Modelling Poverty by not Modelling Poverty: An Application of a Simultaneous Hazards Approach to the UK

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CASEpaper 106
January 2006

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Editorial Note and Acknowledgements

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Thanks to the ESRC for funding this project, and to Stephen Jenkins and Fiona Steele for comments.

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Abstract

We pursue an economic approach to analysing poverty. This requires a focus on the variables that individuals can influence, such as forming or dissolving a union or having children. We argue that this indirect approach to modelling poverty is the right way to bring economic tools to bear on the issue. In our implementation of this approach, we focus on endogenous demographic and employment transitions as the driving forces behind changes in poverty. We construct a dataset covering event histories over a long window and estimate five simultaneous hazards with unrestricted correlated heterogeneity. The model fits the demographic and poverty data reasonably well. We investigate the important parameters and processes for differences in individuals' poverty likelihood. Employment, and particularly employment of disadvantaged women with children, is important.

Keywords: poverty dynamics; poverty transitions; simultaneous hazards.
JEL Codes: I32

Non-technical summary

In this paper we bridge two different traditions in analysing poverty. Much of the economics research on poverty has concerned measurement, clearly a key task, but only a starting point. The analysis has typically been atheoretical, focussing on statistical issues or decompositions of poverty trends. Examples of the former include Cappellari and Jenkins (2004), which provides a detailed analysis of the dynamics of individual poverty experience. An example of the latter includes Hoynes et al (2005), which provides a thorough decomposition of poverty trends in the US. These studies are very useful, but do not connect with the core of economic analysis – the analysis of economic decisions. We argue below that they cannot connect with this because individuals do not make decisions directly about their poverty status. They may not even know whether they are (officially) poor or not since this depends on a comparison of their income with (60% of) the national median.

The tradition in social policy is to focus on a set of events that happen to people and propel them into poverty. This includes unemployment, divorce, the arrival of children, sickness, and old age. The analysis proceeds by quantifying the impact of these events on subsequent income and poverty status. The classic exposition of this view was developed by Rowntree (1901). Beveridge drew heavily on it in his report (Glennerster and Evans 1994). More recently Piachaud and Webb (2004) compare the causes of poverty analysed in this way for 1899 and 2001/2 and compare the size of the poverty gap resulting from such events (pp48-50). This focus on the underlying events is useful since these are the true drivers of poverty dynamics. However, treating marriage and divorce, fertility and employment transitions as exogenous events runs against a lot of accumulated evidence showing that these are decision variables that individuals exert some (but not complete) control over. For example, an individual's wage rate has been shown to influence her propensity to have children at a particular age, to marry and to divorce. Ignoring this will lead to biased conclusions. For example, if some individuals are disproportionately likely to divorce, if their characteristics also make them susceptible to poverty, this would be inappropriately assigned to the effects of divorce.

In this paper, we bring these perspectives together. Relative to a social policy approach, we treat these life events as inter-related, endogenous processes. This makes the basis for our statistical inference more secure. Relative to the existing economic literature, by tying an analysis of poverty to individual decisions, we facilitate the use of economic analysis in empirical models of poverty.

We study working age individuals (so ignoring poverty in old age), and focus on marriage (union) and separation, having children and transitions into and out of employment. We create a dataset of long life histories of these events from the British Household Panel Survey retrospective files. We utilise these plus other socio-economic data to produce economic models of these demographic and employment transitions. The model fits the demographic data well. We move from this analysis of the underlying endogenous events to a model of poverty by adding a straightforward income model. We show that this fits the data on poverty well.

The fruits of this approach are two-fold. First, it opens the door to the economic analysis of poverty. Second, we can use it to isolate what are the important factors for poverty. We simulate the effect of marginal changes in the chance of making the different transitions, and compare the outcomes. It is important to be clear that this takes account of all the undoubted interaction between the processes; so, for example, changing the propensity to become married influences marital status but also, through that, employment status and fertility. All these combine to change poverty. These parameter experiments show that the employment transitions are the most important. We also show that for disadvantaged women, the chance of being employed whilst having a young child is a key factor. This all gives support to a "work first" policy.

1. Introduction

Poverty remains a major issue, even in the developed world. The Lisbon Summit of the European Union in 2000 noted that the Union contained 60 million people poor or at high risk of poverty. In the UK, the Labour government ambitiously pledged to halve and then eliminate child poverty. In the US, there remain over 35m people in poverty, despite the most prolonged economic upturn for many years. Despite this, there are few empirical analyses of poverty in economics, certainly compared to the substantial literatures on measuring poverty, or on analysing earnings inequality. For reasons we set out shortly, poverty is a more complex phenomenon than earnings inequality and consequently harder to model in a useful way. In this paper, we pursue a different way of analysing poverty, which comes at the problem indirectly.[1] We implement this using a long panel of UK data, and assess the important processes that influence individuals' likelihood of poverty.

Poverty is essentially a binary state, and almost all studies measure and analyse it as such.[2] In this paper, we argue that it makes little sense to analyse poverty as a standard dichotomous variable or a Markov renewal process. Unlike a binary decision to go to college (for example), or decisions about repeatedly moving in and out of unemployment, poverty is not a decision variable. Two points make this very clear. First, an individual will in general not even know whether s/he is officially poor or not. Second, an individual can transit in or out of being officially poor even if nothing in his/her own circumstances changes. So an economic analysis, based on individuals and households making decisions, using this approach is unlikely to be fruitful.

One short-cut out of this problem is to use the well-developed models of earnings, and to argue that this constitutes the core of poverty. In fact, it is now well known that demographic changes are as important as changes in earnings,[3] so this becomes a very partial approach. Unlike earnings, poverty is a characteristic of households rather than individuals.[4] If households were fixed in

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1 This is a continuation and extension of our earlier work on poverty in the US using the NLSY (see Burgess and Propper, 1998).

2 Some authors blur the distinction at the margin by using a 'fuzzy' poverty line, for example, Cerioli and Zani (1990), Betti and Verma (1999), Maggio (2004).

3 Bane and Ellwood (1986), Stevens (1994, 1999), Jarvis and Jenkins (1996), Jenkins (2000).

4 There are an increasing number of studies that examine the intra-household allocation of resources.

composition, then the only extra factors between earnings and household income would be labour supply, and the matching of individuals into households. But of course this is not the case – households form, dissolve and reform, potentially many times. These processes are endogenous to income, to labour supply and to each other.

We propose to empirically model the behavioural decisions underlying poverty: whether to work, to have children, to form or to end a union. This analysis is econometrically complex as these decisions are very likely to be linked. Accordingly, we estimate a model with five simultaneous hazards (for fertility, union transitions and employment transitions), allowing for extensive cross-process interactions and correlated heterogeneity.[5] We construct a long panel of event histories for fertility, union, dissolution and spells in and out of work for Britain for the analysis. The estimation is successful and fits the data on demographic spells and transitions well.

From this analysis plus a simple model of income, we construct an analysis of poverty itself. The strategy of the paper is to focus on explaining demographic and employment transitions as the key to explaining poverty dynamics, and we use our estimates of state transitions to model time spent in particular demographic/employment states. The simple process we assume for income generation within these states means that we can use the mean poverty rates in those narrowly defined states[6] to translate this analysis into an analysis of individual poverty. In our data, between-state differences in poverty explain over half of the variation in individual poverty status, as opposed to within-state variation. Thus while we clearly cannot hope to explain all differences in poverty using this approach, we are addressing the key source of variation.

The results are encouraging, and the model fits the demographic patterns well.[7] The approach does a good job of capturing the key facts of dynamic poverty experiences. We use the model to examine what the important processes are for poverty, simulating the dynamic properties of the model. We show that generally the employment process is most important. This works both through a direct impact on poverty, but also on marriage and fertility hazards. For disadvantaged women, what matters most is the link between employment and children; that is, changing the ease of getting a job for someone with young children brings the biggest reduction in sustained poverty of all our

5 This builds on Aassve *et al* (2004) which describes the estimation of the demographic transitions in detail, but is not a model of poverty.

6 For example, such a state might be "not employed, married, with two children".

7 We discuss the demographics *per se* in detail elsewhere (Aassve *et al*, 2004).

experiments. Our analysis is empirical comparative dynamics, not detailed policy analysis, but these results give some support to the idea that work promotion and child care may be important focuses for anti-poverty policy.

We structure the paper as follows. Section 2 reviews different methodologies for analysing poverty and Section 3 presents our approach. Section 4 then describes our dataset, and Section 5 the econometric model. The results of the estimation follow. Sections 7 and 8 present our main results – first evaluating how well the model fits poverty, and second exploring what the model says about the key dynamic processes for poverty. Section 9 concludes.

2. Modelling Poverty Dynamics – A Review of the Literature

We review different empirical methodologies for analyzing poverty.[8] We can broadly characterise approaches to modelling poverty into five differing methodologies, though there are obviously areas of overlap. These are: (a) components of variance models; (b) hazard rate models; (c) Markov transition models; (d) dynamic discrete choice models; and (e) decomposition methods. Each has its merits, but none fully capture the jointly determined inter-related labour market and demographic processes which result in the poverty outcome.

a. Components of variance models

These models allow for a complex error structure to capture the dynamics of income and predict the fraction of the population that are likely to be in poverty and for how long. Originally used by Lillard and Willis (1978) this method has been employed more recently by Stevens (1999) and in the UK by Devicienti (2001). As Bane and Ellwood (1986) highlight and as echoed by Jenkins (2000), these models have appeal in their ability to decompose income changes into permanent and transitory components and therefore provide a more accurate assessment of an individual's long term position. Moreover examining income rather than just a binary poverty indicator means that no information is discarded, and it can be seen whether individuals move just out of poverty or move clear above the poverty line.

However, these models also have notable disadvantages in this context. The main short coming is that they can only really explain the poverty dynamics of one homogenous set of individuals at a time, being unable to accommodate the fact that poverty is a feature of households and that household composition

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8 We do not review the results on poverty dynamics - see Jenkins and Rigg (2001) for the UK. Nor do we attempt to review the vast separate literatures on fertility, marriage transitions, or employment transition - see Aassve *et al* (2004) for a partial review.

changes over time. These models do not address demographic or labour market events. A further problem is the common assumption of the same dynamic process applying to the richer and the poorer individuals, which is unlikely to be the case.

Stevens (1999) and Devicienti (2001) both conclude that in comparison to the duration modelling that they implement, the components of variance models of poverty perform less well in fitting the observed patterns of poverty in the US and UK respectively. Jenkins (2000) concludes that these models are best applied to the context that they were originally taken from and that is the analysis of the income dynamics of a single homogenous group – for example prime-age males. This circumvents the need to consider all of the household's income sources and the effects of changing household composition.

b. Hazard rate models

A long-standing approach is to model poverty transitions using a hazard rate framework. This approach was taken by Bane and Ellwood (1986) and has since been modified and used by inter alia Stevens (1994, 1999) in the US and Devicienti (2001)in the UK. Bane and Ellwood examined poverty by looking at exit probabilities for individuals in the PSID between 1970 and 1982. Spells of poverty are identified and hazard functions for exiting poverty are estimated and used to generate distributions of spell lengths for new spells and also for completed and uncompleted spells at a given point in time.

Bane and Ellwood also look at events associated with poverty transitions according to a hierarchical structure of possible 'trigger events' – first of all any changes in head of household in the preceding two years are looked for. If such a change has occurred then the transition is associated with this 'trigger event'; if no such change has occurred the next thing that is examined is the change in the income/needs ratio and whether this has been more caused by changes in the numerator (income events) or changes in the denominator (demographic events). In such a way Bane and Ellwood classify the triggers for a poverty spell's beginning or end, as well as looking at the expected duration of spell lengths according to the event that triggered the spell both for those just commencing a poverty spell and those already in poverty because of the associated trigger event.

However, research since then has highlighted the limitations of the analysis of single spells only, chiefly the fact that a single spell analysis does not take into account that those who climb out of poverty are likely to fall back into poverty. Stevens (1999) in particular augments the Bane and Ellwood methodology to allow for multiple spells of poverty. Stevens analyses poverty persistence in the same PSID dataset by simultaneously estimating two separate hazard rates for those who are ever poor: the hazard for exiting poverty depends on a function of individual and household characteristics, the duration of the current spell of poverty and an individual heterogeneity term; similarly the hazard for re-entering poverty depends on a function of individual and household characteristics, the duration of the current non-poverty spell and a separate individual heterogeneity term. Stevens addresses the initial conditions problem and, given multiple spells, time-invariant individual fixed effects terms are included within each process to account for correlation across an individuals exit and re-entry probabilities over time. Stevens demonstrates that the multi spell model of poverty fits the observed pattern of poverty persistence much better than the single spell model. Implementing a model very similar to the Stevens model, Jenkins and Rigg (2001) and Devicienti (2001) demonstrate that the necessity of modelling multiple spells of poverty applies equally to the UK.

There are, however, a number of problems with the hazard rate approach in this context. While these models take a broadly dynamic approach, there is still a considerable static element to their analysis. The time-varying covariates are assumed fixed for the duration of the (non)-poverty spell in question, but can vary between spells. Therefore while Stevens and Devicienti can model and simulate the multi-year poverty spells for different household types, they cannot allow for the effects of changes that take place during a poverty spell. Another specific problem with these hazard rate models is their inability to separately identify the effects of income events and demographic events that occur simultaneously, nor indeed the subsequent effects that these events have on each other. Both of these points highlight the inability of this approach to model the complex interactions between the demographic, employment and poverty processes.

There are additional problems with models that incorporate event variables as explanatory variables. As Jenkins (2000) highlights there are econometric problems of simultaneity and endogeneity introduced when event variables are used to explain poverty transitions – the underlying processes are likely to be jointly determined. Moreover, it is difficult to disentangle the effects of an event once the new demographic and employment status is controlled for – what is the effect of the being in a state and what is the effect of moving into a state? There is also the problem that incorporating event variables constrains all of their effects to be contemporaneous – the event variable is 1 in the period that it occurs and zero in subsequent periods. However, it may be that the effects of events persist over time – there may be effects of losing a job for example, which continue to affect individuals over and above the effect of being unemployed itself. Furthermore if individuals anticipate events and change behaviour in advance this will further undermine the assumption of purely contemporaneous effects of events.

Finally, in any model based on analysing poverty spells directly, the arbitrary nature of the poverty line is important. As is often noted, it is somewhat arbitrary to turn a continuum of income into a poverty dichotomy and though Bane and Ellwood and others take measures to avoid spell endings and beginnings being recorded for small random income fluctuations around the poverty line, this remains a problem inherent in modelling poverty directly.

c. Markov models

Cappellari and Jenkins (2004b) propose a model to complement both the exit/entry hazard rate approach and the components of variance model, by using an extension of a first-order Markov model for low income transitions. The model is estimated for working age adults in the UK (using British Household Panel Survey (BHPS) data – see data section) and is designed to reveal who is likely to enter poverty/remain in poverty and to derive estimates of state dependence. The probability of selection into initial state, the probability of sample retention and the low income transition are simultaneously simulated to deal with the initial conditions problem and the issue of potentially non-random attrition. The pooled-panel nature of the data means that there are multiple pairs of observations from the sample individual as well as observations from individuals in the same household, however these considerations are controlled for in the estimation. The model can be used to make a wide range of specific predictions of poverty rates, exit rates, re-entry rates, total time in poverty for individuals with differing characteristics.

This paper provides a useful advance in modelling low income experiences. However, there are a number of issues. First, it may be that the restriction to first order dynamics only is inappropriate for the data. Second, the assumed lag structure (to minimise simultaneity issues) has current poverty status modelled as a function of lagged characteristics, lagged poverty status and attrition. This rules out the possibility of instantaneous effects of changes in characteristics for poverty status – for example changes in employment status are not allowed to affect poverty until the next (year) period. The model cannot tell us about the dynamics of poverty other than from one year to the next. However, these predictions rely on the stability of covariates – something that we do not expect to be the case, we expect that there will be inter-related changes in household composition and labour market attachment and the effects of these cannot be captured in this sort of model.

d. Dynamic discrete choice models

Biewen (2004) has developed an alternative methodology for distinguishing the effects of state dependence from those of individual heterogeneity, in a model which also reveals the way in which past poverty can have an indirect effect on future poverty via feedback to employment and household formation decision.

Biewen highlights that in the context of looking at persistence in poverty, the necessary assumption of strict exogeneity of the regressors in a dynamic discrete choice model is unlikely to hold. This assumption is necessary to be able to distinguish a state dependence effect from the effect of unobserved heterogeneity. Previous poverty status which is used as a regressor for current poverty status is also likely to feedback to influence current employment status and perhaps marital status, thus violating the assumption of strict exogeneity of the regressors.

