POVERTY PERSISTENCE IN BRITAIN: A MULTIVARIATE ANALYSIS USING THE BHPS, 1991-1997

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Abstract

This paper uses longitudinal data from the BHPS, waves 1-7, to document low-income dynamics for individuals living in Britain in 1990s. Poverty entry and exit hazard rates are estimated and used to calculate the distribution of time spent poor over a six-year period. The results underline the importance of accounting for individuals' repeated spells of poverty when measuring poverty persistence. Using discrete-time proportional hazard rate models, the paper then seeks to 'explain' and forecast the observed chances of exit/entering poverty and the distribution of time spent in poverty for individuals with selected characteristics. The socio-economic correlates of the observed poverty patterns are investigated, including the relative importance of both household and individual characteristics.

Keywords: poverty dynamics, poverty persistence, multiple spells, hazard rate models

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1 INTRODUCTION

This paper presents new evidence on poverty dynamics and poverty persistence in Britain in the 1990s, using longitudinal data from the British Household Panel Survey (BHPS), waves 1-7. Until recently, policymakers interested in poverty have mainly relied on information coming from cross-sectional studies, in which the focus is the static view of poverty intensity at a point in time, as measured say by the proportion of the population whose income is below a low income threshold.

A more complete picture of the poverty problem, however, requires that this static view be supplemented by longitudinal information about the length of time people spend with low incomes, and this can only be estimated if panel data are available. For the design of effective anti-poverty measures it is important to know whether poverty is a transitory status that a large proportion of individuals in the population experience at some time or another in their lifetime, or is rather a persistent curse that sticks on groups with particular socio-economic characteristics. Government's programs also try to alleviate poverty by providing assistance to those with low incomes. Given that these intervention schemes can be highly expensive it becomes crucial to provide the policymakers with indications on how to tailor specific policy measures to the most at risk groups. In this respect, identifying those groups of the population which tend to suffer longer and recurrent spells of poverty and so remain eligible for public assistance year after year becomes of particular policy relevance.

Jarvis and Jenkins (1997) use the first four waves of the BHPS to study the dynamics of low income in 1990s Britain, the size of the 'persistent poverty' problem and the amount of low income turnover. Low income exit and re-entry rates are estimated and these are then used to calculate the distribution of total time spent below the poverty line out of a 3-year window. This provides a first estimate of poverty persistence in Britain over repeated spells. As individuals who exit low income are at risk of falling back below the poverty line, and particularly so soon after the transition out of poverty, it assumes relevance to provide a measure of poverty persistence that takes into account both the chances of exiting and the chances of re-entering. Jarvis and Jenkins (1997) also use various cross-tabulation techniques to examine the characteristics and events associated with making a transition out of low income or making a transition into low income. This allows them to investigate the extent to which those who remain poor for most of the observation window (persistent poor) are systematically different from those who tend to have short spells in and out poverty (transitory poor). Jenkins (1999) uses the first six waves of the BHPS and provides further analysis of income and poverty dynamics in Britain and their socioeconomic correlates. He applies the pioneering methods of Bane and Ellwood (1986) to British data and reviews the multivariate modelling framework which might be used to explain and forecast observed patterns in poverty dynamics. Even though he provides estimates for the exit and re-entry rates, he does not calculate the distribution of time spent in poverty over multiple spells. Nor does he apply any multivariate methods to his data.

This paper extends previous UK research in two ways. First, I expand the observation window to the first seven waves of the BHPS. With four waves only the pattern of possible repeated spells is clearly drastically limited and poverty persistence can only be assessed over a very short interval of time. As the panel length increases, however, the estimate of the total time spent below the poverty line becomes both more interesting and more accurate. I first calculate exit and re-entry rates over a six-year time interval and then use them to estimate a measure of poverty persistence over multiple spells. These calculations constitute a longitudinal complement to the British official statistics on low income (Department of Social Security, 1999), largely based on cross-section data. Similar estimates of poverty persistence over multiple spells already exist for the US (Stevens, 1999) and their development should be encouraged in other countries too.

Second, I employ a multivariate modelling approach to help us understanding the factors more likely to be associated with recurrent transitions in and out of poverty or more permanent stay below the low income cut-off. In particular I estimate discrete-time proportional hazard rate models for both exit and re-entry rates, controlling for duration dependence and a bunch of fixed and time-varying covariates. This allows me to present new evidence on the determinants of the length of time people spend in poverty. The relative importance of individual and household characteristics and local economic conditions is investigated and results are then used to derive forecasts of the poverty experience of different groups of the population.

2 DATA AND DEFINITIONS

The data used in this analysis are from the BHPS, waves 1 to 7. The first wave of the BHPS was designed as a nationally representative sample of Great Britain living in private households in 1991. First wave interviews were carried out in autumn 1991 and households interviewed were selected by an equal probability sampling mechanism. The achieved sample comprises about 5,000 households, which correspond to a response rate of about 65 per cent of effective sample size. At wave 1, over 90 per cent of eligible adults (approximately 10,000 individuals) provided full interviews. Original sample respondents have been followed and reinterviewed at approximately one-year intervals subsequently. Children in original sample households are also interviewed when they reach the age of sixteen. The sample therefore remains broadly representative of the British population as it changes through the decade.[1] At each interviews, respondents are asked detailed questions related to their income, employment status, household composition and individual demographics.

The definitions I use for my analysis of poverty dynamics are standard, at least within UK research on the topic. The unit of analysis is the individual, this being necessary to follow individuals as they move from one household situation to another over time. However as individuals live in households where they share resources and events, I assume that the living standard of an individual is measured with reference to the net income of the household to which s/he belongs. The net household income variables that I use in the paper have been recently provided by Bardasi, Jenkins and Rigg (1999), as an unofficial supplement to the BHPS data. Household net income is: the sum across all household members of cash income from all sources (income from employment and self-

[1] The wave-on-wave response rate was about 88 per cent for wave 1 to wave 2, and over 90 per cent thereafter.

employment, returns from investments and savings, returns from private and occupational pensions, and other market income, plus cash social security and social assistance receipts plus private transfer) minus direct taxes (income tax, employee National Insurance contributions). All incomes have been converted to January 1998 prices. To account for differences in household size and composition, net household income is divided by the 'McClements Before Housing Costs' equivalence scale rate.[2] The time period over which income is measured is the year, and in particular refers to the 12 months interval up to September 1 of the year of the relevant interview year. For example the wave 6 annual income refers to the period 01.09.95 until 31.08.96.[3] In what follows "poor" is anybody whose 'needs-adjusted household net income' is less than a chosen poverty line. Reflecting previous UK research, I have initially considered two alternative definitions for the low income cut-off: half wave 1 mean income is chosen as an absolute (fixed in real terms) poverty line, while half contemporaneous mean income is taken as a relative poverty line.

To each poverty and non-poverty spells experienced by a sample member, I have attached a vector of demographic and labour market characteristics which are generally time-varying, unless otherwise specified. For transitions occurred between time t and t+1, covariates refer to the value that the relevant characteristics assume at time t.[4] In addition, I have matched in the unemployment rate in each individual's travel-to-work area to provide information on local labour market conditions.[5]

For the cross-section analysis (Table 1), I work with the subsample of those individuals for whom household net income could be calculated. As explained in Bardasi, Jenkins and Rigg (1999) this could be done only when all eligible households members gave a full interview. For the dynamic analysis (Tables 2-9), I additionally restrict the sample to the 6,425 persons (adult and children) present in each of the seven waves of the BHPS and whose household net income could be estimated at each wave. This last restriction, which amounts to eliminating those individuals whose income sequences features missing income information at some waves, is necessary in order to determine the exact length of current and past poverty and non-poverty spells. The further requirement of a balanced panel subsample follows by the objective of examining the low income status of the individuals over a seven-wave observation window.[6,7]

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[2] The scale rate for a childless married couple is normalised to 1.0; for single householder the rate is 0.61; rates also vary by children's age (see Department of Social Security, 1999).

