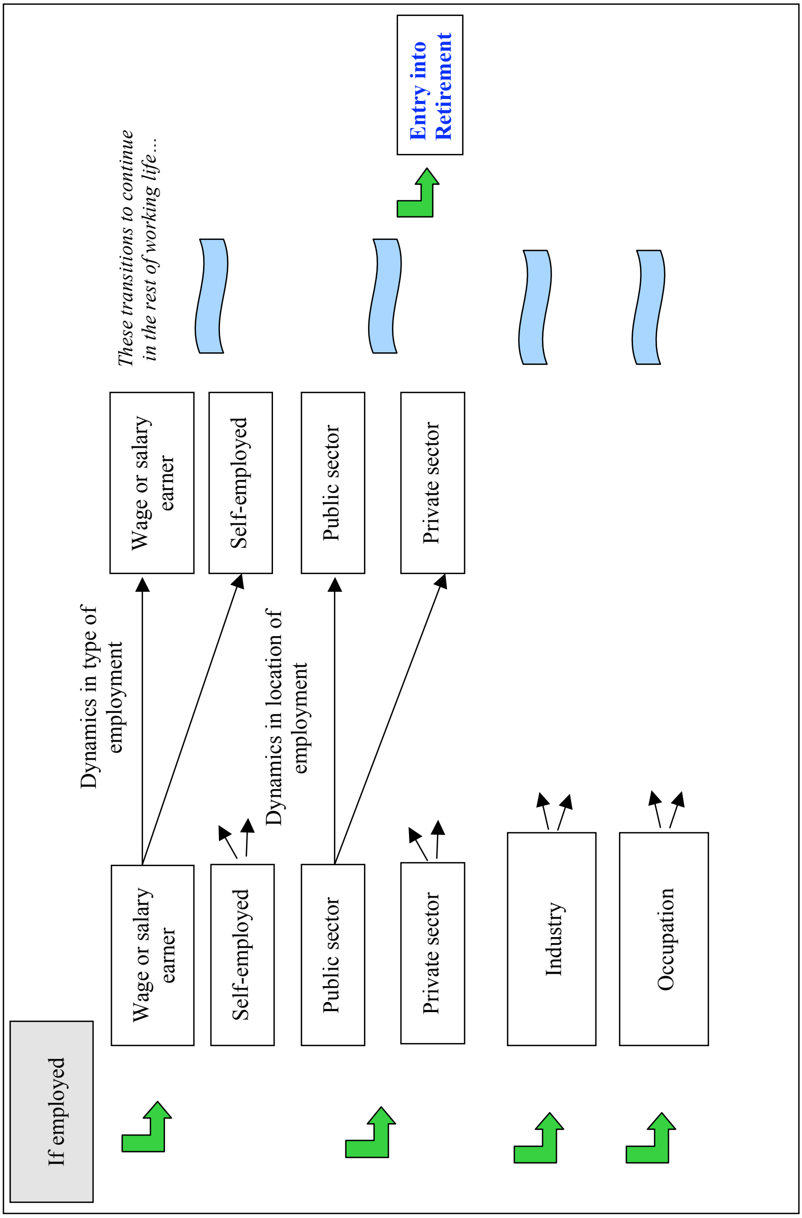
Figure 1: Dynamics in the employment status



FT→FT	FT→PT	FT→U	FT→N
PT→FT	PT→PT	PT→U	PT→N
U→FT	U→PT	U→U	U→N
N→FT	N→PT	N→U	N→N

Notes: FT stands for full-time employment, PT for part-time employment, U for unemployment and N for inactivity status.

Figure 2: Dynamics in the type and the location of employment



All employed persons were further categorized into subgroups on the basis of their level of employment (full-time or part-time), type of employment (employee or self-employed), sector of employment (private or public sector), industry (e.g. agriculture, manufacturing, or services) and occupation (e.g. manual or non-manual). The necessity and the significance of these attributes were determined by the differences in the empirical patterns of employment and earnings and differences in pension schemes across these categories. The arrows in Figure 2 point to the possible transitions that one can observe in the type and location attributes. The type and location attributes were taken as time-invariant attributes in the SAGE model.[6] All such attributes were determined at the time of completion of education (at age 22), and they include education level attained, industry, occupation and sector.

2.1 *Predictors of employment dynamics*

In order to distinguish between differential experiences of employment, we need to identify strong predictors for duration of and changes in employment, unemployment and inactivity. Since some predictors, such as gender, interact with many other predictors, it is crucial to identify the groups for which separate estimation should be carried out. For our purposes, the potential list of predictors and estimation groups had been constrained by the availability of variables in the base dataset.[7] However, we also imputed certain variables in the base data, using correlates between available and non-available variables in related sample surveys, which facilitated using a larger set of predictors for the simulation of employment dynamics.[8]

To estimate the pattern of transition between different employment states over time, two datasets that provide longitudinal information for the British population were available: the Quarterly Labour Force Survey (QLFS), and the British Household Panel Survey (BHPS). The QLFS had a much larger sample size, so we used this database to estimate employment dynamics. However, the panel element in the QLFS is restricted to five quarterly observations, and the earnings data are much less comprehensive

6 See Scott and Zaidi (2004) for reasons underlying this empirical choice as well as its implications.

7 See Zaidi and Scott (2001) for further discussion on issues relevant to the choice of the base dataset.

8 More details of imputation of missing variables are given in Scott and Zaidi (2004).

than in the BHPS. Therefore, we used the QLFS to derive parameters for employment transitions, whilst the BHPS was used for estimating earnings equations.

We used 27 waves of the QLFS, beginning with the December 1992 – February 1994 wave, and ending with the June 1999 – August 2000 wave. Each wave contains approximately 12,000 individuals who were followed over five quarters, providing four cases of transition/non-transition between employment states. In total, this dataset provided observations on over 1.2 million employment transitions. We grouped the data by year, where the years correspond to the quarter in which the respondent was first surveyed.[9] Our subsequent modelling work is based on the transitions that people observed between the 4^{th} and 5^{th} quarter, allowing us to take as much account of previous work history as possible by drawing upon the information on employment experience over the previous three quarters captured in the QLFS.