In response, Biewen develops an econometric model which allows for feedback from poverty status to future employment status and household composition by jointly estimating individual poverty status, individual employment status and whether the individual lived in a one-person household. Comparing both the results of his model and the results from a pooled estimation similar to the Cappellari and Jenkins (2004b) model, which also tackles the feedback effects problem, with results from a model that does not allow for these effects, Biewen concludes that these feedback effects play a significant part in the dynamic poverty process. This is evidence of the importance of simultaneously modelling the demographic and employment processes which underlie the poverty outcome.

There are however, limitations and problems with this model. The specification of the household composition equation allows only for the dichotomy between whether the individual lived in a single person household or not, therefore ignoring all of the other demographic changes. For example, in the model marriage, another adult joining the household and a child being born are all observationally equivalent, as are divorce and a dependent child leaving home. Though this may not be as much of a problem when trying to delineate the effects of state dependence from those of individual heterogeneity, for the purposes of unravelling the dynamics of poverty it is important to be able to distinguish between these events.

Moreover, there is a question of whether poverty experience affects individuals as they may not know whether they are officially in poverty or not, it is more the effect of low income that is the driving force and this is proxied by an arbitrarily defined poverty status. Individuals in the regions just above and just below the line will experience the same effects but only some of them will have their feedback effects captured in the model, thus reducing its power.

e. Counterfactual decomposition methods

This approach aims to provide an assessment of the relative impacts on the poverty rate of changes in a country's demographic composition, wage structure, labour market attachment and welfare policy and benefit levels over a period of years. Dickens and Ellwood (2001) provide such a decomposition of poverty rate changes for Great Britain and the US between 1979 and 1999 (using CPS data for the US and FES data for the UK).

In their methodology, Dickens and Ellwood estimate, for each year, what each sample members' wages, work status, hours and benefits ***would be*** given the wage structure, labour market and benefit regime of 1979. From this it is then estimable what the poverty rate would have been if one or more of these 1979 conditions had remained. So the first thing that Dickens and Ellwood do is apply the 1979 models of work, wages and benefits (including appropriate residual terms) to the actual characteristics of the sample individuals in each year since 1979. They then compute the poverty rate in each year given these circumstances. For each year, comparing this counter-factual poverty rate to the actual observed poverty rate reveals the effect that demographic changes have had on poverty from 1979 up until the year in question. Following this, wages are returned to their actual observed levels in each year, yet work and benefits continue to be held at their 1979 levels, and the poverty rate for each year is calculated under these circumstances. Now for each year, comparing this poverty rate with the previously constructed counter-factual poverty rate (which estimated the effect of demographic change) reveals the effect on poverty of changes in the structure of wages since 1979. This procedure is then continued to next see the contribution to poverty of changes in employment levels and finally of changes in benefits since 1979.

Gottschalk and Danziger (2003) employ a similar methodology to delineate the relative impacts on the poverty rate of changes in mean income, demographics and income inequality, in the US between 1975 and 2001 (using CPS and PUMS data). Using US Census data Burtless (1999) looks at the changing income distribution between 1979 and 1996, and performs decomposition analysis to assess the impacts of changes in the structure of pay, family compositional changes and changes in work patterns and husband/wife earnings correlations, on overall income inequality.

These descriptive decompositions are illustrative and show the importance of taking into account factors other than just income changes when analysing poverty. However, the main difficulty is that these methods have to make the assumption that changes over time in these different processes are exogenous to each other and poverty. The decompositions show for example, the *ceteris paribus* effect of changing employment patterns, but this fails to consider the implication for employment of changing household structures. It is unlikely that family structure and behaviours could change from the 1975 pattern to the 2001 pattern with no effect on labour market participation, and *vice versa*. The approach cannot answer the question of what causes individuals to fall into poverty, how important employment and family changes are and to what extent they cause and react to each other, and the process through which this results (or does not) in poverty. Also, as Dickens and Ellwood acknowledge, the order in which the counter-factual changes are introduced influences the results, indicating a further limitation of this approach.

3. Modelling Framework

We argue that a major benefit of our approach is the ability to tie an implementable empirical analysis of poverty to economic behavioural modelling. This is not possible with the currently used methodologies as outlined above. This section sets out a simple example of this.

In contrast to this literature, the approach we take is to model the demographic and employment transitions underlying poverty transitions, following our previous approach (see Burgess and Propper, 1998; Burgess, Propper and Dickson, 2005). We argue that these transitions are stochastic, but with parameters that can be influenced by the agents. To be precise, we assume that individuals can invest to change the probability of a change of state. This investment is assumed imperfect in that the probability cannot be forced to zero or one. Individuals optimise the investment to maximise their expected utility stream. This section presents the framework for this analysis.

The realisation of the transition processes locates the individual in one of a set of states – for example, 'single, with no children and in work'. Let there be *S* potential states an individual can be in at any one time, denoted *s*. These are exhaustive and mutually exclusive. The transitions that we model empirically are the individual processes – that is, into employment, or adding children etc, but as we explain below, these individual processes are all estimated jointly.

Utility depends on (net) income, leisure (or its inverse, employment (*l*)), marital status (*m*) and the number of dependent children (*d*). All of these bar income are incorporated in the definition of the state (that is, 'single, with no children and in work' defines the state and defines the amount of these factors the individual is enjoying). The utility individuals derive from their demographic and employment status depends on their characteristics (*x*) and unobserved heterogeneous preferences (ε). The income process for individual *i* in state *s* at time *t* is:

$$y_{ist} = \mu_i + \theta_{st} + \varepsilon_{ist} \qquad (1)$$

where $\mu_i = \tilde{\beta}_{xi} + \varpi_i$ is an individual effect depending on observed human capital and background (*x*) and fixed but unmeasured income relevant heterogeneity

(ϖ), and θ_{st} captures in a simple way the impact of state on income, and ε is noise. We keep this deliberately simple, since we do not empirically model the income process below. This is because we only have data on income from 1991 onwards, unlike the demographic and employment state data for which we have a full recall history. As we will see shortly, we allow income to influence transitions, but simply substitute it out of the estimating equations using (1).

Turning to the transition processes, we assume that they are influenced by the transition investments (γ) plus a process-specific parameter (α). The probability of moving from state k to state j per unit time is:

$$p_{kj} = f(\gamma_{kj}, \alpha_{kj}) \qquad (2)$$

For example, this might be the probability of moving from employed to non-employed. The cost of investing is increasing and convex in γ. The individual chooses her current investments to maximise her expected discounted lifetime utility, $\mathrm{E}\sum_t \delta^t U(y_t - c_t, l_t, m_t, d_t)$, where c is the sum of investment costs. Each individual first computes her best future state at each moment in time. This will depend on her characteristics, her values of heterogeneity parameters, and her current state denoted *S*, and the common process parameters. Then she calculates the optimal level of transition investments trading off the costs and benefits. The solution to this problem makes the optimal investments γ^* a function of the individual's income, characteristics, the transition parameters and her current state occupancy. Note that this means that the model encompasses the idea of feedback from income to demographic transitions, though these are implicit and not separately identified here. Income is substituted out using (1) to give:

$$\gamma^*_{kji} = g(\alpha_{kj}, \mu_i, \theta; \Sigma_i) \qquad (3)$$

where Σ_i is i's current state across all processes (for example, "single, working, no children"). Individuals only observe current or time-invariant information. We assume that expectations are formed as projections of current information. Thus (3) represents a reduced form model combining both direct causal links and expectation formation. We substitute this into the transition functions (2) to obtain the transition rates:

$$p^*_{kji} = f(\alpha_{kj}, \mu_i, \theta; \Sigma_i) \qquad (4)$$

This implies that the transition probabilities depend on: current state occupancy in all states (so for example, transitions into work may depend on the number of children), and (through μ_i) on observed personal characteristics (x) and unobserved personal characteristics (ϖ).

4. Data

The primary dataset we use is the British Household Panel Survey. The first wave of the BHPS was designed as a nationally representative sample of the population of Great Britain living in private households in the autumn of 1991. Approximately 5,500 households, containing about 10,000 persons, were interviewed. These original sample members are re-interviewed each successive year, and if they split off from their original households to form new households, all adult members of these new households are also interviewed. Similarly, children in the original sample households are interviewed when they reach 16 years of age.

In addition to providing information on respondents within the Panel survey period (1991 onwards) the BHPS asked respondents to provide detailed retrospective work, family and fertility histories in 1992. These retrospective data are matched to the within-panel data (dated to the month) to construct detailed marriage, fertility and work histories from age 13 for all adult respondents. Thus individual specific behaviour is modelled from this age and avoids the initial conditions problem normally encountered when estimating duration models based on the panel component only. We have created five detailed event histories for each individual: forming and dissolving a partnership, - having a(nother) child, entering and leaving employment. Overall, our dataset comprises the complete retrospective histories, plus merged within-panel data for the period 1991-1996. These event histories are all at a monthly frequency.

Turning to the definition of the demographic states, we consider marriage, employment and child birth. As cohabitation is an increasing form of union in the UK (either as a precursor to legal marriage or as a substitute), we define marriage as living in union with a person of the opposite gender, regardless of legal marital status. For the within-panel data we use the self-reported marital status, which takes the following categories: "married", "living as a couple", "separated", "divorced", "widowed" and "never married". We classify "married" and "living as a couple" as *de facto* married, with the remaining categories being *de facto* not married. We use the same categories for the retrospective sample data.[9]

[9] BHPS data files BMARRIAG and BCOHABIT. We combine these so that for example the start of a pre-marital cohabitation marks the start of a period of union.

Individuals are defined as being employed if they are in full-time paid employment, part-time paid employment or paid self-employment. Individuals who are on long-term leave due to sickness are classified as not-employed.[10] An individual is classified as changing employment status only if s/he moves into or out of paid employment. So in all the following examples, there is no change in recorded employment status: where individuals change employer, but remain continuously employed; individuals changing from full time to part time; and individuals moving from full-time education to job seeking. For the within-panel data, we use an annual self-reported employment status and the wave-by-wave employment history files from wave three.[11] For the retrospective history we have each individual's complete paid employment histories from the age that they first left full-time education up to 1992.[12] We assume that all individuals are in full-time education and therefore non-employed at age 13.

Births occurring during the panel years are constructed from the household record of the respondent.[13] In the majority of cases, there is only one birth event in the household in a given wave; there are just nine observations with two birth events within one wave and one observation with three. The retrospective history collected in 1992 records the dates of birth of all the respondent's natural children to that date.[14] These data are recoded into a monthly panel of data covering the birth events in each individual's life up to the time of their interview in wave two. These are then merged with the within-panel data to create one event history file, which records the conceptions of children, where the conceptions are assumed to have taken place 9 months before the birth date. We do not model children leaving home, so do not create a file of children

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10 Maternity leave does not count in this instance as being "in paid employment". There are 1039 observations coded as maternity leave in the employment history datasets that we use, which represents just 0.8% of the total number of observations.

11 Respectively the variable wJBSTAT and files wJOBHIST. The file contains details of all employment status spells since the 1st September in the year before the interview. In cases where individuals have employment changes the gaps between the annual wJBSTAT are filled with spells from the wJOBHIST files and recoded as "in paid employment" and "not in paid employment" as defined above.

12 This is the BLIFEMST file.

13 In each wave details of new household members are recorded in the dataset wINDALL. The variable wNEWHY provides information about whether the new household member is "new baby". If this is the case the event is dated by using month and year variables.

14 The details for an individual's natural children are recorded in the dataset BCHILDNT.

leaving home dates.[15] These data are also used to create stocks of each process as well as durations. In the case of stocks of children, we assume that children leave home at 21, so decrease any positive stock by 1 at the date at which the oldest child will be 21.

For the panel component of the dataset we have good data on household income. Using this information, we create the net equivalised household income distribution for each year of the BHPS,[16] with all household members included in the distribution. We set the poverty line at 50% of the median income within each year. Individuals have poverty status assigned for annual intervals. Having defined the poverty line, and determined poverty status, we then drop all of the observations that are not from our estimation sample of 2499 males and 2630 females. For both the males and the females, the sample members range in age from 15 to 55, though we are interested in looking at their poverty status only in the years when they are 18 years old or older. Not every individual in the sample has full household income information[17] in every wave of the panel from 1991-1996, therefore we have between 1 and 6 observations for each sample member. For some members however, none of the observations in which their household provides full income information, are years in which the individual is 18+ years old. For these individuals therefore we have no observations with income non-missing. This affects 79 males (3.15% of the original male sample) and 154 females (5.86% of the original female sample) such that the samples upon which we perform the poverty analysis comprise 2420 males aged between 18 and 55, and 2476 females aged between 18 and 55 years old, each with between 1 and 6 observations. For the males more than 50% have income information non-missing in all 6 years, and for the females the figure is just under 50%. See the Appendix B Table B3 for the frequency distribution for each sex.

In general the data contained in the BHPS is of high quality (Lynn 2003; Dex and McCulloch 1997). However, it is generally known that misreporting among men can be a problem, and this may be a problem both in reported fertility histories (Rendall et al 1999), as well as in job histories (Elias 1997). It is also

15 This is simply because five processes is the limit of feasible estimation on a dataset of this size and complexity.

16 We adopt the 'before housing costs' measure, equivalised using the McClements scale.

17 We use derived net household income variables (hhneti and loctax) constructed by Jarvis and Jenkins; therefore in line with their rules, we only have household income information from households in which **all** household members gave full income information.

possible that recall errors will be a problem, although presumably less so for births and marriages. Given the already complex nature of our model, we are unable to make corrections for potential mis-reporting, recall errors or attrition (see Cappellari and Jenkins, 2004a, for an analysis of attrition in the BHPS).

5. Estimation Framework

Following Lillard (1993) we specify a model of related dynamic discrete choices, where these are defined over childbearing, union formation, union dissolution, employment, and non-employment. The model considers the dynamics of these processes jointly and allows the realisations of any of the related processes to enter as time varying variables in the other processes. Each of the processes is specified as a hazard function, which is conditional both on exogenous and endogenous covariates, as well as potentially correlated unobserved heterogeneity components. Note that we estimate these separately for women and men, so there is no issue of intra-household correlation of errors. The states are denoted as: $B_n(t)$, a binary indicator taking value 1 if the individual has *n* children and 0 otherwise; *M(t)* is a binary indicator for marital status; and *E(t)* a binary indicator for employment status. All of these are time varying. The hazards are h^j_t, with *j* indexing the process, *j = B, M, D, E, U* are the hazards of a birth (measured at the time of conception), union formation, union dissolution, employment and non-employment respectively. These are as follows:

$$\ln h_t^B(t) = b_1 M(t) + b_2 E(t) + \underline{b}_3 T^B(t) + \underline{b}_4 A^B(t) + \underline{b}_7 \underline{x}^B + \underline{b}_8 \underline{P}^B + \varepsilon^B \tag{5}$$

$$\ln h_t^M(t) = \sum_{n=1}^{6} m_n B_n(t) + m_7 E(t) + \underline{m}_8 T^M(t) + \underline{m}_9 A^M(t) + \underline{m}_{10} \underline{P}^M + \underline{m}_{11} \underline{x}^M + \varepsilon^M \tag{6}$$

$$\ln h_t^D(t) = \sum_{n=1}^{6} d_n B_n(t) + d_7 E(t) + \underline{d}_8 T^D(t) + \underline{d}_9 A^D(t) + \underline{d}_{10} \underline{P}^D + \underline{d}_{11} \underline{x}^D + \varepsilon^D \tag{7}$$

$$\ln h_t^E(t) = \sum_{n=1}^{6} e_n B_n(t) + e_7 M(t) + \underline{e}_8 T^E(t) + \underline{e}_9 A^E(t) + \underline{e}_{10} \underline{P}^E + \underline{e}_{11} \underline{x}^E + \varepsilon^E \tag{8}$$

$$\ln h_t^U(t) = \sum_{n=1}^{6} u_n B_n(t) + u_7 M(t) + \underline{u}_8 T^U(t) + \underline{u}_9 A^U(t) + \underline{u}_{10} P^U + \underline{u}_{11} \underline{x}^U + \varepsilon^U \tag{9}$$

Individuals are assumed to be at risk of having the first conception from age 13, and are consequently starting the childbearing process (i.e. $\ln h_t^B(t)$) at this age. Once the first child is born, individuals become at risk of having the second conception, once the second child is born they become at risk of having the third conception, and so on. Thus conceptions are specified within one hazard function. The processes of union formation, union dissolution, employment and non-employment are similar in structure, except that being in a union and single are mutually exclusive, as are employment and non-employment. At age 13, which is the start of the union formation and employment processes, individuals are single and not working. As soon as employment is obtained individuals are at risk of entering the state of non-employment, and as soon as they enter a union they become at risk of union dissolution. These events may be repeated several times.