[3] Previous UK research on poverty dynamics using the BHPS has used *current* income instead of *annual* income. Current income is defined with reference to the month prior to the date of the interview. There are advantages and disadvantages with both measures (see Jenkins, 1999). However, my estimates of the exit and re-entry rates obtained with annual income (Table 4 and 5 in the appendix) do not differ much from those obtained by Jenkins (1996) using current income. See also Böheim and Jenkins (2000).

[4] This should reduce endogeneity and simultaneity problems.

[5] The local market information is taken from the National Online Manpower Information Service (NOMIS), and is matched to the BHPS by date of interview and travel-to-work area.

[6] The analysis of Jenkins (1999) is instead based on an *un*balanced subsample of the BHPS, comprising all persons (in complete respondent households) for all waves in which they are in the panel. His estimated exit and re-entry rates are very similar to the ones I estimate below using my balanced subsample. Attrition bias does not seem then to constitute a major problem in this data set.

[7] Once the sample has been restricted to those individuals living in complete respondent households at each wave in which they are in the panel, then of the 9528 persons present at wave 1, 8398 (88%) are still in the panel at wave 2, 7707 (81%) still at wave 3, 7303 (77%) still at wave 4, 6808 (71%) still at wave 5, 6646 (70%) still at wave 6 and 6425 (67%) are present at each of the seven waves.

3 STATIC VERSUS DYNAMIC POVERTY PERSISTENCE: NEW EVIDENCE FOR BRITAIN

3.1 Cross-section poverty rates and poverty persistence

Table 1 (all tables are collected in the appendix) provides a standard cross-sectional perspective on changes in the distribution of needs-adjusted household income in Britain during the 1990s, derived from the BHPS. Over this period, average income rose on average by about 8 per cent and, partially reflecting this, the proportion of individuals with income below the absolute poverty line has decreased, at last from 1993 to 1996.[8] This downward trend in poverty levels is somewhat less evident if the relative poverty line is considered instead. As the two low income cut-offs do not give a dramatically different picture, I have decided for sake of brevity to focus on the absolute one only in what follows.[9]

The static view offered in Table 1 can be compared with the longitudinal perspective pictured in Table 2 and 3, in which the focus is the individuals' poverty experience over the entire time period. Although poverty rates at a point of time are on average about 15% (Table 1), much higher is the fraction of the population that had low incomes at one period or another. Table 3, in fact, shows that almost one third (32%) of the sample is touched by poverty at least once and confirms the well-established fact that the number of people experiencing low income over a period of time is fundamentally different from that at a point in time. Table 2 highlights that in many cases individuals have non-consecutive interviews in poverty (multiple spells). When we turn the attention to those persistently in poverty, we notice that only a tiny minority (1.8%) had low income at each of the seven waves, while the great majority (68%) has never been poor in the 1991-1997 period. The expected stay in poverty for someone just entering in the panel and who will be interviewed for the next 7 years is only 0.78 years. If we consider those who ever become poor, the expected time spent below the poverty line is about 2.9 years.

So far I have simply counted the number of waves spent in poverty for the individuals in my data set, but it is well known that this simple descriptive method has an important shortcoming. People who end (or begin) the period in poverty may be starting a long stay in poverty, despite the fact that they appear to be poor only in one or two of the observed years. This leads to an understatement of poverty persistence, since some of those observed to be poor only a short time are actually in the midst of lengthy poverty spells that are censored by the beginning or end of the sample frame. In response to this problem, researchers have devised more appropriate approaches for studying income and poverty dynamics and these have been discussed in some details by Bane and Ellwood (1986), Jenkins (1999) and Stevens (1999), among others. Not only are these more advanced techniques immune from the previous problem, they also lend themselves to multivariate analyses of the factors that affect transitions in and out of low income. Among them, Jenkins distinguishes between (a) longitudinal poverty pattern models: e.g.,

[8] Over the 1990s inequality in needs-adjusted household net income, as measured by the Gini coefficient, barely changed in my sample. It was equal to 0.30 in 1991 and 0.31 thereafter.

[9] Estimated survivor functions for those just starting a spell with their income above (below) the relative poverty line are similar to those obtained with the absolute poverty line and discussed below. For this reason only the latter are reported in the appendix tables.

Hill and Jenkins (1998), (b) variance components models: e.g., Duncan and Rodgers (1991), Stevens (1999), (c) transition probability models, e.g. Stevens (1999), Cantó (1996), and (d) structural models, e.g. Burgess and Propper's (1998). Both offer advantages and disadvantages that Jenkins describes in terms of the different degree to which they satisfy three main desiderata: "being practical models", "fit the past and be able to provide forecasts about the future", and "being structural". As he discusses, an approach may come closer to one of these desiderata but be less appropriate for satisfying the others, and the challenge for the analyst is to find a balance between the various trade-offs. Here I do not intend to compare these alternative approaches any further as the interested reader can refer to the existing review sections of the papers mentioned above. I would rather simply quote Jenkins' remark that "the number of applications of these multivariate models to income dynamics is actually very small, at least by comparison with models of the dynamics of wages, welfare benefit receipts, (un)employment, and household formation". In the next section I only employ transition probability models to study poverty persistence, leaving to future research the comparison of predictions obtained from transition probability models with those obtained by employing variance components models. This sort of evaluative work has been undertaken for the US by Stevens (1999) but has not been done for the UK yet.[10]

3.2 Low income exit and re-entry rates

I start analysing the broad pattern of exit from and returning into poverty by using simple non-parametric estimates of the exit and re-entry rates, and look at how they vary with the length of time people have had in poverty and out of poverty, respectively. The exit rates that are relevant in this context are the ones that refer to a cohort of persons just falling into poverty and hence at risk of exit thereafter. The re-entry rates refer instead to a cohort of persons just starting a spell out of poverty, and so at risk of re-entering.[11] Exit rates are calculated by dividing the number of persons ending a spell after d years in poverty by the total number with low income for at least d years. Re-entry rates were calculated analogously. Unlike the simple count of number of years in poverty, the spell-approach can easily incorporate right-censored spells. Persons who remain in poverty through the end of the sample contribute to the estimation of the exit rates (through the denominator of the exit rates) in all years through the censored year. In my 7-wave data set, the exclusion of left-censored spells implies that only spells just starting in wave 2 or in later waves can be considered. Therefore, exits from the state can occur only at any of the at-most 5 interviews following the one in which the individuals is first found in poverty. Including the latter, then, each individual can be observed between 1 or at most 6 interviews in poverty.

[10] But see Ramos (1999) for a comparison of the two models using earnings of male full-time employees, from the BHPS.

[11] By construction, those who are just starting a non-poverty spell were poor at the previous wave. When the current non-poverty spell ends, they will then *re*-enter poverty. Note that, given the panel length, it is not possible to estimate first-entry (as opposed to re-entry) rates. In other words, my re-entry rates refer to the chances of entering poverty for those who have already experienced it, not also for those who are currently non-poor and have never been poor before.