As a starting point, we initially considered three basic employment states – employed (E), unemployed (U) and inactive (N). Transitions between these states were to be modelled with a series of nested dichotomous choices, thus: E $\Rightarrow$ E or E $\Rightarrow$ non-E, and if non-E, then U or N (and likewise for transitions originating in U or N). However, our exploration of the QLFS data revealed that there was an additional transition of considerable importance for the British population – between full-time and part-time work. We therefore further subdivided those in employment into part-time and full-time employment. This was based on the variable FTPTWK: whether full- or part-time in the main job.[10] We therefore ended up working with four possible employment states – full-time work (FT), part-time work (PT), U and N. Instead of modelling this as a series of nested dichotomous choices, we chose to model it as a simultaneous polychotomous choice, using multinomial logit.

Models were estimated separately for four population groups:

9 Details of the data files used to construct the estimation database are provided in Zaidi (2004).

10 The variable FTPTWK was verified against reported total number of hours worked. In short, all those who work full-time have on average 40.5 hours of work per week, and all those who work part-time have on average 16 hours per week. Obviously, these averages hide some extreme values of working hours for both full-time and part-time workers.

1. Males with non-advanced qualifications,[11]
2. Males with advanced qualifications,
3. Females with non-advanced qualifications, and
4. Females with advanced qualifications.

The labour force state can take one of four values in a single quarter: 1. FT, 2. PT, 3. E, 4. N. Transitions between these states were determined by multinomial logistic regression models with four possible outcomes. Outcome 1, FT, was taken as the reference level, and in each model there were three equations giving the relative risk of outcomes 2, 3 and 4, in relation to outcome 1:

$$R_i = \exp\left(\beta_{i0} + \beta_{i1}X_1 + \beta_{i2}X_2 + \ldots + \beta_{ik}X_k\right) \quad (i = 2,3,4)$$

where X_j represent the values of predictor variables relating to characteristics of the individual and β_{ij} are coefficients provided in a parameter table. The relative risks R_2, R_3, R_4 were computed, depending on the individual's characteristics, and the relative probability thresholds were cumulated as:[12]

$$P_1 = 1; \quad P_2 = 1 + R_2; \quad P_3 = 1 + R_2 + R_3; \quad P_4 = 1 + R_2 + R_3 + R_4$$

A pseudo-random number r was generated in the range (0, P_4) and compared in turn with P_1, P_2, and P_3. The outcome was the first level i for which $r < P_i$.

Since the models were estimated for the four origin states for each of four population groups, defined by sex (2 levels) and possession of advanced qualifications (2 levels), there were 16 models and 48 equations. The explanatory terms in the regression equations were:

(Constant term)
Qualification (2 levels within advanced/non-advanced group)
Age (whole years)
Age squared

11 Education status was defined in a four-category variable: 1) "No qualifications", 2) "GCSE, etc.", 3) "A-level, etc.", and 4) "Higher qualifications". The first two categories define non-advanced levels of qualification, and the last two refer to advanced qualifications.

12 This method was considered more computationally efficient than the more conventional method where the thresholds are divided by P_4 and the random number is in the range (0, 1).

Aged 16-22 (indicator)
Children: number and age of youngest (grouped interaction, 6 levels, for females only)
Partner employment status (3 levels: no partner, partner working, partner not working)
Health restricts work (indicator)
Status change in last year (indicator)
Duration of non-employment and age (3 levels for non-employed)
Employment sector (3 levels for employed)
Occupation (6 levels)
Industry (6 levels)

Most of the predictors were indicator (dummy) variables, while others were categorical variables and had coefficients for several levels represented by indicator variables. Age and age squared entered the equations as interval-level variables and had one multiplicative coefficient each.

Two variables of employment history had been of particular relevance. First, the variable "*duration of non-employment*", calculated only for those who were currently non-employed, was measured in quarter years and was used only to distinguish those who have not had a job in the last eight years (i.e. threshold 32). Second, the variable "*status change in last year*" indicated a change between employment, unemployment or inactivity in the last year and is computed as a derived variable from the observed employment status in each of the last four quarters.

The results for the final specification of the regression equations estimated are reported in Tables 8 to 19 of Zaidi (2004a). As a way of an illustrative example, we include (in Annex A) results of the multinomial logit models for the origin state of **full-time work**, for both males and females and for those with advanced and non-advanced qualifications.

2.2 *Estimation of earnings equation*

The aim of the earnings equation has been to capture the cross-sectional heterogeneity amongst workers as well as determine how time-variant attributes affect earnings. A simple approach would have been to estimate the wage equation on the basis of a large cross-sectional dataset and use the resulting relationship for the prediction of wages in each model time period. However, this approach implies that individuals will be subject to the same cross-sectional variation in each time-period and the link with one's own wages of the immediate past will be lost.

This problem was resolved by working with both static and dynamic aspects of the random effect panel data model. Random-effect linear regression models, with first-order disturbance terms, for the log monthly earnings, were estimated for all employees. To this, we added a separate single model for self-employed persons. The form of the equation is:

$$\log(y_{jt}) = \alpha + X_{jt}\beta + \mu_j + \varepsilon_{jt} \qquad (j = 1,\ldots,N;\ t = 1,\ldots,t_j) \tag{1}$$

where u_j is the time-invariant individual effect, representing fixed unobserved attributes. The time variant error term, $\varepsilon_{jt,}$ satisfies

$$\varepsilon_{jt} = \rho\varepsilon_{jt-1} + \nu_{jt} \tag{2}$$

in which $|\rho| < 1$ and ν_{jt} are independent and identically distributed with zero mean and standard deviation σ_ν.

The dataset used for the estimation of earnings equations was derived from the 11 waves of the BHPS, covering the period 1990-2000. This survey was preferred for a number of reasons. *First*, the longitudinal nature of the BHPS data offered us the possibility to estimate a panel data model. *Second*, the quality of the wage variable was better than that recorded in other large-scale datasets (e.g. QLFS). *Third*, the survey provided detailed attributes of individual wages, including a possibility to work with both gross and net wages.

The estimation sample was restricted to those of working age and who had non-missing wage data. The sample was pooled across 11 waves of the BHPS; thus results were representative of the trends and patterns observed during the whole of the 1990s. The estimation groups for the wage equation were the same four population groups as used for employment transitions, defined by sex, and possession of advanced qualifications. In particular, the distinction across individuals with advanced and non-advanced qualification levels offered large explanatory power in wage progression.