For each process *j* we include a control for the stock of each event (parity) P^j, which implemented as dummy variables, and detailed controls for age effects, denoted as $A^j(t)$ and defined as a piece-wise linear spline function. By specifying several node points – not necessarily the same for each of the processes - the formulation allows for a variety of patterns of duration dependence. The baseline hazard function, $T^j(t)$, is defined in a similar way.

We also condition on a set of assumed exogenous variables, $\underline{x}^j$. Note that although the BHPS panel contain a wealth of background information for both individuals and households, a very limited set only is available for the period covered by the retrospective histories, so limiting the number of exogenous covariates we can include in our estimation.[18] We include completed education (5 levels), cohort of birth (in four groups – born in the 1940s, 50s, 60s and 70s), parental socio-economic status, ethnic origin, and a binary variable indicating whether the respondent lived with both of their natural parents from birth up to the age of 16.[19]

For each of the five related processes we specify a random heterogeneity component. These will capture unobserved heterogeneity affecting (each of) the processes that is not picked up by the observed covariates. However, given that the processes are related, it is likely that there will be correlation between the unobserved heterogeneity terms across the five processes. The correlation arises from two sources. First, there might be unobserved characteristics, such as the level of family orientation of individuals and couples, which may impact all processes. Recall that we have a small observed state space because of the need to use the retrospective data; for example, in the retrospective data we do not

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18 Essentially, the retrospective histories only provide the date of demographic and employment events, There is no data, for example, on where the individual was living, their attitudes, their income or their health. To the extent that these are determined by socio-economic status, we do measure them by including parental SES and completed education.

19 These controls are used because they measure important dimensions of socio-economic status or, in the case of living with natural parents from birth until age 16, have been found to be important in earlier research on family formation and dissolution.

even know an individual's region. Secondly, the introduction of endogenous covariates will generate correlation since these variables are realisations and therefore functions of the other processes. For instance, the union state *M(t)* in equation (5) is an outcome of the functions $\ln h_t^M(t)$ and $\ln h_t^D(t)$, which in turn depends on ε^M and ε^D, respectively. Likewise, $B_i(t)$ in equation (6) and (7) are outcomes of the function $\ln h_t^B(t)$, which in turn depends on the unobserved heterogeneity component ε^B. To allow for these various sources of correlation we specify the unobserved heterogeneity components to have joint normal distribution:

$$\begin{pmatrix} \varepsilon^B \\ \varepsilon^M \\ \varepsilon^D \\ \varepsilon^E \\ \varepsilon^U \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_B^2 & \rho_{MB} & \rho_{DB} & \rho_{EB} & \rho_{UB} \\ \rho_{BM} & \sigma_M^2 & \rho_{DM} & \rho_{EM} & \rho_{UM} \\ \rho_{BD} & \rho_{MD} & \sigma_D^2 & \rho_{ED} & \rho_{UD} \\ \rho_{BE} & \rho_{ME} & \rho_{DE} & \sigma_E^2 & \rho_{UE} \\ \rho_{BU} & \rho_{MU} & \rho_{DU} & \rho_{EU} & \sigma_U^2 \end{pmatrix}\right) \tag{11}$$

By integrating out over the correlated unobserved heterogeneity components, the observed completed durations and outcomes are independent, and can therefore be estimated by maximum likelihood techniques.

Identification is ensured by the fact that all events are repeated, whereas the unobserved heterogeneity components are assumed fixed over individuals' lifetimes (see originally Lillard (1993) and recently Steele et al (2004) for a similar identification strategy). The endogenous variables defining an individual's current state are themselves realised outcomes of the processes. Crucially they always enter the other processes as lagged explanatory variables, which ensure identification of their parameters (Maddala 1983). For instance, a birth outcome will enter the employment and union formation processes as an explanatory variable, but always at a time prior to the next realised outcomes of the union and employment processes.[20]

We could in principle still identify all the parameters and allow for separate parameters for different orders of each process by adding equations. For example, we could estimate separate hazards for first and all subsequent births, with the constraint that the error term be the same across both equations (to allow identification from the repeated nature of the events). This would mean adding further equations and restrictions to the already large system, and therefore we did not pursue this line of enquiry.

20 There is of course the possibility of events taking place at the same time given that they are measured to the nearest month. But these are few and do not jeopardise identification.

Our specification of childbearing and union formation/dissolution deviates somewhat from the norm in the demography literature. It might, for instance, be more intuitive (and is more common) to formulate specific processes according to birth parity and the order of the union. The reason for this is not only that the baseline hazard is likely to differ by parity but also the explanatory variables may have quite different effects. Our focus on lifecycle relationships based five related processes comes therefore at a cost. The estimated parameters are *not* specific to *each* parity and order of events, so that (for example) the impact of education is the same for the first and all subsequent transitions into employment. In addition, the constraints on the size of the estimation problem means we cannot distinguish between either cohabitation and marriage, or part-time and full-time work. Despite these drawbacks, however, we show below that the specification is able to replicate the empirical distributions rather well.

We use the BHHH algorithm to estimate the model. The 5-valued normal heterogeneity distribution is approximated using Gaussian quadrature with 4 support points for each of the 5 terms. The choice of the normal distribution over the gamma distribution or a non-parametric approach may not be trivial. While Heckman and Singer (1984) show that parameter estimates are sensitive to the choice of distribution, Ridder (1987) shows that this problem is much reduced if a flexible baseline is used, as we do here. We estimate this by maximum likelihood, using aML.

6. Estimation Results

This section briefly describes the key parameter estimates of the econometric model, displayed in Appendix A, tables A1 through A7. The results are discussed in greater detail in Aassve et al (2004). We do not discuss here the role of the background variables, education or the duration and age patterns, but focus on the interactions between the processes, particularly those that we highlight later as mattering for poverty dynamics, and the correlated heterogeneity.

We start by considering the impact of marital status and employment status on child bearing. The results show that being in a union has a large positive impact on fertility events, and that the effect remains strong, controlling for unobserved heterogeneity. Being in employment has a negative impact on child bearing, but while the parameter estimate is highly significant, it is not large, implying that working is not a particularly strong deterrent to having children. The relatively weak effect most likely reflects the fact that part time and full time work are incorporated into the same category. It is possible, for instance, that women in full-time work have a much lower fertility rate than women working part-time.

The positive impact of employment for men on having children fits with previous findings. The parameter is highly significant, but again the magnitude is somewhat small. Note again that the parameter estimate here averages over all birth orders so the impact may be stronger for the timing of first birth, and even weaker for subsequent births.

When considering the impact of child bearing on union formation, we see that the impact very much depends on the birth order. For instance, experiencing a first birth has a strong positive impact on forming a union, and this is the case for both genders. However, if the second birth is outside a union, this actually lowers the rate of union formation. The positive impact of the first birth event is consistent with economic theory, in that individuals consider a cohabiting union or a marriage more beneficial once they have acquired marital specific capital. However, there might also be normative forces at play, in the sense that individuals might feel a pressure to "legitimise" the child. The negative sign of second birth-event indicates that those who do not form a union after the first birth are at a disadvantage in the marriage market when they have the second child. The subsequent birth events have no significant impact on union formation. Work status has a positive and highly significant impact on union formation for both men and women, a finding consistent with most previous research (see Oppenheimer 2004 for a review).

Turning to the union dissolution hazard, we find parameter estimates consistent with our expectations. The negative impact of first and second birth on dissolution indicates the role of children as marital specific capital.[21] The impact of children is strong, even controlling for unobserved heterogeneity. The third birth event does not have any statistically significant impact on dissolution, whereas higher birth orders generally have a positive impact, but these variables are not particularly well defined due to small sample sizes. The impact of work status on divorce is not particularly strong, especially for men. For women, on the other hand, work has a positive impact only when we control for unobserved heterogeneity.

The rate of entering employment is negatively associated with a first birth event. Although the impact is negative for both genders, it is considerably weaker for men. This negative impact for men is somewhat surprising as the financial costs associated with childbearing, and the traditional division of labour between men and women just after child-birth, would suggest a greater

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[21] Our specification does not include duration splines for the birth events, so we do not examine the impact of the age of the children on the rate of dissolution (see, for instance, Lillard and Waite (1993) who show how dissolution depends on the age of the children).

incentive for men to enter employment. For second births, there is no significant effect for women, whereas there is a weak negative effect for men. For higher birth orders the negative impact for women and men (apart from the third birth order) persists. Being in a union reduces the employment rate for women, while for men there is no significant impact.

Our estimates of the relationship between employment exits and childbearing show interesting, although not entirely unexpected results. For women, the first birth has a strong and positive impact on employment exits, whereas for men there is no significant effect. Bearing in mind that further child events represent increasing *stock* of children, we see that the second birth reduces the rate of employment exits. Again, the birth event does not have any impact on men's employment decision. Marital status has a similar effect as the birth events. That is, women in a union have a considerably higher rate of employment exits. For men there is no impact.

Estimates of the age and duration spline parameters are presented in Aassve (2004). The estimates of the parameters of the unobserved heterogeneity terms are reported in Tables A6 and A7. All of the standard deviations in A6 are significantly different from zero. Most of the correlations in A7 are positive, though there are differences between men and women in terms of magnitude. As events are repeated (as opposed to single spell processes) in our model, a positive correlation generally reflects that individuals who make frequent or rapid transitions in one process also tend to do so in the other processes. The estimates of the unobserved heterogeneity terms may also be influenced by the fact that we have not separated out cohabitation from marriage, part-time from full-time work and merge education with other non-employment spells.

We find positive correlations between fertility, union formation and union dissolution, which indicate that individuals more prone to childbearing also make more rapid transitions in forming and dissolving unions, a result consistent with Upchurch et al (2002) for US data. The positive correlation between union formation and dissolution indicates that there are women (the correlation for men is positive but not significant) who both form and dissolve unions relatively quickly. The strong positive correlation between union formation and employment entry suggest that individuals more likely to form a union are also more likely to return to employment quickly. In contrast there is no strong correlation between union formation and employment exits, nor between employment entry and union dissolution. In addition, there is little to suggest that there are any *common* unobserved factors driving employment entries and exits. This is an interesting result, since it suggests that, those who tend to find employment quickly, conditioning on the observed covariates used here, do not necessarily have a higher rate of exiting employment. The estimates also show that individuals who are more prone to union dissolution are also more prone to employment exits, which is again interesting given the positive correlation between union formation and employment entry, and between union formation and union dissolution.

The unobserved heterogeneity terms are often smaller and less significant for men. This is particularly the case for union formation and dissolution, and fertility and employment entries and exits. The latter suggesting that men's employment movements are less associated with changes taking place in terms of fertility (again conditional on the observed covariates).

We evaluate the overall fit of the model in another paper, Aassve et al (2004). We use the model to simulate demographic and employment histories. Comparing these to the data, we find that a variety of different summary statistics of the duration and state occupancy patterns generally fit very well.

7. Analysing Poverty I: Explaining poverty

Given our empirical model of the behaviours underlying poverty transitions, we are ready to analyse poverty itself with the help of simulations. In doing so we first ask how well we explain poverty over 1991 – 1996 using this approach of focusing on demographic and employment status. This comparison provides a benchmark of the extent to which the correlated demographic and employment transitions themselves can explain poverty. Second, in the next section, we ask what matters for poverty – that is, which of the processes are most important and how that differs for different groups.

The model is too complex for simple goodness of fit statistics, so we evaluate its explanation of poverty dynamics by comparing summary statistics from simulated lives with the equivalent from the data. This extends Aassve et al (2004). We first discuss the nature of the simulations, and how we assign state-specific poverty rates to the simulants.

a. Simulations

We simulate the lives of all of the original 2499 males and 2630 females from the BHPS, a total of 20 times each, giving 49,800 male simulants, and 52,600 female simulants. These simulated individuals have the same background characteristics (ethnic background, cohort, parents' characteristics, education) as the original sample. In contrast, the time varying variables will depend directly on the simulated paths, as they are generated from the simulation themselves. Simulation of the unobserved heterogeneity terms is relatively straightforward. Each simulated individual is given a value drawn from the estimated five-dimensional joint normal distribution. This value is simply added to the log hazard, which is used to construct the inverted survival function (Galler 1997; Panis 2003).

We follow standard principles for micro-simulations (e.g. Citro and Hanushek 1991). We record the timing of their simulated demographic and labour market transitions from the age of 13 up to the end of the simulated panel in 1996, along with background information and non-time varying characteristics. We retain observations for each year that the simulant is 18 years old or older, during the years 1991-1996. This results in a male sample of: 45,800 simulants (91.64%) with 6 observations, 1680 (3.36%) with 5, 1360 (2.72%) with 4, and 1140 (2.28%) with 3. The corresponding figures for females are: 48,940 (93.04%) with 6 observations, 1020 (1.94%) with 5, 1200 (2.28%) with 4 and 1440 (2.74%) with 3.

Every individual is simulated from the age 13. From this age, we simulate the timing of 1) the first birth event, 2) the first union event, and 3) the first employment event. The lengths of the three simulated durations are compared, and the shortest is selected and taken to be the first event for this simulated individual. Based on the timing of the event the baseline duration dependence and the age dependency are updated. Starting from the time of the first event all other events are simulated. Again, the shortest of the three durations are selected and recorded. This procedure is repeated until the censoring date is reached. Being in a union and being single are taken to be mutually exclusive states as are being in employment and being not-employed. Fertility events, in contrast, are repeated and irreversible. The censoring date for childbearing was set to 45 years of age for women, and 55 years of age for men, whereas the censoring ages for the remaining processes were given by individuals' reported age in 1999 – at most 59 years of age.

b. Poverty Assignment

This modelling strategy captures the dynamics of the inter-related demographic and labour market processes that underlie the poverty outcome. We translate the simulated dates of events in the model's five inter-related processes into a status at a point in discrete time, with status in January of each year taken to be the status for that entire year. For each gender we create a distinct state variable comprised of 16 different categories that are generated by the permutations of: *de-facto* marital status [0,1], paid employment status [0,1] and number of dependent children [0,1,2,3+]. Then for each simulant in each year, we assign [0,1] poverty status by a random draw with the probability of being in poverty determined by the within state poverty rate that year for the state that the simulant is in that year. This conditional randomization lacks any persistence, and so forces the only source of persistence to be from the demographic and employment processes. Consequently, we do not expect to be able to fully match the poverty persistence in the data. This comparison provides a benchmark of the extent to which the correlated demographic and employment transitions themselves can explain poverty.

Returning to the household income process from section 3,

$$y_{ist} = \mu_i + \theta_{st} + \varepsilon_{ist}$$

we define an individual as being in poverty if their income falls below a fixed line, $\bar{y}_t$. The chance that *i*, in state *s* at *t*, is poor is given by:

$$\pi_{ist} = F_{st}\left(\bar{y}_t - \mu_i - \theta_{st}\right) \tag{12}$$

where F_{st} is the distribution function of $\varepsilon_{i(s)t}$, with the variance allowed to depend on *s* and *t*. Averaging over all individuals in state *s* at *t*, we write the mean poverty rate as:

$$\bar{\pi}_{st} = \pi\left(\theta_{st}, \bar{\mu}_s\right) \tag{13}$$

This depends on the state specific factor, and (in expectation) the mean person effect among the types of person typically found in state *s*. Thus assigning the empirical state-year poverty rate to each individual is a good approximation to the individual's own likely poverty rate.

By assigning poverty status this way, the model should necessarily fit aggregate poverty data as well as it fits the demographic and employment pattern. In a sense, the aggregate poverty summary data provide a weighted measure of the fit of the demographic and employment pattern, with the weights being the poverty rates. We also focus on comparisons of disaggregate and longitudinal poverty statistics from the simulants and the data.

It is useful to consider the implicit treatment of assortative mating in this approach. Consider a woman who is in a union state. By assigning her the mean poverty rate of that state, we are implicitly assigning her the mean partner's income of women in that state. So we are including a data-driven degree of assortative mating, albeit in a reduced form way. Note that when she transits between different union states, the change in the assigned mean poverty rate also can be interpreted as a change in mean partner behaviour.

Ideally we would like to use the BHPS to generate the state poverty rates for each year. In order to generate reliable, stable poverty rates, we require sufficient numbers with household income non-missing in each state in each year. This is not possible in the BHPS due to cell size (see Appendix B for details), and so we are forced to turn to a much larger data set, the Family Expenditure Survey (FES). The FES is a household based survey interviewing a different cross section of approximately 6500 private households in each year. As the original focus of the FES was household incomes as well as expenditures, the FES has the advantage that there are very few cases in which full income information for a household is missing. Therefore though the number of households involved each year is only approximately 1000 more than is the case in the BHPS, there are in each year around double the number of households with income information non-missing (see Appendix B). We construct the state variables for each gender in the FES to be precisely the same as they are in the simulations, and use the FES data for 1991 to 1996 to calculate the state poverty rates for each gender for each year, constructing the poverty indicator in exactly the same way in the FES as we do for the BHPS. Finally we construct the poverty rates for each state in each year for each gender (see Appendix B Table B1 for these state poverty rates in addition to details of the construction of the poverty rates).