In many but not all papers on poverty dynamics, concern is expressed for those transitions in and out of low income that occur within a small interval centred over the poverty line. For example one may not want to regard as genuine a transition out of poverty if it involved somebody whose pre-transition income is one pound below the poverty line and post-transition income is merely one pound above. These transitions may simply reflect measurement errors or transitory income shocks that do not significantly affect the individual's living standard. In order to reduce the potential biases caused by this problem, Bane and Ellwood (1986), Duncan et al (1984) and Jenkins (1999) define exits from poverty (out-of-poverty) as occurring only if post-transition income is greater (less) than 110% (90%) of the poverty line. For the same reasons and in order to facilitate comparisons with previous UK research, I have decided to follow this practise in this paper too. However, these adjustments to the actual transitions are somewhat arbitrary and it is not clear whether they can really filter out 'genuine' poverty transitions only. As estimated hazard rates turn out to be sensitive to the used definition of transitions, I have also reported and discussed rates obtained without any modifications to the actual transitions.

Out of the 1272 transitions out of poverty observed in my data, 20% refer to individuals who jump the poverty line but land within a 10% interval on its right. When we turn our attention to transitions in poverty, we find that a much higher number of them (66% of the total 725) are associated with income drops that do not overtake a 10% interval on the left of the poverty line. As the adjusted definition of transitions makes it more difficult for an individual to cross the poverty line, it is not surprising to observe a decrease (increase) of the estimated exit rates (survivor function) in Table 4. This is even more dramatic in the case of the estimated re-entry rates and survivor function reported in Table 5, as I discuss below. It is interesting to note that, while previous research on poverty dynamics has been aware of the problem, no sensitivity analysis has been carried out in these works.

As illustrated in Table 4, estimated hazard rates show evidence of negative duration dependence: the longer an individual stays in poverty the less likely it is that she will leave that state in the next period. For the cohort of individuals just starting a poverty spell, about two fifths (41%) would have left after the first year if the adjusted definition of transitions is used; after five years the probability of escaping poverty is only 15 per cent. However, if no adjustments are made to the observed transitions, the exit rates at duration one is estimated at 50%, about 22% higher than before. In subsequent years the exit rates estimated in column 6 of Table 4 remain higher than those reported in column 4. As a consequence, after 6 years 22% of the cohort is still below the poverty line if the adjusted transitions are used; otherwise the proportion is only 13%.

Table 5 shows the estimated re-entry rates and survivor function out-of-poverty. Negative duration dependence emerges once again: the longer an individual stays out of poverty the less likely it is that she will return below the poverty line in the next period. Re-entry rates are much smaller than exit rates but still point to a significant risk that individuals fall back below the poverty line, particularly in the years just after an exit from poverty. If the adjusted transitions are considered (column 4), almost 10% of the individuals ending a poverty spell will again have income below the poverty line after the first year; within four years, 20% of the poverty escapers will have fallen back in poverty. Much higher are the estimated re-entry rates in column 6, where the unadjusted transitions are used. In this case the probability of returning to poverty after one year is 27%, almost three times as much as reported in column 4.

Taken together the results of Table 4 and 5 imply that the extent of low-income turnover is relatively high. Although there is a small group of people who are persistently poor, there is a relatively large number of poverty escapers and entrants from one year to the next.

The pictures emerging from the estimated exit and re-entry rates can be brought together in order to derive the 'distribution of time spent poor' over multiple spells, a fundamental measure of poverty persistence which - with the exception of Jarvis and Jenkins (1997) over a 3-year window - has never been provided in the UK. The second column of Table 6 shows the distribution of years spent poor in single spells of poverty, calculated using only the exit rates (i.e. not taking multiple spells into account). Column 3 on the contrary uses both exit and re-entry rates to estimate years spent poor over a six-year window that includes both consecutive and non-consecutive years in poverty. In columns 4 and 5 the same calculations are repeated using unadjusted transitions.

Formal formulae for computing the distributions of total time spent poor in single and in multiple spells are described in Stevens (1999). However it may be more helpful to illustrate with a simple example the way in which these distributions are calculated in practice. Call M the total number of (not necessarily consecutive) interviews in poverty for an individual just starting a poverty spell in wave 2. For instance suppose that we want to calculate Prob(M=4). This is given by the sum of the probability of all the possible income sequences over the 7-wave period in which a total of four interviews in poverty are found. One such sequence is, for instance, (H,L,L,H,H,L,L), where a L at rank ith denotes low-income at interview i and a H denotes out-of-poverty. Over the entire time period, the individual represented in that sequence has had 4 interviews in poverty. We then need to calculate Prob(H,L,L,H,H,L,L). As we exclude the first left-censored non-poverty spell, this income sequence is clearly composed by a two-year completed poverty spell, a two-year completed non-poverty spell, and finally by a one-year censored poverty spell. Denoting with $e(d)$ and $r(d)$, respectively, the exit and re-entry rates at duration d, as estimated in Tables 4 and 5, then we can write:

$$\text{Prob}(H,L,L,H,H,L,L)=(1-e(1))e(2)(1-r(1))r(2)(1-e(1)).$$

In plain English, the probability of observing that income sequence is found as the product of the probability of the constituent spells. One then needs to compute the probabilities of all possible sequences that generate a total of four years in poverty, in order to obtain the value of Prob(M=4) reported in column 3 of Table 6. Note that in a single spell approach of column two, the only event giving rise to four years in poverty is the income sequence (H,L,L,L,L,H,H) which has probability $(1-e(1))(1-e(2))(1-e(3))e(4)$.

As a way of comparing predictions based on the single and the multiple spell approach, I have computed the distribution of M emerging from the actual patterns observed in the panel data. In particular, column 6 in Table 6 derives from a simple count of the interviews in poverty for the wave-2 low-income entry cohort, i.e. sequences (H,L,x,x,x,x,x) in Table 2, where x=H,L.

Look now at the results presented in Table 6. Comparing columns 2 to 6, we can see that there is clear evidence that the single-spell approach estimates a distribution of M in which a larger proportion of the population experiences short stays in poverty. For example, 41% of the population will have only one interview (out of the next six) in poverty according to the single spell approach; however, allowing for repeated spells the figure decreases at only 33% in column 3. The figure obtained from the actual patterns observed (column 6), is about 20%. At longer duration, on the other hand, the single spell approach tends to underestimate the distribution of time spent poor, while a repeated spell approach does a better job in replicating observed patterns. For example, about 34% of the those starting a poverty spell will spend at least 4 years below the poverty line if repeated spells are accounted for, while only 28% is the corresponding figure in a single spell predicting framework. The actual proportion in the sample that spent four out of six interviews in poverty is about 39%. Certainly the repeated-spell approach provides better predictions of poverty persistence than the more traditional focus on single spells does.

Table 6 also shows that, if the hazard rates based on unadjusted transitions are used instead, the distribution of time spent poor over multiple spells (column 5) further outperform that over single spells (column 4). In this case, 34.7% are predicted to spend at least four interviews below the poverty line if multiple spells are accounted for; in single spells the corresponding figure is only 17.4%. However, that unadjusted hazards come closer at replicating patterns observed in panel data should not constitute in itself a valid reason for preferring the unadjusted definition of transitions. Observed poverty patterns in column 6 record the total number of interviews in poverty, independently of whether the transition above/below the poverty line occurred within a small interval around it. Consequently, the reason why predictions based on the unadjusted transitions better reproduce the 'actual' distribution of time spent poor may simply be due to the fact that actual patterns are themselves calculated using the unadjusted transitions.

It should be emphasised that the previous analysis assumed that all the observed spells refer to a completely homogeneous population. It is instead more likely that individuals with particular observable and unobservable characteristics face different risks of exiting from - and re-entering into - poverty, and therefore of being persistently poor.