A whole range of explanatory factors was tested to see their impact on wages. The potential set of explanatory variables and their different categorizations were chosen on the basis of their relevance but also their availability in the base dataset and their inclusion in the estimation of employment transitions. Amongst the most notable are variables that report on the most recent employment experience. Other variables are age, age squared, educational attainment, occupation, industry, partnership status, employment status of the partner, whether health restricts work, and public/private sector distinction. Number of children living at home and age of youngest child (grouped interaction, 6 levels, for females only) have also been included. Full-time and part-time status, along with its interaction with other attributes, is also used. Part-time employment indicator was used in interaction with young age, private sector, employment history (for females) and professional/managerial occupation. Many of the predictors were common to the employment transition and wage equations. The regression results for the earnings equation are reported in Zaidi (2004b). As a way of an illustrative example, in Annex B, we report the coefficients of the final specification of the wage equation for male employees, with advanced and non-advanced qualifications.

It was useful to split the regression results (for the log wage) into three parts for implementation:

- The time-invariant portion, which we term the base log wage. This includes the terms for: constant, qualification, occupation, industry, and the individual effect u_j of equation (1).
- The time-variant error term. This auto-regressive term was initially drawn from a normal distribution with mean 0 and standard deviation σ_ε, and was updated each year using formula (2), where ν_{jt} was drawn from a normal distribution with mean 0 and standard deviation σ_ν, which was computed as $\sqrt{(1-\rho^2)}\ \sigma_\varepsilon$.
- The time-variant deterministic portion, including terms for: age, age squared, health, children, partner's employment, employment history, part-time employment (including interactions).

The time-invariant portion and error term were assigned to each individual along with the other time-invariant characteristics upon entry to the labour market. Each subsequent year, and for each individual of working age, the error term was updated using stored parameters ρ (RHO) and σ_ν (SIGMA_N).[13] Earnings were calculated after the labour market transitions for the year had been computed. NEMPHIST was also updated, reflecting the employment status in the fourth quarter of the current year, after the computation of employment transitions and earnings.

13 This method was considered more computationally efficient than the more conventional method where the thresholds are divided by P_4 and the random number is in the range (0, 1).

Table 1a: Variables included in the population database for the labour market event

ID	*Person identifier*
NSEX	*Sex* 1 "Male" 2 "Female"
NAGE	*Age in years*
NEDSTAT	*Educational status* 1 "No qualifications" 2 "GCSE, etc" 3 "A-level, etc" 4 "Higher qualification"
IDPART	*Partner's ID* 0 "n/a (not currently partnered)"
NCHILD	*Number of own/partner's children under 16*
NYCAGE	*Age of youngest child in family* -1 "unborn child (woman pregnant)" -9 "n/a (no children under 16)"
NHEALTH	*Health status* 0 "No health problem" 1 "Health restricts work"
NSECT	*Sector* 1 "Public employee" 2 "Private employee" 3 "Self-employed"
NINDUS	1 "Agriculture/ fishing/ Construction" 2 "Manufacturing/Energy & water" 3 "Catering/ transp/ communication" 4 "Finance" 5 "Public services" 6 "Other services"
NSOC	1 "Managers & administrators" 2 "Prof, assoc prof & tech" 3 "Clerical & secretarial" 4 "Craft/personal protec serv" 5 "Plant & machine operatives" 6 "Sales/ Other occupations"
NEMP1, NEMP2, NEMP3, NEMP4	*Employment status in each quarter* 1 "Employed full-time" 2 "Employed part-time" 3 "Unemployed" 4 "Inactive"
NDURLM	*Duration of labour market spell in quarters*
NEMPHIST	*Two-year labour market status history*
FWAGE_B	*Base log wage (time-invariant)*
FWAGE_E	*Wage error term (auto-regressive)*
MWAGE	*Annual earnings*

Notes: The table includes variables needed for computing derived variables, as well as direct predictors, in the labour market module. See Section 3.1 for a description of NDURLM and NEMPHIST. The health status variable was initially defined to be static and it was based on the presence of "limiting long-term illness" in the base dataset; subsequently, health transitions were also implemented during the whole of the working life.

Table 1b: Derived variables used in the labour market event

AGE2	Square of NAGE
NCHB	Number of children born
NEMP	Initial employment status for transition
EMPPT	Partner employment status 0 "No partner" 1 "Partner not employed" 2 "Partner employed"
CHNG	Status change in the last year
DAS	No job / sector lookup values
RHO, SIGMA_N	Coefficients for updating wage error term

3 Implementing the labour market event

The implementation part of the labour market module had been the most demanding part of the work undertaken in the SAGE model. Not only were the transition rules complex, with multiple states in the case of labour market status, and multiple estimation groups, but the dependence on variables included in other modules was complicated, and a large amount of information had to be imputed in the base data. This section describes briefly the salient aspects of this work.

For implementation purposes, some of the labour market variables were stored in the population database and could be referred to directly in the implementation rules; whilst others had to be computed as derived variables. Table 1a shows the names and coding of the variables in the population database, and Table 1b the derived variables.

3.1 Employment history variables

The variable NDURLM, mentioned in Table 1a, measured the length of the current employment spell, which was defined as the number of quarters during which the person has been either continuously employed or continuously non-employed. It was set to 1 whenever a transition results in a change between employment and non-employment, and incremented at each transition not resulting in a change. Other variables made use of the information recorded in NDURLM. For instance, the derived variable CHNG, "status change in last year", was set to 1 if NDURLM<4 and 0 if NDURLM>= 4 and the person was currently employed. If NDURLM>= 4 and NEMP4>2 (either unemployed or inactive), it is necessary to distinguish people who have switched between unemployment and inactivity in the last year. This was established by examining the variable "*employment status in each quarter*" (NEMP1 to NEMP4, each having values 3 or 4 in this case).

For earnings, we utilized the variable NEMPHIST, which indicates the previous two years' employment history categories, used in the equation for the time-varying portion of wages. Employment history was coded using the values 0=student (S), 1=employed (E), 3=unemployed (U), 4=inactive (N). The codes of NEMPHIST are shown below in Table 2.

The labels of NEMPHIST indicate the current status first, followed, in order, by the status in the previous two years. The current status is always E, "employed", when wages are being calculated. The history was based on the employment status in the last quarter of each of the previous two years. This choice was made in order to be consistent with the estimation data, which use employment status in the week before interview, in an annual panel survey.