Clearly for this strategy to work well, poverty rates in the FES and BHPS must be very similar. In fact, this was more problematic than we had anticipated, with considerable differences in the lower end of the distribution of income from the two sources. Investigation revealed that these derive from differences in the income of non-workers. The line we took is set out in Appendix C.

c. Model Performance

We start by comparing the simplest measure – the average poverty rate over all observations (N*T for real data, where N is the number of individuals, T the number of time periods, and N*T*R for simulated data, where R is the number of replications per simulant). Given our approach, this is essentially a weighted average of employment and demographic state occupancy, with the weights given by actual FES poverty rates. For women, the simulations produce a mean poverty rate of 16.39% (over 307860 observations) compared to 16.56% (11674) in the real data. For men, the mean simulated poverty rate is 12.91% (292060) compared to 13.61% (11450) in the data. This implied a close fit of the demographic structure.

We disaggregate this comparison in Table 1, examining the fit by cohort of birth and age-band. In the table, each row represents a different cohort: the first row being the oldest cohort (born in the 1940s), the last the youngest cohort (born in the 1970s). The columns represent the different age-bands, each approximately 10 years, from the youngest 18-29 years old to the oldest 50+ years old. The oldest individuals in the data are 55 in 1996, so this final age-band is around half the width of the other bands. In each cohort*age-band cell, the top figure is the overall poverty rate in this cell for the real data, with the number of real data observations in this cell below that; then below these is the overall poverty rate in this cell for the simulated data, and again below that we have the number of observations in the simulated data for this cell.

Table 1: Poverty Rates, by cohort and age-group

Male

Cohort and Age-group Analysis **Top figure = male poverty rate, real data**

Lower figure = male poverty rate, simulated data

Cohort	18 to 29 years old	30 to 39 years old	40 to 49 years old	50+ years old
born in 1940s	-	-	11.54	9.86
	n = 0	n = 0	n = 1976	n = 872
	-	-	9.90	8.69
	n = 0	n = 0	n = 47060	n = 24460
born in 1950s	-	13.26	13.50	-
	n = 0	n = 2021	n = 1385	n = 0
	-	12.33	13.96	-
	n = 0	n = 46620	n = 34740	n = 0
born in 1960s	12.06	13.09	-	-
	n = 1866	n = 1635	n = 0	n = 0
	10.75	11.60	-	-
	n = 47940	n = 42180	n = 0	n = 0
born in 1970s	20.65	-	-	-
	n = 1695	n = 0	n = 0	n = 0
	20.94	-	-	-
	n = 49060	n = 0	n = 0	n = 0

The oldest cohort are born in the 1940s therefore by 1991, the youngest in the cohort (born in 1949) will be at least 41, and the oldest in the cohort (born in 1940) can be, by the end of the sample window in 1996, up to 56 years old – therefore this cohort will have individuals in the 40-49 years old bracket and the 50+ years old bracket. The youngest cohort however, born in the 1970s, can only possibly be in the age range 18-29 years old.

Female

Cohort and Age-group Analysis **Top figure = male poverty rate, real data**
Lower figure = male poverty rate, simulated data

Cohort	18 to 29 years old	30 to 39 years old	40 to 49 years old	50+ years old
born in 1940s	-	-	11.72	13.89
	n = 0	n = 0	n = 2013	n = 979
	-	-	12.96	9.99
	n = 0	n = 0	n = 52160	n = 27760
born in 1950s	-	17.25	14.51	-
	n = 0	n = 1867	n = 1427	n = 0
	-	18.82	18.01	-
	n = 0	n = 45660	n = 39180	n = 0
born in 1960s	16.90	19.75	-	-
	n = 2112	n = 1701	n = 0	n = 0
	15.33	18.53	-	-
	n = 52980	n = 44820	n = 0	n = 0
born in 1970s	21.52	-	-	-
	n = 1575	n = 0	n = 0	n = 0
	19.50	-	-	-
	n = 45300	n = 0	n = 0	n = 0

Looking at the poverty fit in this way gives a more detailed picture of the extent to which the model fits poverty. In each cell the simulated data poverty rate and the real poverty rate are close, in most cases the simulations under-estimate poverty in the aggregate. For males, the 18-29 years old band for the cohort born in the 1970s has the closest fit, the simulations poverty rate of 20.94% being just above the actual poverty rate in this cell of 20.65%. The greatest discrepancy between the real poverty rate and the simulations poverty rate is in the 40-49 year old band for the cohort born in the 1940s, in which the simulated poverty rate at 9.90% is 1.64 percentage points below the real poverty rate 11.54%. For females, the fit is less good, but the largest discrepancies are in the least populated cells. The closest fit comes for the cell 30-39 years old and born in the 1960s, where the simulated poverty rate of 18.53% is just 1.22%-points lower than the real rate of 19.75%. The greatest discrepancy comes in the cell 50+ years old and born in the 1940s, where there is a 3.90%-point difference between the real poverty rate of 13.89% and the simulated rate of 9.99%.

The aim of the model is to explain the dynamics of poverty. Table 2 compares the stability of poverty in the two datasets. The upper panel refers to the real data for males. The "Overall" section of the table refers to the entire N*T panel dataset, and replicates the overall poverty rate of 13.61%. The "between" column tabulates the poverty indicator, referring to individuals rather than individual-waves. The table shows that almost all men (95.45%) spent at least one year out of poverty. Of the 2420 males in the data, 721 (29.79%) spent at least one year poor. The combined percentage 125.25% reflects the dynamics, individuals spend time in both states, and provides a measure of heterogeneity amongst the males in terms of poverty. The higher the combined percentage, the less is basic heterogeneity: if everyone experienced both states the total would be 200%, and if no-one ever changed, it would be 100%. Thus the 125.25% figure reflects a strong degree of heterogeneity in the real data, with poverty concentrated on a group of approximately 30% of the males.

The persistence of each state, both poor and not poor, is also reflected in the "within" section of the table. These show the mean fraction of time spent in the state, conditional on at least one observation with that value. Reading across the first row, of those men ever non-poor, they spend on average nearly 90% of their time not poor. This reflects the stability of non-poverty and the heterogeneity in the data, and reflects the extent to which non-poverty is concentrated on certain individuals. Similarly, conditional on an individual having one observation in poverty recorded, there is a 45.24% chance that if we choose at random any of his observations it will be in poverty. Again this reflects the stability of poverty, and a relatively high degree of heterogeneity in the data. The total "within" percentage of 78.76% is a measure of the overall stability of the poverty indicator variable;[22] a figure of 78.76% shows that the poverty indicator is stable to a large degree. There is clearly a substantial degree of both persistence and heterogeneity in the real poverty data; the heterogeneity is reflected in the stability of the poverty indicator and by the concentration of poverty on certain individuals as shown in Table 2.

[22] It is the normalized between-weighted average of the within percents.

Table 2: Poverty Persistence
Male

	Overall		Between		Within
Real data	**Freq.**	**Percentage**	**Freq.**	**Percentage**	**Percentage**
in poverty 0	9892	86.39	2310	95.45	89.22
1	1558	13.61	721	29.79	45.24
Total	11450	100.00	3031	125.25	78.76
			n = 2420		
Simulated data	**Freq.**	**Percentage**	**Freq.**	**Percentage**	
in poverty 0	254356	87.09	49595	99.23	87.70
1	37704	12.91	20384	40.78	31.93
Total	292060	100.00	69979	140.01	71.45
			n = 49980		

Female

	Overall		Between		Within
Real data	**Freq.**	**Percentage**	**Freq.**	**Percentage**	**Percentage**
in poverty 0	9741	83.44	2315	93.50	87.60
1	1933	16.56	811	32.75	49.44
Total	11674	100.00	3126	126.25	77.70
			n = 2476		
Simulated data	**Freq.**	**Percentage**	**Freq.**	**Percentage**	**Percentage**
in poverty 0	257413	83.61	52126	99.10	84.33
1	50447	16.39	26278	49.96	32.78
Total	307860	100.00	78404	149.06	67.06
			n = 52600		

In each dataset only observations in which the individual is 18 years old or older are included. The "**Overall**" section of each table refers to the entire N*T panel dataset i.e. the overall male poverty rate is 13.61%. The "**Between**" column tabulates the poverty indicator, referring to individuals rather than individual-waves – showing for each state how many of the individuals ever experience that state e.g. 95.45% of the men spent at least one year out of poverty; 29.79% of the men spent at least one year in poverty. The higher the combined percentage (in the Total row), the less is basic heterogeneity: if everyone experienced both states the total would be 200%, and if no-one ever changed, it would be 100%. The "**Within**" section of the table shows the persistence of each state. These figures show the mean fraction of time spent in the state, conditional on at least one observation with that value i.e. reading across the first row of the male table: conditional on a man having one observation not poor there is a 90% chance that if we choose at random any of his observations the man will not be in poverty; similarly, conditional on a man having one observation in poverty recorded, there is a 45.24% chance that if we choose at random any of his observations it will be in poverty. The total "Within" percentage is a measure of the overall stability of the poverty indicator variable,[23] the higher the figure the more stable the variable overall.

[23] It is the normalized between-weighted average of the within percents.

The lower panel of Table 2 has the corresponding figures for the simulated data. Looking at the "between" section, we see that almost every simulant experiences at least one observation when they are not in poverty. Of the 49,980 simulants, 40.78% are ever poor, considerably greater than the 29.8% in the data. The measure of basic heterogeneity is 140.01% in the simulated data, and we see that we do not capture all of the heterogeneity that is in the real data where the figure is 125.25%; that is, the simulations have excess dynamics. Less heterogeneity means that poverty is less concentrated on certain individuals – in the real data poverty is exclusive to 29.79% of the males, whereas in the simulations more of the population experience poverty, they are more homogenous.

The "within" percentages also reflect the lower persistence and the lower level of heterogeneity in the simulations. The fraction of time spent in each state is lower for the simulants, though only marginally for the non-poor. This again reflects the excess dynamics and not enough heterogeneity. The total "within" percentage of 71.45%, which is 7.31%-points lower than in the data, shows the relative lower stability of poverty in the simulations.

The lower panels of Table 2 look at the stability of poverty amongst females in the real and the simulated data. Much the same story is true here, though generally the simulations capture a little less of the persistence in the female data. Again, comparing the data and the simulations, it is clear that the latter exhibit excess dynamics, and insufficient heterogeneity and persistence. The stability of poverty in the female simulations is lower than in the male simulations, and the female simulated figure is further from the data figure than is the case for males.

Table 3 provides more detail from a longitudinal perspective on the distribution of poverty experiences. The simulated mean of 1.85 years in poverty for males is appreciably lower than the corresponding real figure 2.16 years. This also reflects the lower level of persistence in the simulations, and the excess of dynamics – more males are poor at least once in the simulations yet they are poor for a shorter time on average as the state of being in poverty is less stable in the simulations. We also see this heterogeneity in the distribution of the number of poverty spells in each dataset as shown in Table 3. In the real data, 70.21% of the males never have a poverty spell; as noted, poverty is concentrated on approximately 30% of the males. In the simulations however only 59.22% of males never experience poverty. The proportion of simulants who experience one poverty spell is appreciably greater at 30.19% as compared with 23.33% in the real data, and the proportion experiencing two or more spells of poverty is approximately double the corresponding proportion in the real data. Again, the story is the same for women, with too much homogeneity at the margin and excess dynamics.

Table 3: Heterogeneity
Male

Poverty Experience	**Real**	**Simulated**
% of individuals who are ever poor after the age of 18	29.79 n = 2420	40.78 n = 49980
Poverty Spells		
no. poverty spells	**Percent**	**Percent**
0	70.21	59.22
1	24.09	30.19
2	5.29	9.67
3	0.41	0.93
Total	100.00	100.00
Distribution of Poverty		
Mean no. years poor after the age of 18 per individual, given poor once	2.16 n = 721	1.85 n = 20384

Female

Poverty Experience	**Real**	**Simulated**
% of individuals who are ever poor after the age of 18	32.75 n = 2476	49.96 n = 52600
Poverty Spells		
no. poverty spells	**Percent**	**Percent**
0	67.25	50.04
1	25.32	34.83
2	6.58	13.60
3	0.85	1.53
Total	100.00	100.00
Distribution of Poverty		
Mean no. years poor after the age of 18 per individual, given poor once	2.38 n = 811	1.92 n = 26278

Table 4 presents the poverty transition matrices for both the real data and the simulated data, thus providing a simple summary of the above findings. These show the rates of inflow into poverty and outflow from poverty for each pair of successive years during the period from 1991-1996. The rows of the matrix represent an individual's poverty status in first year of the pair, the columns represent poverty status in the following year. For example, in the real data during this time period, in 60.39% of cases where an individual is in poverty one year they are also in poverty in the following year. Looking at the upper panel, it is clear that in the real data non-poverty exhibits a great deal of persistence: in 93.34% of cases, if an individual is not in poverty in one year, they will not be in poverty in the following year. The overall average annual inflow rate into poverty is consequently just 6.66%. The outflow rate from poverty is much greater at 39.61%, reflecting that poverty is less persistent than non-poverty – in only 60.39% of cases does an individual in poverty in one year remain in poverty in the following year.

The lower panel of table 4 shows the transition matrix for the simulated data for males. We anticipate that we will not have enough persistence in poverty since by construction we do not allow for persistence in the income process. In fact, we find that this demographic and employment focused approach does yield significant persistence. The persistence in non-poverty of 90.85% for males is not far away from the corresponding figure for the real data. The persistence in poverty in the simulations is much lower at 37.15% than in the real data. The counterpart of this is higher dynamics, shown by the higher inflow rate into poverty and the higher outflow rate. Therefore, while, as expected, the simulations do show excess dynamics, it is clear that demographic changes can account for a substantial part of the persistence of poverty status.[24]

For females, actual poverty is slightly more persistent than for males and non-poverty slightly less so; alternatively, the inflow into poverty is greater for females, the outflow from poverty is lower. Again for females, the simulated data capture some of the observed persistence in non-poverty; women remain non-poor with a 92.5% chance in the data and 87.7% in the simulations. But again, the model does a poorer job of capturing persistence in poverty.
To summarise, we have shown that this approach is able to capture poverty dynamics rather well, though for the reasons set out above, we do not generate enough heterogeneity and persistence.

[24] There is an issue of differential attrition in the real data, though obviously not in the simulations.

Table 4: Poverty Transitions

Male

REAL DATA		poverty status year (t+1) 0	1
poverty status	0	93.34	6.66
year t	1	39.61	60.39
Total		86.30	13.70
SIMULATED DATA		poverty status year (t+1) 0	1
poverty status	0	90.85	9.15
year t	1	62.85	37.15
Total		87.25	12.75

Female

REAL DATA		poverty status year (t+1) 0	1
poverty status	0	92.46	7.54
year t	1	34.92	65.08
Total		83.33	16.67
SIMULATED DATA		poverty status year (t+1) 0	1
poverty status	0	87.70	12.30
year t	1	62.81	37.19
Total		83.66	16.34

In each dataset only observations in which the individual is 18 years old or older are included.

8. Analysing Poverty II: Understanding poverty

We analyse which demographic transition processes have the greatest effects on poverty. We explore this by changing certain parameters in the demographic hazards, and then running further micro-simulations, analysing the effects on different metrics of poverty when compared with these metrics in the base run case. This is an analysis of the empirical comparative dynamic properties rather than policy analysis.

Unlike the initial simulations, there is no real time element in these simulations. The only temporal structure in the simulated panel comes from the age and duration structure in the hazards. There is no comparison to real year poverty rates, so the primary requirement is that the time-constant state poverty rates for the different states are consistent in relation to each other. In this case, we are able to pool the observations across the FES for the years 1991 to 1996 and calculate the poverty rate within each state evaluated over the entire time period, providing more observations per state. Appendix B Table B2 shows poverty rates generated by averaging over 1991-1996.

To get a clean measure of the effect that changing parameters has on various measures of poverty, we select for each gender, two different 'type's and simulate their lifetimes, 1000 times each, from the age of 13 until 1999. Each type was born in 1945 and therefore is 54 when we stop the simulations in 1999. Though we simulate their lives from the age of 13, we are interested in their poverty experience from the age of 18 onwards so each simulant has 37 observations. The two types were chosen so as to provide a contrast in background and qualifications:

- The type 1 male and female are <u>advantaged</u>: they are white, with high parental social class, their qualifications are 'A'-level or equivalent, and they lived with both natural parents all of the time from birth until the age of 16;
- The type 2 male and female are <u>disadvantaged</u>: they are non-white, with low parental social class, no qualifications and did not live with both natural parents for all of the time from birth up until the age of 16.