To provide a more realistic picture of the different risks faced by various groups of the population, I now move from the simple life-table estimates presented so far to multivariate techniques that allow exit and re-entry rates to depend on important socio-economic correlates of poverty transitions. The use of this sort of modelling can be interpreted as a simple descriptive device, in which the longitudinal poverty experience of subgroups of the population - homogeneous in selected characteristics - is studied. Alternatively, but more questionably, these models can be employed in an effort to 'explain' the observed poverty patterns, though one should be aware that it is unlikely to make justice of the plethora of underlying demographic/economic dynamic processes that determine poverty unless truly structural models are devised. While this task is already hard when modelling individual's earnings, it is even harder in the case of needs-adjusted household net income (Jenkins, 1999).

4 MODELLING POVERTY EXIT AND RE-ENTRY RATES: A MULTIVARIATE APPROACH

4.1 Modelling framework

I now estimate discrete-time proportional hazard rate models, separately, for poverty exit and for poverty re-entry. The discrete time hazard rate for a person *i* in the time interval *j* to leave a certain state (poverty or non-poverty) is specified following Prentice and Gloecker (1978) as

$$h_j(X_{ij}) = 1 - \exp(-\exp(X_{ij}'\beta + \theta(t))) \tag{1}$$

where X_{ij} is a set of covariates (time-varying or fixed), β are the coefficients we want to estimate and $\theta(t)$ is some functional form of how duration of the spell affects the hazard rate.[12] This complementary log-log model can be interpreted as the discrete-time counterpart of an underlying continuous-time proportional hazard model (see Allison 1982, Jenkins 1995). Assumptions on the form of the baseline function $\theta(t)$ can unnecessarily constrain the way the hazard vary with duration and also potentially bias the estimates of β. It is therefore important to allow for fairly general specifications, e.g. a non-parametric one. Following Meyer (1990), I have used a fully flexible non-parametric specification, with interval-specific dummies for the baseline hazard. In other words, I assume that for each time interval there is a specific parameter that is constant over that period. This parameter can be interpreted as the logarithm of the integral of the baseline hazard over the relevant time interval.

Meyer (1990) has extended the model in (1) using a gamma distributed random variable to allow for unobserved heterogeneity. An additive individual-specific effect is included in the interval-specific hazard with the intention of capturing a myriad of unobservable differences in the individuals. It has long been recognised that ignoring unobserved heterogeneity too can result in underestimation of how the hazard rate changes with duration and overstate the effect of the covariates on the hazard rate (see for example, Lancaster, 1990). In this paper I have chosen not to control for unobserved heterogeneity for two main reasons. First, as for instance recognised by Meyer (1990) himself, the bias in the parameters caused by omitting unobserved heterogeneity is negligible if a sufficiently flexible specification is adopted for the baseline hazard. Second, the estimation routines currently available for estimating the Meyer (1990) discrete-time proportional hazard rate model with unobserved heterogeneity (e.g., *pgmhaz* in Stata, by Jenkins, 1995) are not readily applicable to models with repeated spells. Ondrich and Rhody (1999) show the closed form solution for the individual contribution to the likelihood function when individuals have repeated spells and the unobserved gamma-distributed individual effect is assumed to be the same across the various spells of an individual. This contribution is not the same as that arising in the

[12] As I am not modelling the separate probabilities of each household member experiencing the various events with repercussions on household income, the model in (1) should essentially be interpreted as a reduced form specification.

single-spell model of Meyer (1990) and on which the available estimation routines are based.

An even more complex approach is that followed by Stevens (1999) in her recent study of poverty dynamics in the US. In her data individuals can have multiple spells of two types: poverty spells and non-poverty spells. She then enters unobserved heterogeneity terms in both the exit and re-entry hazard rate specifications and assumes that these terms are correlated across multiple spells of the same type and across spells of the other type. A joint bivariate discrete distribution is assumed for the unobserved heterogeneity terms, with the support points of this distribution to be determined by the data. Covariate coefficients, number of support points and corresponding probabilities of the unobserved heterogeneity distribution are all jointly estimated by maximising a likelihood function defined on both poverty and non-poverty spells of each individual. These more complicated approaches are more demanding to estimate and constitute the agenda for future research.

5 ESTIMATION RESULTS

The papers that have used the hazard rate approach to the study of poverty dynamics differ not only in the types of covariates included in the regressions and in the functional forms adopted, but also in the inclusion or exclusion of the poverty spells referring to some groups of the population and in the unit of analysis. This is hardly surprising given that, while economic theory provides a unified and well-developed framework for studying earnings and income dynamics, no similar theory exists in the more complicated case of the dynamics of 'net equivalised household income'. As a consequence researchers have to undertake a more empirical approach and justify their modelling choices on intuitive grounds, rather than formal ones.[13] For example, Cantó (1996) adopts the household as the unit of her analysis, Schulter (1997) restricts attention on poverty spells occurring to all adults aged more than 21, while Stevens (1999) includes spells for all the groups of the population and has the individual as the unit of her analysis.

In principle, there are good reasons for including and excluding spells that refer to children. From the one hand, children's spells simply reflect their parents' socio-economic decisions about labour supply, household dissolution or formation, etc. If included, therefore, these spells are bound to simply replicate the spells of one (or both) parents. From an econometric point of view, the problem is that spells referring to members of the same household, and to children in particular, do not satisfy the independence assumption necessary to guarantee a good precision of the estimates (Stevens, 1999). On the other hand, though, childhood is a particular delicate period with respect to poverty incidence and persistence and it would clearly be an advantage if we could provide a picture of the experience of any group in the population. Furthermore, only by following children over time as individual units it is possible to assess the impact that such demographic changes like separation and divorce, which imply a move to a new household structure, have on their longitudinal poverty experience. The issue partly

[13] Jenkins (1999) discusses at some depth the various modelling issues arising in empirical research of income mobility and poverty dynamics.

depends on what interpretation is placed on the models one is estimating. If it is more a 'description' of poverty dynamics, then it is clearly an advantage to include all persons in the population. If, however, one moves on to try to 'model' the reasons why the observed outcomes are as they are, then the argument in favour of the exclusion of children's spells becomes stronger. Here, rather than accepting a priori one view over the other I have preferred to estimate two versions of my models, one based on all persons (adults and children) and the other only on adults (individuals aged seventeen or more), and to comment on the differences.

A second and related point is what covariates should be included in the regressions. In principle a whole variety of characteristics of - and events occurred to - one member of the household can be thought of as important determinants of lifetime poverty of any other member. Most used household-level covariates refer to the household head, as for instance his or her education, labour market status, age, etc. After controlling for these variables, however, it becomes important to include individual-level variables as well, so that the differential poverty experience of individuals subject to particularly high risks can be isolated. Once again, I have followed an eclectic approach and have included, in one version of my regressions, the age group dummies as the main individual-level covariate.[14] This is potentially helpful in that it allows me to examine how more at risk the very young and the elderly are from the rest of the population.

Another issue is whether "event variables" like getting a job, experiencing a divorce, the birth of a child, etc., should be included once controls for the demographic and labour market status *at a point in time* have already been used. There are various reasons in favour and against such a practise (Jenkins, 1999). In her empirical analysis of poverty dynamics in the US, Stevens (1999) finds that very few of these event variables are significant once controls for female headship and education of the household head have already been included. One of the reasons is that, once controls for demographic and labour market status at a point in time are allowed to be time-varying, most of the "events" occurring to the household are already subsumed in the changes of these controls over time. For example, it is obvious that an increase in the household size and the number of children must imply the event "birth of a child". In my regressions below I have decided not to included "event variables" as I already control for many time-varying covariates reflecting various demographic and economic status at a point in time.

