

Labour Supply Estimation Project

Report 2

A DYNAMIC MODEL OF LABOUR MARKET TRANSITIONS AND WORK INCENTIVES

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1 Introduction

1.1 Aims of model

This is the report from the second phase of a project funded by HM Treasury, the Department for Work and Pensions, the Inland Revenue, and the Economic and Research Social Council under the broad heading ‘Labour Supply Estimation’. The purpose of this project is fourfold:

1. To design a model of transitions and flows between non-employment (non-participation, unemployment) and employment which shows how they are affected by various measurable characteristics of working age individuals and the labour market environment. Crucially, the model aims to show how entry into work and exit from work are related to the financial incentives that individuals face in making these transitions. These are affected by several factors – wage levels in the labour market, the number of hours of work, the affordability and availability of childcare, and the tax and benefit rates set by government.
2. To estimate the model using the most suitable recent UK data sources.
3. To use the model to simulate the effect of a variety of labour market reforms on employment inflows and outflows, and hence on overall labour market participation.
4. To investigate the best way for this model to be made available to HMT, IR and DWP to use for their own simulation work.

The report from the previous phase of this project (Report 1) offered important preparation for the construction of the model by undertaking a detailed review of the literature on theory and estimation of models of labour supply. The review was arranged in two parts. Part 1 concentrated on ‘static’ models of labour supply, reviewing the theory of single-period and intertemporal optimisation subject to budget constraints, focusing in particular on family labour supply, estimation in the presence of budget constraint non-linearities, allowing fixed and variable costs and controlling for non take-up. Part 2 offered a review of labour supply literature and related areas

that focus on transitions between various labour market states, including search theory, hazard modelling, and models of job creation and destruction. It also looked at the returns to experience and tenure in the labour market, the wage penalty to displacement from work, and related areas. We will draw on the work surveyed in Report 1 throughout this phase of the report.

1.2 Layout of this report

The structure of this report is as follows. In section 2 we outline the two main building blocks of the modelling process, by describing the idea behind the employment transitions model and the techniques used to generate the income measures which are used as explanatory variables in the model. Section 3 describes the data we use for the analysis.

The detailed model of transitions in the labour market is presented in section 4, which describes the methodologies we use for modelling single individuals and people in couples. For individuals living in couples we develop a method based on a multinomial choice model, which we believe is the first time such a method has been used in what we call “semi-structural” labour supply modelling. Description of the methodology we use in the transitions model is followed by a detailed explanation of how we propose to model the financial incentives variables. In section five we describe our suggestions for modelling wages, hours of work, childcare costs and the take-up of in-work benefits. Our specifications, in conjunction with the use of the IFS tax and benefit model, allow for the calculation of expected measures of income for our selected sample of benefit units in the Family Resources Survey (FRS).

The cross-sectional nature of the FRS data makes it impossible to use the FRS on its own as a dataset for modelling employment transitions. Our methodology relies on matching the calculated incomes variables with the Labour Force Survey (LFS) panel data set. Section 6 describes various options for matching between the data sets at group level, and the factors which need to be taken into account in the process.

The last three sections focus on results from and extensions of the project. In section 7 we describe how to interpret the outcomes of the model, and how it can be used in simulation analysis. In this section we also suggest some robustness and sensitivity analyses which can be conducted to test the model. Section 8 presents extensions of the model. Section 8.1 examines an important issue of take-up modelling concerning some major changes of the tax and benefit, while the possibility of using other data sources is explored in section 8.2.

The results from estimation of the model, sensitivity and robustness analyses, and any extensions to the model which are implemented, appear in Report 3 from this project.

2 An overview of the model

This section outlines the overall modelling process. We first introduce the methodology used to model labour market transitions, and then describe the modelling of incomes which appear as explanatory variables in the transitions model. These two parts of the modelling process are described in detail in sections 4 and 5.

2.1 Modelling labour market transitions

The aim of the model is to examine the importance of financial incentives for labour market transitions. We want to analyse to what extent movement in and out of work relates to incomes in different labour market states, whether sensitivity to financial incentives differs by family type and how transition rates differ between people from different demographic groups. Identification of the importance of financial incentives for labour market transitions will allow us to simulate the effect of fiscal changes on people's employment behaviour.

The basic idea is straightforward, and boils down to modelling how a transition from employment to non-employment, or vice versa, between periods $t-1$ and t relates to various characteristics including the level of income in and out of work. The probability of changing employment states, conditional on the state in period $t-1$, is regressed on demographics and on income variables. In its simplest form the model for individual ' i ' is:

$$P(D_{i,t} = k | D_{i,t-1} = K) = f(X_{i,t}, Y_{i,t,D=0}, Y_{i,t,D=1})$$

where:

'D' – is employment state

'k' and 'K' – is either 0 (for non-employment) or 1 (for employment), and X is a vector of demographic characteristics.

Y_t – is income (in work for $D=1$, and out of work for $D=0$)

Section 4 provides details of the modelling methodology for single individuals and for people in couples. In the latter case, in the light of the labour market literature presented in Report 1, we chose a multinomial framework as the most suitable version of the model for couples. The basic idea is essentially the same, but couples are modelled as choosing among *four* labour market states, each corresponding to a combination of the employment states of the two partners.

2.2 Modelling incomes

The model is based on, and depends crucially on, matching incomes information from the FRS with employment state transition information from the LFS. In attempting to model incomes as accurately as possible, we address five issues:

- Wages
- Hours worked if employed
- Fixed costs of work (in the case of this model, only childcare costs are considered)
- Take-up of means-tested benefits (in the case of this model, only the take-up of FC/WFTC is considered)
- Take-up of childcare

The first three of these are used as inputs into a tax and benefit micro-simulation model (for example the IFS's TAXBEN model) which then generates net incomes given: wages, hours of work and childcare costs (the latter are used to determine the amount of childcare subsidies) and a specified tax and benefit system. The latter two – benefit take-up and childcare take-up – are modelled following the net income calculations to account properly for the interaction between FC/WFTC (including childcare subsidies) and other means-tested benefits. Childcare take-up modelling is needed to ensure that we subtract the correct amount of money spent on childcare in order to capture the financial fixed costs of working.

Since we do not account for fixed costs and take-up for people without children, the final measure of income for single individuals without children is:

$$Y_{final} = f(\hat{w}_h, \hat{h}_h, \zeta) \quad (2.1)$$

while for couples without children it is:

$$Y_{final} = f(\hat{w}_h, \hat{h}_h, \hat{w}_s, \hat{h}_s, \zeta) \quad (2.2)$$

where both wages (\hat{w}) and hours (\hat{h}) are modelled (regardless of whether we have actual information on wages of the individuals or not, i.e. regardless of whether they are recorded as working in the FRS) and the h and s subscripts refer to 'head' and 'spouse' of the tax unit. ' ζ ' refers to the tax and benefit function which determines the net income given expected gross wages and hours worked.

The calculation is more complex for people with children. Let us define three variations of the tax and benefit system:

- ' ζ_1 ': a system with FC/WFTC childcare subsidies where everyone takes up 100% of their modelled FC/WFTC entitlement
- ' ζ_2 ': a system without FC/WFTC childcare subsidies where everyone takes up 100% of their modelled FC/WFTC entitlement
- ' ζ_3 ': a system where no one takes up FC/WFTC

Labelling ' γ ' as a vector of predicted hours and wages (\hat{h}, \hat{w}) and $\hat{C}\hat{C}$ as the predicted childcare cost, we can define three measures of net income:

$$Y_{FCWithCC} = f(\gamma, \zeta_1, \hat{C}\hat{C})$$

$$\begin{aligned} Y_{FCNoCC} &= f(\gamma, \zeta_2) \\ Y_{NoFC} &= f(\gamma, \zeta_3) \end{aligned} \quad (2.3)$$

where the first measure accounts for any additional subsidies towards childcare costs. Let \hat{P}_{FC} be a predicted measure of FC/WFTC take-up (i.e. between 0 and 1) and \hat{P}_{CC} be a predicted measure of childcare take-up; then the final measure of income for people with children (net of childcare cost) is:

$$Y_{final} = Y_{NoFC} + [Y_{FCNoCC} + (Y_{FCWithCC} - Y_{FCNoCC}) * \hat{P}_{CC} - Y_{NoFC}] * \hat{P}_{FC} - CC * \hat{P}_{CC} \quad (2.4)$$

Following the calculation of the ‘final’ values of incomes for various labour market states of singles and couples we match them across to the LFS data to include them as explanatory variables in the labour market transitions model.

2.3 Previous research in this vein

This section explains briefly how our model relates to previous empirical research on labour supply and labour market transitions. A detailed survey of previous research in these fields is contained in Report 1 from this project (‘A Review of Static and Dynamic Models of Labour Supply and Labour Market Transitions’, by Michal Myck and Howard Reed). We reference chapters and sections from Report 1 with the format (1: __) in this report.

When modelling the labour market transitions of couples, our model draws on the latest theoretical advances (given in 1:1.2), particularly the ‘collective model’ (see, for example, Chiappori 1988, 1992). In terms of the distinction between ‘structural’ and ‘reduced form’ labour supply models explained in 1:2.1, our model is structural to the extent that we model the budget constraint facing individuals and couples under the prevailing labour market conditions and tax-benefit system as accurately as we are able to, and in that we attempt to model take-up and childcare costs in this structural framework. However, our model does *not* explicitly estimate a utility function defined over net income and hours. Instead, we rely on exogenous variation in the budget constraint induced by changes in wage levels (and the returns to education and other features of workers) and by changes in tax and benefit policy to uncover the magnitude and direction of movements in employment states which we might expect to arise from future changes to tax and benefit policy. We go into more detail concerning the strategy by which this model is identified in Section 5.6 of this report.

The discussion of wage modelling in 1:2.1.2 looks at two main options for estimating the wage level which a currently non-working person might get if they entered work; selectivity-adjusted wage predictions (following Heckman, 1979) and entry wages (following Gregg and Wadsworth, 2000 and Gregg, Johnson and Reed, 1999). We use both methods in this project, which will allow us to compare the results from the two techniques. For estimating the hours levels at which currently unemployed or inactive people might enter work and calculating expected hours for those observed as working, we use an hours imputation mechanism which is basically a simplification

of the discretisation procedure discussed in 1:2.1.5. Whilst not an ideal solution to the problem of hours heterogeneity, this procedure at least allows us to model the overall distribution of hours for people in our sample with some degree of realism, and is probably the best treatment of hours choices available to us given our determination to model transitions in and out of work accurately, rather than just using a static cross-sectional labour supply model.

Modelling of childcare costs is explored in 1:2.1.7. Rather than attempting to estimate a full joint model of childcare choice and labour supply, our approach, following Blundell et al (2000), is to include an estimated childcare expenditure variable as an extra determinant of the budget constraint in the labour supply equation. We also include controls for take-up of in-work benefits (e.g. WFTC), drawing on Keane and Moffitt (1998) (this is as discussed in 1:2.1.8). We do not however attempt to structurally identify a ‘benefit stigma’ parameter.

Part 2 of Report 1 examines the dynamics of the labour market. What we are attempting with our labour supply model is to combine certain elements of dynamic modelling with the best features of traditional labour supply analysis. 1:4.1 deals mainly with the human capital explanation for wage growth (or decline) on the job and between jobs. Because our focus is on transitions in and out of the labour market we do not incorporate on-the-job wage growth into our model, but the question of wage progression for new entrants into work is addressed to some extent by the choice of which imputed wage estimate to use in the transition equations.

Our model fits comfortably into some, but not all, variants of the ‘search-matching’ framework as outlined in 1:4.2. The imputed wage distribution can be characterised as a wage offer distribution for (potential) work entrants. In the model we effectively assume that all unemployed or inactive workers receive a wage offer (at their imputed wage level). Hence we do not allow for a distinction between the wage offer distribution for unemployed work seekers and for the inactive. This is partly because the data show a good number of individuals flowing directly from inactivity into work without an intermediate search stage. As an interesting extension of the model it would be possible to examine the model with different wage offer distributions for the inactive and the unemployed, or with inactive people having a less than 100% chance of receiving a wage offer. Additionally, we could experiment with using the LFS information on whether non-working individuals are seeking work by various means as an explanatory variable in the transition equations. We are not able to allow for multiple transitions between labour market states in the model as it currently stands because the LFS can only really be used to look at a single transition per individual, as it is a short panel with income information only available at the start and end of the panel. However, we hope to estimate variants of the transition model on panel data with many more waves in the future (e.g. BHPS, or FACS).

On the job exit side, we relate job separations to the financial incentives to remain in work vis-à-vis the net income available when each individual in the LFS is not working. As will be shown in Report 3 (the results of the model estimation), it appears that in many cases, financial incentives matter for job exit as well as job entry. Job exits may also be related to other features of the job, e.g. deterioration in match-specific productivity, or an improvement in offers from alternative jobs. Unfortunately, because the LFS only contains two waves of income data per

individual, it is impossible to tell what happens to wages prior to job separation for those who exit the labour market during the panel (as we only have the first wave wage observation). It would be useful to supplement our model with multi-wave panel data on wages (e.g. BHPS) in future, to address this question.

The work by Alan Manning (2001a) discussed in 1:4.2.6 suggests that search/matching models may give predictions of the labour supply effect of tax and benefit changes which differ from those of conventional static models, for example if the effectiveness of on-the-job search differs from off-the-job search. Although our model does not model search intensity explicitly, it is flexible enough to deliver labour supply estimates which are not constrained by the conventional static theory (largely because we eschew estimation of a utility function in the transition equations). In our interpretation of the results in Report 3 we will examine whether any of the labour supply responses to tax and benefit changes that we estimate differ significantly from the predicted responses from conventional static models, and if so, why this might be.

Chapter 6 of Report 1 examines the empirical estimation of several types of dynamic models. The data which we use to estimate our model – essentially two-wave panel data from the LFS combined with detailed estimation of the budget constraint and labour market incentives in different employment states using the Family Resources Survey – are unfortunately not well suited to the hazard models examined in 1:6.1, the structural models of labour market search summarised in 1:6.2 and 1:6.3, or the life cycle labour supply models looked at in 1:6.4. Our approach is in many ways an extension and improvement on the work entry model used by Gregg, Johnson and Reed (1999) which is covered in 1:6.5. In particular, Gregg *et al* only modelled work entry, whereas we model entry and exit. Our model of labour market transitions for couples is also much more sophisticated as it allows for the husband's and wife's labour supply decisions to depend on each other. Finally, we exploit time series variation in financial incentives over a number of years to provide better identification for our model than was possible for the Gregg *et al* model, which was based on one year of cross-sectional data.

3 The data

For the purposes of this project we would ideally like an individual level data set with the following characteristics:

- Panel data (so that we can observe transitions into and out of work). Furthermore, we would ideally like several observations on individual labour market status (or duration data) so that we can track people over time.
- Hourly wage information at all points that the individual is in work.
- Individual control variables (e.g. age, educational attainment, area of residence, family type, housing tenure etc.).
- Information on labour market search.
- Information on the reason for job separations if and when each individual leaves work.
- Information on other job characteristics (apart from the wage) when the individual is in work.
- Information on rent paid (or mortgage payments), eligibility for non means-tested benefits and receipt of other incomes. This enables calculation of the main parameters of the budget constraint using a tax/benefit model. (Means-tested benefit eligibility is not strictly necessary in the data as it can be calculated by such a model without needing additional information).