Each type is also characterised by a once-only draw from the unobserved heterogeneity distribution, set to zero.

a. Simulation experiments

We simulate lifetimes for these two types and both genders 1000 times each, and calculate averages of a set of poverty metrics. The measures that we look at for each type are: the mean poverty rate over all of the type's lifetimes, the mean number of spells of poverty that a type has over his/her lifetimes, the mean duration of a poverty spell over his/her lifetimes, and the percentage of a type's spells which are greater than 1 year in duration.

Experiment 1 is the base run in which we use the estimated parameters. In all subsequent experiments, the changes made are all relative to the values of the parameters in the base run and only the parameters that the experiment changes are different to their values in the base run case. In the second experiment we increase the likelihood of experiencing a birth. We do so simply by increasing the intercept by 10%, thereby increasing the probability of a birth for all individuals irrespective of the number of children that they already have and irrespective of their position with regard to the other processes. Experiment 3 makes it more likely that an unmarried individual will become married, irrespective of the number of times they have been married, their employment and their fertility status, and more likely that a married individual will stay married, again irrespective of all other factors. To do this, we increase the intercept on the union formation hazard by 10% and reduce the intercept on the union dissolution hazard by 10%. Similarly, experiment 4 increases the intercept on the employment hazard by 10% and reduces the intercept in the non-employment hazard. Experiments 5 and 6 focus on cross-process effects. Experiment 5 increases the first two birth parameters in the employment transitions whilst leaving the union transitions unchanged. This has the effect of increasing the likelihood that an individual with children will gain employment and keep it. Finally, experiment 6 alters the employment parameter in the birth transitions, the union transition parameters unchanged. This has the effect of reducing the likelihood of having children whilst working compared with the likelihood in the base run experiment.

Table 5 contains the results for the males. Each row of the table presents the results for a different experiment, and the columns are different metrics of poverty. The first four columns contain the values of these metrics for each experiment for the advantaged males, while the second four columns contain the values of these same metrics for the disadvantaged males.

Reading across the first four columns of the first row, we see that in the base run model, the advantaged individuals have a poverty rate of 0.1139, will have on average 2.90 spells of poverty during the 37 years of their lifetime from the age of 18, that a poverty spell will on average last 1.45 years and that 26.13% of the spells that they have will be in excess of 1 year in duration.

Looking at the results in the other rows for the first four columns, we see that for advantaged males, experiment 4 (raising the employment hazard and lowering the non-employment hazard) has the greatest effect across all measures of poverty. In this experiment, the mean poverty rate is reduced by almost half to 0.0628, and advantaged individuals will on average experience approximately one fewer poverty spells (1.91) than in the base run. Moreover, these spells will be shorter in length as reflected by both the reduction in the mean length of a spell – the mean is 1.22 years duration compared with the base run value of 1.45 years – and the reduction in the proportion of spells that are greater than 1 year in duration – down to 15.26% from the base run proportion of 26.13%.

Table 5: Experiment Results: Males

	ADVANTAGED				DISADVANTAGED			
	Mean Pov Rate	Mean no. Pov Spells	Mean Duration of Pov Spell, years	% spells with duration >1year	Mean Pov Rate	Mean no. Pov Spells	Mean Duration of Pov Spell, years	% spells with duration >1year
Experiment 1 (base)	0.1139	2.90	1.45	26.13	0.2452	5.00	1.82	39.24
Experiment 2	0.0866	2.33	1.38	22.75	0.2114	4.52	1.73	37.46
Experiment 3	0.1085	2.80	1.43	25.79	0.2441	4.95	1.82	38.32
Experiment 4	0.0628	1.91	1.22	15.26	0.1414	3.44	1.52	27.81
Experiment 5	0.0822	2.34	1.30	19.73	0.1815	4.21	1.60	31.81
Experiment 6	0.1043	2.68	1.44	25.63	0.2313	4.87	1.76	39.04

Experiment 1: base run
Experiment 2: the intercept on the birth hazard increased by 10%
Experiment 3: the intercept in the union formation hazard is increased by 10% and the intercept in the union dissolution hazard is reduced by 10%
Experiment 4: the intercept in the employment hazard is increased by 10% and the intercept in the unemployment hazard is reduced by 10%
Experiment 5: 0.5 is added to the two first birth parameters in employment transitions - so this makes it easier to work whilst having children. Marriage transitions are left untouched.
Experiment 6: employment parameter is changed in the birth transitions - so this makes it less likely to have children when working.Marriage transitions are left untouched.
Type 1: Advantaged - White; parental social class is high; qualification level is 4 (= 'A'-levels or equivalent); lived with both natural parents from birth to age 16.
Type 2: Disadvantaged - Non-white; parental social class is low; qualification level is 1 (=no qualifications); did not live with both natural parents from birth to age 16.
All results for men; all counts and durations refer to years when simulants are 18+ years old and include censored spells

The experiment with the second greatest effect on advantaged males is experiment 5, which makes it easier to get and keep a job when there are children present in the household. The mean poverty rate is reduced significantly, down to 0.0822, as is the average number of spells of poverty, 2.34 compared with 2.90 in the base run, and spell length. Experiment 2, raising the birth hazard, is the only other experiment which has a marked effect on the poverty experience of the advantaged males.

The disadvantaged individuals start from a base run position where they have a mean poverty rate (0.2452) that is just over double the poverty rate of the advantaged individuals. On average they will experience two more spells of poverty than the advantaged, experiencing 5.00 spells on average during their lifetime from the age of 18. Moreover, at 1.82 years, the mean duration of a poverty spell is 25% longer for the disadvantaged and a significantly greater proportion of their spells of poverty are more than just a one-year dip into poverty – 39.24% for the disadvantaged as compared with 26.13% for advantaged.

As with the advantaged, experiment 4 has the most dramatic effect, almost halving the mean poverty rate to 0.1414 and reducing the mean number of poverty spells from 5.00 to less than 3.5, and reducing their length. Experiment 5 significantly reduces all of the measures of poverty and the same is true of experiment 2, though to a lesser extent. Experiments 4, 5 and 2 have similar effects on each type. In fact, the greatest relative reductions in poverty are achieved by advantaged, but the greatest absolute reduction is for disadvantaged.

It is not surprising that experiments that increase participation in employment (experiments 4 and 5) have the most substantial effects on the average poverty experience of the individuals. The poverty experience of each individual is dependent purely on the state that they are in - the assignment to poverty depending on the state poverty rate for that state. We know that there is a substantial difference in the poverty rates between a state where the individual is employed and the corresponding state where he is not, and this is the case irrespective of the individual's marital and fertility status. Therefore experiments which increase the individual's employment hazard will necessarily reduce the mean poverty rate, number of poverty spells and duration of a poverty spell. Note that because of the various cross-process links, all the experiments can influence employment status.

It is perhaps more surprising that the increase in the birth hazard has the effect of reducing poverty. Although the states in which individuals have children but are not married and/or employed have very high poverty rates, there is only one state which has a lower poverty rate than the states in which individuals are married, with children and in employment. So the effect of more children is definitely bad from some starting points, but beneficial from others. Crucially the presence of children enters in the processes for employment and marriage formation. Therefore it must be the case that increasing the fertility hazard has a net beneficial effect on each type in terms of their other transitions, such that they increase their time spent in the low poverty state of married, employed and with children to an extent that the time that they spend in high poverty states is counter-balanced.

Table 6 contains the experiment results for the females. Of the five experiments that we report in the table, the three that had the greatest impact for the males also matter most for females. However, the ranking is not the same, and there is more variation amongst the females as to which experiment affects which outcome the most. Moreover, for females there is a difference between the advantaged and the disadvantaged in the experiments that have the greatest effect on the outcomes that measure poverty experience.

The first four columns of the first row give the base run position of the advantaged females: their poverty rate is 0.1293, they have on average 3.29 spells of poverty during their lifetime from the age of 18 onwards, these spells have a mean duration of 1.45 years and in 25.11% of cases a spell is greater than 1 year in duration. Reviewing the results in the remaining rows of the table, we see that, as with the males, experiment 4 has the greatest effect on the mean poverty rate and on the average length of a poverty spell for advantaged females. In this experiment, the mean poverty rate is reduced by almost two-fifths to 0.0807, and the poverty spells that the individuals do experience are more likely to be shorter in length. The mean duration of a poverty spell is reduced to 1.27 years and the proportion of spells that are more than a 1-year dip into poverty is reduced to 17.75%. There is also a reduction of almost one spell in the average number of poverty spells (2.36) that the advantaged individuals will experience. Of the other runs, experiments 2 and 5 have the greatest effects.

The disadvantaged females start from a position in which their poverty rate (0.3250) is just over two-and-a-half times the poverty rate of the advantaged. On average they will experience 5.85 spells of poverty, two-and-a-half more spells than the advantaged. Moreover, the mean duration of a poverty spell is substantially longer at 2.06 years for type 2, and there is a sizeable difference in the proportion of spells that are more than just a one-year dip into poverty: 41.33% for disadvantaged compared with only 25.11% for advantaged.

Table 6: Experiment Results: Females

	ADVANTAGED				DISADVANTAGED			
	Mean Pov Rate	**Mean no. Pov Spells**	**Mean Duration of Pov Spell, years**	**% spells with duration >1year**	**Mean Pov Rate**	**Mean no. Pov Spells**	**Mean Duration of Pov Spell, years**	**% spells with duration >1year**
Experiment 1 (base)	0.1293	3.29	1.45	25.11	0.3250	5.85	2.06	41.33
Experiment 2	0.0814	2.29	1.31	19.86	0.2272	4.73	1.78	35.06
Experiment 3	0.1255	3.36	1.38	23.51	0.3001	5.96	1.86	38.67
Experiment 4	0.0807	2.36	1.27	17.75	0.2261	4.81	1.74	34.36
Experiment 5	0.0903	2.56	1.30	19.52	0.2101	4.73	1.65	33.16
Experiment 6	0.1164	3.01	1.43	23.08	0.3038	5.59	2.01	40.82

Experiment 1: base run
Experiment 2: the intercept on the birth hazard increased by 10%
Experiment 3: the intercept in the union formation hazard is increased by 10% and the intercept in the union dissolution hazard is reduced by 10%
Experiment 4: the intercept in the employment hazard is increased by 10% and the intercept in the unemployment hazard is reduced by 10%
Experiment 5: 0.5 is added to the two first birth parameters in employment transitions - so this makes it easier to work whilst having children. Marriage transitions are left untouched.
Experiment 6: employment parameter is changed in the birth transitions - so this makes it less likely to have children when working.Marriage transitions are left untouched.
Type 1: Advantaged - White; parental social class is high; qualification level is 4 (= 'A'-levels or equivalent); lived with both natural parents from birth to age 16.
Type 2: Disadvantaged - Non-white; parental social class is low; qualification level is 1 (=no qualifications); did not live with both natural parents from birth to age 16.
All results for females; all counts and durations refer to years when simulants are 18+ years old and include censored spells

The same three experiments that have the greatest effect on the advantaged have the greatest impact on disadvantaged though interestingly, and unlike the males, not in the same order. For disadvantaged it is experiment 5, which makes it easier to gain employment and remain employed when there are children present in the household, which has the most dramatic effect on all of the poverty measures, cutting the poverty rate by more than one-third to 0.2101, and reducing the mean number of poverty spells by more than 1 to 4.73. Furthermore, with a mean duration of 1.65 years, the poverty spells are on average 20% shorter, and are more likely to be just a one-year spell of poverty, the proportion of longer spells falling to 33.16%.

Experiments 2 and 4 have a similar overall effect on poverty for disadvantaged. The reduction in the poverty rate is almost identical in each case: in experiment 2 the poverty rate is 0.2272, in experiment 4 it is 0.2261, and these reductions are only 1.5 percentage points less than is the case in experiment 5. Therefore though they are not far behind experiment 5 in terms of mean poverty rate and number of poverty spells, experiments 2 and 4 have less of an effect on the mean duration of the poverty spells and the proportion of spells that are longer than 1 year. Again experiments 3 and 6 have very little effect on the poverty experience of the disadvantaged individuals.

Changing the employment hazard has the greatest effect on the more educated advantaged. For disadvantaged, however, it is the experiment that makes it easier to work when with children that has the greatest effect. This makes sense in that, in the base run data, the disadvantaged spend more than double the time that the advantaged spend in states in which they are with children but not employed. There are large differences between the poverty rates for states where females have children and are working and those in which the females have children and are not working, therefore moving people from the latter to the former will have a great effect on the overall poverty status of the females. Thus given their much higher state occupancy in the children but no employment states in the base run, we would expect that making it easier to work with children would have a greater effect on the disadvantaged.

Again it is less straightforward to explain why it is that the increase in the birth hazard intercept, experiment 2, would have a strong positive effect on poverty outcomes. However, it must be the case that the increase in time spent in married, employed, with children states as a result of the change in the birth intercept, in conjunction with the very low poverty rates in these states, is enough to counter balance the negative effect of being more likely to have children in the unmarried and/or unemployed states, such that the net effect is an unambiguous reduction in overall poverty experience.

In summary, parameter experiments relating to fertility, employment and the link between them reduce all measures of poverty for both types considered. And while it is the advantaged who get the greatest relative benefit, the disadvantaged benefit in all of these experiments and particularly in experiment 5 which increases the chances of getting and keeping employment when there are children in the household. These experiments support the importance of employment in poverty dynamics. This importance arises both directly and indirectly through the impact on the other transition processes.

b. Illustrative simulated lives

To illustrate the importance for poverty of inter-related demographic and employment transitions, Table 7 is a schematic representation of the lives of two pairs of male simulants from the base run micro-simulations. These are illustrative not representative. The first pair of simulants, A and B, are advantaged while C and D are disadvantaged. Each pair within each type have the same (zero) unobserved heterogeneity. The left-most column in the diagram shows the age of the simulant, and for each simulant (column) the entries in the cells in the main body refer to the demographic*employment state that the simulant is in at the age corresponding to that row. The shaded cells represent years in which the simulant is in poverty, with the column totals at the bottom giving the sum of years (out of 37) that each simulant is in poverty. Looking at the contrasting fortunes of these simulants, from the same initial position, illustrates the way in which these processes affect each other, and how this impacts on poverty experience. The only difference within each pair is simply the outcome of the stochastic process. This works through the five hazards representing the dynamic process to produce divergent outcomes.

Considering first the two advantaged simulants, A and B, each simulant begins in the "not married, employed, no children" state and has two years in this state. A then loses his job and spends four years single and without a job or a child. He then gets married whilst unemployed and one year later has a child whilst still unemployed. He never regains employment and spends more than half of his observations in poverty after losing his job. Simulant A illustrates the negative impact of children on the chance of entering employment, and the consequences that this has for poverty.

Due to the different poverty rates in the different states, if an individual has a child whilst not in employment, whether married or not, he will be in a state with a high poverty rate (63.5% if single, 48.6% if married). Therefore there is a good chance that the simulant will experience poverty - especially if he remains in such a state for a number of years. The presence of children adversely affects the probability of gaining employment, thus re-enforcing the poverty mechanism. We can see this at work in the results for A: of the 21 years that he is married, not employed and with one child, 14 are spent in poverty. Once the child has left the household, though he does not regain employment, he is in a state with a poverty risk of only 20.5% and therefore has much less experience of poverty in his remaining observations.

In contrast, after two years in the “not married, not employed, no children” state, B gets married in the third year. He remains employed throughout his first marriage, then gets divorced yet still remains employed for the duration of the time that he is single again. B then re-marries remaining in employment and crucially he is employed when he has a child. He loses his job for one period while he is married and has a child and dips into poverty during this one spell of unemployment; however, he then gets a job again straightaway after this and remains poverty free.

A remains married yet never re-gains employment after losing it early on in life. In contrast, B gets married, divorces and later re-marries but crucially remains in employment for almost his entire lifetime, illustrating that with regard to poverty it is more important to maintain employment than it is to remain in a union. This is especially the case when children are born.

Turning to the two disadvantaged simulants, we see that C has a short spell of unemployment to begin with but then he gets a job, gets married, has children and has no poverty experiences up to the age of 29. However, he then gets divorced and experiences poverty at this stage. C loses his job and has a prolonged period of unemployment; he still has 3 children in the household and spends all of the 12 years before he regains employment, in poverty. When he does become employed again, and lifts out of poverty, he loses the job straightaway and never gains employment thereafter. From this point he then spends 9 of his last 10 years in poverty.