The results of the discrete time hazard rate models are presented in Table 7 (exit rates) and Table 8 (re-entry rates). The figures reported are the estimated coefficients. The proportionate impact of each variable on the hazard rate can be calculated by taking the exponent of the coefficient.

In my regression analysis I have estimated versions of my models using both the adjusted and unadjusted definition of transitions in and out of poverty, and have reported examples of both in Tables 7 and 8. As we saw in section 3.2, the hazard rates calculated on the unadjusted transitions deliver a closer reproduction of the income sequences observed in the panel data. At the same time, though, it is more likely that the unadjusted transitions include a higher proportion of poverty line crossings due to measurement errors or transitory income shocks, irrespective of any real change in the individual's well

[14] It is again on the grounds of a distinction between description/behavioural modelling that one may question the use of the person's age. The age dummies are time varying.

being. In this case, the effects of exogenous factors on the probability of leaving/entering poverty may be better estimated by using the adjusted definition of transitions.

5.1 Who moves out of poverty?

I start discussing the chances of leaving poverty for those just falling below the poverty line. By examining the coefficients of the interval-specific duration dummies, it can be noted that the data confirm some evidence of negative duration dependence, as already found with the simple life-table estimates of Table 4. As one might have expected, though, its importance and significance is somewhat reduced given that I am now controlling for many other economic and demographic factors. This is often the case in duration models and is generally taken as an indication that the duration dependence is at least partly due to sorting effects (those with favourable characteristics tend to leave earlier) rather than indicating a true ‘scarring’ effect (e.g. due to depreciation of human capital).

Household and individual characteristics impact the probabilities of exiting and returning to poverty in predictable ways. As shown in Table 7, models estimated on all persons (models 1 and 2) and those estimated on adults only (model 3) do not significantly alter the size and sign of the coefficients. Model 4, unlike models 1-3, is estimated using the unadjusted transitions and this is reflected, for some variables, in a significant change in the coefficient size, but none of the qualitative results is altered. In view of that, I focus my discussion below on the models estimated on the whole population (children included) and, unless otherwise specified, I use the coefficients reported in model 1 for my calculations of relative risks.

The number of children in the household has a negative impact on the probability of leaving poverty. The reasons for higher poverty chances if there are children are not surprising: many people have children before their earning power has reached its peak; it is hard for parents looking after their children to work full-time; as household income is adjusted for household size, people’s income falls as soon as they have children. Other things equal, someone living in a household with 3 children has an exit rate almost 55% lower than someone living in a household where there are no children. When there are children aged less than 6 the hazard decreases by about 23%, as they generally require particular care from the parents, reducing the chances that the latter can increase their work effort in order to raise the household above the poverty line. Once I control for the number and age of children, though, the number of members in the household significantly increases the chances of leaving poverty. This is likely to reflect the fact that more adult household members are likely to contribute to household income through their paid work (e.g. earnings of the spouse) or other sources of income (e.g. pension income of the elderly living in the household). Other studies using different approaches have highlighted the importance of secondary earners in lifting up poor households above the low income cut-off (Jenkins, 1999; OECD, 1998). Those living in households headed by a woman do not appear to face a significantly higher risk of remaining in low income. Though the coefficient is negative, it is not significant at conventional levels. This finding is at variance with what suggested by previous research about Britain (e.g.

OECD, 1998) and, even more, with recent US research using the PSID (Stevens, 1999), both indicating a significant negative impact of female headship.[15]

Ethnicity seems to play a role too, with individuals in the non-white group (mainly Afro-Caribbean, Indian, Pakistani) having about 35% less chances of exiting poverty, other things equal.[16]

The coefficients of the age of the household head and its square in model 1 of Table 7 imply that individuals living in households with relatively young or old heads are less likely to escape poverty, with the minimum found at age 47. This is likely to reflect the higher proportion of household structure changes (household formation/separation) that occur at these stages of the individuals' lifetime. Turning the attention to the age of individual members (model 2), estimates seem to confirm that the elderly face relatively higher risks of suffering longer spells of low income, while those in middle age groups are in a relatively safer position. Dummy variables for individuals aged less than 6 and between 6 and 12 were included but were dropped due to collinearity with the other demographic variables already discussed.

For those living in a household whose head has a high level of education (A-levels[17] or more), chances of experiencing relatively long spells of poverty are relatively lower, as for these people it is relatively easier to leave poverty. The estimated coefficient for this variable in model 1 is 0.15 (significant at 10%) and this translates into a hazard rate that is approximately 17% higher than for those living with a low-educated head.

The status of the household head in the labour market is also an important determinant of the chances of escaping poverty. As one might expect, particularly strong is the effect of having an unemployed household head: in that case the probability of crossing the poverty line in the next period is about 35% lower than if the head has a job. If the head is retired, the hazard rate is about 25% lower than the baseline case (employed head). Living in a household where the head is disabled or unable to work for other reasons (e.g., maternity leave or government training schemes) reduces the exit rate by approximately 23%.

The local unemployment rate in the individual's travel-to-work-area has a significant negative impact on the probability of leaving poverty: a 1% increase in the local unemployment rate reduces the hazard rate by almost 5%. The extent to which the individual was below the poverty line at the start of the spell has, as one might expect, a large and well-determined impact on the hazard. Individuals who start a poverty spell with their income much below the poverty line find it more difficult to cross it than those with a less severe poverty gap.

Looking at model 2 in Table 7 we find that there is evidence of correlation across past (completed) spells and current spells.[18] Those who suffered relatively long spells in the past appear more likely to have a smaller hazard in the current spell, and therefore to continue to suffer relatively long spells. This scarring effect of previous poverty

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[15] One of the reasons might be that in the PSID terminology a female head is equivalent to a single female head of household, while this is not necessarily the case in the BHPS.

[16] A more detailed unravelling of the effect of race on the hazard rate was not attempted, given the small sample size of these minority groups in my sample. Less than 3% of the individuals in the sample were non-white.

[17] A-level is the level of academic achievement often used in Britain as the basis for admission to a university. It generally corresponds to 13 years of schooling.

[18] In my data about 11% of the population had 2 or 3 poverty spells.

experience suggests that policies aimed at reducing poverty incidence can have longer term effects.[19] There is also some indication of correlation across spells of poverty and non-poverty. Specifically, those who had repeated spells of non-poverty (alternating them with poverty spells) appear to be less likely to escape poverty, though the effect is not statistically significant.

Finally, note that the main effect of considering the unadjusted transitions, as in model 4, is to increase (in absolute value) the size of the labour market status variables, unemployment of the household head in particular.

5.2 Who moves back into poverty?

I now discuss the chances of returning into poverty for those who have just exited poverty and are therefore starting a non-poverty spell (Table 8). It is important to note from the beginning that estimated coefficients are here subject to a greater variability in size and precision than in the case of the exit rates. In particular, the use of the adjusted, as opposed to the unadjusted, transitions implies some relevant differences in the quantitative assessment of the results. In view of that I limit my discussion below to the qualitative effects of the socio-economic factors considered. Once again, however, the exclusion of spells that refer to individuals aged less than seventeen does not significantly alter the size of the estimated coefficients. Negative duration dependence is confirmed for the hazard rate of returning in poverty, and it is statistically significant in model 1-3, though not in model 4. As for household and individual controls, it is generally the case that variables that have a positive effect on exit rates have a negative effect on re-entry rates.