As is usually the case the ‘ideal’ data set is not available to us, and we therefore use information in two separate surveys and match them together to combine information from both of them. Below we outline the information contained in the two datasets and the scope of the data we use.

3.1 The Labour Force Survey

The Labour Force Survey (LFS) is a dataset which has operated in its present format in Great Britain and Northern Ireland since 1992. It is a ‘short panel’ survey based on household interviews (around 60,000 households per quarter). The survey is a ‘rolling’ panel where households in the sample stay in the survey for five consecutive quarters. Individuals in employment are asked for their wage in the first and fifth quarters of the survey. Therefore the LFS is a good source of information on labour market transitions (albeit over a short period), and it has wages for those who enter work, those who exit work, and for the rest of the in-work sample. Additionally it contains some information on the methods which jobseekers use to look for work, and the job characteristics of employees (e.g. industry, occupation, employer size), some or all of which may turn out to be useful in estimating our model. However, the LFS is not a good source of information on the kind of detailed data which is needed to construct accurate budget constraints. In particular:

- The survey has no information on the rent levels paid by tenants, or the mortgage payments of owner-occupiers. Without this housing costs information it is impossible to model the budget constraint properly due to the interaction of housing costs and the benefit system.
- The information on unearned sources of income which the household receives (e.g. investment income, pension income, maintenance payments etc.) is very

limited. Once again it is difficult to model the tax and benefit system accurately without at least some idea of the extent of these incomes for each household.

Hence we view it as a difficult or impossible task to use the LFS as the sole source of information for our labour supply model, as the individual budget constraints necessary for accurate labour supply analysis cannot be modelled properly using the LFS alone. Nonetheless it will be our main source of data on labour market transitions and wages on entry to and exit from work.

3.2 The Family Resources Survey

The Family Resources Survey (FRS) is a cross-sectional data set of around 26,000 households which has been collected annually in Great Britain (but not Northern Ireland) since 1994. Its purpose is to collect detailed information on income for a large sample of British households. The income data in the FRS is very well suited for use in tax-benefit modelling to construct the budget constraint necessary to analyse labour supply incentives. Thus, it is the primary data set used for the IFS tax and benefit model to analyse the effect of direct taxes and benefits on the distribution of incomes and on labour supply in cross-sectional analyses such as Blundell, Duncan, McCrae and Meghir (2000) and Brewer et al (2002). Its strengths and weaknesses are the reverse of the LFS. It is very good for constructing budget constraint information, but as it is a cross section (and has only limited information on labour market history),¹ we do not observe the same people in different periods and thus cannot observe their labour market transitions.

3.3 The scope of the data used

The main data source for the model will be data from the Family Resources Survey from Spring 1997 until Spring 2002 inclusive. This period includes data from before and after the implementation of the main ‘welfare-to-work’ reforms of the Labour government, such as the 10p tax rate, Working Families Tax Credit and the national insurance reforms. One possible extension of the model would be to go back three years to cover the full time series of the FRS (starting from April 1994).

The data for entry and exit rates are taken from the Labour Force Survey. The LFS data used run from 1996 through to Spring 2002.

3.4 Sample selection

¹ A cross sectional data set *could* conceivably be used for the type of model that we are estimating if it had reliable data on labour market history for the men and women sampled. Recent entrants could be identified by having low current tenure and recent exiters by having low current duration of unemployment (or ideally, time since last job). The model would have to be recast slightly as the dependent variables would be being measured at time $t+q$ rather than time t but this does not seem to be a huge difficulty. The FRS only contains the tenure variable necessary to identify work entrants in the most recent wave of the survey at the time of writing (2000/01). There is a ‘time since last worked’ variable which could hopefully be used to identify recent exits in the cross-section (although the wage in the previous job would be a missing variable). Hence an individual level labour supply model is potentially estimable using just the FRS, although this is only possible for a cross-section rather than the 5 or 6 years of data on which we are planning to estimate the model which combines LFS and FRS.

The model is estimated using men and women aged 20 to 55 inclusive. We exclude the under-20s and over-55s as many of the transitions for men and women outside this age range are due either to entering a job after finishing full-time education (for young people) or due to early retirement (for old people). We feel that in both of these cases, transitions into and out of work are less likely to be based on short-run financial incentives than for people within the age range 20 to 55. This can of course be tested by widening the age range for inclusion within the sample as part of a sensitivity analysis.

We also exclude the self-employed. Whilst ideally we would like to include self-employed people as part of the in-work sample, in practice we do not have enough information from the Family Resources Survey on their incomes to construct their budget constraints and financial incentives accurately.

Individuals who are long-term sick, on disability benefits, or listed in the LFS or FRS data as 'early retired' are also excluded from the model sample as they are less likely to make transitions back into work than either unemployed work seeking people or people who are inactive in other ways (for example, looking after children). Obviously the sensitivity of the model to including the sick, disabled and retired can also be tested and we experiment with this in the results presented in Report 3 of this project.

We also exclude from the model individuals for whom information in the data is inconsistent (e.g. age left full time education is greater than current age), and those changing marital status between wave 1 and 5 in the LFS panel. Because, as explained in Section 4.2 of this report, we model couples focusing on the couple (rather than the individual) as the primary unit of observation, we are forced to drop individuals who are married to, or cohabiting with, someone with one or more of the characteristics that we are excluding from the sample (e.g. whose wife or husband is under 20 or over 55, sick, disabled, self-employed, etc). This makes the sample selection for couples more severe than it would be if we focused purely on individuals. Report 3 gives further details of how sample selection affects the usable sample size. The implications of the sample selection strategy for the grossing factors which need to be used when estimating the employment effects of policy reforms are given in Section 7.4 of this report.

4 The transition equations

Below we present details of the estimation of the transitions model. We develop separate methodologies for modelling single people (section 4.1) and people in couples (section 4.2).

4.1 Modelling single people

4.1.1 Entry equation

The entry equation is estimated on the sub-sample of people who were not employed in period $t-1$. Defining $work_{i,t}$ as 1 if person i works at time t and 0 if he/she is not working at time t , we define the ‘entry dummy’ variable:

$$D_{it} = 1\{work_{i,t} = 1 \mid work_{i,t-1} = 0\}$$

The entry-into-work equation is then:

$$\Pr(D_{it} = 1) = f(X_{it}, Y_0(\zeta_t), Y_1(\zeta_t, \hat{w}_{it}^{entry}, \hat{h}_{it}^{entry} \hat{C}_t^{entry})) \quad (4.1)$$

for $i=1,2,\dots,I$ in a sample of **non-workers** at time $t-1$.

The dependent variable is binary: 1 if the individual enters, and 0 if he/she stays out of work.

The regressor variables include:

- X , a vector of observable control variables (e.g. year, sex, age, region, etc.).
- Y_0 , an out-of-work income variable. This will measure the ‘vertical intercept’ of the budget constraint, i.e. the net income of a person (or household) if not in work. It is affected by the parameters of the tax and benefit system ζ_t (e.g. the income support level, etc.)
- Y_1 , an in-work income variable. This is shown as depending on:
 - ◆ The estimated entry wage \hat{w}_{it}^{entry} . This may be a single wage prediction, or a distribution of wages based on survey information relating wages earned in jobs taken on entry into the labour market. Such survey information would come either from panel data or datasets which contain job tenure information (so that short-tenure jobs could be identified for entry wage purposes). The issue of which wage measure is the correct one to use – whether we should be using entry wages at all, or some other measure attempting to take account of wage progression – is discussed in detail in Section 5.1.
 - ◆ Estimated hours of work for the entrant, \hat{h}_{it}^{entry} . Once again this needs to be derived from the distribution of observed entry hours (or perhaps the overall observed hours distribution, maybe controlling for worker characteristics). We discuss the derivation of the hours function in Section 5.2.

- ◆ The tax and benefit system ζ_t . This is obviously a key determinant of financial incentives.
- ◆ Estimated costs of work \hat{C}_{it} . This term measures the reduction in work incentives arising from costs which are paid whilst working. This can include fixed costs (such as travel to work and equipment) and variable costs (such as childcare). In practice many of these items are very difficult to measure in most available data. In this project we focus on modelling childcare (Section 5.3).

Exit-from-work equation

Let us define the ‘exit dummy’ variable:

$$E_{jt} = 1\{\text{work}_{j,t} = 0 \mid \text{work}_{j,t-1} = 1\}$$

for people employed in period $t-1$. For these people the exit-from-work equation is:

$$\Pr(E_{jt} = 1) = g(Z_{jt}, \Psi_0(\zeta_t), \Psi_1(\zeta_t, \hat{w}_{jt}^{exit}, \hat{h}_{jt}^{exit}, \hat{C}_{jt})) \quad (4.2)$$

for $j=1,2,\dots,J$ in the sample of **workers** at time $t-1$.

The dependent variable here is the probability of *leaving* work and going into unemployment or inactivity in a given time period. Again, the default time period here is exit between time $t-1$ and time t .

The financial variables Ψ_0 and Ψ_1 are the direct analogues of the in-work and out of work income variables in the exit equation. As we can see from equation 4.2 the exit-from-work equation includes in-work income measures which are calculated using predicted values for wages, hours worked and childcare. We use predicted values despite the fact that this information is observed in the data in order to avoid an asymmetry between the entry and exit equations (we discuss this problem in more detail below).

4.2 Modelling the labour supply decisions of couples

The work entry model of Gregg, Johnson and Reed (1999) models the labour supply of every partner in a couple individually. The probability of changing labour market state is modelled in the same way as for single individuals with the exception that income of the partner in state $t-1$ is included in the vertical intercept of the budget constraint. So for example, in the entry equation (4.1), when estimating the husband’s probability of moving into work, the wife’s labour supply is fixed and her net income is included in Y_0 .

This approach necessarily implies that in all couples where one person changes his or her economic status, we condition the other person’s transition probability on an

incorrect intercept of the budget constraint. The problem is even worse when both partners change their economic status between $t-1$ and t . For example, let us consider a situation where neither of the partners works at time $t-1$. The individual level model used in Gregg, Johnson and Reed (1999) examines the probability of entry of each of the partners assuming that the other person remains outside employment at time t . This means that it models the probability of entry given the income at entry relative to income if both remained without a job. Yet, if partner 'A' moves into work, then the probability of entry of partner 'B' should not be modelled assuming that partner 'A' is still out of work. One reason for this is because the out-of-work income level on which we condition the 'income in work' variable for partner 'B' depends on 'A's' employment. Moreover, the level of net income when employed will itself change, as several elements of the tax and benefit system are subject to joint assessment (e.g. the WFTC).

The assumption that the partner does not change his or her employment status is clearly unsatisfactory, as shown by the data: in 10.5% of couples in our sample, one of the partners changes his/her economic status within one year, and in 0.5% of the sample, both partners change their employment status.

We could improve the individual level model by assigning the level of income in and out of work at time t depending on the actual employment status of the partner at time t . The entry equation would then be:

$$\Pr(D_{it} = 1) = f(X_{it}, Y_{0jt}(\zeta_t, w^{spouse}, h_{it}^{spouse}), Y_{1jt}(\zeta_t, \hat{w}_{gt}^{entry}, \hat{h}_{it}^{entry}, \hat{C}_t^{entry}))$$

where income level out of work is now conditional on the partner's economic status at time t , rather than $t-1$. An important shortfall of this method, however, is that it relies on knowing the economic status of the partner at time t . Since one of the purposes of the model is to predict entry probabilities given changing financial incentives, any method which relies on knowing the future is unacceptable, as it assumes part of what we are trying to predict.

In the individual approach to modelling couples, the only way in which each partner's decision to enter (or leave) work is affected by his or her spouse's economic status is via the spouse's net income at time $t-1$. However, one could plausibly argue that entry (or exit) decisions in couples where one person works and where no one works (or both work) are of a different nature and should be treated separately. This suggests an approach in which we distinguish *couples* (rather than individuals) on the basis of their employment status, and hence look at the situation of both partners together.

Below we present an approach to the dynamic modelling of couples' behaviour which recognises and incorporates the possibility that one partner's labour supply affects the behaviour of the other person. Decisions are assumed to be made by the couple. We therefore identify initial situations at the level of the couple and not the individual, and then model couples as choosing from a set of available employment states. The approach can be modelled using the multinomial logit model, and can be extended to account for random parameter variability using the random parameter logit (RPL) model outlined by McFadden and Train (2000). The models are run on couple level information concerning couples' state at time t conditional on their state at time $t-1$.

As in the model for single people, each couple is assigned group level information concerning their incomes in different employment states and other characteristics. The RPL model is an extension of the multinomial logit model, which allows us to relax the assumption of independence of irrelevant alternatives. This assumption is the major weakness of the multinomial logit, and although in our case tests of this assumption do not suggest that it is being violated, we use simulated likelihood methods to estimate the RPL model as a preferable alternative. For reasons of programming efficiency the RPL model will be run as a random parameter extension of a single-equation form of the multinomial logit model (the conditional logit model), which is described briefly after discussion of the multinomial logit model (for comparison of the multinomial logit and conditional logit models see for example: Davidson & MacKinnon (1993), ch.15, Greene (1997), ch.19).

4.2.1 Couples in our model

The literature review (Report 1, section 1.2) outlined two approaches to modelling couples in the structural framework. In the ‘collective’ model individuals are assumed to make optimal decisions given their earnings potential and the bargaining power within the couple, which determines the final allocation of resources. On the other hand, the ‘unitary’ model of couples’ behaviour treats the couple as a single decision making unit, thus neglecting any possible bargaining which might take place between partners, and treating the couple as a ‘black box’. In the unitary model, a couple which chooses the level of consumption and the levels of partners’ leisure considers the trade-offs between these in the same way that, say a single individual might consider when choosing to allocate his/her income between three goods.

Making the distinction between these two models in the framework of our approach is impossible, as unlike conventional structural labour supply models, our model does not explicitly estimate a utility function. The models are distinguished precisely by their structure underlined by a different process of decision making within couples. The approach described below will not allow us to verify or reject either of the theories. Nevertheless, it is a method consistent with the view that decisions of one member of the couple affect and are affected by the choices of the other, and represents a natural extension of the methodology we use to model single individuals.²

In the outline of our entry and exit models for single individuals we distinguished two states that an individual can be in at time $t-1$: employment or non-employment (unemployment or inactivity). When observed in period t the individual will either be in the same state or will have moved. His/her choice during the year can then be related to individual characteristics and the (financial) incentives to change. The sample in period $t-1$ is therefore divided into two sub-samples: the employed in time $t-1$ ($D_{it-1}=1$) and the non-employed in $t-1$ ($D_{it-1}=0$). The first is used to model exit and the other to model entry *conditional* on state at time $t-1$.

² Note, however, that simulated reforms which only have effect on the distribution of income in couple, and not on the level of income, will have no labour market effect on either of the partners. From this point of view one could argue that the approach is closer to the unitary model.