In contrast, D begins with a longer period of unemployment, during which he spends 4 years out of 7 in poverty. Then just like C, he gains a job, then gets married and then has children. Unlike C however, D manages to maintain his employment for the entire time from when he first gets the job until the end of his observations. As such, even when he has two children he only dips into poverty for two years out of 20.

After gaining a job, D only spends three years in poverty, and it is only because he is relatively unlucky to have 4 out of 7 years in poverty when in the “not married, not employed, no children” state, while C is lucky not to experience poverty in any of his 3 years in this state, that the poverty experience of the two is not even more stark than it is.

Table 7: Example Simulated Lives

	Advantaged		Disadvantaged	
	Person A	Person B	Person C	Person D
Age	State	State	State	State
18	notM **EMP** 0	notM **EMP** 0	notM notE 0	notM notE 0
19	notM **EMP** 0	notM **EMP** 0	notM notE 0	notM notE 0
20	notM notE 0	**Marr EMP** 0	notM notE 0	notM notE 0
21	notM notE 0	**Marr EMP** 0	notM **EMP** 0	notM notE 0
22	notM notE 0	**Marr EMP** 0	**Marr EMP** 0	notM notE 0
23	notM notE 0	**Marr EMP** 0	**Marr EMP** 1	notM notE 0
24	**Marr** notE 0	**Marr EMP** 0	**Marr EMP** 1	notM notE 0
25	**Marr** notE 1	**Marr EMP** 0	**Marr EMP** 2	notM **EMP** 0
26	**Marr** notE 1	**Marr EMP** 0	**Marr EMP** 3	**Marr EMP** 0
27	**Marr** notE 1	**Marr EMP** 0	**Marr EMP** 3	**Marr EMP** 0
28	**Marr** notE 1	**Marr EMP** 0	**Marr EMP** 3	**Marr EMP** 1
29	**Marr** notE 1	**Marr EMP** 0	**Marr EMP** 3	**Marr EMP** 2
30	**Marr** notE 1	**Marr EMP** 0	notM **EMP** 3	**Marr EMP** 2
31	**Marr** notE 1	**Marr EMP** 0	notM **EMP** 3	**Marr EMP** 2
32	**Marr** notE 1	**Marr EMP** 0	notM notE 3	**Marr EMP** 2
33	**Marr** notE 1	notM **EMP** 0	notM notE 3	**Marr EMP** 2
34	**Marr** notE 1	notM **EMP** 0	notM notE 3	**Marr EMP** 2
35	**Marr** notE 1	notM **EMP** 0	notM notE 3	**Marr EMP** 2
36	**Marr** notE 1	notM **EMP** 0	notM notE 3	**Marr EMP** 2
37	**Marr** notE 1	notM **EMP** 0	notM notE 3	**Marr EMP** 2
38	**Marr** notE 1	notM **EMP** 0	notM notE 3	**Marr EMP** 2
39	**Marr** notE 1	notM **EMP** 0	notM notE 3	**Marr EMP** 2
40	**Marr** notE 1	**Marr EMP** 0	notM notE 3	**Marr EMP** 2
41	**Marr** notE 1	**Marr EMP** 0	notM notE 3	**Marr EMP** 2
42	**Marr** notE 1	**Marr EMP** 1	notM notE 3	**Marr EMP** 2
43	**Marr** notE 1	**Marr EMP** 1	notM notE 3	**Marr EMP** 2
44	**Marr** notE 1	**Marr EMP** 1	notM **EMP** 3	**Marr EMP** 2
45	**Marr** notE 1	**Marr EMP** 1	notM notE 3	**Marr EMP** 2
46	**Marr** notE 0	**Marr EMP** 1	notM notE 2	**Marr EMP** 2
47	**Marr** notE 0	**Marr EMP** 1	notM notE 1	**Marr EMP** 2
48	**Marr** notE 0	**Marr EMP** 1	notM notE 1	**Marr EMP** 2
49	**Marr** notE 0	**Marr EMP** 1	notM notE 1	**Marr EMP** 1
50	**Marr** notE 0	**Marr** notE 1	notM notE 0	**Marr EMP** 0
51	**Marr** notE 0	**Marr EMP** 1	notM notE 0	**Marr EMP** 0
52	**Marr** notE 0	**Marr EMP** 1	notM notE 0	**Marr EMP** 0
53	**Marr** notE 0	**Marr EMP** 1	notM notE 0	**Marr EMP** 0
54	**Marr** notE 0	**Marr EMP** 1	notM notE 0	**Marr EMP** 0
Sum poverty	18	1	22	7

These simulated histories illustrate how crucial it is to maintain employment to remain generally poverty free. This is even more so the case for the disadvantaged simulants who have lower education. We see starkly with these simulants how especially crucial the maintenance of employment is when children are in the household and particularly if there is more than one child. This ties in well with the results from the experiments in Tables 5 and 6, which shows the importance of the employment hazard, and the relationship between employment and having children.

9. Conclusion

We have pursued an economic approach to analysing poverty. This necessarily requires us to focus on the decision variables that individuals can influence, such as forming or dissolving a union, having children, finding or losing employment. These in turn are combined with an income process to model poverty. We argue that this indirect approach to modelling poverty is the right way to bring economic tools to bear on the issue. This is the central advantage of this innovative approach – it allows an economic analysis of poverty that current approaches do not. The implementation of this approach in this paper focuses heavily on demographic and employment states, and endogenous transitions between them as the driving forces behind changes in poverty. Once this method is established, the economic modelling can be made more elaborate.

We construct a dataset covering event histories over a long window (for all our sample from age 13). Using this we estimate five simultaneous hazards with unrestricted correlated heterogeneity, and append a simple income process. Because the model consists of a complex set of dynamically inter-related processes, we evaluate it using simulation methods. The model fits the demographic and poverty data reasonably well. As expected, we capture a lot but not all of the heterogeneity and persistence in longitudinal poverty experiences.

Given the model, we investigate the important parameters and processes for differences in individuals' poverty likelihood. Getting and keeping a job show up as having a substantial impact on poverty for most groups. Interestingly, for disadvantaged women, the most important parameter is that governing the difficulty of securing a job whilst there are young children in the household. We do not push this all too far given that this is not detailed policy analysis, but it does give some support to those who support anti-poverty policies based on 'work first' and the importance of affordable child care.

There are a number of caveats to bear in mind in this implementation. Whilst the estimation is generally unrestrictive in terms of temporal structure and cross-process correlation, computational complexity forces some decisions on us. For example, not being able to fully distinguish between first and subsequent spells of the hazard processes is likely to be a restriction. Second, we adopted a relatively simple income process to allow us to focus on employment and demographics. This means that we do not address issues such as the low pay/no pay cycle. Third, whilst we include and then substitute out income from the demographic transition processes, there may be second order effects on these from more complex dynamic patterns in income (such as prolonged spells of low income) that we do not capture. One area for further work is to introduce some persistence into our simple income process.

Nevertheless, we believe that this paper has shown this to be a useful framework for analysing poverty. Unlike the other major approaches, it is coherent with an economic viewpoint as we analyse variables that individuals make decisions on, and we take seriously the household basis for poverty. It focuses attention on the dynamic processes that are most important for initiating and ending spells of poverty, and offers scope for further work to develop specific processes in more detail.

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Appendix A: Estimation Results

Table A1: Fertility Transitions

	Women	Men
BIRTH ORDER 2	-0.9432 ***	-1.2704 ***
	(0.1221)	(0.1672)
BIRTH ORDER 3	-2.7509 ***	-2.9772 ***
	(0.1444)	(0.2044)
BIRTH ORDER 4,5 & 6	-3.8723 ***	-3.8089 ***
	(0.1888)	(0.2559)
COHORT 1950 – 1960	-0.0275	-0.0626
	(0.0636)	(0.0689)
COHORT 1960 – 1970	-0.3909 ***	-0.5677 ***
	(0.0686)	(0.0832)
COHORT 1970 +	-0.9392 ***	-0.8396 ***
	(0.1315)	(0.1753)
DID NOT LIVE W BOTH NATURAL PARENTS FROM BIRTH UP TO AGE 16	0.2832 ***	0.2260 ***
	(0.0701)	(0.0832)
FATHER PROFESSIONAL OCC.	-0.1409 **	-0.1082
	(0.0700)	(0.0718)
MOTHER PROFESSIONAL OCC.	-0.0407	0.0380
	(0.0927)	(0.0997)
ETHNIC ORIGIN	0.3133 ***	0.4530 ***
	(0.1170)	(0.1346)
SUB O-LEVEL QUALIFICATION	-0.3583 ***	0.0177
	(0.0917)	(0.1108)
O-LEVELS OR EQUIVALENT	-0.6063 ***	-0.1186
	(0.0813)	(0.0885)
A – LEVELS OR EQUIVALENT	-0.7259 ***	-0.2454 ***
	(0.0804)	(0.0799)
HIGHER QUALIFICATION	-0.9509 ***	-0.4605 ***
	(0.0998)	(0.1071)
MARRIED OR COHABITING	1.7611 ***	2.0787 ***
	(0.0598)	(0.0782)
WORKING (INCL. PART TIME)	-0.1885 ***	0.3832 ***
	(0.0505)	(0.0893)

Table A2: Union Transitions

	Women	Men
MARRIAGE ORDER 2	-1.3474 ***	-0.4008
	(0.2238)	(0.2981)
MARRIAGE ORDER 3 OR 4	-1.8064 ***	-0.7455 **
	(0.2945)	(0.3662)
COHORT 1950 – 1960	0.1907 **	-0.0640
	(0.0772)	(0.0777)
COHORT 1960 – 1970	-0.1526 **	-0.1149
	(0.0778)	(0.0827)
COHORT 1970 +	-0.5513 ***	-0.7884 ***
	(0.1079)	(0.1226)
DID NOT LIVE W BOTH NATURAL PARENTS FROM BIRTH UP TO AGE 16	0.2767 ***	0.2455 ***
	(0.0777)	(0.0856)
FATHER PROFESSIONAL OCC.	-0.0070	-0.0381
	(0.0734)	(0.0736)
MOTHER PROFESSIONAL OCC.	-0.0278	-0.0962
	(0.0956)	(0.1068)
ETHNIC ORIGIN	-0.4329 ***	-0.4978 ***
	(0.1217)	(0.1474)
SUB O-LEVEL QUALIFICATION	-0.2824 **	0.1596
	(0.1113)	(0.1242)
O-LEVELS OR EQUIVALENT	-0.2774 ***	0.3215 ***
	(0.0877)	(0.1049)
A – LEVELS OR EQUIVALENT	-0.2843 ***	0.2503 ***
	(0.0873)	(0.0884)
HIGHER QUALIFICATION	-0.6370 ***	0.0548
	(0.1063)	(0.1073)
FIRST BIRTH	0.9186 ***	1.2512 ***
	(0.0661)	(0.0849)
SECOND BIRTH	-0.6107 ***	-0.9079 ***
	(0.1019)	(0.1276)
THIRD BIRTH	-0.2261	-0.0149
	(0.1493)	(0.2388)
FOURTH BIRTH	-0.0552	-0.2928
	(0.2712)	(0.4548)
FIFTH & SIXTH BIRTH	-0.0174	-0.8058
	(0.3801)	(0.6903)
WORKING (INCL. PART TIME)	0.5405 ***	0.7354 ***
	(0.0633)	(0.0880)

Table A3: Dissolution Transitions

	Women	Men
DISSOLUTION ORDER 2	-0.3074	
	(0.3061)	(0.2895)
DISSOLUTION ORDER 3 OR 4	-0.0294	0.0841
	(0.5252)	(0.5049)
COHORT 1950 – 1960	0.6332 ***	0.6654 ***
	(0.1256)	(0.1401)
COHORT 1960 – 1970	1.1336 ***	1.3202 ***
	(0.1478)	(0.1815)
COHORT 1970 +	1.8736 ***	1.6712 ***
	(0.2204)	(0.2724)
DID NOT LIVE W BOTH NATURAL PARENTS FROM BIRTH UP TO AGE 16	0.5218 ***	0.3572 ***
	(0.1189)	(0.1322)
FATHER PROFESSIONAL OCC.	0.1125	0.0740
	(0.1048)	(0.1193)
MOTHER PROFESSIONAL OCC.	0.0306	0.0788
	(0.1401)	(0.1564)
ETHNIC ORIGIN	0.1260	-0.0644
	(0.1848)	(0.2763)
SUB O-LEVEL QUALIFICATION	-0.1898	0.1501
	(0.1614)	(0.2244)
O-LEVELS OR EQUIVALENT	-0.1865	0.1194
	(0.1367)	(0.1775)
A – LEVELS OR EQUIVALENT	-0.0031	0.1431
	(0.1308)	(0.1541)
HIGHER QUALIFICATION	-0.0828	0.1443
	(0.1526)	(0.1752)
FIRST BIRTH	-0.2409 **	-0.5765 ***
	(0.1114)	(0.1219)
SECOND BIRTH	-0.2831 **	-0.3995 ***
	(0.1190)	(0.1451)
THIRD BIRTH	0.0041	-0.3401
	(0.1324)	(0.2157)
FOURTH BIRTH	0.2017	0.2630
	(0.2044)	(0.2954)
WORKING (INCL. PART TIME)	0.2215 **	0.0831
	(0.0889)	(0.1352)

Table A4: Employment Entries

	Women	Men
EMPLOYMENT ORDER 2	-0.4763 ***	-0.9114 ***
	(0.0761)	(0.1240)
EMPLOYMENT ORDER 3	-0.1767 *	-0.8783 ***
	(0.0993)	(0.1454)
EMPLOYMENT ORDER 4 OR HIGHER	0.0151	-0.9520 ***
	(0.1190)	(0.1544)
COHORT 1950 – 1960	0.1779 ***	-0.1940 ***
	(0.0390)	(0.0508)
COHORT 1960 – 1970	0.0223	-0.3944 ***
	(0.0445)	(0.0608)
COHORT 1970 +	-0.0643	-0.3791 ***
	(0.0635)	(0.0694)
DID NOT LIVE W BOTH NATURAL PARENTS FROM BIRTH UP TO AGE 16	0.0634	0.0177
	(0.0410)	(0.0582)
FATHER PROFESSIONAL OCC.	-0.1040 ***	-0.1384 ***
	(0.0379)	(0.0532)
MOTHER PROFESSIONAL OCC.	-0.1066 **	-0.0313
	(0.0516)	(0.0744)
ETHNIC ORIGIN	-0.4454 ***	-0.5195 ***
	(0.0702)	(0.0967)
SUB O-LEVEL QUALIFICATION	0.1536 ***	0.0136
	(0.0550)	(0.0796)
O-LEVELS OR EQUIVALENT	0.1910 ***	0.0790
	(0.0491)	(0.0646)
A – LEVELS OR EQUIVALENT	0.0719	-0.0908
	(0.0472)	(0.0564)
HIGHER QUALIFICATION	-0.3384 ***	-0.9084 ***
	(0.0533)	(0.0862)
FIRST BIRTH	-0.8402 ***	-0.2186 ***
	(0.0529)	(0.0783)
SECOND BIRTH	0.0355	-0.1927 **
	(0.0554)	(0.0835)
THIRD BIRTH	-0.2550 ***	-0.0100
	(0.0652)	(0.1041)
FOURTH BIRTH	-0.3277 ***	-0.6219 ***
	(0.1119)	(0.1547)
FIFTH & SIXTH BIRTH	-0.5858 **	-0.4822
	(0.2462)	(0.4064)
MARRIED OR COHABITING	-0.2875 ***	0.0539
	(0.0466)	(0.0659)

Table A5: Employment Exits

	Women	Men
UNEMPLYMENT ORDER 2	-1.2456 ***	-0.1405
	(0.0773)	(0.1211)
NON-EMPLOYMENT ORDER 3	-1.3764 ***	-0.2159
	(0.1106)	(0.1854)
NON-EMPLOYMENT ORDER 4 OR HIGHER	-1.4982 ***	-0.3358
	(0.1442)	(0.2419)
COHORT 1950 – 1960	0.2001 **	0.6976 ***
	(0.0808)	(0.0957)
COHORT 1960 – 1970	0.4847 ***	1.4182 ***
	(0.0831)	(0.1151)
COHORT 1970 +	1.3409 ***	2.2532 ***
	(0.1057)	(0.1440)
DID NOT LIVE W BOTH NATURAL PARENTS FROM BIRTH UP TO AGE 16	0.1886 **	0.0494
	(0.0782)	(0.0874)
FATHER PROFESSIONAL OCC.	-0.0935	-0.1997 **
	(0.0719)	(0.0835)
MOTHER PROFESSIONAL OCC.	-0.1494	-0.0103
	(0.0939)	(0.1112)
ETHNIC ORIGIN	0.1354	0.1259
	(0.1271)	(0.1536)
SUB O-LEVEL QUALIFICATION	-0.2330 **	-0.2912 **
	(0.1093)	(0.1376)
O-LEVELS OR EQUIVALENT	-0.6139 ***	-0.4298 ***
	(0.0976)	(0.1093)
A – LEVELS OR EQUIVALENT	-0.4706 ***	-0.3978 ***
	(0.0911)	(0.0970)
HIGHER QUALIFICATION	-0.3115 ***	-0.2671 **
	(0.1012)	(0.1339)
FIRST BIRTH	2.0790 ***	-0.0181
	(0.0512)	(0.0826)
SECOND BIRTH	-1.0061 ***	-0.0155
	(0.0564)	(0.0944)
THIRD BIRTH	-0.2559 ***	0.0457
	(0.0810)	(0.1183)
FOURTH BIRTH	-0.0731	0.3016
	(0.1268)	(0.2012)
FIFTH & SIXTH BIRTH	0.3840	0.4655
	(0.2553)	(0.4355)
MARRIED OR COHABITING	0.8027 ***	-0.0787
	(0.0510)	(0.0747)