For the parameter estimation for females, the coding of the history variable was extended to cover the interaction with part-time working (by adding 100 to the value for women working PT). Thus, for males, the code values run from 0 (ESS) to 44 (ENN) and for females, from 0 to 144. In both cases, the reference category in the wage equation was 11 (EEE, FT).

Table 2: Coding of employment history variable

Codes	includes	labels†	FT code	PT code
0		ESS	0	100
1	3 4	EES EUS ENS	1	101
11		EEE	11	111
13		EEU	13	113
33	14 31	EEN EUE EUU) combined	33	133
34		EUN††) for all but	44	111/100
41		ENE) PT females	44	141
44	43	ENN ENU	44	144

Notes: † The labels indicate the current status first, followed, in order, by the status in the previous two years; E = Employed; U = Unemployed; N = Inactive; S = Student.
†† EUN is combined for PT females with EEE or ESS according to level of education: non-advanced.

3.2 *The labour market parameter tables and rules*

There were 16 models of employment transitions, subdivided by sex, qualification group (2 levels) and origin state (4 levels). For each of these models there were three equations, with up to 12 predictor variables. The coefficients associated with one or more predictors were grouped in panels in the parameter table. The panels were named as:

QUA (for qualification and age terms),
CHA (for number of children and age),
HPT (for health status and partner's employment),
DAS (for employment duration, age and employment sector),
SOC (for occupation) and
IND (for industry).

Each panel contains three columns of beta coefficients (e.g. *BQUA2*, *BQUA3*, *BQUA4*) for the three outcome levels: while outcome 1, full-time work, was taken as the reference level, the beta coefficient gave parameters for employment transitions to part-time work, unemployment and inactivity, respectively. Panels also included one or more columns of lookup values for the predictors. Some examples of the panels included in the employment transitions parameter table are provided in Annex C.

Using the parameter table, *four* transitions of employment status were performed: from the fourth quarter of the previous year to the first quarter of the current year (NEMP4 to NEMP1) and then successively to the second, third and fourth quarters of the current year. Each of the four employment status variables ("*employment status in each quarter*": NEMP1 to NEMP4) was successively overwritten by the new value.

The parameter table for the simulation of wages was smaller than that for employment transitions, since only the time-variant portion of the log wage regression equation needed to be computed (nb. log base wage was computed at the time of entry into the labour market), and there were fewer equations. The table was arranged in sub-tables and panels, as for the employment transition equations, but there were only five sub-tables: four for employees, grouped by age and qualification group as above, and one for self-employed persons. The panels included in the wage parameter table are specified in Annex D, which also includes the full parameter table for the time-variant component of the wage equation.

If a person had not worked at all during the year, there was no need to do any wage computation, and the wage was set to 0. Otherwise the time-variant portion of the log wage was computed separately for any periods of full-time and part-time work during the year, using the appropriate parameters. These terms were then combined with the base log wage and wage error term and exponentiated to obtain the quarterly full-time and part-time earnings. The annual earnings were assigned as a weighted sum, according to the time spent employed full-time and part-time during the year.

NEMPHIST was also updated, reflecting the employment status in the fourth quarter of the current year. These updates were performed after the computation of employment transitions and earnings. The assignment of labour market predictors on entry to the labour force took place in the *AgeOneYear* event and is described in Scott and Zaidi (2004). For the initial labour market status, NEMP4 was set to 3 "Unemployed" and NDURLM remains at its default value of 0. This was predicated on the supposition that new entrants were actively seeking work, and were not yet scarred by unemployment of a year or more. NEMPHIST also remained at 0, as this was the code for student history over the previous two years.

4 Testing and validation

A protocol for testing and validation of simulations of the labour force event was established, so as to see whether the model works as intended and to "validate" the simulated results.[14] This step was important as it contributed to enhancing the credibility of the model among its producers and users. For the labour market event, we performed *logic testing*, to check that the rules and parameter tables were correctly specified, and *statistical evaluation*, to check whether the model output was consistent with the data used to design the simulation.

4.1 Logic testing – employment transitions

Because of the large number of terms and predictor values, it was not practicable to check the rules for computation of the transition equations using log output for selected individuals. Instead, we used the predict command

14 Validation can be defined as the comparison of model's results with counterpart values that come from independent sources and are known to be "correct" and/or credible.

in Stata (Stata Corporation, 2001) which could output the values of the estimated outcome probabilities and the linear estimators, for any set of observations, immediately after estimating the logit model.

The first test undertaken compared the linear estimators and outcome probabilities estimated by Stata with probabilities computed by the simulation programme. It used a base dataset with 10,364 observations from the QLFS data. The test simulated the labour market event for one year only, using adapted transition rules, which performed only the first quarterly transition. The output data after one year was then analysed to see that the SAGE-derived variables and probabilities agreed with the ones generated by Stata's predict command. Errors were discovered in this way in the coding schemes of some of the variables. Further tests enabled checking of the allocation of outcome states and updating of duration, the re-computation of probabilities when states change, and the sequencing of the quarterly transitions, which were not covered by the first test.

Another test used a small base dataset containing 3 couples and 2 unpartnered individuals, running for two years. It executed the labour market event, which did all four quarterly transitions, with detailed log output. It also executed the *AgeOneYear* event, so that ages were incremented for the second year. The test was used to hand-check the derived variables, in particular partner employment status when the partner was older (including over 64) and the correct lookup in case of pregnancy. A further test, which was performed on output from a larger number of years, had been to check that there were no systematic differences in transition rates by quarter, depending on whether there had been changes earlier in the same year. This suggested that there were no differences in the rules between quarters. The output from the adjustment of employment status in the base data when there were no changes in the other population characteristics indicated that the labour market changes were smooth over each year.

4.2 Logic testing – earnings simulation

We used Stata's predict command to provide an alternative computation with which to test the earnings simulation. Since the earnings depended on employment in each quarter of the current year, we could not use a prediction from the base data, but used a sample of data from the first year simulation output and computed "out of sample" predicted log wages, using coefficient estimates saved in Stata for each estimation group. We added the error term from the base data to the predicted log wages, before the annual earnings were derived, and compared with the simulated earnings.

To check that the error terms were being updated correctly, the distribution of the error term after one year in each estimation group was checked to see that it was $N(0,\sigma_\varepsilon)$ and that the correlation with the base data error term was ρ. The updating of employment history was checked by tabulating new against old histories by current employment status. The initialization of the base wage and error term on entry to the labour market was checked by looking at their distributions for new entrants in the output for 1991 and 1992.