If we consider individuals in couples as making their choices together then to be consistent with the approach we take for single individuals we should distinguish between four states a couple can be in:

- man working, woman working (which we refer to as a (1,1) couple, to which we assign the parameter value $D_{it}=1$),
- man working, woman not working (a (1,0) couple, $D_{it}=2$),
- man not working, woman working (a (0,1) couple, $D_{it}=3$),
- man not working, woman not working (a (0,0) couple, $D_{it}=4$),

The aim of our dynamic labour supply model, which treats decisions of the two partners simultaneously, is to model transitions between these states conditional on state at time $t-1$. We therefore divide the sample into four sub-samples: (1,1), (1,0), (0,1) and (0,0), and model a multinomial choice the couples make between $t-1$ and t when they are observed for the second time.

The LFS sub-sample sizes for the years 1996-2002 are presented in table 4.1. Details of the sample selection procedure are given in Section 3.3 of this report, whilst further details of how the sample selection procedure affects the usable sample size are available in Report 3 from this project. One thing to note here is that situations in which both partners change their labour market status are very rare. This applies especially to the situation where at time $t-1$ only one of the partners works. We considered the possibility of simplifying the model by treating a couple as if it did not change its employment status in the case where the couple moves from (1,0) to (0,1) or vice-versa, or in fact treating (1,0) couples in the same way we treat (0,1) couples. Although this approach could simplify the estimation of the model, it is not obvious how financial incentives should be treated in such a one-earner scenario. We therefore decided to estimate the model with four employment states.

Table 4.1. LFS entry and exit – couples (waves starting 1996/97-2000/01)

State in time $t-1$	Full sample	State in time t				Exit rate for men	Exit rate for women	Entry rate for men	Entry rate for women
		(1,1)	(1,0)	(0,1)	(0,0)				
(1,1)	30573	28863	1256	418	36	1.5%	4.2%	-	-
(1,0)	7245	1612	5439	32	162	2.7%	-	-	22.7%
(0,1)	769	382	18	338	31	-	6.4%	52.0%	-
(0,0)	872	56	223	54	539	-	-	32.0%	12.6%

Source: LFS, spring 1996- spring 2002.

4.2.2 Multinomial logit model

The model for single individuals relates the probability of entry or exit to the financial incentives the individual faces, i.e. his/her income in and out of work. This can be run on individual or on group level data. In the first case individuals are assigned value 1 if they change their state and 0 if they don't, while in the second case groups are assigned the group probability of moving in or out. The problem facing us if we want to apply this methodology to couples is that couples can change their state and move to one of three other states.

Calculating income in different employment states

Let us for the moment consider a couple where neither of the partners works in time $t-1$, i.e. $D_{it-1}=4$. Between $t-1$ and t the couple can change to either $D_{it}=1$, $D_{it}=2$, or $D_{it}=3$. Otherwise both partners can remain out of the labour market. Each of the three states corresponding to at least one person entering is associated with a different level of income, Y_{ij} , which is determined by the wages and hours of work of the entrants, and by the tax and benefit system which determines the level of income in the reference state (0,0) and the in-work incomes of the entrants. We therefore have three variables which are equivalent to the single individual's in-work income variable:

$$Y_{ij} = f(\zeta_t, \hat{w}_{it}^m, \hat{h}_{ijt}^m, \hat{w}_{ijt}^w, \hat{h}_{it}^w, \hat{C}_{ijt}), \text{ for } j = 1, 2, 3$$

where j corresponds to the D_{it} states, and \hat{w} and \hat{h} serve to indicate predicted wages and hours worked by men and women (superscribed: m and w respectively). Since here we focus on a (0,0) couple at time $t-1$, the wages represent entry wages for both partners. Of course, depending on the initial state of the couples we will use entry, exit or in-work wages. The 'income in work' variables will be calculated as the total income of the couple as a whole. Fixed costs of working will have to be estimated separately for the partners and then, depending on whether only one or both of them work, the appropriate sum will be subtracted from the couple's total income for the corresponding choice. Therefore, while probability of entry in the model for single people is conditioned by one 'income-in-work' variable, in the couples' case the model has to include *three* such variables:

- Y_{it1} for income if the couple changes to (1,1),
- Y_{it2} if it changes to (1,0),
- Y_{it3} if it changes to (0,1).

Multinomial logit for individual level dependent variable

[note: this section is quite technical]

The multinomial logit model has been used extensively in the literature to model unordered multinomial choice. The model handles $J+1$ responses and the probability that any one is chosen is:

$$\Pr(y_{it} = 0) = \frac{1}{1 + \sum_{j=1}^J \exp(x_{it} \beta^j)}$$

$$\Pr(y_{it} = l) = \frac{\exp(x_{it} \beta^l)}{1 + \sum_{j=1}^J \exp(x_{it} \beta^j)}, \quad \text{for } l = 1, \dots, J \quad (4.3)$$

The model results in J vectors of parameters, β^1 through β^J . The above formulation of the model is a result of a normalisation assuming that one vector of parameters, β^0 , is equal to zero. This is necessary since in the general specification of the multinomial logit:

$$\Pr(y_{it} = l) = \frac{\exp(x_{it} \beta^l)}{\sum_{j=0}^J \exp(x_{it} \beta^j)}, \quad \text{for } l = 0, \dots, J \quad (4.4)$$

an identical set of probabilities results for any $\beta^{l*} = \beta^l + q$, where q can be an arbitrary vector. This is because all the terms involving q drop out of the probability. It does not matter which of the choice categories is assigned as the ‘base category’, i.e. the category for which the vector of parameters is β^0 ; each one is as good as any other. In our specifications, we shall always make the $t-1$ employment state of couples the base category, so as to make interpretation of the results more straightforward.

Writing the model as shown in (4.3) implies that the relative probability of ($y_{it}=1$) to the base category ($y_{it}=0$), known as the relative risk ratio, is equal to:

$$\frac{\Pr(y_{it} = 1)}{\Pr(y_{it} = 0)} = \exp(x_{it} \beta^1) \quad (4.5)$$

If the x_{it} vector is equal to $(x_{it}^1, \dots, x_{it}^k)$ and correspondingly β^l is a vector of coefficients equal to $(\beta^{l1}, \dots, \beta^{lk})$, the relative risk ratio for a one-unit change in, say x_{it}^2 , is:

$$\frac{\exp(x_{it}^1 \beta^{11} + (x_{it}^2 + 1) \beta^{12} + \dots + x_{it}^k \beta^{1k})}{\exp(x_{it}^1 \beta^{11} + x_{it}^2 \beta^{12} + \dots + x_{it}^k \beta^{1k})} = \exp(\beta^{12}) \quad (4.6)$$

This is a very convenient way to analyse the results of the model. For example, x_{it}^2 could be the income when the woman enters work. Equation 4.6 tells us that the exponential value of the coefficient gives us the change in the relative risk ratio resulting from a one-unit change of a corresponding variable.

The outcomes of couples’ choices can be coded in an arbitrary way. We can thus use our D_{it} variables as the dependent variables. If we consider the model at an individual (and not grouped) level, then for each couple we have a record of the state in which they are observed at time t (conditional on being in a given state at time $t-1$), and for

each couple we have information on the change in it's the couple's financial situation, Y_{itj} , corresponding to the three choices relative to the initial state. For example, focusing on (0,0) couples, for each couple we have their income in state at time $t-1$ (as the dependent variable) and three 'income in work' variables associated with entry of both partners (Y_{it1}), of the man only (Y_{it2}), and of the woman only (Y_{it3}). In addition, characteristics of the couple such as ages of partners, area of residence and the number of children are included in the vector of explanatory variables. Table 4.2 gives an example of how the data would be structured in the individual-level (and not grouped) model.

Table 4.2. Multinomial logit on individual data, an example.

Couple:	D_{it}	Y_{it1}	Y_{it2}	Y_{it3}	Age_g (m)	Age_g (w)	School (m)	London	Kids
1	4 (0,0)	200	160	150	19-32	19-32	2	0	1
2	4 (0,0)	220	180	180	19-32	19-32	2	0	1
3	1 (1,1)	340	230	220	19-32	19-32	2	0	1
4	3 (0,1)	280	190	210	19-32	19-32	2	0	1
5	1 (1,1)	300	220	240	33-44	19-32	1	1	1
6	1 (1,1)	200	170	160	33-44	19-32	1	1	1
7	4 (0,0)	210	170	160	33-44	19-32	1	1	1
8	2 (1,0)	250	200	180	33-44	19-32	1	1	1

Notes: in the example we limit explanatory variables to men's age group, women's age group, man's school, whether living in London and the number of children.

As we pointed out above, couples' incomes in different scenarios cannot be calculated using the LFS for which we have labour market transition information. They have to be 'imported' from the Family Resources Survey on which we run the IFS's TAXBEN model. To match couples from the two data sources, as in the case of singles, we have to group them by certain characteristics (see section 6 for the description of our approach to grouping the sample). If we grouped the couples from the example presented in Table 4.2, defining the groups by age groups of partners, man's education, the London dummy and the number of children, then the structure of our couples dataset becomes that shown in Table 4.3. 'Income in work' variables are now the same for all couples in the same group (these are the averages from the individual level example). Such a representation of the model is a group level analysis although we use an individual level dependent variable. This is necessary since we cannot use the group average of the D_{it} variable as the dependent variable in the multinomial logit model.

Table 4.3. Multinomial logit on individual data with group-level financial incentives, an example.

Couple:	Group:	D_{it} (m,w)	ω_{it1}	ω_{it2}	ω_{it3}	Age_g (m)	Age_g (w)	School (m)	London	kids
1	A	4 (0,0)	260	190	190	19-32	19-32	2	0	1
2	A	4 (0,0)								
3	A	1 (1,1)								
4	A	3 (0,1)								
5	B	1 (1,1)	240	190	185	33-44	19-32	1	1	1
6	B	1 (1,1)								
7	B	4 (0,0)								
8	B	2 (1,0)								

Notes: in the example we limit explanatory variables to men's age group, women's age group, man's school, whether living in London and the number of children.

Standard statistical packages which handle multinomial logit estimations facilitate predicting the probability of particular choices, both for the estimated sample and initial values of the variables, as well as for changed values of the variables, given the estimated coefficients.

Testing the IIA assumption

Underlying the multinomial logit model is the ‘independence of irrelevant alternatives’ (IIA) assumption. This is a direct consequence of the specification of the model as shown in (4.3). From this we can derive that the ratio of two probabilities $\Pr(y_{it} = l) / \Pr(y_{it} = k)$ is independent of any other alternative that can be chosen (say: m and n). We can write the ratio as:

$$\frac{\Pr(y_{it} = l)}{\Pr(y_{it} = k)} = \frac{\exp(x_{it}\beta^l)}{\exp(x_{it}\beta^k)}$$

This assumption requires that the inclusion or exclusion of categories does not affect the relative risks associated with the regressors in the remaining categories. How strong this assumption is can be illustrated by an example relating to our use of the multinomial logit. For the case of (0,0) couples, for example, it suggests that the ratio of the probability that the man enters to the probability that both partners enter should be the same regardless of whether the option of the woman alone entering exists or not.

Hausman’s (1978) specification test can be used to test whether in a specific case the assumption holds or not. However, if the test is applied to a model which is not very strongly identified (i.e. in which few coefficients are statistically different from the base category) the test is unlikely to reject the IIA assumption (in fact the assumption is not rejected in either of the cases we examine). Thus we suggest that, regardless of the results of the test, we shall perform an extension of the multinomial logit model which relaxes the IIA assumption by allowing random variation of coefficients among couples. The Random Parameter Logit (RPL) will be applied to a single-equation equivalent of the multinomial logit, the conditional logit model.

Relaxing the IIA assumption – the Random Parameter Logit

[Note: this section is technical]

The basic principles of the Random Parameter Logit were described in Report 1, in the context of a ‘discretised hours’ approach to the estimation of the utility function (see Report 1, Section 2.1.5). Here we explain in more detail how we can apply it to our multinomial logit estimation of the couples’ choice of employment state.

The Random Parameter Logit will be applied to a single equation version of the multinomial logit – the conditional logit. In the conditional logit, the choice variable is regressed on attributes of the agent making the choice and (unlike in the multinomial logit) on attributes of the alternatives he/she faces (for example: van

Soest (1995)). The multinomial logit is thus a simpler form of the conditional logit, and as such each (multi-equation) multinomial logit model can be represented as a single equation conditional logit. The statistical properties of such a transformation and the estimated coefficients are exactly the same as in the original multinomial logit.

In the multinomial representation, for each observation we regress the choice an agent makes out of ‘ n ’ alternatives (in our case coded 1,2,3 or 4) on a set of explanatory variables ‘ X ’. The outcomes of the regression are $(n-1)$ equations corresponding to the $(n-1)$ alternatives.

The dependent variable in the conditional logit model for every observation is a set of n observed probabilities of choosing a particular alternative (since we observe each agent as making one choice this means we have three ‘0’s and one ‘1’ as the dependent variable for each observation). Corresponding to these are $(n-1)$ sets of ‘ X ’ variables multiplied by dummy variables. In this framework, the contribution of agent ‘ i ’ to the likelihood function is:

$$\Pi_i = \frac{\sum_{j=1}^J \exp(\beta X_{ij}) * P(z_{ij})}{\sum_{j=1}^J \exp(\beta X_{ij})} \quad (4.7)$$

where $P(z_{ij})$ is the probability of agent ‘ i ’ making a choice j (or otherwise is the random variable indicating choice). If the choice made is k , we can thus write the probability of agent’s ‘ i ’ making this choice as:

$$P(z_i = k) = \frac{\exp(\beta X_{ik})}{\sum_{j=1}^J \exp(\beta X_{ij})} \quad (4.8)$$

It is clear that since the explanatory variables X are multiplied by dummy variables corresponding to each choice, the contribution to the likelihood function of the individual is the same as in the case of the multinomial logit.

If we add unobserved heterogeneity among agents the IIA assumption is no longer necessary. We do this by making one (or more) of the parameters random. For example for individual i we could have:

$$\beta_{Vi} = \beta_{V0} + \eta_i$$

Where V is one of the elements of the ‘ X ’ vector of regressors. The random parameter logit method aims to estimate the standard errors of the random coefficients in the equation. It assumes that η_i is normally distributed with mean zero and estimates its variance together with the rest of the coefficients. In this setting, the probability that individual i makes choice k depends on the entire distribution of the coefficients vector β^{RPL} :

$$P(z_i = k) = \int \frac{\exp(\beta^{RPL} X_{ik})}{\sum_{j=1}^J \exp(\beta^{RPL} X_{ij})} f(\beta^{RPL}) d\beta^{RPL}, \quad k \in \{1 \dots J\} \quad (4.9)$$

Because it is impossible to derive an analytical solution to the log likelihood function resulting from the above expression, we use simulated maximum likelihood methods to estimate the parameters of the utility function and variances of the random terms. In the estimation the probability that individual i makes choice k becomes:

$$P(z_i = k) = \frac{1}{R} \sum_{r=1}^R \frac{\exp(\beta_i^{RPL} X_{ik})}{\sum_{j=1}^J \exp(\beta_i^{RPL} X_{ij})}, \quad k \in \{1 \dots J\} \quad (4.10)$$

where:

$$\beta_i^{RPL} = [\beta_{X-V} \quad \beta_{V_i}]$$

and:

$$\beta_{V_i} = \beta_{V_0} + \eta_{ri}$$

η_{ri} is drawn from a normal distribution with mean zero. In the RPL estimations we usually use about 100 draws for every individual and allow one or two parameters to vary randomly. For relaxation of the IIA assumption it is enough to make just one parameter a random variable.