Persons who have just exited poverty are more at risk of falling again below the low income cut-off if they live in households where there is a relatively large number of children. It interesting to note that the size of the coefficient of the 'number of children' is more than twice that estimated for the exit rate regression. The presence of children aged less than six however reduces the risk of re-entering poverty, probably a reflection of poverty-alleviating measures targeted at households with children.[20] Living in larger households helps individuals at staying out of poverty, with a coefficient that is larger in absolute value than for the exit rate. This seems to confirm the idea that income accruing to members other than the household head are important means to keep the household above the poverty line. This finding has also been highlighted by the cross-tabulation analyses of Jenkins (1999) and OECD (1998) and suggests that policies that encourage two-earner households (subsidised child care, tax breaks for second earner, etc.) can have an important role in anti-poverty programs. Observe that the coefficients of 'household size' and 'number of children' are of a notably greater magnitude in the re-entry rate regression than in the exit rate regression. This might be taken as an indication that

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[19] A similar conclusion is found in the literature studying unemployment duration. See Böheim and Taylor (2000) for a recent example.

[20] Most poverty alleviating programs existing in the UK during the time period covered by my analysis are particularly relevant for families with children. Two obvious examples are the Child Benefit and One parent Benefit. Moreover, programs like Income support, Housing benefit and Council Tax benefit, Job Seeker's allowance all include age-related allowances for children.

demographic factors and events are more important for pushing the household below the poverty line rather than lifting it above that threshold.

As we have already noted for the exit rate, there is no statistical evidence that those living in households headed by a woman face a higher risk of re-entering poverty, once they have managed to escape it in the first place. Though the coefficient is positive, it is not significant at conventional levels. The re-entry rate does not seem to be influenced by ethnicity or by the education of the household head, nor there seem to be a well defined pattern with respect to age of the household head or to the individual age.

The status of the household head in the labour market is, as one might expect, crucially associated with transitions from above to below the poverty line, and the magnitude of the effect is even larger than what I have found for the exit rates. Particularly strong is the impact of having a household head that is unemployed, though the size of the coefficient is not well determined. Substantial additional risks are also faced by those living with a retired head or with a head unable to work because of disability, maternity leave or government training schemes.

The risk of returning into poverty does not seem to be significantly affected by the local unemployment rate in the individual's travel-to-work-area, nor I find evidence of a significant correlation between previous spells and current ones. Finally, the extent to which the individual was above the poverty line at the start of the spell has a large and well-determined impact on the hazard. Individuals who start an out-of-poverty spell with their income well above the poverty line find it less likely to re-experience low income in the future.

5.3 Predicted poverty persistence

I conclude my analysis by using the coefficients estimated in Table 7 and 8 to draw some implications for the poverty persistence of selected groups of the population. Specifically, I calculate the distribution of 'time spent poor over the next 6 interviews' for individuals that the previous econometric analysis has indicated as more at risk of experiencing a long stay in low income. The interval-specific hazard function $h_j(X_{ij})$ in (1) is computed for each group of interest by substituting the values of X_{ij} for that group and the β estimated in Table 7 and 8. Once exit and re-entry rates at various durations have so been calculated, the multiple-spell methodology discussed in section 3.2 is then used to calculate the distribution of time spent below the poverty line by individuals in the group considered. Results are presented in Table 9 using the 'more conservative' coefficients estimated in model 1 of Tables 7 and 8.

For somebody living in a household with three children, whose single parent is aged 20, has low education and is unemployed, the distribution of time spent poor over a six-year window is shown in column 3 of Table 9. The mean number of interviews in poverty is then estimated to be equal to 4.53. This is more then twice as much the expected number of years poor for members of a two-adult household, with no children and where at least the head is well-educated and employed (column 2). A single person, retired, with less than A-levels of education and aged 70 (column 4) is estimated to spend, on average, 3.35 years below the poverty line. Finally, in column 5 the case of a two-member household of ethnic minorities, whose head is aged 20, has relatively low levels of education and is unemployed is predicted to stay in poverty for about 3.35 years.[21]

6 CONCLUSIONS

This paper has provided new evidence on low-income dynamics for individuals living in Britain in 1990s using a nationally representative data set. The importance of allowing for multiple spells when estimating how persistent is poverty in the population of interest has been particularly stressed. Previous longitudinal research in the UK has been constrained by the limited number of waves of the British Household Panel Survey. As 7 waves of the BHPS are used in this study, it has been possible to estimate exit rates from and re-entry rates into poverty and the distribution of total time spent poor over a relatively long time period. Results have shown that, while a tiny minority (less than 2%) of individuals have been poor for the whole time period considered, those touched by poverty at some wave or another are a much higher proportion of the population (32%). The amount of low income turnover is relatively high, given that about 41% of those just falling below the poverty line are predicted to leave after only one year. However, almost 10% of those ending a poverty spell will again have income below the poverty line after the first year; within four years, 20% of the poverty escapers will have fallen back in poverty. The total number of years spent in poverty should therefore be measured over a fixed observation window (e.g., the next six interviews), so that non-consecutive years in poverty are fully accounted for when assessing poverty persistence. For the population as a whole, my results show that 34% of the individuals is predicted to spend at least four years in poverty when the measurement allows for multiple spells; the corresponding figure is only 28% in single poverty spells. These findings suggest that for a relatively large proportion of the population in the UK, poverty is not simply a transitory phenomenon which strikes at random and for a limited duration. Even though the majority of individuals manage to escape poverty after short spells, the danger of falling below the poverty line again in the near future remain relatively high, and that is particularly true for individual with adverse socio-economic characteristics.

The paper has also highlighted that results on poverty persistence can be sensitive to the way transitions in and out of poverty are defined.

Using a multivariate-modelling framework, my analysis has shown that there are groups of the population that not only are systematically more at risk of falling below the poverty line, they are also more likely to remain below it for a much longer number of years. Those living in households with many children, fewer adult members and whose family head is relatively young or old, with low levels of education are found to be more at risk of persistent poverty. Belonging to ethnic minorities makes things even worse, as does living in areas with a high local unemployment rate. Particularly at risk are those living in households where the head does not work because of unemployment, retirement,

[21] The mean stay in poverty has been recalculated in the last row of Table 9 using the coefficients estimated in model 4 of Table 7 and 8. This confirms the higher risks of poverty persistence faced by some subgroups of the population.

disability or maternity leave. These findings should be of interests for policy-makers committed to helping the long term poor.

My data reveal evidence of a negative relation between the hazard rates and duration, even after controlling for individual heterogeneity. Those with relatively long stays in poverty find it more difficult to escape deprivation with their own means and constitute a group on which policies should be targeted. I also find a scarring impact of previous poverty experience, which suggests that policies aimed at reducing poverty incidence will have longer term effects.

Using predictions from discrete-time proportional hazard rates models for exit and re-entry rates, the distribution of total time in poverty over a six-year period has been calculated for selected groups. Children living in a lone-parent household constitute a striking example of groups that need specific policy attention. When they leave with a single parent who has low levels of education and is unable to work, these children can end up spending in deprivation a number of years that is more than double that of persons living in a childless working couple.

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APPENDIX: Tables and results

TABLE 1: Cross-sectional poverty in the sample

	1991	1992	1993	1994	1995	1996	1997
Mean needs-adjusted household net income	14284	14566	14747	14655	15143	15308	15431
Mean needs-adjusted household net income (1991=100)	100.0	101.9	103.2	102.6	106.0	107.2	108.0
Proportion poor:							
Absolute poverty line	15.7	16.6	16.9	16.2	14.9	13.7	14.6
Relative poverty line	15.7	17.2	18.0	17.4	16.8	16.8	17.0
No. persons	11634	11001	10473	10476	10119	10511	10497

Table 1 is based on an unbalanced sample of persons (adults and children) in complete respondent households for all waves for which they are in the sample. Absolute poverty line is half wave 1 mean income. The relative poverty line is half contemporaneous mean income. BHPS 'cross-sectional enumerated weights' have been used in Table 1, in order to account for differential household non-response rates and, within responding households, for differential individual non-response (see Taylor, 1998, chapter V, vol. A, for details).