4.3 *Statistical evaluation – employment transitions*

For comparison with available time series, and with the estimation data (QLFS 1994-2000), we used a simulation from 1990 to 2000 and analysed all individuals of working age (16-59/64) at the time of the employment transition, including students, who were classified as inactive. The data included an average of 17,097 males and 15,960 females each year from 1990 to 2000.

We compared the simulated outcomes with the LFS time series for the UK produced by ONS, for 1991-2000, by sex (ONS, 2003). Table 3 shows the proportions of each sex who were employed, or active (employed or unemployed) at the beginning and end of the decade in the official figures and in the simulation. The proportions in the base data are also shown here for comparison purposes.

It can be seen that both employment and activity rates were much lower in the base sample than in the LFS for 1991. By the end of the decade, the employment rates for both men and women in the simulation were only marginally higher than those in the LFS, but the activity rates were around 1% higher for both sexes.

Table 3: Employment states compared

	Male 16-64 (% employed)	Male 16-64 (% active)	Female 16-59 (% employed)	Female 16-59 (% active)
LFS Mar-May 1991	79.9	88.1	66.0	71.3
Base data (v. 1.6)	76.9	82.0	63.7	67.2
LFS Jun-Aug 2000	79.3	84.1	69.6	73.1
Simulation 2000 Q4	80.1	85.5	69.8	74.1

Note: Full-time students are included as inactive.

Further comparisons in the employment states over the 1990s with the LFS time series show that simulated rates converged with the LFS time series towards the end of the decade, but inactivity rates were too low.

4.4 Statistical evaluation – earnings results

Since earnings were dependent on the time spent in full-time and part-time employment during each year, we show results only for those who were employed full-time throughout the year in question. The analysis is of simulated data for the years 1991 to 1999. Tables 3 and 4 show statistics for the annual earnings (in 1991 prices, but 1993 earnings levels) for various subgroups of the population. The mean, standard deviation, median and 10th and 90th percentiles are shown.

Table 4 shows the distribution of earnings in each of the estimation groups, with self-employed disaggregated by sex. Self-employed earnings are more variable than those for employees. The relationship with sex and education status is as expected.

Table 4: Earnings distribution by estimation group

Estimation group	mean	s.d.	p10	p50	p90	N
Male non-advanced	12664	6425	5945	11380	20983	43270
Male advanced	18501	9840	8321	16462	31077	55113
Female non-advanced	8153	4656	3498	7094	14070	31068
Female advanced	13314	8049	5355	11430	23495	23803
Male self-employed	17328	27229	2247	9237	38924	20147
Female self-employed	8043	12209	1027	4330	18091	2981

Notes: Educational attainmant is defined as: 1 "No qualifications" 2 "GCSE, etc" 3 "A-level, etc" 4 "Higher qualifications". The first two categories define non-advanced levels of qualification, and the last two refer to advanced qualifications.

The corresponding distributions for 1993 (the reference year) in the estimation data are given in Table 5. Note that the requirement to be employed full-time all year in the simulation is more restrictive than the requirement to be employed full-time in the week before interview in the BHPS. The number of female self-employed is also rather small to make a comparison. The distributions are roughly the same as in the simulation. Differences are to be expected because of compositional differences in the two datasets, Monte Carlo variation in the simulated data, and less-than-perfect model fit in the estimation data.

Table 5: Earnings distribution in the estimation data for 1993

Estimation group	mean	s.d.	p10	p50	p90	N
Male non-advanced	13349	7999	6741	12029	21378	994
Male advanced	18180	9476	8378	16680	29069	773
Female non-advanced	9306	4405	4668	8807	14522	676
Female advanced	13937	6899	6282	12788	22818	439
Male self-employed	14293	13589	3148	10185	32407	384
Female self-employed	8663	8611	648	6481	18519	92

The distribution of earnings in the simulation by age group and sex is shown in Table 6. The full-time earnings of both sexes peak between the ages of 36 and 50, but the peak for women is less marked than that for men.

Table 6: Earnings distribution by sex and age, for 1993

Age group	mean	s.d.	p10	p50	p90	N
Males						
16-22	8602	7632	3548	7256	14134	9060
23-35	14543	11653	5898	12242	24734	42993
36-50	19292	16295	7256	16401	32727	45936
51-64	15937	12625	5634	13378	27933	20541
All males	16171	13905	5681	13445	28454	118530
Females						
16-22	6582	3962	2636	5721	11434	7177
23-35	10352	6852	3992	8705	18552	22251
36-50	11550	8056	4193	9498	21422	21848
51-64	9771	7017	3559	8082	17981	6576
All females	10271	7242	3707	8453	18889	57852

5 Conclusions

The labour market module is a key element of every dynamic microsimulation model. Its requirements are manifold, including estimation of parameters of employment transitions and earnings dynamics from the existing datasets and undertaking all imputations necessary in the base dataset to enable the implementation of the labour market event. Then, there is the process of testing, evaluation and validation of simulated results to measure the credibility of the model. This chapter describes how this work had been undertaken for the SAGE dynamic microsimulation model of Great Britain.

The estimation data for employment transitions came from the Quarterly Labour Force Survey, covering the period between December 1992 and August 2000. This dataset had the advantage of large sample size, as it provided over 1.2 million observations on employment transitions, but it lacked information on employment history beyond a single year. However, the lack of a job in the last eight years, inferred from missing values, proved to be an important predictor of the probability of transition into employment.

For earnings, the estimation data were taken from the British Household Panel Survey, covering 11 waves during the period 1990-2000. Random effect linear regression models, with first-order autoregressive disturbance terms, produced cross-sectional earnings distributions for full-time workers that reasonably reflected the distributions in the donor data. The form of the equations allowed for a permanent individual component to be calculated once only, in the base dataset, and imputed by donation to new labour market entrants. This meant that the time-variant component, which had to be recalculated each year according to the individual's current circumstances, was relatively simple to compute.

Further validation of the long-term trajectories of employment and earnings produced by the model will be necessary. Unfortunately, there is as yet little reliable independent data available with which to compare the simulated results. Period and cohort effects are also important and projection of future employment behaviour and earnings without disentangling these effects must inevitably entail some degree of doubt. We cannot assume that those entering the labour market in the 1990s will follow the same trajectories as the previous generation. In basing our estimations on 1990s data only (because of lack of availability of comprehensive data from earlier periods), we confound the cohort and period effects that shaped the experience of older people still in the labour market.