Using the RPL for estimation of the model presents a problem if we want to use a bootstrap process for estimating the standard errors. Computing one model usually takes several hours and if we wanted to estimate standard errors by bootstrapping the sample and running the model say 500 times, this might take several weeks! Nevertheless we suggest using the RPL to test if the point estimates of the coefficients are different between RPL and the simple multinomial logit.

5 Calculating incomes in different employment states - tax and benefit microsimulation

The transitions model presented above relies on the possibility of calculating incomes in different employment scenarios. These calculations will be done on the FRS sample using the TAXBEN model and will subsequently be matched with the LFS to be included in the transitions equations.

The IFS microsimulation model, TAXBEN, calculates disposable incomes under specified scenarios using information from the Family Resources Survey. The FRS contains information on incomes from various sources and on people's employment and demographics (see section 3.2). Given these and a specified tax and benefit system TAXBEN calculates net incomes for every benefit unit in the data. Additional model flexibility allows changing the underlying information, which is fed into TAXBEN, to simulate incomes for these benefit units in circumstances which are different than those reported in the data. For example, while the standard output of the model is a calculation of net income at reported hours of work and reported gross wage, we can substitute these and calculate net income at different hours and at a different wage. We shall use this extra flexibility extensively in the modelling of incomes for our study.

Section 2.2 outlined the overall approach to modelling the income variables and the steps used in the process. Here we expand on the details of the estimation procedures, describing the way we model:

- Gross hourly wages
- Hours of work when employed
- Childcare cost (as fixed cost of working for people with children)
- Probability of take-up of in-work benefits
- Probability of take-up of childcare

Some of these parameters are observed and recorded in the FRS data. For people in work, we have information on gross wages and hours worked as well as their actual cost of childcare. However we use predicted values of all these variables as inputs in the net income calculation using TAXBEN regardless of whether we have information on these in the FRS data. This ensures that econometrically those who work and those who don't are treated in the same way in the model. Otherwise, i.e. if we used actual wages, hours and childcare cost for those in work and predicted values for those out of work, we would be allowing exogenous variation in the variables for those in work while eliminating it for those out of work. Such an approach would not be econometrically correct, as the fact that the tax and benefit system is non-linear with respect to the gross wage means that the relationship between gross income and net income is also non-linear. Thus, a distribution of predicted gross wages (based on observable characteristics) without any additional exogenous variation in wages (i.e. the 'error term' in a wage equation) will not, in general, produce the same average net incomes, or any other moment of the distribution of net incomes, as a distribution of actual observed wages which includes exogenous variation. Using predicted wages

for non-workers, but actual wages for workers, would generate biased predictions of work incentives when running the model.³

For every individual in the data we shall generate a predicted value of their wage and hours of work for the ‘in work scenario’. For people with children we shall also compute predicted values of childcare and take-up of in-work benefits.

5.1 Modelling wages

As explained in Section 2.1.3 of Report 1, there are several ways one can think of to model the wages which individuals might earn when at work. Apart from taking account of observed individual characteristics, an ‘ideal’ wage prediction would also include the possible effects of the following factors:

- the extent to which currently working people are held to differ from currently non-working people in the level (and/or growth potential) of the wages they might earn, with respect to factors which are *unobservable* by the researcher;
- the extent to which wages might increase after entering work or when deciding to remain employed;
- the extent to which individuals take these potential increases into account when deciding whether to enter/exit work.

Conducting a detailed analysis of wage progression which would allow us to take account of the last two points is beyond the scope of this study.⁴ The issue of sample

³ One possible extension of the modelling method which we present in this report would involve adding ‘noise’ to the distribution of predicted wages for people in and out of work so that the distribution of predicted wages (conditional on observable factors) looks more like the actual distribution of wages. In other words we would construct a distribution of predicted wages with randomly allocated errors built into the predictions. This would be a useful avenue for future development of the model.

⁴ Studies of wage growth on the job and between jobs (documented in Section 5.1 of Report 1) seem to agree pretty much unanimously that there is some return to labour market experience (at least for young people), and some studies also find a return to job tenure. If wages do increase as length of time in the job (or in the labour market as a whole) increases, then we would expect forward-looking rational individuals to take this increase into account when deciding on whether to supply labour. In these circumstances, the entry wage would mismeasure work incentives and would presumably lead to biased and incorrect estimates of the work incentive effects of policies which altered incentives to work. In defence of the entry wage measure, we might wish to point out that many of the studies of the returns to tenure and experience only provide a single average estimate of wage growth, which aggregates the returns to workers of all characteristics. Where returns to tenure and experience are disaggregated, the results may place the entry wage measure in a more favourable light. For example, Dustmann and Meghir (2001) find (using German data) that whilst skilled workers benefit from incremental returns to experience for much of their working lives, for unskilled workers the return to experience beyond the first two years in the labour market is essentially zero on average. Also, returns to tenure for unskilled workers appear to be smaller than for skilled workers. If the findings of Dustmann and Meghir were generalisable to the current UK labour market, this may indicate that the raw entry wage measure for unskilled workers is a reasonably good measure of their long-run earnings prospects. However, even this statement is questionable, as there is another reason why the entry wage might be lower than the wage for people who have been in the job even for just six months or a year. This is that starting wages on jobs are often low due to the worker being hired on a ‘trial’ basis or having to pay for induction training which is paid for upfront by the firm but deducted from initial

selection and unobservable differences between employed and non-employed populations is extremely important, though, and we address it in detail below.

We analyse several options for modelling wages below. We think that it makes sense to try a range of different predictions in our labour supply model, to compare what the results look like under the different assumptions and how sensitive the final results are to the wage definition we use.

We suggest testing the following approaches to modelling wages:

- linear wage regression on the sample of entrants in the LFS
- linear wage regression on the sample of people who exit work in the LFS
- linear wage regression on the sample of employed individuals in the LFS
- linear wage regression on the sample of employed individuals in the FRS
- selection-corrected versions of the four methods above

Since we need to use the FRS for the calculation of net incomes predictions, if we use the LFS to predict wages we will need to run a wage equation on the LFS data and then use the estimated parameters to predict wages in the FRS. We suggest comparing estimates from wage equations and samples estimated on the FRS with similarly defined specifications estimated on the LFS to ensure consistency between them and to justify the ‘transfer’ of parameters across the samples.

The final choice of the wage definition should be made considering:

- the extent of differences of wage predictions from different samples
- the possibility of identification of sample selection when using selection corrected wages.

5.1.1 Linear model of wages

The simplest method of computing predicted values of wages is a simple linear regression of wages (or log-wages) on the employed sample of people for whom we have recorded information on the level of their wage. Such a regression usually has the following form:

$$\ln w_i = \alpha + \beta' X_i + \varepsilon_i \quad (5.1)$$

The logarithm of the observed gross hourly wage w_i is regressed on a set of observed characteristics X_i . Predictions of wages for the overall sample (of workers and non-workers) are generated using the estimated coefficients. The wage equation we use in the model has the following form:

$$\ln w_i = \alpha' [t]_i + \beta^1 [age]_i + \beta^2 [educ]_i + \beta^3 married_i + \beta^4 LonSE_i + \varepsilon_i \quad (5.2)$$

where $[t]_i$ is yearly time dummies, $[age]_i$ a cubic in age, $[educ]_i$ are dummies for leaving full-time education at ages (16 or less, 17 or 18, 19 or older), $married$ is a

wages. For example, the National Minimum Wage includes a provision for a reduced ‘training rate’ to be legally paid to workers in the first six months of a job for which training is required.

marital status dummy, *LonSE* a dummy for residence in London or the south-east, and ε is an i.i.d. error term.

Gregg, Johnson and Reed (1999) pioneered a more complex approach using the basic linear equation. The authors used data on the wages of people who had entered work during the LFS panel to derive a distribution of entry wages. The exact process used by GJR is discussed in Section 6.5 of Report 1. Briefly, the expected wage variable is estimated by modelling the probability that unemployed and inactive individuals would receive a wage offer at different ‘decile points’⁵ in the wage distribution and then using these estimated probabilities to calculate the expected entry wage for individuals of given observable characteristics. The approach could of course be applied not only to the sample of entrants but also to those who exit work and to the overall sample the employed population.

The main strengths of either of the two above wage measures are that they are simple to construct and that they correspond to the actual wages which individuals receive in empirical data.

However, they take no account of sample selection bias arising from the fact that we only observe the wages of employed people – we know nothing about the wages which individuals who are out of work *would* earn were they to enter work. The overall concern is whether people who are observed as working have, *conditional on observable characteristics*, the same earning potential as those who are not employed. In other words if a non-employed person is, on average, capable of earning as much as someone who has a job of the same age, educational attainment, region etc. then there is no problem. But if the non-employed have systematically lower earnings potential than observationally similar workers (perhaps, for example, because their motivation is not as good, or they have worse social skills) then a wage measure which does not control for this systematic variation in ‘unobservables’ will be biased. This concern applies equally to all samples we consider for wage estimation. For example in the sample of entrants the question would be whether, of the non-employed individuals observed in period $t-1$, those who have jobs by time t (and for whom we have a measure of ‘entry wage’) are any different from those who don’t because of some unobservable characteristics.

The standard econometric approach to dealing with sample selection biases is the ‘Heckman selectivity adjustment’, pioneered by Heckman (1974, 1979). We outline the approach below (see also section 2.1.3 in Report 1).

5.1.2 Modelling wages using a selectivity correction

The Heckman selectivity adjustment relies on estimating a two-equation model of labour market participation (employment) and earnings which identifies the selection bias through one of two methods:

1. An assumption over the functional form of the equation which determines participation in the model.

⁵ The decile points of the entry wage distribution were derived by ranking hourly entry wages in the LFS in ten equally-sized portions (‘deciles’) and then taking the cut-off points between them.

2. An assumption that there is at least one observable variable which affects the likelihood of employment but not wage levels conditional on employment.⁶

Assumption 1 is generally seen as too weak to be convincing as identification on its own. Most selection-adjusted wage estimates are therefore conducted using the second assumption, although convincing instruments are generally hard to find. Blundell, Reed and Stoker (2003) have recently proposed an instrument which we use in our study for the FRS sample. The instrument is a TAXBEN-generated ‘income when out of work’ variable. One can plausibly argue that it is correlated with participation but generally not with the level of wages.

The Heckman selectivity correction involves modifying equation (5.2) by inserting an additional term $\beta^5 \lambda_i$, where λ_i is the inverse Mills ratio from a probit of employment on various characteristics. We use a selectivity-adjusted wage equation with the following specification for the employment equation:

$$\Pr(emp_i = 1) = \Phi(\alpha^1 [t]_i + \beta^1 [age]_i + \beta^2 [educ]_i + \beta^3 [married]_i + \beta^4 [LonSE]_i + \beta^5 [select]_i + \eta_i) \quad (5.3)$$

Where $emp_i=1$ if person i is in employment, and the regressors are as for (5.1) with the addition of the variables $[select]_i$ which identify the Heckman model (this is where the FRS ‘income out of work’ variable is included in the FRS equation). The selectivity-corrected wage prediction takes account of the fact that the sample of people in employment is not random, and recognises that the work decision is (presumably) related to the wages which individuals can earn when in work.

The Heckman technique is normally used to make the selectivity correction to models of wages estimated over the whole working sample. If the identifying assumptions are valid then this should control for sample selection of the working sample vs. the non working sample. It is quite clear that the selection issues are slightly different between the sub-samples of entrants, or people who exit, and the overall sample, and that the selection problem may be less severe in the sub-samples. For example, in the sub-samples of entrants it is at least the case that entrants into work were unemployed or inactive to start with, whereas in the overall sample workers may have been working at the start of the sample period or indeed may have been in work since leaving full-time education in some cases. Any differences in the unobservable characteristics of non-workers and the full working sample are likely to be greater than the differences between the sample of work entrants and the people who stay out of work over the sample period.

⁶ Examples of variables which have been used in this role in empirical papers which have implemented the Heckman procedure include family demographics, housing tenure, and benefit rates.

5.1.3 Choice of sample for the wage equations

In terms of employment status over the first and fifth waves of the LFS ($t-1$ and t respectively), we can distinguish four broad sub-samples:

- a) not employed in period $t-1$ and t
- b) not employed in period $t-1$ but employed in period t
- c) employed in period $t-1$ and t
- d) employed in period $t-1$ and not employed in period t

The most obvious wage definitions, data permitting, would be:

- i) a selection corrected entry equation based on the entry sample for sub-samples (a) and (b)
- ii) a selection corrected exit wage equation run on the exit sample for sub-sample (d)
- iii) a selection corrected wage equation run on the overall sample for sub-sample (c)

In Report 3, we examine differences between different predicted wage measures and the degree of identification of the selection criteria to determine which of the above definitions should be applied. We believe that if sample selection is intuitively not a major problem and if we cannot identify the selection term correctly, then it is better to use a linear wage equation on the working sub-sample of the population.

Apart from the estimation issues, there are also other factors which may suggest different wage definitions from the three suggested above. For example a wage estimate based on the overall sample when applied to the entry sample may provide a better measure of the 'long-run' wage which a person of given attributes might expect to earn in the labour market. If the person is making his or her labour supply decision with that long-run wage level in mind, this is likely to be a more accurate representation of work incentives than the entry wage measure. We take factors like these into account when choosing the final wage measure to be used.

5.2 Modelling hours of work

As well as a wage measure, TAXBEN needs a measure of hours in order to evaluate in-work income for the FRS sample. We examine the following options for modelling hours of work:

- A fixed hours level (40 hours of work): this is a reasonable approximation to 'full-time' hours levels for men, but for women, it is an over-simplification, as we know that a substantial proportion of women work part-time.
- Separating out full time and part time work in the entry-exit models. This would require extending the multinomial framework to single individuals since we would be modelling a choice between: not working, working part

time and working full time. For couples, even if we only wanted to model part time work of women this would require modelling a choice from *six* alternatives. We have doubts as to whether such a flexible specification could be identified in the data.

- Using an hours equation to predict the hours level at which individuals of different characteristics will work, deriving a set of average hours points by group, and then running the FRS sample through TAXBEN at the group average hours points (according to which group they are in).
- Running individuals in the FRS through TAXBEN at a number of hours points - say (0, 16, 24, 32, 40, 48) for example. We could then use the information on entry hours for entrants in the LFS to relate entry at the hours level nearest to one of these 'hours points' to a number of explanatory variables. This could then be used to predict probability of entry at different hours points for individuals in the LFS sample in each group. If this approach is combined with using several different wage predictions as well, then the number of TAXBEN runs required for the FRS sample becomes large; if there are W separate wage levels and H separate hours levels (for example) then each FRS individual has to be run through TAXBEN $H*W$ times. Given the current speed at which the model runs this should present no real difficulties. However, since this procedure would require conducting the whole income modelling process (i.e. net incomes calculation and the take-up modelling stage) at each of the hours points, the overall process might be relatively long.