Table A6: S. D. of Unobserved Heterogeneity Terms

	WOMEN	MEN
FERTILITY:	0.9430 ***	0.7913 ***
	(0.0463)	(0.0696)
UNION FORMATION:	0.8396 ***	0.7776 ***
	(0.0703)	(0.0868)
UNION DISSOLUTION:	0.8333 ***	0.8036 ***
	(0.2175)	(0.2268)
EMPLOYMENT:	0.2214 ***	0.4221 ***
	(0.0454)	(0.0416)
NON-EMPLOYMENT:	0.9711 ***	0.8517 ***
	(0.0410)	(0.1005)

Table A7: Correlations between Unobserved Heterogeneity Terms

	WOMEN	MEN
FERTILITY & UNION FORMATION:	0.4809 ***	0.5460 ***
	(0.0567)	(0.0886)
FERTILITY & DISSOLUTION:	0.2525 **	0.2852 *
	(0.0989)	(0.1500)
FERTILITY & EMPLOYMENT ENTRY:	0.4548 ***	0.2717 ***
	(0.1326)	(0.0890)
FERTILITY & EMPLOYMENT EXITS:	0.5632 ***	0.1239 *
	(0.0400)	(0.0693)
UNION FORMATION & DISSOLUTION:	0.5135 ***	0.3221
	(0.1228)	(0.2094)
UNION & EMPLOYMENT ENTRY:	0.7789 ***	0.6166 ***
	(0.1395)	(0.0992)
UNION & EMPLOYMENT EXITS:	0.0876 *	-0.0806
	(0.0487)	(0.0721)
DISSOLUTION & EMPLOYMENT ENTRY:	0.0031	-0.2513
	(0.1652)	(0.1641)
DISSOLUTION & EMPLOYMENT EXITS:	0.5088 ***	0.5262 ***
	(0.1142)	(0.1350)
EMPLOYMENT ENTRY & EMPLOYMENT EXITS:	0.1113	-0.0451
	(0.1379)	(0.1145)

Appendix B: Poverty Assignment Tables

Table B1: Poverty Rates used in the Simulations, by year and state

MALES

state/year	1991	1992	1993	1994	1995	1996
notM notE 0	54.9	56.5	54.5	57.9	58.4	55.3
notM notE 1	64.0	74.8	76.0	72.5	69.9	77.2
notM notE 2	70.7	82.5	83.8	79.9	77.1	85.2
notM notE 3+	89.4	104.4	106.0	101.2	97.6	107.8
notM EMP 0	3.1	3.5	3.2	3.8	2.5	3.0
notM EMP 1	3.4	3.9	4.0	3.8	3.7	4.1
notM EMP 2	4.9	5.7	5.8	5.5	5.3	5.9
notM EMP 3+	16.1	18.8	19.1	18.2	17.6	19.4
Marr notE 0	22.5	20.2	21.1	19.6	19.0	20.7
Marr notE 1	47.5	50.0	53.1	52.4	43.3	46.3
Marr notE 2	63.3	66.7	53.6	52.0	69.1	76.3
Marr notE 3+	84.0	98.0	99.6	95.0	91.7	101.3
Marr EMP 0	1.0	1.2	1.4	1.5	1.4	0.6
Marr EMP 1	3.2	3.5	3.0	2.5	3.1	2.9
Marr EMP 2	7.5	6.1	6.6	5.8	5.7	6.0
Marr EMP 3+	16.3	14.8	19.9	15.2	17.2	21.1

FEMALES

state/year	1991	1992	1993	1994	1995	1996
notM notE 0	49.0	45.8	47.4	54.2	43.8	54.8
notM notE 1	75.7	77.7	74.6	82.5	81.3	86.7
notM notE 2	83.9	95.1	80.0	88.7	87.2	102.2
notM notE 3+	94.4	107.0	112.8	109.5	106.0	114.9
notM EMP 0	6.5	3.4	3.5	2.9	4.0	3.5
notM EMP 1	18.1	19.6	21.6	20.9	20.3	25.0
notM EMP 2	28.6	32.5	34.2	33.2	32.1	34.9
notM EMP 3+	44.9	50.9	53.7	52.1	50.4	54.7
Marr notE 0	8.8	9.7	10.6	12.0	14.1	12.6
Marr notE 1	20.6	20.3	22.6	23.1	23.3	21.5
Marr notE 2	26.6	31.5	27.2	28.9	29.6	31.8
Marr notE 3+	42.9	49.5	51.9	49.2	47.0	62.1
Marr EMP 0	1.2	1.3	1.9	1.8	1.3	0.8
Marr EMP 1	1.1	3.2	3.3	3.3	2.1	4.4
Marr EMP 2	3.4	5.0	4.1	2.6	3.2	4.5
Marr EMP 3+	11.9	5.9	10.8	12.1	15.3	12.0

As is shown in Tables B4, there are states in which even in the FES, the numbers in the state in each year are insufficient to give a non-noisy poverty rate. We consider 100 observations sufficient to provide a non-noisy poverty rate. This is inevitable given that, for example, being a single male working father of 3 children is not very likely in any year in a sample based dataset, especially when the sample sizes are cut down further by the requirements of full income information in each year. However, in almost every state-year we have more observations in the FES data, considerably more so in the case of the married states.

In the cases in which there are insufficient observations in a state, we impute the state poverty rate by taking the ratio of the mean poverty rate in the state across all years to the mean poverty across all states and all years, and multiply this by the mean poverty rate (across all states) in the year in question:

$$\Pi_{st} = \frac{\overline{\Pi}_s}{\overline{\overline{\Pi}}} * \overline{\Pi}_t$$

This procedure is used to obtain the poverty rates in each year for the following male states:
not married, not employed, 1 child;
not married, not employed 2 children;
not married, not employed, 3+ children;
not married, employed, 1 child;
not married, employed, 2 children;
not married, employed, 3+ children;
married, not employed, 3+ children.
The procedure is also used to obtain the poverty rate in 1991 only for the state: married, not employed, 1 child; and is used in the years 1991, 1995 and 1996 to obtain the poverty rate for the state: married, not employed, 2 children.
The states for the females that rely on this procedure in every year are:
not married, not employed, 3+ children;
not married, employed, 2 children;
not married, employed, 3+ children.
The procedure is also used to obtain the poverty rate for the state: not married, not employed, 2 children, in 1991, 1992 and 1996; and in 1991, 1993, 1994 and 1995 for the state: not married, employed, 1 child.

Table B2: Number of Observations and Poverty Rates by state, used for the second set of micro-simulations

MALES

State	Poverty Rate	No. obs
notM notE 0	56.3	1138
notM notE 1	63.5	74
notM notE 2	78.6	28
notM notE 3+	94.7	19
notM EMP 0	3.2	2275
notM EMP 1	19.2	100
notM EMP 2	21.9	49
notM EMP 3+	43.5	10
Marr notE 0	20.5	1328
Marr notE 1	48.6	591
Marr notE 2	59.5	603
Marr notE 3+	81.3	497
Marr EMP 0	1.2	6516
Marr EMP 1	3.0	3479
Marr EMP 2	6.3	4319
Marr EMP 3+	17.4	1791
Total		22817

FEMALES

State	Poverty Rate	No. obs
notM notE 0	49.1	903
notM notE 1	79.8	672
notM notE 2	84.2	551
notM notE 3+	92.2	371
notM EMP 0	3.9	2035
notM EMP 1	23.6	564
notM EMP 2	26.8	392
notM EMP 3+	53.3	122
Marr notE 0	10.9	2547
Marr notE 1	21.8	1450
Marr notE 2	29.2	1751
Marr notE 3+	50.6	1163
Marr EMP 0	1.4	5297
Marr EMP 1	2.9	2620
Marr EMP 2	3.8	3171
Marr EMP 3+	11.4	1125
Total		24734

As we can see for the males, there are some states in which, despite the FES data being pooled over all 6 years, there are still few individuals in the state. In the states “notM EMP 1”, “notM EMP 2” and “notM EMP 3+” this led to erratic and unreliable poverty rates. In each of these problem male states the corresponding female state has sufficient numbers to provide a reliable poverty rate. Therefore in these states, we derived a poverty rate by taking the ratio of the female poverty rate to the male poverty rate for the “notM EMP 0” state – for which both females and males have sufficient numbers to provide a reliable poverty rate – and multiplied the female state poverty rate for the problem states by this ratio and imputed this as the male poverty rate in these problem states.

Table B3: Frequency Distributions for the Number of Observations with Income Non-Missing in the BHPS Estimation Sample

MALE

Number	Frequency	Percent	Cumulative
0	79	3.16	3.16
1	135	5.40	8.56
2	244	9.76	18.33
3	207	8.28	26.61
4	231	9.24	35.85
5	336	13.45	49.30
6	1267	50.70	100.00
Total	2499	100.00	

FEMALE

Number	Frequency	Percent	Cumulative
0	154	5.86	5.86
1	181	6.88	12.74
2	220	8.37	21.10
3	206	7.83	28.94
4	210	7.98	36.92
5	359	13.65	50.57
6	1300	49.43	100.00
Total	2630	100.00	

Table B4 (M): Number of Observations with Income Non-Missing in the BHPS Estimation Sample and in the FES, by year and state

MALE

	1991		1992		1993		1994		1995		1996	
state/year	**BHPS**	**FES**	**BHPS**	**FES**	**BHPS**	**FES**	**BHPS**	**FES**	**BHPS**	**FES**	**BHPS**	**FES**
notM notE 0	128	164	176	214	172	178	185	197	112	197	94	188
notM notE 1	3	15	2	11	4	13	4	7	3	8	2	20
notM notE 2	2	2	1	4	1	5	2	5	2	5	1	7
notM notE 3+	0	3	1	3	2	5	1	2	0	3	1	3
notM EMP 0	393	419	436	401	372	374	358	391	352	358	355	332
notM EMP 1	8	13	6	20	5	14	7	18	11	20	10	15
notM EMP 2	1	6	1	8	1	9	0	12	1	4	0	10
notM EMP 3+	1	1	0	3	0	1	0	3	1	2	0	0
Marr notE 0	39	191	52	248	45	265	51	209	48	231	51	184
Marr notE 1	31	90	29	106	22	98	26	105	25	97	30	95
Marr notE 2	39	99	41	126	36	110	29	98	30	80	26	90
Marr notE 3+	19	71	25	90	23	82	31	88	24	71	21	95
Marr EMP 0	458	1173	565	1167	518	1035	475	1074	494	1049	527	1018
Marr EMP 1	268	619	280	602	266	564	295	554	253	555	240	585
Marr EMP 2	355	731	338	758	299	722	276	710	264	736	282	662
Marr EMP 3+	120	295	116	311	108	316	100	289	100	296	94	284
Total	1865	3892	2069	4072	1874	3791	1840	3762	1720	3712	1734	3588

Table B4 (F): Number of Observations with Income Non-Missing in the BHPS Estimation Sample and in the FES, by year and state

FEMALE

	1991		1992		1993		1994		1995		1996	
state/year	**BHPS**	**FES**	**BHPS**	**FES**	**BHPS**	**FES**	**BHPS**	**FES**	**BHPS**	**FES**	**BHPS**	**FES**
notM notE 0	75	143	136	168	126	156	122	177	106	144	84	115
notM notE 1	40	103	56	112	54	122	59	103	53	112	44	120
notM notE 2	27	64	22	94	18	100	20	97	22	109	17	87
notM notE 3+	19	47	23	61	16	72	18	65	10	68	14	58
notM EMP 0	305	325	337	355	288	342	294	345	259	354	266	314
notM EMP 1	53	75	52	107	49	97	46	90	46	95	54	100
notM EMP 2	29	55	31	61	23	61	27	73	23	67	27	75
notM EMP 3+	8	15	8	23	7	28	3	14	2	21	2	21
Marr notE 0	71	514	94	544	87	529	79	334	85	333	108	293
Marr notE 1	87	272	81	301	78	243	86	238	82	215	77	181
Marr notE 2	126	323	130	324	104	316	92	270	73	260	90	258
Marr notE 3+	59	189	56	216	54	212	52	187	57	164	49	195
Marr EMP 0	511	850	585	871	532	771	514	949	510	947	513	909
Marr EMP 1	210	437	205	407	195	419	216	421	190	437	209	499
Marr EMP 2	245	507	223	560	198	516	176	538	179	556	173	494
Marr EMP 3+	75	177	69	185	63	186	59	190	47	203	45	184
Total	1940	4096	2108	4389	1892	4170	1863	4091	1744	4085	1772	3903

Note: the state labels identify: the de facto marital status in the state: not married (notM) or married (Marr); the employment status of the state: not employed (notE) or employed (EMP); and the number of children that the individual in this state has: 0,1,2 or 3+.

Appendix C: Reconciling FES and BHPS

For our approach to modelling poverty to succeed, the FES poverty rates and the BHPS poverty rates should be close to one another. We compare the overall male and female poverty rates in each dataset in each year from 1991-1996, and compare the poverty lines in each year (see Table C1 below). In doing so we discover a problem in that, despite the poverty lines being close in terms of equivalised (McClements) £s, the BHPS poverty rates are systematically lower than the corresponding rates from the FES. This presents a problem as we will not be able to fit poverty at all in the simulations if the poverty rates that we use in them are systematically higher than in the "real" BHPS data – we will always be over predicting poverty.

Looking at the distribution of income in each dataset reveals that, in each year, the driving force behind the disparity is the difference in the distribution of income amongst workers and non-workers in the two datasets. Graphs C(i) and C(ii) below, show respectively, the distribution of income in 1996 for male BHPS members of our estimation sample and the corresponding distribution for males in the FES. In each case the poverty line is marked. We can see that there is a large spike just below the poverty line in the FES income distribution – hence the differing poverty rates.

Graphs C(iii) – C (vi) below, reveal that this is the case because the income of non-workers in the BHPS is more spread than is the case in the FES. The non-worker incomes in the FES are much more positively skewed to the right with a large spike just below the poverty line, pushing the poverty rate up markedly higher than the BHPS poverty rate. The BHPS non-worker incomes are positively skewed but much less so than the FES, the non-workers exhibiting more of a spread of incomes and with much less of a spike just below the poverty line. The graphs show similar features in each year from 1991-1995 and can be obtained on request from the authors. The female graphs exhibit the same patterns and can similarly be obtained from the authors.

However, though we know the reason why the rates are different, we cannot simply lower the FES state poverty rates in certain states as it would be arbitrary as to what they should be lowered to – it is because in many states in each year of the BHPS we do not have sufficient numbers to give reliable estimates of the state poverty rates that we use the FES.

The solution to this problem is to calculate the FES poverty rate across **both** men and women in each year, and use this as the benchmark, evaluated as it is over many more individuals than are in the BHPS in each year. The mean number of observations on men and women in each year of the FES is 7925 – more than double the BHPS mean of 3854, and in each year it is the case that the FES has approximately double the number of observations in the BHPS (for details see Table C2 below). We then take our sample of BHPS individuals and raise the monetary value of the poverty line in each year such that the overall poverty rate across men and women is the same in each year of the BHPS as the overall poverty rate across men and women in each year of the FES. We look at the poverty rates across the men and women together so that we generate a household poverty status – if we had looked to raise the poverty lines such that the annual male poverty rates in the BHPS were equal to the corresponding FES rates and done likewise for the females, we would be in danger of creating cases where, for example, the male in a household is in poverty but the female in the household – who has the same household income – is not in poverty due to the differing income distributions of males and females. As poverty is a feature of households rather than individuals, we align the poverty rates across men and women together in each year, in each of the datasets.