In analysing the results, account must also be taken of Monte Carlo and other sources of variation. Because of the high dependency of the outcomes on modelled changes in individual circumstances, model-runs with different random number seeds will produce varying outcomes at macro as well as individual level, and this variation should be assessed by making a number of different runs for each analysis. Analysis of other sources of variation, such as sampling and imputation variation in the base data and variation in parameter estimates, should be performed. It is possible that Monte Carlo variation in the execution of the transition rules will provide the biggest source of variation, especially as these differences are cumulative over time.

With these reservations, the logic testing and statistical evaluation showed that the model produced a realistic distribution of employment and earnings, which was related to individual circumstances in a way that no static or macro model could achieve. It will also be possible to add alignment, or time-varying parameters, into the rules in future versions of the SAGE model, in order to explore the effects of different economic and policy scenarios in the future.

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Annex A: Regression results for employment transitions (from full-time work)

Table A.1: Relative risk ratio (derived from the multinomial logit models) of quarterly employment transitions of working age males, originating from full-time work status

Males												**Relative risk ratio**
	A-level or higher qualification						*GCSE or lower qualification*					
	Part-time		Unem-ployed		Inac-tive		Part-time		Unem-ployed		Inactive	
Age	0,771	***	0,976		0,682	***	0,778	***	0,985		0,741	***
Age squared	1,003	***	1,000		1,005	***	1,003	***	1,000		1,004	***
Couple	0,645	***	0,657	***	0,623	***	0,753		0,660	***	0,925	
Head of family unit	0,987		0,740	**	0,710		0,733		0,762	*	0,997	
Have child of age less than 2	1,155		0,753		0,457	*	1,541		0,944		0,788	
Lowest educational attainment	0,705	***	1,188	*	1,129		0,903		1,069		1,155	
Health restricts work	1,904	***	1,576	***	4,112	***	1,857	***	1,521	***	4,180	***
Employment history: employed for one year or more	0,203	***	0,118	***	0,128	***	0,250	***	0,132	***	0,184	***
Employment status: self-employed	2,881	***	0,786	**	0,591	***	2,357	***	0,784	*	0,690	**
Employment sector: private	1,169		1,493	**	0,922		1,122		1,160		0,906	
Managers and administrators	0,434	***	0,722	*	0,684	*	0,415	***	0,556	***	0,818	
Professionals and associated professionals	0,531	***	0,743	*	1,144		0,779		0,511	***	0,622	*
Clerical and secretarial occupations	0,681		1,291		1,224		0,354	***	0,672	**	1,162	
Craft related occup., personal and protective services	0,456	***	0,922		0,861		0,521	***	0,687	***	0,732	*
Plant and machine operatives	0,728		0,926		1,266		0,423	***	0,777	**	0,938	
Agriculture and fishing; construction	0,467	***	1,098		0,927		0,602	***	1,540	***	0,764	
Energy and water; manufacturing	0,483	***	0,972		1,000		0,407	***	1,098		1,137	
Banking and financial sector	0,584	***	0,777	*	0,743		0,976		1,409	**	1,322	
Public administation, education and health	1,350		0,799		0,827		1,178		1,152		1,078	
Other services	1,612	**	1,151		0,913		1,541	*	1,645	**	1,233	
1994/95	1,134		1,452	***	1,417	*	1,342		1,305	**	1,684	**
1995/96	1,436	*	1,362	**	1,314		1,124		1,312	*	1,426	
1996/97	1,555	**	1,104		1,290		1,246		1,269		1,592	**
1997/98	1,450	*	1,127		1,400	*	1,110		1,164		1,354	
1998/99	1,394		1,410	**	1,261		1,488	*	1,515	***	1,425	
1999/00	1,608	*	1,299		1,114		1,274		1,016		1,388	
Autumn	0,989		1,170		1,379	**	1,269		0,953		0,910	
Winter	1,046		0,949		0,715	**	0,986		1,196		0,916	
Spring	1,000		1,116		0,764	*	1,060		1,044		0,860	
Pseudo- R square	0,123						0,124					
Number of observations	69.431						46.053					

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%

Table A.2: Relative risk ratio (derived from the multinomial logit models) of quarterly employment transitions of working age females, originating from full-time work status

Females												Relative risk ratio	
	A-level or higher qualification							*GCSE or lower qualification*					
	Part-time		Unem-ployed		Inac-tive			Part-time		Unem-ployed		Inac-tive	
Age	0,876	***	0,908	**	0,710	***		0,905	***	0,919	**	0,780	***
Age squared	1,002	***	1,001	**	1,005	***		1,001	***	1,001	*	1,003	***
Couple	1,307	**	0,646	*	0,856			1,314	**	0,788		0,650	***
Have child of age less than 2	4,567	***	2,361	**	5,635	***		4,884	***	0,886		3,613	***
Have child of age 2-4	1,152		0,953		1,664			1,143		0,764		1,152	
Have child of age 5-9	1,060		1,361		1,217			1,040		0,856		0,828	
Have child of age 10-15	1,141		1,300		1,146			1,320	*	0,764		0,487	***
Number of children aged less than 16	1,268	**	0,972		0,969			1,275	**	1,340		1,748	***
Wife or partner of head	1,198		0,908		1,258			1,138		1,011		1,622	***
Lowest educational attainment	0,954		1,072		1,145			1,112		0,928		1,300	**
Health restricts work	1,570	***	1,358		3,575	***		1,507	**	1,115		3,800	***
Employment history: employed for one year or more	0,345	***	0,091	***	0,136	***		0,282	***	0,163	***	0,306	***
Employment status: self-employed	2,409	***	0,665		0,965			1,654	***	0,625		1,031	
Employment sector: private	1,082		1,705	**	1,044			1,008		1,019		1,367	*
Managers and administrators	0,429	***	1,055		0,773			0,399	***	0,613	*	0,902	
Professionals and associated professionals	0,547	***	0,707		0,899			0,578	***	0,740		0,858	
Clerical and secretarial occupations	0,561	***	0,886		0,940			0,538	***	0,645	**	0,820	
Craft related occup., personal and protective services	0,962		0,721		1,415			0,762	**	0,895		1,381	*
Plant and machine operatives	1,115		1,557		1,765			0,639	**	1,176		1,114	
Agriculture and fishing; construction	0,645		0,719		0,470			1,171		1,215		0,881	
Energy and water; manufacturing	0,598	***	0,865		0,848			0,572	***	0,866		1,157	
Banking and financial sector	0,836		0,798		0,476	***		0,843		0,890		0,945	
Public administation, education and health	0,789		1,042		0,743			1,137		0,662	*	1,045	
Other services	0,851		1,354		0,527	**		1,133		1,267		1,029	
1994/95	1,010		2,451	***	1,596	*		0,906		1,319		1,029	
1995/96	1,066		2,520	***	1,563	*		0,899		1,172		1,099	
1996/97	0,966		1,831	**	1,442			0,851		1,340		1,025	
1997/98	0,852		1,501		1,081			0,705	**	0,973		1,060	
1998/99	1,066		1,955	**	1,338			0,727	*	0,975		1,111	
1999/00	1,449	*	2,443	**	0,453	*		0,922		1,306		0,999	
Autumn	1,690	***	1,425	*	1,549	**		1,340	**	1,151		1,241	
Winter	1,078		0,837		0,818			1,161		0,723	*	1,009	
Spring	1,191		1,159		0,901			1,159		1,104		1,029	
Pseudo- R square	0,101							0,088					
Number of observations	28.522							29.340					