Of the four options presented above, we suggest using the third one (predicting hours for each group via an hours equation) for the purpose of the model. The procedure should allow enough variation in the distribution of hours worked (including the possibility of working part-time), and at the same time is relatively simple to apply.

5.3 Modelling childcare cost

Predicted childcare cost is based on information on childcare use from the FRS. Predicted cost of childcare is included as a fixed cost of working for people with children. The information is also used to estimate the amount of childcare subsidies under Family Credit or the Working Families Tax Credit. For the latter purpose the estimated childcare cost is read into TAXBEN together with estimates of wages and hours (see equation 2.1).

In our estimation, we predict an overall cost of childcare, without distinguishing between formal and informal types. The predicted measure of childcare cost is therefore an average of formal and informal types of childcare. This is probably an accurate way to represent the fixed cost of childcare for working people with children. However, childcare subsidies are only available to those using 'formal' childcare, and not to all people who use paid childcare. This would suggest that we should distinguish between formal and informal cost for the calculation of subsidies in TAXBEN. This would require modelling take-up of childcare as a multinomial problem (since we would be modelling three options: no paid childcare, formal childcare and informal childcare). Given the additional complexity and the fact that

initial probit estimates of the probability of take-up of formal childcare and paid childcare gave similar predicted probabilities overall, we decided to simplify the estimation process by using the overall average for cost of childcare and take-up of childcare as well (thus calculating the ‘final’ measure of income as suggested by equation 2.1). This means the childcare subsidies that we model are likely to be overestimates of the overall cost. Similarly, we will have to be cautious in the analysis of the effects of fiscal reforms affecting childcare subsidies.

5.3.1 Childcare price equation

The FRS contains information on the number of hours of childcare used and on the overall weekly cost of childcare. On the basis of this we predict the hourly cost of childcare in a linear (or median) regression where hourly cost is regressed on a set of year dummies, a series of regional dummies and dummies for age groups of the youngest child. The same regression is used for singles and couples on the assumption that cost is exogenous to family type. We exclude other personal characteristics from the regression (like education, age, etc.) in order to restrict childcare cost to being an exogenous variable, independent of personal preferences. If P_C is the hourly price of childcare the linear form of the regression is:

$$P_{Ci} = f([t]_i, region_i, age_youngest_i) \quad (5.4)$$

As with the modelling of wages, we experiment with using the hourly price equation in levels and logs.

5.3.1 Childcare hours equation

The second stage of the process is an estimation of hours of childcare used, which when combined with the average hourly costs gives a total figure for childcare cost. We use a log-linear equation in which the log of hours of childcare is regressed on year dummies, education variables, age group of youngest child, a regional dummy for London, a dummy for whether people have 3 kids or more, the predicted hourly cost of childcare, and a set of variables indicating employment type⁷:

$$\ln H_C = g([t]_i, [education]_i, [age_youngest]_i, LonSE_i, 3kids +_i, P_{Ci}, [emp_type]_i) \quad (5.5)$$

The regression is run only for those who use paid childcare and is limited to single employed people and couples where at least one person is in paid employment. Predicted hours of childcare for single people should be calculated taking account of their predicted hours of work (we suggest distinguishing whether people work full time or part time). For couples we need to predict three different childcare hours

⁷ Note: in the paper we distinguish between employment ‘state’ (employed and not-employed) and employment ‘type’. The latter refers to whether people are part-time or full time employees. For single people employment type will simply be: part-time or full-time; for couples it may be various combinations of the partners’ employment, for example: man full time - woman part time, or man not employed – woman full time employed, etc.

points, depending on whether one person works (for scenarios: 0-1 and 1-0) or whether both partners are employed (for scenarios 1-1).

The total cost of childcare is then calculated as:

$$CC_cost_{iS} = \hat{P}_{Ci} * \hat{H}_{CiS} \quad (5.6)$$

where ‘S’ stands for employment state.

5.4 Running the model

The set of input variables as constructed above is ‘imposed’ on the FRS population. Every individual has one hours of work and one wage prediction and there is a prediction of childcare cost for singles if they work and for couples for each of the three employment states: (1,0), (0,1) and (1,1). Depending on the tax and benefit system these inputs result in a vector of net income variables for various employment states: two values for single people and four for couples. Thus for each tax-benefit system we run TAXBEN twice for singles and four times for couples. Since for people with children we have to run the model on three sub-systems (‘ ζ_1 ’, ‘ ζ_2 ’, ‘ ζ_3 ’, see section 2.2), for single parents it needs to be run four times and for couples with children eight times.⁸ Of course if we want to address take-up questions concerning people without children (e.g. in modelling of the working tax credit) we will then need two sub-systems (with 100% take up and with 0% take up) to be run for these groups as well.

Using the labels from section 2.2, we calculate the following for single people without children:

$$Y_{0,final} = f(\hat{w}_h, h = 0, \zeta), \text{ as non-employment income}$$

$$Y_{h,final} = f(\hat{w}_h, \hat{h}_h, \zeta), \text{ as income in work}$$

For couples without children, the four income measures corresponding to employment combinations of the partners are:

$$Y_{00,final} = f(\hat{w}_h, h_h = 0, \hat{w}_s, h_s = 0, \zeta)$$

$$Y_{10,final} = f(\hat{w}_h, \hat{h}_h, \hat{w}_s, h_s = 0, \zeta)$$

$$Y_{01,final} = f(\hat{w}_h, h_h = 0, \hat{w}_s, \hat{h}_s, \zeta)$$

$$Y_{11,final} = f(\hat{w}_h, \hat{h}_h, \hat{w}_s, \hat{h}_s, \zeta)$$

For singles and couples with children in scenarios where at least one person is employed we calculate incomes under each of the tax and benefit sub-systems (see

⁸ This is because for couples in scenarios (0,1) and (1,0) we don’t have to run the model with childcare subsidies since only couples with two people in work are eligible for these. Otherwise we would of course need to run couples with children 10 times (once in (0,0) state and three times in each of the others).

section 2.2.). Let ‘ γ ’ again be a vector of predicted hours and wages (\hat{h}, \hat{w}) and \hat{CC} the predicted childcare cost. Then the three measures of net income in work calculated in TAXBEN are:

$$\begin{aligned} Y_{FCWithCC} &= f(\gamma, \zeta_1, \hat{CC}) \\ Y_{FCNoCC} &= f(\gamma, \zeta_2) \\ Y_{NoFC} &= f(\gamma, \zeta_3) \end{aligned}$$

The section below describes the steps we use to arrive at the final measure of income for people with children. The final stage of income calculation involves the estimation of FC/WFTC and childcare take-up probabilities for families with children. These are done using input from: the raw FRS (for data on childcare), the results of TAXBEN model runs on the FRS, and the FRS HBAI dataset (for data on FC/WFTC receipt for the take-up model).

5.5 Modelling take-up of childcare

This section extends the modelling of childcare described above. We can use the TAXBEN calculations to relate the take-up of childcare to the predicted cost. Since the cost of childcare will depend on the level of childcare subsidies, we have to run the probit equation after the TAXBEN calculations. The childcare use probit is run on the sample of working families with children in the FRS. The specification of the regression is:

$$P(C_i) = \Phi([t]_i, [educ]_i, [age_youngest]_i, [emp_type]_i, LonSE_i, kids3+_i, ext_adult_i, \hat{CC_cost}_i) \quad (5.7)$$

where we regress the probability of using childcare on time dummies, education, age of the youngest child in the benefit unit, employment type,⁹ a London/South East dummy and a dummy for whether people have more than two children. The equation also includes a dummy for whether there is an adult in the household who is not a member of the benefit unit, is not employed and is not a student. This is included to control for availability of informal childcare in the household. The last explanatory variable is the predicted childcare cost. This is estimated on the basis of the childcare cost calculations presented in section 5.3 but augmented by the fact that for some people this cost may be lower due to receipt of childcare subsidies. We calculate childcare cost extending equation (5.6) to include childcare subsidies:

$$\hat{CC_cost}_{iS} = \hat{P}_{Ci} * \hat{H}_{CiS} - (Y_{FCWithCC,S} - Y_{FCNoCC,S}) * P_{FC,S}, \quad (5.8)$$

where $Y_{FCWithCC}$ and Y_{FCNoCC} are defined as in section 5.4 and P_{FC} is the probability of taking up in-work benefits. However, including the last element of the childcare cost

⁹ In each employment ‘state’ there may be more than one employment type: for example in couple state (0,1) the two employment types can be: man not working - woman working part-time or man not working - woman working full-time.

calculation leads to an identification problem, described in more detail in the next section (5.6).

For the sample of people with children we suggest running three childcare take-up probits, separately for working single parents, for one-earner couples and for two-earner couples. Predicted probabilities of take-up will then be constructed on the basis of these probits. Employment ‘types’ (see footnote 7) for the predictions should be based on the predicted level of hours worked.

5.6 Modelling take-up of benefits

By default, the TAXBEN model which we use for calculating net government transfers to each ‘benefit unit’ in the FRS data assumes that take-up is 100% and there is no fraud or mistaken payments. This means that each family in the FRS data receives the exact amount which they are assessed as being eligible for using the information in the data, which is fed through TAXBEN's calculation routines. The strategy for modelling take-up which we propose is based on modelling incomes in TAXBEN assuming 0% or 100% take-up and then using the FRS information to examine the difference between these incomes and the probability of actually receiving benefits.

Non take-up of benefits/tax credits means that income from these government transfers is no longer included in the calculation of the budget constraint. If the benefits are received when out of work (e.g. Jobseekers Allowance) then non-take up should increase the incentives to work relative to a situation of 100% take-up. For in-work benefits (FC/WFTC), the reverse is the case.

How serious an issue is non take-up of benefits and tax credits in the UK? Two measures of take-up can be used:

- take-up by caseload (i.e. the percentage of eligible men and women taking up each of the benefits).
- take-up by expenditure (i.e. the amount spent on each benefit as a percentage of the amount that would be spent if all eligible men and women were to take up the benefit).

Official DWP statistics show that take-up rates for Housing Benefit and Income Support are very high. HB take-up is at least 95% by expenditure for non-pensioner households. IS take-up is at least 90%. However, for Council Tax Benefit, Working Families Tax Credit and non-contributory Jobseekers Allowance, the take-up rates are lower. CTB take-up appears to be around 80%, NC-JSA around the same, whilst WFTC take-up appears to be between 85 and 90% for single women with children and around 65% for married or cohabiting women with children.

These figures indicate that there needs to be some control for benefit take-up in the labour supply model to ensure that the model produces as accurate a reflection of reality as possible. In our model we confine ourselves to partial take-up of the Working Families Tax Credit only. This is more straightforward as we are only considering a one-dimensional take-up model. The model could be extended to

include joint modelling of partial take-up of WFTC, CTB and NC-JSA. These are the three benefits with a substantial proportion of non-take up by expenditure (i.e. more than 10%). Obviously this case is harder to deal with econometrically as it involves calculating take-up probabilities over three dimensions.

5.6.1 Modelling take-up of FC/WFTC – the modelling framework

We start with a 'benefit unit' u in the Family Resources Survey dataset.¹⁰ We use the FRS because it has three crucial pieces of information which we need to model take-up:

- i) Information on the actual amount of benefit received in the interview week.
- ii) Information which allows a researcher to determine the eligibility for the benefit.
- iii) Information which allows a researcher to determine how much benefit an eligible benefit unit would receive if the claim were processed correctly.

For (ii) and (iii), it is necessary to use the TAXBEN model to process the FRS data so as to provide a prediction of benefit eligibility under full take-up. The notation in the following section follows Brewer (2002) as much as possible, who in turn follows Duclos (1995).¹¹ Let B_u^* be the true amount of means-tested benefit entitlement of a benefit unit as determined by the means tested benefit rules laid down in legislation. Let us label the analyst's assessment of benefit entitlement as B_u^a and the actual benefit received as T_u (i.e. T for take-up). Thus, of the pieces of information given above, (i) corresponds to T_u and (ii) and (iii) allow the determination of B_u^a . For the moment we will ignore any discrepancies between B_u^* and B_u^a .

In terms of classifying the discrepancy between actual benefit take-up and modelled benefit entitlement, for the moment let us view modelled entitlement and actual take-up both as simple binary variables (i.e. ignoring the amount of benefit actually received). In this case we can classify the population into four categories as shown in Table 5.1.¹²

¹⁰ A benefit unit is here defined as a set of family members who are treated by the Inland Revenue as a single unit for the assessment of their eligibility to the WFTC. This could be a single (childless) adult, a lone parent, or a married or cohabiting couple, with or without children. Children living with their parents who are over 18 (or who are married and under 18) are classified as separate benefit units in their own right.

¹¹ Section 2.1.8 of Report 1 examines the problem of modelling take-up more generally.

¹² Entitled benefit units might not claim for a number of reasons: lack of information, 'hassle costs', stigma, or not wanting to reveal information to the benefits authority. On the other hand, people who are actually claiming benefit might appear not to be entitled for the following reasons:

- a) fraud,
- b) a mistake on the part of the benefits agency,
- c) in the case of WFTC, the fact that it is not continuously assessed on the basis of current characteristics but is initially assessed and then awarded at a fixed level for six months; the researcher's assessment of eligibility is based on a snapshot of personal characteristics which may differ from those in place at the time the benefit was awarded;
- d) when benefit rules are changed there are often some benefit units who stand to lose out from the change (e.g. the 'Fowler reforms' of 1988 which introduced Income Support and Family

Table 5.1. Classification of benefit entitlement and take-up.

	Not entitled ($B_u^a=0$)	Entitled ($B_u^a>0$)
Not taking up ($T_u=0$)	Non-entitled non-claimant	Entitled non-claimant
Taking up ($T_u>0$)	Non-entitled claimant	Entitled claimant

Table 5.2 shows a breakdown of people in our sample including: the ‘Non-entitled claimant’ group, the overall entitled sample and the proportion of benefit units in the entitled sample who claim the payments.

Table 5.2. Take-up in the FRS data.

Year	Couples			Singles		
	Not entitled, taking up	Entitled, both taking up and not	Proportion of entitled who take up	Not entitled, taking up	Entitled, both taking up and not	Proportion of entitled who take up
1997	82	328	50.30%	40	299	69.23%
1998	77	296	60.14%	26	322	74.84%
1999	95	306	58.50%	61	389	73.78%
2000	87	601	48.42%	75	507	71.20%

Source: FRS 1997-2000, TAXBEN, HBAI 1997-2000. Based on the selected sample used for the study.

Of these four groups, what we are most concerned about in this project is the size of the group of entitled non-claimants and how it affects our estimates of budget constraints for individuals in and out of work, and our estimates of the effect of policy reforms on the public finances. The size of the group of non-entitled claimants is also important for both of these calculations. However this problem is very difficult to circumvent and at the moment we have no good suggestions as to how we can solve it. The non-entitled claimants are simply left out of the take-up probit.

Of course if the group of entitled non-claimants and the group of non-entitled claimants were both empty, then modelled entitlement would be identical to actual benefit receipt.¹³

Credit abolished a lot of the special premia which had existed in the old Supplementary Benefit system), to soften the blow of changes like this, existing claimants who would be worse off under the new system are often allowed to go on claiming at their existing rate of benefit (which is fixed in nominal terms and therefore gradually eroded by inflation until it falls into line with the amount received under the new benefit regime).