Since we know that the non-workers' incomes are more spread out in the BHPS sample and that they overlap more with workers' incomes, we know that as we raise the poverty line, we will arrive at the FES aggregate poverty rate before we reach the level of poverty in the real BHPS non-worker states that we find in the FES non-worker states – therefore the poverty rates in the real BHPS non-worker states will be below the corresponding FES figures. Moreover, as we have raised the poverty line we have placed more of the lower income workers – those with similar net household incomes as the non-workers – in poverty, thus increasing the poverty rate in some working states in the real BHPS data above what it is in the FES. Thus the poverty rates in certain states will be higher in the real BHPS data than is the case in the FES (which we use to provide the poverty rates in the simulations), and lower in other states; however by raising the poverty line we have made poverty in the BHPS more like the poverty in the FES.

The rates in the FES states used for the simulations and the "real" BHPS are clearly not going to be identical. That would give a perfect test of the simulations since if the model fitted the demographic and employment states occupation correctly we would then have the poverty rate exactly right. Rather the poverty rates that we use from the FES are similar, they are not perfectly right in every state – some are too high, some are too low – but they are close enough that if we simulate the demographic and employment transitions accurately we will have an overall poverty rate which is close to the real BHPS poverty rate since we know that in the BHPS the overall rate is the same as it is in the FES.

For this strategy to be effective the relationship between the male and female components of overall poverty in the BHPS have to be the same as they are in the FES. The reason why we have to make this assumption is because it is the overall (across men and women) poverty rates that are lined up to be the same in each year, in both datasets. The aggregate male poverty rate and the aggregate female poverty rate in each year will only be the same in each dataset if the male contribution to aggregate poverty and female contribution to aggregate poverty is the same in each dataset. We can check this by calculating the male and female poverty rates separately in each dataset in each year from 1991-1996. Table C3 shows the annual poverty rates for each gender in our BHPS sample with the poverty line raised such that the poverty rate across men and women is the same as it is in the FES. Alongside these in the table are the annual poverty rates for each gender in the FES. We can see that in each year though the male poverty rates are not identical, they are very close, slightly higher in the BHPS than is the case in the FES. Given that we know the poverty rate across men and women in the BHPS is equated to the corresponding rate in the FES, the male BHPS rates being slightly higher than the male FES rates dictates that the BHPS female rates must be lower than the corresponding FES rates. Again though, they are very close in each year.

As the male and female poverty rates in each year in the BHPS are very close to the corresponding rates in the FES, we know that for each gender the state poverty rates in the simulations will aggregate out to be close to the real BHPS figure, if the demographic and employment transitions are accurately modelled. Differences in the poverty experience between the “real” data and the simulations will primarily reflect differences in demographic and employment state occupation and the fact that there is no persistence in income in the simulations.

Table C1: BHPS (in sample) and FES annual poverty rates and poverty lines

MALE POVERTY RATES

Year	BHPS	FES
91	7.74	11.54
92	7.98	13.26
93	8.46	13.35
94	7.39	12.79
95	6.79	12.23
96	6.45	13.32

ANNUAL POVERTY LINES IN MCCLEMENTS EQUIVALISED £S

Year	BHPS	FES
91	112.22	134.15
92	116.05	124.42
93	119.94	126.92
94	122.40	132.73
95	130.30	137.77
96	136.66	139.96

FEMALE POVERTY RATES

Year	BHPS	FES
91	9.88	14.79
92	9.39	16.68
93	9.20	17.67
94	8.15	17.26
95	9.35	16.35
96	8.57	17.81

Poverty rates are calculated for all individuals in households in which the head of household is 60 years old or younger. The poverty line in each case is set at 50% of the median (before housing costs) net household equivalised (McClements) income. The median is assessed whilst all individuals within each household are in the data with their household income recorded, hence it is an individual level measure of poverty. In the FES, in all couple households the man is taken to be the head of the house. Therefore in order to construct female poverty rates it is necessary to include married males as females.

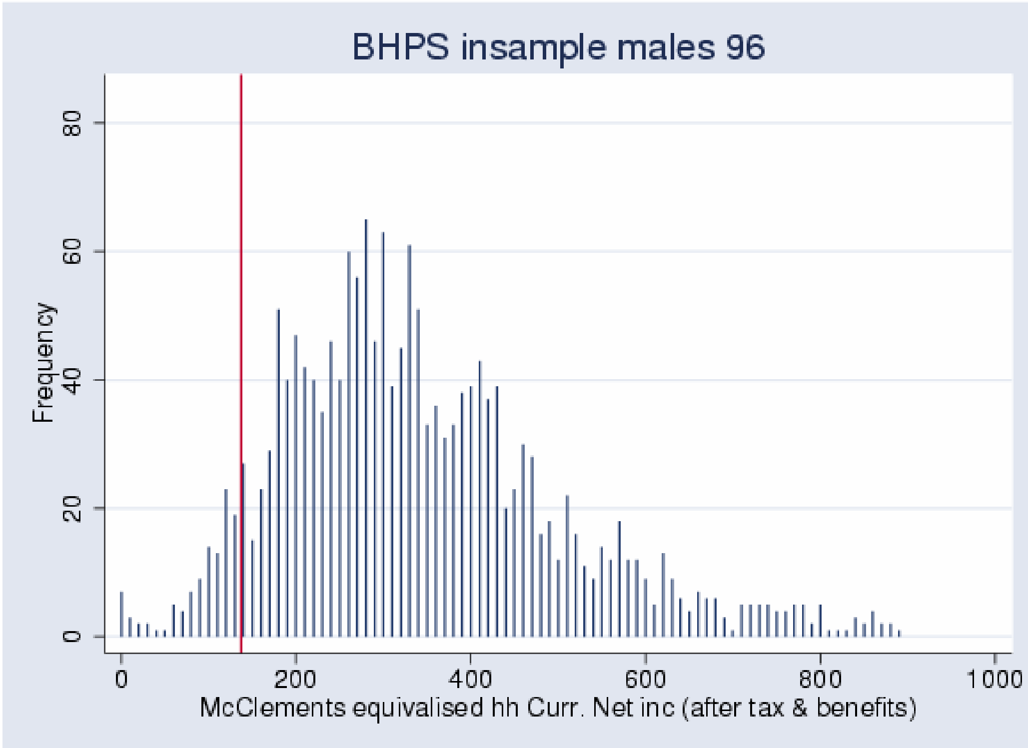
Table C2: Number of Observations with Income Non-Missing across male and females combined in the BHPS Estimation Sample and in the FES, by year

Year	BHPS	FES
1991	3914	7988
1992	4311	8461
1993	3876	7961
1994	3814	7853
1995	3583	7797
1996	3626	7491
Total	23124	47551

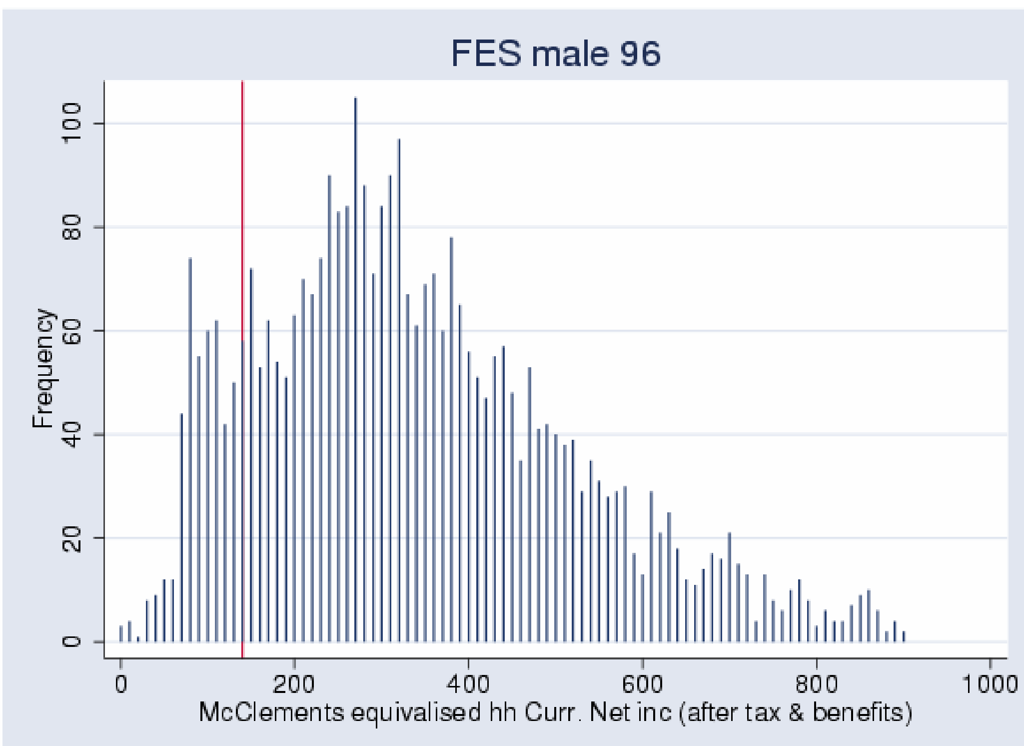
Table C3: BHPS and FES annual poverty rates, by gender

	Male Poverty		Female Poverty	
Year	BHPS	FES	BHPS	FES
1991	11.8	11.3	14.6	15.1
1992	13.9	13.1	16.6	17.1
1993	14.8	13.3	16.9	18.0
1994	14.2	12.7	16.5	17.5
1995	13.3	12.3	16.6	16.9
1996	13.6	13.6	18.2	18.4

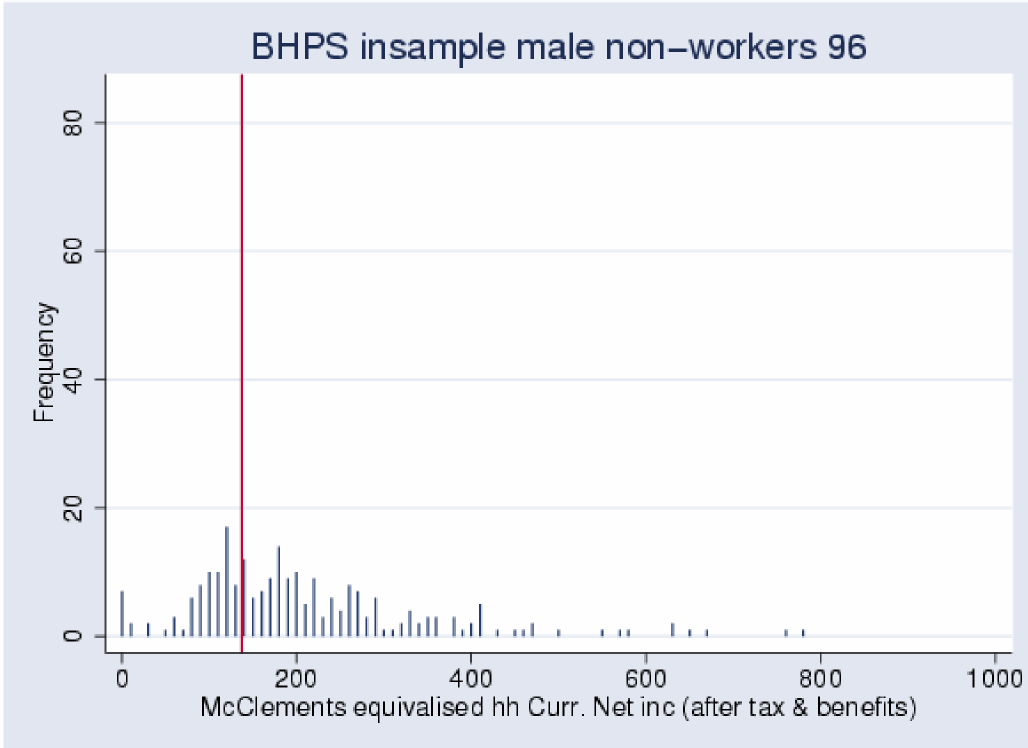
Graph C(i)



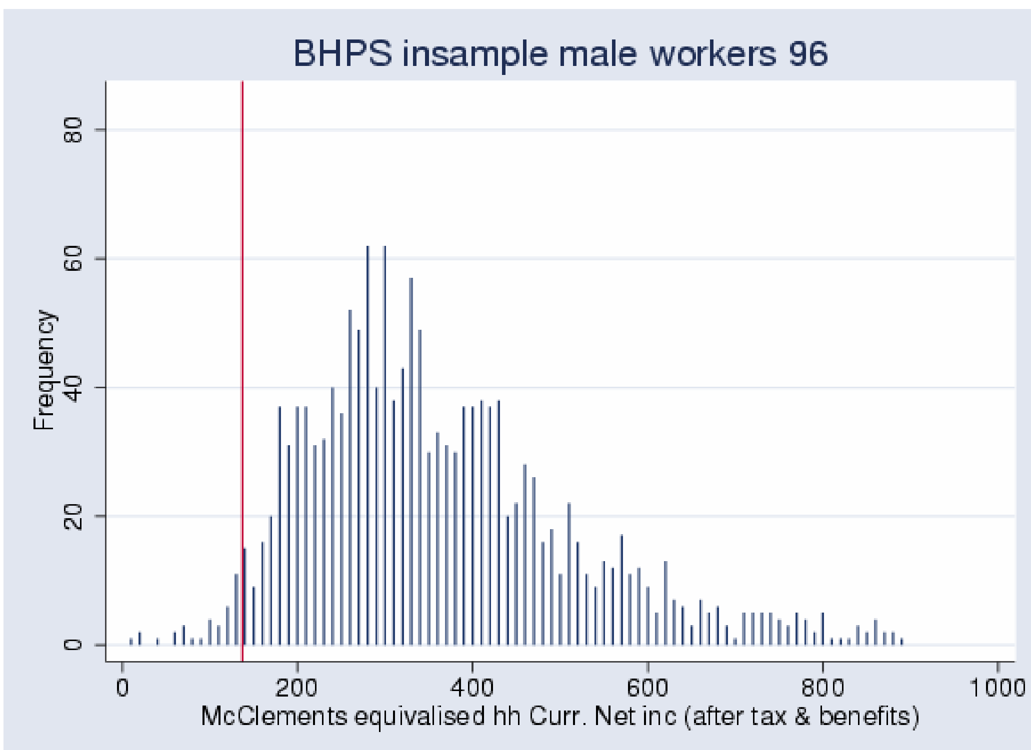
Graph C(ii)



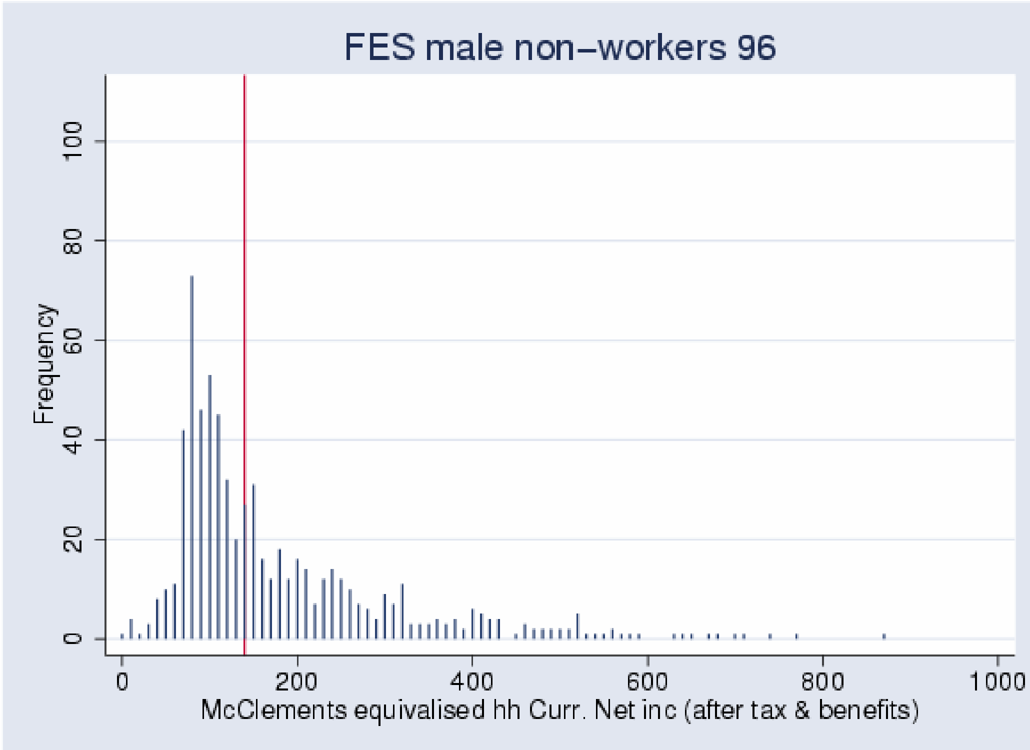
Graph C(iii)



Graph C(iv)



Graph C(v)



Graph C(vi)