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%

Annex B: Wage equation for male employees

Table B.1: Wage equation for male employees, further subdivided between those with advanced and non-advanced qualification

Males					
	Advanced qualification			*Non-advanced qualification*	
	Coefficient	Significance		Coefficient	Significance
Age	0,119	***		0,092	***
Age squared	-0,001	***		-0,001	***
Aged 16-22, working part-time	-0,415	***		-0,288	***
Health restricts work	-0,052	***		-0,040	**
No partner	-0,045	***		-0,051	***
Partner working	0,046	***		-0,010	
Employment history - ESS	-0,243	***		-0,640	***
Employment history - EES, EUS, ENS	-0,128	***		-0,289	***
Employment history - EEU	-0,108	***		-0,090	***
Employment history - EEN, EUE, EUU	-0,202	***		-0,171	***
Employment history - EUN, ENE, ENN, ENU	-0,327	***		-0,272	***
Employed part-time	-0,411	***		-0,689	***
Manager, part-time	0,077	*		0,230	***
Private sector, part-time	-0,157	***		0,127	**
Lowest educational category (within group)	-0,257	***		-0,107	***
Managers and administrators	0,196	***		0,171	***
Professionals and associated professionals	0,106	***		0,145	***
Clerical and secretarial occupations	0,031			0,032	*
Craft related occup., personal and protective services	0,047	**		0,062	***
Plant and machine operatives	0,065	***		0,081	***
Agriculture and fishing; construction	0,118	***		0,035	***
Energy and water; manufacturing	0,106	***		0,066	***
Banking and financial sector	0,103	***		0,107	***
Public administation, education and health	0,071	***		0,052	**
Other services	0,008			-0,053	**
Constant	4,801	***		4,973	***
rho_ar	0,414			0,350	
sigma_u	0,320			0,324	
sigma_e	0,261			0,280	
rho_fov	0,601			0,574	
R-sq within	0,416			0,378	
between	0,680			0,724	
overall	0,558			0,618	
Number of observations	8.867			9.551	

Notes: Model is the GLS estimator for random effects models, assuming the disturbance term is first-order autoregressive. Reference categories for the categorical variables: For occupation: Sales and other occupations; for industry: Catering, transport and construction; for partner: partner not working; for work history: EEE.

Annex C: The employment transitions parameter table – an example

The parameter table is arranged as 16 sub-tables corresponding to the 16 estimated models, indexed by sex (2 levels), qualification (2 levels) and origin state (4 levels). Each sub-table consists of six panels containing the groups of coefficients:

QUA	Qualification and age coefficients
CHA	Number and age of children
HPT	Health and partner's employment
DAS	Duration and age or sector
SOC	Occupation
IND	Industry

Categorical predictors were represented in the transition equations by a set of dummy variables taking the value 0 or 1 for each category. Since the categories are mutually exclusive, it was not necessary to compute $\beta_{ij}X_j$ for each of the dummies, but merely look up the β_{ij} for the relevant category and add this into the linear predictor expression. Thus, for a particular model, the three coefficients for each level of, e.g., NSOC are arranged as follows:

NSOC	BSOC2	BSOC3	BSOC4
1	-0.0519	-0.2371	0.0355
2	0.8051	-0.1384	-0.0693
3	-0.2335	-0.0687	0.1014
4	0.1350	-0.0328	-0.0053
5	0.9181	0.3084	0.1858
6	0	0	0

The NSOC column provides the lookup values. BSOC2 represents the log relative risk ratio of outcome 2 (part-time employment) compared to outcome 1 (full-time employment) associated with being in the relevant category of NSOC (relative to the reference category, 6), and so on. Note that the reference category had to be included explicitly in the panel, with zero coefficients. The fieldnames for the coefficients started with B, so as to indicate β, followed by SOC as an indicator of the predictor variable, and ending with a digit indicating the outcome level to which they refer.

Altogether, each panel has six rows of coefficients. Three panels have four columns: one lookup value and three coefficients (as shown in the SOC panel above). The other three panels, which contained interactions, had columns for two lookup values and three coefficients. The six panels therefore used 27 fields and 6 rows. The whole table has 3+27=30 fields and 16x6=96 rows.

Annex D: The wage parameter table – specification and initial values

There are five sub-tables in the wage parameter table and they are stacked vertically (as shown in Table D.1). The first four sub-tables are for employees, corresponding to the estimation groups male/female with advanced/non-advanced qualifications, indexed by NSEX (values 1, 2) and NEDSTAT (thresholds 2, 4). Self-employed people form a single separate estimation group and the parameters for this subgroup are included in the fifth sub-table. The sub-table for self-employed was differentiated by adding 2 to the NSEX value, and using threshold 4 for both NSEX and NEDSTAT.

Each sub-table has lookup values for the estimation subgroups, given by NSEX and NEDSTAT. They also have five panels, each having column(s) for lookup values (prefixed by N) as well as the value of the parameter (prefixed by B). The five panels are defined as follows:

AGE	(also used to store coefficients updating the error term),
CHILD	(number and age),
HPT	(health and partner's employment),
HISTORY	(including interaction with part-time work), and
SSP	(interactions of NSOC and NSECT with part-time work).