¹³ In this zero-one framework only. Of course, in a framework where we were modelling the actual amount of benefit received vis-a-vis the amount of entitlement, the two figures could still differ for each case even if there was a complete match between eligible benefit units and actual recipients.

5.6.2 Modelling take-up of WFTC – the take-up probit

Take up of FC/WFTC is estimated using simulated entitlement calculated using TAXBEN, and recorded claims from the raw FRS data on benefit receipt, as used in the DWP's HBAI (Households Below Average Income) series. The HBAI information is used to construct a dummy variable which takes the value 1 if people claim and 0 if they don't but according to TAXBEN are entitled to it:

$$P_{FC}(T_e > 0) = \Phi([t]_i, [educ]_i, [age_youngest]_i, [emp_type]_i, LonSE_i, kids3+_i, FC_WFTC_{ie}) \quad (5.9)$$

We regress the take-up dummy on: year dummies, education variables, age groups of youngest child, a set of employment type dummies (see footnote 7), a dummy for London/South-East, a dummy for whether people have more than two children, and the FC/WFTC amount (uprated to constant prices). The FC_WFTC_{ie} variable is the TAXBEN-calculated eligibility to Family Credit or WFTC. This is calculated as the difference in income between 100% and 0% take-up using *actual* FRS hours and wages (of both partners in the case of couples) under a given tax and benefit system, ζ , and includes the childcare subsidy if people are recorded as using childcare:

$$FC_WFTC_{ie} = Y_{FC/WFTC}(h, w, CC, \zeta) - Y_{NoFC/WFTC}(h, w, CC, \zeta) \quad (5.10)$$

5.6.3 Predicting take-up in policy simulations

For the take-up predictions the value of FC/WFTC is calculated as:

$$FC^{h,s} = (Y^{h,s}_{FCWithCC} - Y^{h,s}_{FCNoCC}) * \hat{P}_{CC} - Y^{h,s}_{NoFC} \quad (5.11)$$

where 'h' and 's' refer to the head's and spouse's hours of work, and 'Y's are the levels of net income in the three sub-systems: ' ζ_1 ', ' ζ_2 ', ' ζ_3 '. We can see that the FC/WFTC childcare subsidy is weighted by the predicted probability of using childcare. This presents a slight problem since the probability of using childcare is itself a function of childcare cost, and thus of childcare subsidy and therefore of the probability of taking it up (see equation 5.8). This combination leads to an identification problem, and to resolve this endogeneity we propose to exclude childcare cost from the childcare take-up regression. We have run various specifications of the childcare probits equations to test the importance of predicted childcare cost for childcare take-up, and it never came out as statistically significant.

As in the case of the childcare take up equations, the FC/WFTC take-up equations include employment 'types'. Once again these are based on the predicted level of hours worked. This means that take-up probability for couples is allowed to vary depending on the employment state and type. For example if a couple is eligible for FC/WFTC in all three states: (1,1), (0,1), and (1,0), the probability of take-up for this couple will be different in each of the states not only because of the difference in the level of eligibility but also because a different employment state/type dummy is set to '1' in the prediction. For singles we will distinguish only between full-time and part-time work. For couples however there may be eight employment states in the

FC/WFTC take-up regression, made up of the combinations of full time, part time and non-employment of the partners.

5.7. Model identification

The model is identified by three forms of exogenous variation in work incentives over the period:

- (i) Variation in the parameters of the tax and benefit system corresponding to the reforms after 1997.
- (ii) Variation in gross wages due to wage growth and the changing distribution of gross earnings. There may also be changes in the wage distribution at the bottom end due to the introduction of the National Minimum wage in 1999.
- (iii) Variation in the level of income from other sources which will count as 'unearned income' in the model.

The relationship of gross wages to net income is non-linear due to the structure of the tax and benefit system (with marginal deduction rates differing substantially according to whereabouts in the income and earnings distributions the individuals in the FRS are). Thus the interaction between (i) and (ii) (and indeed (i) and (iii)) above also helps identify the model.

Additional identification is achieved by excluding education level variables from the transitions equations, thus assuming that education only affects the rates of entry and exit through its effect on financial incentives (this exclusion was necessary due to strong collinearity of education levels and income variables; the problem of collinearity was also encountered by Gregg, Johnson and Reed (1999)).

6 Groups in the model

As we said earlier, our model relies on matching information from the FRS and LFS. This section presents one of the methods of matching which can be used, based on grouping people into cells defined by certain characteristics in both samples and matching information by group. We outline the consequences of varying the number and categories of grouping variables (below we refer to the number of ‘group defining characteristics’ which is the sum of categories across grouping variables). We examine the FRS sample to check what proportion of it is allocated to cells of sizes below various thresholds. The problem with small cell sizes in the FRS is lack of accuracy in calculating the mean of the income variables which are used in the LFS entry and exit models. In addition to increasing the proportion of the sample falling into groups of small cell-size a higher number of cells leads to a larger potential mismatch between the FRS and LFS samples. By mismatch we mean the inability to find in the FRS cells which exist in the LFS. Such mismatch leads to a reduction of the LFS entry and exit samples sizes since for these cells we cannot transfer the appropriate income information from the FRS.

Below we first explain how groups can be created and what consequences increasing the number of group defining characteristics has for the number of cells into which we divide the sample. We then present some information on cell size for the overall FRS sample using various examples of sample grouping. This exercise gives an idea of the consequences of increasing the number of group defining characteristics. We must note, however, that the numbers presented in this section are based on the overall FRS sample, while in the actual modelling process groups will be created conditional on (FRS recorded) employment state. For example, while below we present the cell sizes for all single people, in the actual model cells are created separately for single employed and single non-employed people.

The final choice of the grouping method will be made given the trade off between:

- a) accurate mean calculation of the income variable in the FRS data (the cell sizes can’t be too small) and the degree of mismatch between the LFS and FRS samples (which is higher the greater the possible variation, i.e. the higher the number of cells)
- b) the extent of variation between groups we allow for and the number of variables we believe should be taken into account in grouping the data (for example because we want to distinguish between certain types of individuals or couples for the purpose of the final model).

6.1 Grouping singles

A method that demonstrates the effect of grouping categories on the number of cells is presented in the tables below. We consider several variables which can be used to define characteristics for groups:

- year of data,

- sex,
- age,
- education,
- region,
- number of children.

For these variables we demonstrate how changing the extent of variation (by changing the number of categories within the variables) affects the number of cells in the sample. Say for example that we have four years of data, and decide that we want to account for possible variation in time. This gives us four categories within the year of data variable. There are two categories within sex, three within education (defined by the age when left full time education) and we consider regional variation distinguishing between people living in London & South-East and living elsewhere (which gives us two categories). Table 6.1 below shows how changing the number of categories of ‘age’ and of ‘number of children’ affects the number of possible cells that can be formed using the specific level of variation. So for example using 3 age groups (say 20-31, 32-43, 44-55) and two categories defined by the number of children (‘none’ and ‘1 or more’) in combination with the other variables and their categories gives the maximum of 288 cells. Increasing the number of age groups up to 5 and accounting for greater variation defined by the number of children (say: no children, one child and more than one child) takes the number of possible cells to 720.

Table 6.1 Grouping singles.

	Variables						Max. no. of cells:
	Year	Sex	Age	Education	Region	Children	
Grouping 1	4	2	3	3	2	2	288
Grouping 2	4	2	4	3	2	2	384
Grouping 3	4	2	5	3	2	3	720

We grouped the FRS sample in four different ways using a set number of categories within the year of data (4: 1997, 1998, 1999, 2000), sex (2: male, female), education (3: left FT education aged 16, 17-18, or 19+), region (2: London/South East or not) and age of youngest child (2: youngest child less than 5 or not) and different numbers of categories within age and the number of children:

Age:

- methods 1 and 2: 3 age groups: 20-24, 25-49, 50-55,
- methods 3 and 4: 4 age groups: 20-24, 25-37, 38-49, 50-55;

Number of children:

- methods 1 and 3: 2 groups: has or does not have children,
- methods 2 and 4: 3 groups: does not have children, has one or two children, has more than two children;

Table 6.2 gives the number of categories within each of the variables while Table 6.3 presents the proportion of the overall sample in cells equal or less than 10 and 20 observations and the number of cells into which this proportion has been divided.

Table 6.2 Grouping singles – four grouping methods.

	Year	Sex	Age	Education	No. children	Age of youngest child	Region
Grouping 1	4	2	3	3	2	2	2
Grouping 2	4	2	3	3	3	2	2
Grouping 3	4	2	4	3	2	2	2
Grouping 4	4	2	4	3	3	2	2

Table 6.3 Grouping singles – four grouping methods: effect on cell size.

	Proportion of sample in cells =<10	Number of cells =<10/Total number of cells	Proportion of sample in cells =<20	Number of cells =<20/Total number of cells
Grouping 1	0.61	70/284	1.13	87/284
Grouping 2	1.20	150/404	2.00	178/404
Grouping 3	1.27	161/503	2.77	211/503
Grouping 4	2.14	297/677	4.09	361/677

6.2 Grouping individuals in couples

Our proposed modelling method for couples treats the couple and not the individuals within the couple as the unit of observation, and therefore grouping of the sample differs accordingly. The group defining characteristics are based on the following variables:

- year of data,
- age of the man,
- age of the woman,
- education of the man,
- education of the woman,
- region,
- number of children.

Some examples of how the number of categories affects the maximum number of cells are given in Table 6.4. If we exclude one partner's characteristics from group variation (grouping 1), and include only three age categories and two child categories, the number of cells is 144 (lower than in the case of single people since we have excluded sex from group defining characteristics). However, as we include the second partner's characteristics the number of cells very rapidly increases. If groups are defined on three age categories and three education categories for both partners, and if we allow for three categories within the number of children characteristic, the maximum number of cells increases to 1,944!

Table 6.4 Grouping couples.

	Variables							Max. no. of cells:
	Year	Age (M)	Age (W)	Education (M)	Education (W)	Region	Children	
Grouping 1	4	3	-	3	-	2	2	144
Grouping 2	4	3	2	3	3	2	2	864
Grouping 3	4	3	3	3	3	2	2	1296
Grouping 4	4	3	3	3	3	2	3	1944

As in the case of singles we present information of the consequences of several grouping methods for the proportion of small cells in the overall FRS sample. We grouped the FRS sample of couples in four different ways using a set number of categories within the year of data (4: 1997, 1998, 1999, 2000), education of the man (3: left FT education aged 16, 17-18, or 19+), age of the man (3: 20-24, 25-49, 50-55) region (2: London/South East or not) and age of youngest child (2: youngest child less than 5 or not) and different numbers of categories within age of the woman, education of the woman and the number of children:

Age of the woman:

- methods 1, 2 and 3: 2 age groups: 20-24, 25-55,

Education of the woman:

- method 4: 2 groups: left full time education at 19+ or below 19,

Number of children:

- methods 1 and 2: 2 groups: have or do not have children,
- methods 3 and 4: 3 groups: do not have children, have one or two children, have more than two children;

Table 6.5 Grouping couples – four grouping methods.

	Year	Age (M)	Age (W)	Education (M)	Education (W)	Region	Children	Age of youngest child
Grouping 1	4	3	-	3	-	2	2	2
Grouping 2	4	3	2	3	-	2	2	2
Grouping 3	4	3	2	3	-	2	3	2
Grouping 4	4	3	2	3	2	2	3	2

Table 6.3 Grouping couples – four grouping methods: effect on cell size.

Grouping method:	Proportion of sample in cells =<10	Number of cells =<10/Total number of cells	Proportion of sample in cells =<20	Number of cells =<20/Total number of cells
1	0.91%	54/201	2.17%	75/201
2	2.42%	143/310	4.20%	173/310
3	3.06%	216/428	4.84%	245/428
4	5.01%	387/731	10.95%	487/731

As we can see from the above examples the number of cells rapidly increases with the number of group defining characteristics. The result of this is an increasing proportion of individuals or couples in cells of small sizes, and thus a reduced precision in the estimation of the mean income for a given cell. Precision of estimation and the degree of mismatch between FRS and LFS have to be taken into account in determining the final characteristics defining the cells.

7 Interpreting and using the results

7.1 Interpretation of the results

The results of the transition models (presented in Report 3) will show the estimated impact of predicted financial incentives on the propensity to change labour market state. For single people there are two equations: an entry equation and an exit equation. Each of these has net income in work and net income out of work as regressors. For the entry equation, which is run on the sample of LFS single people not working in the first wave of the LFS, the income variables are therefore ‘income if stays out of work’ and ‘income if moves into work’ respectively. Conversely, for the exit equation the income variables are ‘income if stays in work’ and ‘income if moves out of work’ respectively.

In the case of couples, there are four employment states and hence four estimations, as explained in Section 4.2. Each multinomial logit has four income variables as regressors: the couple’s net income in each alternative labour market state.

Our main results, as given in Report 3, use *log* average income measures rather than levels of average income for each FRS group. This means that they show the relationship between movements in and out of work and a proportionate change in incomes in a given state, rather than changes in the absolute level of income. We decided that this was preferable to using levels of income because it is quite possible that someone on a very low income in their initial labour market state would be more likely to respond to a given monetary change in the financial incentives to change state than would someone with a higher starting income.¹⁴

In the model for singles, we can examine a specification which uses a common income measure for all groups, and also an alternative specification which splits the income measure up for childless men, childless women and lone mothers. This would allow us to assess whether any of these three groups is more or less responsive to financial incentives than the others. We conducted initial tests to split the income measures for the couples model into incomes for families with children and incomes for families without children but none of the income measures seemed to be significant for such a specification. This means that the structure of the couples model, given the available sample size, was too complex to support “breaking down” the income measures in this way.

All the transition models also contain other explanatory (control) variables as given in sections 4.1 and 4.2. In most cases these are time and policy-invariant, at least as regards the time-frame of the model. We offer some interpretation of the regression

¹⁴ Evidence from the work entry model of Gregg, Johnson and Reed (1999) supports this view. Section 5.3 of that paper experiments with allowing financial incentives to have a different effect for groups where the average gain from working in was less than £100 per week in April 1995 prices. The results indicated that groups with smaller average gains to work had larger estimated work entry responses for a given increase in the returns to working (in £ per week).

coefficients on these other variables when we examine the results from the model in Report 3.

7.2 Simulation analysis

The simulation stage follows the process of estimation of the transition equations. Here we use the estimated equation coefficients together with calculated incomes from some reformed tax and benefit systems to examine how transition probabilities adjust when net incomes change following the reform.

The FRS data are grouped and matched to transfer income information to the LFS, following which transition models are run (in STATA) to generate model results and the respective transition predictions for each individual/couple. The predictions are then used as the base for estimates of the effects of the reform. For the tax and benefit reform simulations, new sets of incomes are generated and used to replace the original income information. The coefficients on financial incentive variables from the labour supply model's transition equations are then used to predict new transition probabilities for the LFS sample. (For the moment we assume that the levels of income in the reformed systems can be generated in the same way as the original incomes, i.e. that there are no major structural changes affecting the tax and benefit system; we address these issues further below).