TABLE 2: Wave1-Wave7 income sequences

Pattern	%	Pattern	%	Pattern	%	Pattern	%
0000000	68.2	0011110	0.08	0111110	0.06	1100000	1.15
0000001	1.57	0011111	0.67	0111111	0.78	1100001	0.2
0000010	1.46	0100000	1.32	1000000	2.67	1100010	0.09
0000011	0.5	0100001	0.22	1000001	0.23	1100011	0.06
0000100	0.93	0100010	0.02	1000010	0.11	1100100	0.29
0000101	0.2	0100011	0.05	1000011	0.03	1100101	0.02
0000110	0.4	0100100	0.19	1000100	0.03	1100110	0.02
0000111	0.65	0100101	0.08	1000101	0.02	1101000	0.06
0001000	1.02	0100110	0.09	1000111	0.12	1101001	0.05
0001001	0.23	0100111	0.03	1001000	0.2	1101010	0.02
0001010	0.09	0101000	0.31	1001001	0.02	1101100	0.06
0001011	0.06	0101010	0.03	1001010	0.02	1101101	0.02
0001100	0.65	0101011	0.29	1001011	0.06	1101110	0.12
0001101	0.08	0101100	0.19	1001100	0.12	1101111	0.09
0001110	0.23	0101101	0.05	1001101	0.08	1110000	0.36
0001111	0.4	0101110	0.12	1001110	0.11	1110001	0.11
0010000	1.53	0101111	0.08	1001111	0.11	1110010	0.11
0010001	0.08	0110000	0.78	1010000	0.37	1110011	0.19
0010010	0.05	0110001	0.11	1010001	0.06	1110100	0.08
0010011	0.06	0110100	0.11	1010011	0.02	1110101	0.09
0010100	0.05	0110101	0.11	1010101	0.02	1110110	0.09
0010101	0.08	0110110	0.12	1010111	0.2	1110111	0.2
0010110	0.16	0110111	0.17	1011000	0.17	1111000	0.34
0010111	0.11	0111000	0.5	1011001	0.06	1111001	0.08
0011000	0.39	0111001	0.19	1011011	0.03	1111010	0.16
0011001	0.14	0111010	0.05	1011100	0.11	1111011	0.23
0011010	0.05	0111011	0.16	1011101	0.08	1111100	0.45
0011100	0.37	0111100	0.33	1011110	0.05	1111101	0.31
0011101	0.16	0111101	0.08	1011111	0.34	1111110	0.51
						1111111	1.81
						TOTAL	**100**

Each pattern represents a 7-wave sequence of poverty status. At each wave an individual can either be poor (denoted by 1 in that wave) or non-poor (denoted by 0 in that wave). For example, the sequence 0111000 indicate that the individual was non-poor in wave 1, poor in wave 2 to 4, and non-poor thereafter. Table 2 includes all patterns observed in the data, with the corresponding frequency.

TABLE 3: Number of waves in poverty

Number of interviews in poverty (*x*)	Freq.	Percent	Proportion poor at least *x* interviews
0	4399	68.5	100.00
1	669	10.4	31.53
2	398	6.2	21.12
3	285	4.4	14.93
4	218	3.4	10.49
5	181	2.8	7.10
6	158	2.5	4.28
7	117	1.8	1.82
Total	6425	100	

Poverty line is half mean wave 1 income. Balanced sample used.

TABLE 4: Survivor function and exit rates from poverty, for all persons beginning a poverty spell (Kaplan-Meyer estimates)

		Adjusted transitions		Unadjusted transitions	
Number of interviews Since start poverty Spell	Number at risk of exit at start of period	Survivor Function (s.e.)	Exit rates (s.e.)	Survivor Function (s.e.)	Exit rates (s.e.)
1	1930	1.00	.	1.00	.
		.	.	.	.
2	1632	0.59	0.41	0.50	0.50
		(0.012)	(0.016)	(0.012)	(0.017)
3	704	0.40	0.32	0.30	0.40
		(0.013)	(0.021)	(0.012)	(0.024)
4	330	0.28	0.30	0.17	0.42
		(0.014)	(0.030)	(0.011)	(0.036)
5	149	0.24	0.15	0.14	0.21
		(0.014)	(0.032)	(0.010)	(0.038)
6	52	0.22	0.06	0.13	0.06
		(0.015)	(0.033)	(0.011	(0.033)

Lifetable estimates based on all non-left censored poverty spells, pooled from the BHPS waves 1-7. Standard errors in parenthesis. 256 exits have been recorded as censored in the calculations based on the ‘adjusted transitions’.

TABLE 5: Survivor function and poverty re-entry rates, for all persons ending a poverty spell (Kaplan-Meyer estimates)

Number of interviews since start non-poverty spell	Number at risk of re-entry at start of period	Adjusted transitions: Survivor Function (s.e.)	Adjusted transitions: Re-entry rates (s.e.)	Unadjusted transitions: Survivor Function (s.e.)	Unadjusted transitions: Re-entry rates (s.e.)
1	1976	1.00	.	1.00	.
		.	.	.	.
2	1694	0.91	0.094	0.73	0.27
		(0.007)	(0.007)	(0.011)	(0.013)
3	978	0.87	0.048	0.60	0.17
		(0.009)	(0.007)	(0.012)	(0.013)
4	621	0.83	0.037	0.56	0.08
		(0.011)	(0.008	(0.013)	(0.011)
5	378	0.80	0.032	0.50	0.09
		(0.013)	(0.009)	(0.015)	(0.016)
6	186	0.78	0.027	0.47	0.07
		(0.016)	(0.010)	(0.017)	(0.020)

Lifetable estimates based on all non-left censored non-poverty spells, pooled from the BHPS waves 1-7. Standard errors in parenthesis. 479 re-entry have been recorded as censored in the calculations based on the 'adjusted transitions'.

TABLE 6: Distribution of the `number of interviews in poverty' out of the next six

Number of interviews with low income out of the next six	Adjusted transitions: Single spell	Adjusted transitions: Repeated Spell	Unadjusted transitions: Single spell	Unadjusted transitions: Repeated Spell	Actual
1	40.7	32.8	50.2	25.3	19.7
2	19.1	19.5	19.8	21.3	23.4
3	11.9	13.9	12.5	18.7	17.6
4	4.4	7.2	3.7	14.3	19.8
5	1.4	4.2	0.8	7.5	7.7
6	22.5	22.5	12.9	12.9	11.8
	100	100	100	100	100

Column 1 and 2 derived from exit and re-entry rates in Tables 4 and 5. Column 3 derives from wave 2 low-income entry cohort (sequences 01xxxxx in Table 2, where x=0,1).