The full wage parameter table used in implementing the time-variant part of the wage equation is given in Table D.1. Below we illustrate the HISTORY panel in some more details.

The HISTORY panel was implemented as a full interaction with FT/PT. There were 8 rows corresponding to the groupings:

0	ESS
1 - 4	EES EUS ENS
11	EEE
13	EEU
14 - 33	EEN EUE EUU
34	EUN[15]
41	ENE
43 - 44	ENN ENU

Coefficients for full-time and part-time wages were stored in separate columns named BHISTF and BHISTP within the history panel. For males, where a full interaction was not estimated, the PT coefficients were obtained by adding the PT main effect to each of the FT coefficients. The categories used are listed in Table 2 above.

15 The coefficients for EUN ENE ENN ENU were equal for all but females employed part-time. For these, EUN was grouped with EEE or ESS according to the non-advanced or advanced qualifications the person has, and ENE (ENN ENU) form separate groups. For more details, we refer to Zaidi (2004b).

Table D.1: Parameter table for time-variant component of the wage equation

NSEX	NEDSTAT	NAGE	BAGE	NYCAGE	NCHILD	BCHA	NHEALTH	NEMPPT	BHPT	NEMPHIST	BHISTF	BHISTP	NSOC	NSECT	BSSP
1	2	9	0.3502	1	0	0.0000	0	0	-0.0511	0	-0.6395	-1.3284	2	1	0.2300
1	2	10	0.2619	1	1	0.0000	0	1	0.0000	4	-0.2889	-0.9777	2	3	0.3570
1	2	11	0.0924	1	9	0.0000	0	2	-0.0100	11	0.0000	-0.6889	6	1	0.0000
1	2	12	-0.0011	4	9	0.0000	1	0	-0.0908	13	-0.0901	-0.7790	6	3	0.1270
1	2	22	-0.2879	9	9	0.0000	1	1	-0.0397	33	-0.1711	-0.8599	0	0	0.0000
1	2	64	0.0000	15	9	0.0000	1	2	-0.0497	34	-0.2715	-0.9604	0	0	0.0000
1	2	0	0.0000	0	0	0.0000	0	0	0.0000	41	-0.2715	-0.9604	0	0	0.0000
1	2	0	0.0000	0	0	0.0000	0	0	0.0000	44	-0.2715	-0.9604	0	0	0.0000
1	4	9	0.4141	1	0	0.0000	0	0	-0.0450	0	-0.2431	-0.6539	2	1	0.0774
1	4	10	0.2372	1	1	0.0000	0	1	0.0000	4	-0.1280	-0.5387	2	3	-0.0793
1	4	11	0.1192	1	9	0.0000	0	2	0.0457	11	0.0000	-0.4108	6	1	0.0000
1	4	12	-0.0014	4	9	0.0000	1	0	-0.0973	13	-0.1078	-0.5186	6	3	-0.1567
1	4	22	-0.4146	9	9	0.0000	1	1	-0.0522	33	-0.2018	-0.6125	0	0	0.0000
1	4	64	0.0000	15	9	0.0000	1	2	-0.0065	34	-0.3274	-0.7382	0	0	0.0000
1	4	0	0.0000	0	0	0.0000	0	0	0.0000	41	-0.3274	-0.7382	0	0	0.0000
1	4	0	0.0000	0	0	0.0000	0	0	0.0000	44	-0.3274	-0.7382	0	0	0.0000
2	2	9	0.4084	1	0	0.0000	0	0	0.0015	0	-0.5976	-1.3574	2	1	0.0575
2	2	10	0.3096	1	1	-0.0642	0	1	0.0000	4	-0.2691	-1.0729	2	3	0.0331
2	2	11	0.0613	1	9	-0.1816	0	2	-0.0616	11	0.0000	-0.5794	6	1	0.0000
2	2	12	-0.0007	4	9	-0.1679	1	0	-0.0308	13	-0.0522	-0.6166	6	3	-0.0244
2	2	22	-0.0315	9	9	-0.1581	1	1	-0.0323	33	-0.1466	-0.7929	0	0	0.0000
2	2	64	0.0000	15	9	-0.0788	1	2	-0.0939	34	-0.4341	-0.5794	0	0	0.0000
2	2	0	0.0000	0	0	0.0000	0	0	0.0000	41	-0.4341	-0.8530	0	0	0.0000
2	2	0	0.0000	0	0	0.0000	0	0	0.0000	44	-0.4341	-0.9703	0	0	0.0000
2	4	9	0.4374	1	0	0.0000	0	0	-0.0202	0	-0.1879	-0.6538	2	1	0.1958
2	4	10	0.2994	1	1	-0.1219	0	1	0.0000	4	-0.1148	-0.5862	2	3	0.1215
2	4	11	0.1100	1	9	-0.2905	0	2	-0.0108	11	0.0000	-0.5257	6	1	0.0000
2	4	12	-0.0014	4	9	-0.2116	1	0	-0.0418	13	-0.1292	-0.7532	6	3	-0.0743
2	4	22	-0.2296	9	9	-0.2280	1	1	-0.0216	33	-0.2152	-0.7961	0	0	0.0000
2	4	64	0.0000	15	9	-0.1555	1	2	-0.0325	34	-0.4021	-0.6538	0	0	0.0000
2	4	0	0.0000	0	0	0.0000	0	0	0.0000	41	-0.4021	-0.8557	0	0	0.0000
2	4	0	0.0000	0	0	0.0000	0	0	0.0000	44	-0.4021	-1.0288	0	0	0.0000
4	4	9	0.2950	1	0	0.0000	0	0	0.0000	0	0.0000	-0.5168	2	1	0.0000
4	4	10	0.8361	1	1	0.0000	0	1	0.0000	4	0.0000	-0.5168	2	3	0.0000
4	4	11	0.0759	1	9	0.0000	0	2	0.0000	11	0.0000	-0.5168	6	1	0.0000
4	4	12	-0.0009	4	9	0.0000	1	0	0.0000	13	0.0000	-0.5168	6	3	0.0000
4	4	64	0.0000	15	9	0.0000	1	2	0.0000	44	0.0000	-0.5168	0	0	0.0000