The set of transition probabilities based on the original and reformed income information is used to generate the population totals in various employment states. This then allows us to calculate the short-run effect of our simulated reforms.

Disaggregating the simulation analysis

The simulation results from the model can be disaggregated by observable characteristics such as age, gender, household type, number of children, region and educational qualification. This is done by simply splitting the sample according to these different characteristics and running the predictions of employment growth separately for each or by grossing probabilities up separately for each group. This disaggregation is likely to be particularly important if the financial incentive variables have been split according to family type (as we are doing for the singles model, as explained in Section 7.1). It can still be done even if the financial incentives have not been broken down by family type in the estimation process, but this does imply a more restrictive specification.

7.3 Population level estimates

This section presents a grossing-up procedure to calculate the population grossed-up effects of reforms to the tax and benefit systems that we decide to simulate.

Using the estimated model coefficients from the transitions equations we produce a vector of predicted probabilities corresponding to potential employment states for each benefit unit:

$$\hat{\Pi}_{ij}(X_i, Y_{ij}(\zeta, \hat{w}_i, \hat{h}_i)) \quad (7.1)$$

where X_i is a vector of individual characteristics included in the model, and Y_{ij} is a vector of incomes in j employment states for individual/couple i (for whom we predicted employment hours \hat{h}_i and wages \hat{w}_i (two of these in the case of couples)) using a tax system ζ . The difference in these predicted probabilities between the base and reform tax systems represents the effect of the reform on this particular individual/couple. If we label the base system as ‘ B ’ and the reformed system as ‘ R ’ the effect of the reform on transition probabilities can be represented as:

$$\begin{pmatrix} \hat{\Pi}_{1B} \\ \cdot \\ \cdot \\ \hat{\Pi}_{JB} \end{pmatrix} - \begin{pmatrix} \hat{\Pi}_{1R} \\ \cdot \\ \cdot \\ \hat{\Pi}_{JR} \end{pmatrix} = \begin{pmatrix} \Delta\hat{\Pi}_1 \\ \cdot \\ \cdot \\ \Delta\hat{\Pi}_J \end{pmatrix} \quad (7.2)$$

where $\sum \Delta\hat{\Pi}_j$ is zero.

Because we want to learn about population-level and not sample-level estimates of reform simulations, the data needs to be grossed up. If the population-level grossing factor for individual/couple i is g_fac_i , then the grossed-up effect of the reform is:

$$\begin{pmatrix} \hat{\Pi}_{1B} \\ \cdot \\ \cdot \\ \hat{\Pi}_{JB} \end{pmatrix} * g_fac_i - \begin{pmatrix} \hat{\Pi}_{1R} \\ \cdot \\ \cdot \\ \hat{\Pi}_{JR} \end{pmatrix} * g_fac_i = \begin{pmatrix} \hat{\Phi}_1 \\ \cdot \\ \cdot \\ \hat{\Phi}_J \end{pmatrix} \quad (7.3)$$

Summing the $\hat{\Phi}_j$ ’s across individuals, we can calculate the estimated changes in the number of people in every employment state for the whole population.

7.4 Grossing factors

The population total we calculate after grossing-up the LFS sample does not add up to the entire UK population. There are three reasons for this.

First of all, the grossed-up figures are lower than the overall population totals because of sample selection. To recall, the model is estimated on people aged 20-55 who are not one or more of the following:

- self-employed,
- long-term sick/disabled,
- early retired,
- students.

We also exclude those for whom information in the data is inconsistent (e.g. age left full time education is greater than current age), and those changing marital status between wave 1 and 5. This means that following sample selection we will not be able to gross the sample up to the overall population total. This is not very much of a problem as the results can be specified as applying only to a subset of the population, or can be re-grossed (i.e. multiplied up) to reflect loss of observations due to poor data quality in the LFS, or changes in marital status which mean that we are forced to drop some of the LFS data.

The second reason is that the LFS grossing factors correspond to the quarterly overall LFS sample. This is divided into five sub-samples corresponding to the five waves. From each particular quarter we only use one of these, the fifth wave, in which people appear for the last time (this is matched with information from the first interview a year earlier). Because for a given year we use a fifth of the sample from all four quarters, this means that with the standard population grossing factors we will underestimate the population by about 20%. To generate the correct population totals we would need a different set of grossing factors, which take into account the fact we only consider 80% of the LFS sample in the model. A crude method of correcting this under-estimate is to multiply the grossing factors or the population totals by 5/4.

The third reason for the underestimation of the population totals arises from the fact that we lose some observations in the two processes of sample matching. The first arises at the level of LFS cross-wave matching necessary to identify employment transitions between the first and last wave. The second is the process of LFS-FRS matching when importing income information from the latter.

The magnitude of these three effects is presented on a chart below. The population totals are calculated using the winter 2000 LFS data.

Table. 7.1 The effect of sample selection on the grossed up population.

LFS sample: winter 2000	Grossed-up population
Entire sample:	58.82m
Population from the quarter used in the model:	12.22m*
Of this:	
in age group 20-55:	5.08m
+ other selection criteria:	3.08m
+ can be matched with 1 st quarter information:	2.68m
+ can be matched with FRS:	2.63m

* - thus population 'coverage' by the model about: $12.22 \times 4 = 48.88\text{m}$

The table shows that:

- Since we are only using one wave per quarter, we underestimate the population by about 20%
- Our selection criteria leave us with about 25% of the population
- Allowing for mismatch reduces the population coverage to about 22%

Since the model is estimated on a selected sub-sample of the population we believe its results should not be generalised to cover the sections of the population which are excluded from it. Yet, in presenting the overall results, there is no reason to exclude those who are not in the sample for reasons going beyond the selection criteria (like sample mismatch or inappropriate grossing factors).

There can be different approaches to restoring population totals. The simplest one is to assume that the grossing factors can simply be 'scaled up' to reflect changes in sample size. Using the example from Table 7.1 correcting the grossing factors by multiplying them by $(3.08/2.63)$ would give us the population totals corresponding to the fifth wave data. Similarly multiplying grossing factors by $1.25*(3.08/2.63)$ would restore the population totals taking account of the fact that the model includes data from four and not five LFS waves.

Another approach, used in Gregg, Johnson and Reed (1999), is to transfer the transition probabilities back to the FRS and use FRS grossing factors to calculate population totals. This approach would not account for LFS-FRS mismatch, though it could be limited by restrictions on the number of grouping factors by which we would match the data (since these could be but would not have to be the same as those used for matching income information).

The first approach is clearly simpler, and ensures that we do not overestimate the population totals. The second, on the other hand, has the advantage that the transferred probabilities in conjunction with TAXBEN outputs could be used in the process of estimating the Exchequer costs and gains allowing for the dynamic response.

7.5 Short and long run effects of labour market reforms

The initial results from our policy simulations simulation give the predicted changes in transition rates between labour market states over the same period that the data is taken from, i.e. over one year, from the 1st to the 5th quarter of LFS. These results can be taken as an accurate estimate of the effects of each policy on employment and non-employment given the following assumptions:

1. labour supply adjustment to the new policy regime is sufficiently fast that it occurs completely within the first year that the policy is in force.
2. the policy change produces a one-off shift in labour supply (corresponding to individuals and families re-optimising in response to a change in their budget constraints) rather than a permanent change in labour market transition rates.

If we feel that the second of these assumptions, in particular, is incorrect, i.e. the policy will produce a permanent change in labour market transition rates, then it may make more sense to look at the predicted *long-run* impact of the policy reforms. This is calculated by assuming that the observed transition rates between employment states in the most recent period of the initial data are ‘equilibrium’ rates, i.e. in the absence of changes to financial incentives, they would persist indefinitely into the future. We would then assume that changes in financial incentives induced by policy changes will produce a *permanent* change in transition rates. The remainder of this section shows how these assumptions can be used to derive long-run equilibrium stocks of people in different labour market states, and the effects of changes in financial incentives on those long-run stocks.

7.5.1 Calculations for single people

Let us introduce some notation for single people. Denoting the (grossed up) stock of working single people at time t as W_t^s , the stock of non-working people as U_t^s and the total stock of (working age) single people as N_t^s ,¹⁵ we see that changes in the stocks of employed and non-employed over each time period are captured by the formulae:

$$W_{t+1}^s = (W_t^s \times (1 - \Pr(\text{exit}_{t+1}))) + (U_t^s \times \Pr(\text{enter}_{t+1})) \quad (7.4)$$

$$U_{t+1}^s = (U_t^s \times (1 - \Pr(\text{entry}_{t+1}))) + (W_t^s \times \Pr(\text{exit}_{t+1})) \quad (7.5)$$

where $\Pr(\text{exit}_{t+1})$ is the probability that a person who is single leaves work by time $t+1$ conditional on their being in work at time t , and $\Pr(\text{entry}_{t+1})$ is the probability that a single person enters work by time $t+1$ conditional on their not being in work at time t . If we assume that the total working age population of singles, N_t^s , is stable over time, we define long-run equilibrium employment as $W_t^s = W_{t+k}^s = W_*^s$, for all k , and likewise for U_*^s and N_*^s . The probabilities of entry and exit, $\Pr(\text{entry}_*)$ and $\Pr(\text{exit}_*)$, are also constant over time in this equilibrium.¹⁶ The long run stocks can be calculated according to the formula:

¹⁵ The approach used here assumes that we are calculating the short and long-run effects for the whole of the sample of single people in the LFS, but we could easily work with subdivisions of the sample (e.g. splitting up lone parents and childless single people). If N_t is defined as the total population of the subgroup we are interested in, and W_t and U_t as its working and non-working components, and the appropriate entry and exit probabilities are used for the subgroup, the analysis remains completely valid. The same is true for the analysis of couples in the next subsection.

¹⁶ Our default assumption is that $\Pr(\text{entry}_*)$ and $\Pr(\text{exit}_*)$ are equal to the most recent entry and exit probabilities observed in the data (the entry and exit rates from LFS for the 2000-01 tax year in the current version of our model). This assumption is open to the objection that the most recent set of entry and exit probabilities reflect a certain point in the business cycle (i.e. entry rates may be particularly high during a boom) and so it does not make much sense to see these as the ‘equilibrium’ entry and exit rates. An alternative approach would be to use a number of years of data on entry and exit rates to produce cyclically adjusted transition rates, for example via residuals from a regression of transition rates on GDP growth rate. We could certainly try this if HMT and DWP are interested.

$$W_*^s = (W_*^s \times (1 - \Pr(\text{exit}_*))) + ((N_*^s - W_*^s) \times \Pr(\text{entry}_*))$$

which re-arranges to:

$$W_*^s = \frac{N_*^s \times \Pr(\text{entry}_*)}{\Pr(\text{exit}_*) \times \Pr(\text{entry}_*)}, \quad (7.6)$$

with $U_*^s = N_*^s - W_*^s$.

In the policy simulation, a tax and benefit reform R produces a new set of entry and exit predictions (call them $\Pr(\text{entry}_*^R)$ and $\Pr(\text{exit}_*^R)$), These are plugged into equation (3) to produce new long-run employment predictions.

7.5.2 Calculations for couples

For couples, the formulae are more complicated due to the fact that we are analysing transitions to and from four labour market states rather than two, but the basic principle is the same. Denoting the stocks at time t as:

WW_t^c = stock of couples with both partners working

WU_t^c = stock of couples with man working and woman not working

UW_t^c = stock of couples with man not working and woman working

UU_t^c = stock of couples with both partners not working,

and the total couples population as $N_t^c = WW_t^c + WU_t^c + UW_t^c + UU_t^c$, we have the transition probabilities:

- $\Pr(WU_{t+1}^c | WW_t^c), \Pr(UW_{t+1}^c | WW_t^c), \Pr(UU_{t+1}^c | WW_t^c)$ denoting the probability of transit to the three other labour market states by time $t+1$ conditional on both partners working at time t ;
- $\Pr(WW_{t+1}^c | WU_t^c), \Pr(UW_{t+1}^c | WU_t^c), \Pr(UU_{t+1}^c | WU_t^c)$ denoting the probability of transit to the three other labour market states by time $t+1$ conditional on the man working and the woman not being in work at time t ;
- $\Pr(WW_{t+1}^c | UW_t^c), \Pr(WU_{t+1}^c | UW_t^c), \Pr(UU_{t+1}^c | UW_t^c)$ denoting the probability of transit to the three other labour market states by time $t+1$ conditional on the woman working and the man not working at time t ;
- $\Pr(WW_{t+1}^c | UU_t^c), \Pr(WU_{t+1}^c | UU_t^c), \Pr(UW_{t+1}^c | UU_t^c)$ denoting the probability of transit to the three other labour market states by time $t+1$ conditional on both partners not working at time t .

The short run changes in employment rates are given as follows:

$$\begin{aligned}
WW_{t+1}^c &= (WW_t^c \times (1 - (\Pr(WU_{t+1}^c | WW_t^c) + \Pr(UW_{t+1}^c | WW_t^c) + \Pr(UU_{t+1}^c | WW_t^c))) \\
&+ (WU_t^c \times \Pr(WW_{t+1}^c | WU_t^c) + (UW_t^c \times \Pr(WW_{t+1}^c | UW_t^c) + (UU_t^c \times \Pr(WW_{t+1}^c | UU_t^c)
\end{aligned} \tag{7.7}$$

$$\begin{aligned}
WU_{t+1}^c &= (WU_t^c \times (1 - (\Pr(WW_{t+1}^c | WU_t^c) + \Pr(UW_{t+1}^c | WU_t^c) + \Pr(UU_{t+1}^c | WU_t^c))) \\
&+ (WW_t^c \times \Pr(WU_{t+1}^c | WW_t^c) + (UW_t^c \times \Pr(WU_{t+1}^c | UW_t^c) + (UU_t^c \times \Pr(WU_{t+1}^c | UU_t^c)
\end{aligned} \tag{7.8}$$

$$\begin{aligned}
UW_{t+1}^c &= (UW_t^c \times (1 - (\Pr(WW_{t+1}^c | UW_t^c) + \Pr(WU_{t+1}^c | UW_t^c) + \Pr(UU_{t+1}^c | UW_t^c))) \\
&+ (WW_t^c \times \Pr(UW_{t+1}^c | WW_t^c) + (WU_t^c \times \Pr(UW_{t+1}^c | WU_t^c) + (UU_t^c \times \Pr(UW_{t+1}^c | UU_t^c)
\end{aligned} \tag{7.9}$$

$$\begin{aligned}
UU_{t+1}^c &= (UU_t^c \times (1 - (\Pr(WW_{t+1}^c | UU_t^c) + \Pr(WU_{t+1}^c | UU_t^c) + \Pr(UW_{t+1}^c | UU_t^c))) \\
&+ (WW_t^c \times \Pr(UU_{t+1}^c | WW_t^c) + (WU_t^c \times \Pr(UU_{t+1}^c | WU_t^c) + (UW_t^c \times \Pr(UU_{t+1}^c | UW_t^c)
\end{aligned} \tag{7.10}$$

For the long-run changes, the notational conventions for the stocks are as for single people, e.g. $WW_t^c = WW_{t+k}^c = WW_*^c$. The equilibrium transition probabilities are denoted as $\Pr^*(WW | UU) = \Pr(WW_{t+k+1}^c | UU_{t+k}^c)$ for all k , and likewise for all twelve transition probabilities. The equations for the long-run stocks are:

$$\begin{aligned}
WW_*^c &= (WW_*^c \times (1 - (\Pr^*(WU | WW) + \Pr^*(UW | WW) + \Pr^*(UU | WW))) \\
&+ (WU_*^c \times \Pr^*(WW | WU) + (UW_*^c \times \Pr^*(WW | UW) + (UU_*^c \times \Pr^*(WW | UU)
\end{aligned} \tag{7.11}$$

$$\begin{aligned}
WU_*^c &= (WU_*^c \times (1 - (\Pr^*(WW | WU) + \Pr^*(UW | WU) + \Pr^*(UU | WU))) \\
&+ (WW_*^c \times \Pr^*(WU | WW) + (UW_*^c \times \Pr^*(WU | UW) + (UU_*^c \times \Pr^*(WU | UU)
\end{aligned} \tag{7.12}$$

$$\begin{aligned}
UW_*^c &= (UW_*^c \times (1 - (\Pr^*(WW | UW) + \Pr^*(WU | UW) + \Pr^*(UU | UW))) \\
&+ (WW_*^c \times \Pr^*(UW | WW) + (WU_*^c \times \Pr^*(UW | WU) + (UU_*^c \times \Pr^*(UW | UU)
\end{aligned} \tag{7.13}$$

$$\begin{aligned}
UU_*^c &= (UU_*^c \times (1 - (\Pr^*(WW | UU) + \Pr^*(WU | UU) + \Pr^*(UW | UU))) \\
&+ (WW_*^c \times \Pr^*(UU | WW) + (WU_*^c \times \Pr^*(UU | WU) + (UW_*^c \times \Pr^*(UU | UW)
\end{aligned} \tag{7.14}$$

The fact that there are four labour market states involved for couples instead of the two which we have for singles means that the long-run stocks of couples in each labour market state cannot be directly computed analytically; however, it is easy to calculate the long-run equilibrium stocks iteratively using a spreadsheet or similar

device. Reforms which produced changes to the predicted transition probabilities can then be run through the spreadsheet to produce long-run predictions of changes in the number of two-earner couples, single earner couples and workless households.