TABLE 7: Poverty exit rate regression

	MODEL 1		MODEL 2		MODEL 3		MODEL 4	
	Coef.	z	Coef.	Z	Coef.	z	Coef.	z
Duration dummies								
1	-0.620	-1.81	-1.407	-3.09	-1.223	-2.53	-0.806	-1.92
2	-0.848	-2.43	-1.647	-3.59	-1.487	-3.05	-1.105	-2.61
3	-1.009	-2.82	-1.820	-3.92	-1.658	-3.38	-1.105	-2.59
4	-1.459	-3.64	-2.275	-4.59	-2.066	-3.95	-1.637	-3.61
5	-2.434	-3.65	-3.243	-4.46	-3.004	-4.04	-2.980	-4.22
Household characteristics								
Number of children	-0.266	-4.13	-0.255	-3.46	-0.251	-3.31	-0.215	-3.15
Children aged<6	-0.257	-1.66	-0.297	-1.85	-0.313	-1.94	-0.399	-2.78
Household size	0.134	2.77	0.098	1.91	0.098	1.86	0.117	2.41
Female headship	-0.001	-0.01	0.007	0.09	-0.002	-0.03	-0.055	-0.75
Age of household head	0.026	2.07	0.047	3.16	0.042	2.67	0.028	2.09
Age of head squared/100	-0.027	-2.18	-0.036	-2.61	-0.033	-2.29	-0.018	-1.46
Head has A-levels or more	0.154	1.71	0.123	1.34	0.102	1.07	0.089	1.04
Unemployed head	-0.430	-3.13	-0.431	-3.12	-0.408	-2.84	-0.661	-5.11
Retired head	-0.291	-1.96	-0.205	-1.29	-0.202	-1.26	-0.316	-2.20
Head is disabled, in maternity leave, etc.	-0.261	-2.66	-0.256	-2.59	-0.271	-2.62	-0.333	-3.66
Local unemployment rate	-0.048	-3.50	-0.054	-3.86	-0.053	-3.67	-0.048	-3.73
Poverty gap	-0.584	-9.08	-0.582	-9.03	-0.571	-8.69	-0.494	-7.83
Individual characteristics								
Non-white	-0.430	-1.54	-0.451	-1.59	-0.367	-1.29	0.045	0.20
Age 0-5								
Age 6-12								
Age 13-16			0.381	1.76			0.352	1.74
Age 17-24			0.476	2.65	0.434	2.27	0.425	2.47
Age 25-33			0.494	2.75	0.449	2.44	0.580	3.46
Age 34-44			0.257	1.65	0.233	1.49	0.333	2.29
Age 54+			-0.247	-1.44	-0.235	-1.36	-0.086	-0.54
Long non-poverty spells			-1.067	-2.04	-0.856	-1.64	-1.418	-2.73
Long past poverty spells			-0.366	-1.32	-0.436	-1.53	-0.302	-1.24
Log likelihood	-1269		-1256.2		-1196.2		-1310.9	
Observations	2086		2086		1981		2086	

Model 1, 2 and 4 include spells that refer to children (individuals aged less than 17 at the spell start), while model 3 does not. Models 1-3 use the adjusted definition of transitions, while model 4 does not. The poverty gap is the difference between needs-adjusted household income and the poverty line (fixed at the start of the poverty spell), divided by the poverty line.

TABLE 8: Poverty re-entry rate regression

	MODEL 1		MODEL 2		MODEL 3		MODEL 4	
	Coef.	z	Coef.	z	Coef.	z	Coef.	z
Duration dummies								
1	-1.355	-1.67	-2.067	-1.66	-2.899	-2.24	1.353	1.83
2	-1.837	-2.24	-2.554	-2.04	-3.367	-2.60	0.946	1.27
3	-2.122	-2.55	-2.829	-2.26	-3.662	-2.82	0.152	0.20
4	-2.278	-2.67	-2.972	-2.35	-3.747	-2.86	0.373	0.50
5	-2.205	-2.42	-2.942	-2.25	-3.720	-2.75	0.346	0.44
Household characteristics								
Number of children	0.601	3.87	0.430	2.46	0.437	2.42	0.661	6.46
Children aged<6	-0.898	-2.19	-0.924	-2.23	-0.887	-2.13	-0.444	-2.31
Household size	-0.369	-2.99	-0.312	-2.35	-0.322	-2.33	-0.421	-5.40
Female headship	0.186	1.12	0.209	1.25	0.238	1.40	0.009	0.09
Age of household head	-0.027	-1.00	-0.012	-0.31	0.011	0.27	-0.085	-3.73
Age of head squared/100	0.029	1.21	0.023	0.79	0.009	0.28	0.065	3.56
Head has A-levels or more	0.033	0.17	0.014	0.07	0.008	0.04	-0.022	-0.19
Unemployed head	0.637	1.92	0.637	1.91	0.719	2.13	1.134	6.52
Retired head	0.615	2.10	0.735	2.30	0.689	2.15	0.612	3.16
Head is disabled, in maternity leave, etc.	0.523	2.34	0.576	2.57	0.530	2.27	0.781	5.94
Local unemployment rate	-0.031	-1.01	-0.037	-1.19	-0.028	-0.90	0.012	0.64
Non-poverty gap	-0.666	-3.11	-0.651	-3.03	-0.634	-2.95	-0.814	-5.84
Individual characteristics								
Non-white	-0.075	-0.13	-0.062	-0.10	0.023	0.04	0.291	0.99
Age 0-5								
Age 6-12								
Age 13-16			0.577	1.05			0.429	1.40
Age 17-24			-0.285	-0.55	-0.183	-0.35	-0.381	-1.17
Age 25-33			0.694	1.58	0.878	1.97	-0.192	-0.70
Age 34-44			0.313	0.84	0.409	1.09	-0.040	-0.17
Age 54+			-0.314	-0.78	-0.364	-0.91	0.334	1.33
Long poverty spells			-0.199	-0.50	-0.157	-0.39	0.155	0.71
Long past non-poverty spells			0.195	0.52	0.119	0.30	-0.151	-0.57
Log likelihood	-628.5		-623.8		-604.0		-1144.6	
Observations	2906		2906		2810		2906	

Model 1, 2 and 4 include spells that refer to children (individuals aged less than 17 at the spell start), while model 4 does not. Models 1-3 use the adjusted definition of transitions, while model 4 does not. Non-poverty gap is the difference between needs-adjusted household income and the poverty line (fixed at the start of the poverty spell), divided by the poverty line.

TABLE 9: Distribution of the `number of interviews in poverty' out of the next six (repeated spell approach). Model 1 estimates.

Number of interviews since start of poverty spell	In work Couple No children	Unemployed Single parent	Single Retired	Non-white unemployed couple
1	0.50	0.11	0.22	0.17
2	0.25	0.10	0.19	0.14
3	0.12	0.09	0.16	0.12
4	0.06	0.08	0.13	0.09
5	0.02	0.08	0.09	0.07
6	0.05	0.54	0.22	0.40
Mean number of interviews in poverty	1.98	4.53	3.35	3.98
Ditto (model 4 estimates)	1.96	5.48	2.67	4.61

The coefficients estimated in model 1 of Table 8 and 9 are used to derive the exit and re-entry rates necessary to calculate the distributions shown above. The methodology is that explained in section 3.2. The single parent here is assumed to be 20, has less than A-levels of education, is unemployed and has 3 children, at least one of whom is aged less than 6. The poverty gap and the unemployment rate are set at their sample mean. In the in-work couple has there are no children and the head of the household is 45, employed and well-educated. The single retired is aged 70, lives alone and has low education. The non-white unemployed couple has the head aged 20, with low education, unemployed and with no children.

The last row reports the mean number of interviews in poverty obtained when the coefficients estimated in model 4 are used.

TABLE 10: Sample Means (over all person-years). Spells In and Out of Poverty.

	In poverty	Out of poverty
Number of children	1.36	1.17
Children aged<6	0.17	0.12
Household size	3.10	3.13
Female headship	0.52	0.44
Age of household head	47.29	49.09
Head has A-levels or more	0.25	0.28
Unemployed head	0.14	0.05
Retired head	0.23	0.23
Disabled, etc., head	0.36	0.22
Local unemployment rate	7.68	7.10
Poverty gap	0.07	0.50
Non-white	0.03	0.02
Age of all individuals	36.49	38.76

All persons in the sample.