7.6 Robustness and sensitivity analysis

7.6.1 Standard errors and confidence intervals on model predictions

It is important to have standard errors on the model results. This is complicated in the current analysis because more than one dataset is used (FRS and LFS), but analytical solutions for calculating standard errors do exist for the case of complementary datasets (e.g. Arellano & Meghir, 1992). An alternative method of calculating confidence intervals for the analysis is to use bootstrap procedures (bootstrapping both datasets simultaneously). This is the approach that we take in Report 3, which provides bootstrapped confidence intervals for the model estimates.

7.6.2 Simulations using different equation specifications and different definitions of wages and hours

The modelling methodology presented in sections 4 and 5 opens up a range of possibilities in terms of the final specification of the model. Sensitivity and robustness analyses are conducted in Report 3 to take account of:

- Different wage definitions: section 5.1 presented a range of options for modelling wages.
- Modelling take-up: we conduct the simulations with and without the take-up modelling stage to check to what extent complicating the model by adding an extra stage to the incomes modelling changes the simulations results.

8 Extensions

8.1 Changing the structure of the tax and benefit system – the question of take-up

One of the key reforms to be run on the IFS Labour Supply Model will be the recently introduced New Tax Credits – the Child Tax Credit (CTC)¹⁷ and the Working Tax Credit (WTC). For people without children the WTC is a new element of the tax and benefit system, while for people with children the reform on the one hand changes the structure of the system in terms of the ‘instantaneous’ budget constraint (i.e. the budget constraint as modelled by TAXBEN), and on the other hand introduces some important changes in terms of the operation of the system. Since these are non-universal means tested tax credits, important questions arise concerning their take up. This section analyses potential approaches to modelling of the new system using the results of early simulations.

When modelling a ‘simple’ reform, which does not change the structure of the system, for example a 2p cut in the basic rate of income tax, the method of calculating net incomes does not need to change. We can generate the resulting new net incomes and apply the same steps and intermediate models (e.g. the FC/WFTC take-up model) to arrive at the final value of income. This can then replace the original incomes in the transition probabilities predictions to generate the simulated set of values.

8.1.1 WFTC and the New Tax Credits

The problem arises when we want to model a reform like the New Tax Credits (NTCs). The most important issue is the modelling of take-up of the new elements of the system. At the moment we assume 100% take-up/payment of all elements of the tax and benefit system except of the WFTC. In the case of in-work benefits the proportion taken up is predicted on the basis of information about modelled eligibility and actual take-up. In the reformed system families with children receive the Child Tax Credit which combines:

- Child-related payments in Income Support (assumed 100% take-up)
- Child credits from the WFTC (take-up can be modelled)
- Children’s tax credit (assumed 100% take-up)

For those without children the Working Tax Credit is an entirely new element of the tax and benefit system and we have no indication concerning the level of its take-up.

We have examined two different approaches to NTCs take-up modelling:

- Including childcare cost and assuming 100% take-up in base (WFTC) and reform (NTC) systems

¹⁷ In this section, ‘CTC’ **always** means Child Tax Credit and **never** Children’s Tax Credit, which is always referred to in its unabbreviated form to avoid confusion.

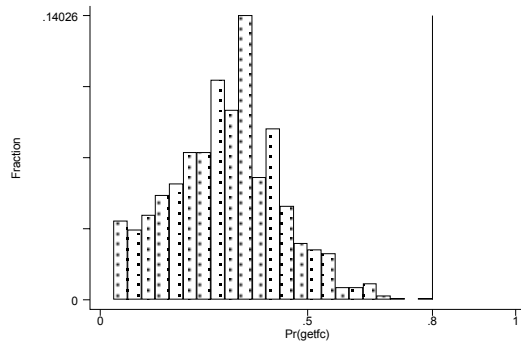
- Including childcare cost and modelling WFTC take-up in the usual way in the base system, and for the reform system assuming: 100% take-up if not working, 80% take-up if have children and working, 60% take up if don't have children and working.

Results obtained from the two simulations were very different, predicting an overall effect in the first case to be three times smaller than in the second case, which shows that the issue of take-up modelling is going to be extremely important. There are several reasons why the results are so different.

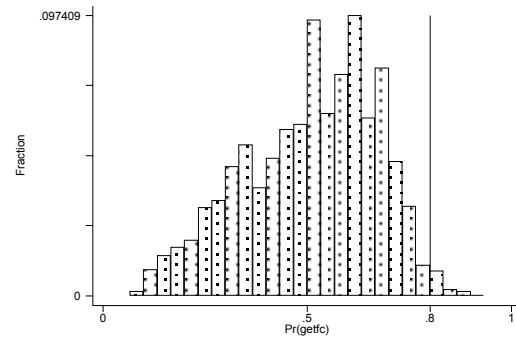
- First of all, using the second method implies an important change in financial incentives between the base (i.e. modelled take-up of the WFTC) and the reform (i.e. exogenous take-up rate) systems. Figure 9.1 shows the distribution of predicted WFTC take up in the base system for all FRS couples using entry wages for both men and women in three scenarios: (0,1), (1,0), (1,1), and for all single parents (again using entry wages) when they are modelled as working. We can see that take-up rates are less than 80% for most of the couples who are eligible for WFTC. For single parents on the other hand, although 80% is close to the average predicted probability of take-up, imposing the 80% on all single parents changes the take up rates for a large proportion of claimants.
- Secondly, for couples who benefit from the Children's Tax Credit, financial incentives to work are reduced by 20% of the Children's Tax Credit if they don't claim WFTC. For those claiming the WFTC in the base system the Children's Tax Credit element is also taken-up at 100%.
- Finally, the take-up restriction of 60% on the Working Tax Credit for people without children, is a significant reduction in the WTC claim relative to the 100% take up assumption. This should be especially important for single people.

Figure 8.1

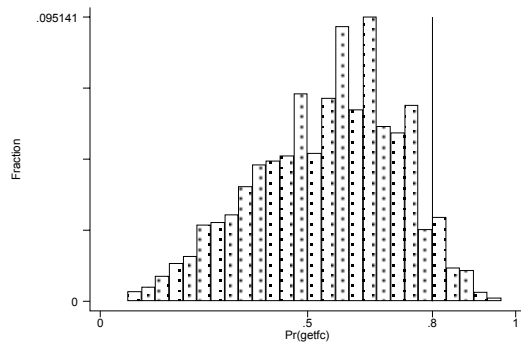
Predicted WFTC take-up for all couples in the (1,1) scenario



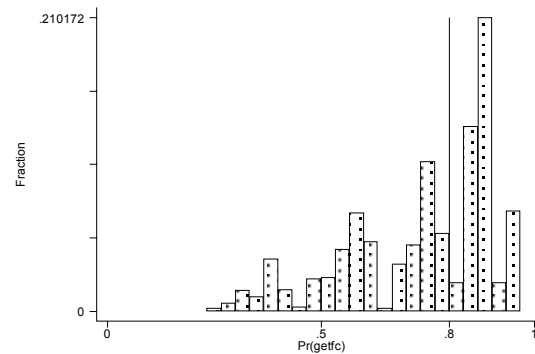
Predicted WFTC take-up for all couples in the (1,0) scenario



Predicted WFTC take-up for all couples in the (0,1) scenario



Predicted WFTC take-up for single parents if modelled as working



8.1.2 Possible solutions for modelling of take-up of the New Tax Credits

Figure 8.1 shows that the distribution of predicted take-up probability is quite widespread. This, together with the disparity in results we obtained using the two simulation methods, suggests that combining our take-up modelling of FC/WFTC (which assigns specific probabilities to individual single parents or couples) with an across the board average is probably an unreasonable solution. Even if the average were chosen in such a way as to reflect the average FC/WFTC take-up in particular groups this would still mean that for a large majority of people we would be using a different value when assigning the FC/WFTC probability and the NTC probability.

In the light of the above we propose the following solution to modelling the take-up of NTCs:

- The assumption 100% take-up probability of Income Support/Child Tax Credit for people out of work should be maintained.
- For people with children, elements of the budget constraint which currently fall within the brackets of WFTC and Children's Tax Credit eligibility should be modelled in the same way in the base and reform system.

- For people without children, an exogenous take-up rate should be applied, with some sensitivity analysis concerning the effects of changing it.

The second of the above suggestions means that in the base system the WFTC and Children's Tax Credit should be treated jointly as one element of the system. In terms of the TAXBEN sub-systems this means that:

- ' ζ_1 ': a system with FC/WFTC childcare subsidies where everyone takes up 100% of their modelled FC/WFTC entitlement and receives the Children's Tax Credit
- ' ζ_2 ': a system without FC/WFTC childcare subsidies where everyone takes up 100% of their modelled FC/WFTC entitlement and receives the Children's Tax Credit
- ' ζ_3 ': a system where no one takes up FC/WFTC and does not receive the Children's Tax Credit

This will allow us to apply the same exogenous take-up probability to the joint WFTC-Children's Tax Credit element in the same way as can be done to the overall NTCs for people with children or to separate out the treatment of the 'Children's Tax Credit-only' section of the budget constraint (both in the base and reform system) from the section where WFTC and Children's Tax Credit currently overlap.

8.2 Using other data sets

FACS

The FACS data being used for the WFTC evaluation which IFS is carrying out for the Inland Revenue includes detailed information on income, taxes and benefit payments, wages and childcare expenditure. It is also in a panel format, and so work entry (and exit) information could be derived from the second subsequent waves. Thus in many ways it is an ideal data set for constructing our model. However there is a drawback; the data set only samples families with children. For couples with children only those above a particular income threshold are included (at least until wave 4); for lone parents however, coverage is complete. FACS could therefore be used for a complete transitions model for lone parents, but for other families with children only low income families could be included if we wanted to use all the waves of the data, and it is unclear how we would gross up any results derived using this data to overall population totals for couples. Childless families are omitted completely. Nonetheless, FACS could certainly be used to compare the accuracy of FRS/LFS employment change estimates for lone parents.

DWP Data

The Department for Work and Pensions has indicated that there are possibilities for labour supply research using the longitudinal, cross benefit administrative datasets which are held within DWP. For example, there is data on a 5% sample of the IS, WFTC and FC caseload population running back to 1992. DWP suggest that the caseload changes arising from changes in policy could be compared with the

predictions of the model and this sounds like a Possible idea for future work. However it is clear that there are limitations to the usefulness of the DWP data for the kind of modelling we have focused on in this project, as we want information on people who move into work and *not* onto in-work benefits (either because their wages are too high to be eligible, or because they are childless) and this would not be covered by the DWP data.

British Household Panel Survey

The British Household Panel Survey has a much longer panel element than the LFS or FACS, as it has been interviewing survey members annually since 1991. It collects information on most if not all of the variables which we need to estimate the model: wages, labour market status, other components of income, housing tenure, job characteristics, demographics and family structure. However, the main drawback of BHPS is that it is **too small**. Only has about 6,000 households and panel attrition means that the number of households surveyed over any length of time is less. This makes it not very useful for estimating a full model of the type we are looking at in this project as any results we do get are likely to have wide standard errors and not be disaggregable. However, it may be possible to exploit the large number of multiple waves in the BHPS data to build a slightly different type of transitions model. This would use a ‘generalised method of moments’ (GMM) systems estimator as outlined by Blundell, Bond and Windmeijer (2001). The GMM systems estimator would use two sets of equations:

- (1) Difference equations, where the dependent variable would be the change in employment status from wave $t - 1$ to wave t of the BHPS for individual i . This would be regressed on *changes* in observable characteristics. The *lagged* levels of observable characteristics are used to instrument these difference equations.
- (2) Levels equations, where the dependent variable would be employment status in wave t of BHPS (as in a standard employment probit). This is regressed on levels of observable characteristics with the lagged differences of observable characteristics used as instruments .

Combining equations sets (1) and (2) yields a robust estimator which has been found to have good properties, provided that the length of the panel is long enough (say $t=6$ or longer) to enable orthogonality conditions between current and lagged values of the regressor variables to be exploited. A problem arises with the definition of the dependent variable, however. The GMM systems estimator has traditionally been used in models where the dependent variable is continuous (e.g. wage equations, or production functions). In an employment model, the dependent variable is essentially binary (working/not working). Application of the GMM estimator to a binary dependent variable is not well developed at the present time; however this remains a plausible topic for further research. For couples, the situation is even more problematic as the dependent variable (as we have modelled it) is a multinomial discrete choice. Nonetheless, the BHPS may present opportunities for novel panel estimation techniques of labour supply models in the future.

New Earnings Survey

NES was suggested as a source of entry wage data by HMT. Whilst it may certainly be useful to check the observed distribution of entry wages in the LFS with what the NES-JUVOS link may suggest, the NES offers very few covariates for any substantive analysis of entry or exit wages. For example, education is not included as a regressor in any shape or form, and even family type information is limited. Hence we do not recommend using the NES as a main source of information for the model.

Other data

Other data sources tend to have a cross-sectional structure similar to that of FRS but are less suitable for our purposes in that their income data is far more limited and they are smaller surveys, e.g. Family Expenditure Survey, General Household Survey. Hence we are not proposing to use them here.