MODELLING LOW INCOME TRANSITIONS

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ISER Working Papers
Number 2002-8

Institute for Social and Economic Research

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The support of both the Economic and Social Research Council (ESRC) and the University of Essex is gratefully acknowledged. The work reported in this paper is part of the scientific programme of the Institute for Social and Economic Research.

Acknowledgement:
Research supported by a Nuffield Foundation New Career Development Fellowship and by ISER's core funding from the ESRC and the University of Essex. We thank our Essex colleagues for helpful discussions and comments.

Readers wishing to cite this document are asked to use the following form of words:

> **Cappellari, Lorenzo, and Jenkins, Stephen P. (May 2002) 'Modelling low income transitions', *Working Papers of the Institute for Social and Economic Research*, paper 2002-08. Colchester: University of Essex.**

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ABSTRACT

We examine the determinants of low income transitions using first-order Markov models that control for initial conditions effects (those found to be poor in the base year may be a non-random sample) and for attrition (panel retention may also be non-random). Our econometric model is a form of endogeneous switching regression, and is fitted using simulated maximum likelihood methods. The estimates, derived from British panel data for the 1990s, indicate that there is substantial genuine state dependence in poverty. We also provide estimates of low income transition rates and lengths of poverty and non-poverty spells for persons of different types.

NON-TECHNICAL SUMMARY

The philosophy of anti-poverty policy in Britain has shifted away from income supplementation of those currently poor and towards providing routes out of poverty and preventing falls into poverty. The motivation is that '[s]napshot data can lead people to focus on the symptoms of the problem rather than addressing the underlying processes which lead people to have or be denied opportunities' (HM Treasury, *Tackling Poverty and Extending Opportunity*, 1999, p. 5). If one takes the dynamic perspective, the salient research questions change from 'who is most likely to be poor at the moment?', to 'who is most likely to remain poor and who is most at risk of becoming poor?' In this paper we provide new answers to these questions about low-income dynamics, using an econometric model of transition rates estimated with data from the British Household Panel Survey.

The research has several distinctive features. First, multivariate models of poverty transitions in Britain are rare: ours is one of the first. Second, we took account of the fact that the individuals who are at risk of exiting poverty (or the individuals at risk of entering poverty) may be a non-random sample of the population, an example of an 'initial conditions' problem. Third, we modelled attrition. Household income data at two consecutive annual interviews are not available for individuals who left the panel altogether between the two waves, or for those individuals living in a household in which at least one other adult did not respond to the survey (so aggregate household income cannot be determined). Our estimates of poverty transition rates allowed for the potential non-random selection into the sub-sample of individuals with two consecutive incomes observed. Fourth, we provide estimates of the extent to which the experience of low income one year raises the risk of having low income in the following year ('state dependence'), while controlling for differences in observed and unobserved characteristics between individuals ('heterogeneity'). Finally, we used our estimates to predict poverty transition probabilities and poverty spell lengths for different types of individual. The main poverty line used in the analysis was 60 percent of median income. (Other poverty lines were also used, but conclusions were robust.)

Our results indicate that the two potential sources of non-random selection (i.e. initial conditions and panel attrition) are indeed endogenous, thus underlining the relevance of our modelling approach.

When looking at the personal characteristics that were associated with higher or lower poverty persistence rates, we found a number of systematic patterns. For example, individuals in households headed by someone with educational qualifications higher than A-levels had poverty persistence rates that were 6 percent lower than for otherwise comparable individuals. Poverty persistence rates were 14 percent higher for individuals of Pakistani or Bangladeshi ethnic group, and 8 percent higher for individuals in households with dependent children. Living in a multi-family household was associated with a poverty persistence rate some 18 percent lower than living in a single-family household. When looking at the personal characteristics associated with higher or lower poverty entry rates, the patterns were similar to those for poverty persistence rates (i.e. higher for individuals in households with dependent children, and so on).

Model estimates were used to derive predictions, for individuals of different types, of the poverty persistence rate, the poverty entry rate, the (unconditional) poverty rate, and the expected length of a spell of poverty were they to fall into poverty, and the time between poverty spells. Two examples are as follows. A married man in full-time work with one child (and various other characteristics specified in detail in the paper) had a predicted poverty persistence rate of 0.480 and a predicted poverty entry rate of 0.068. These rates imply a probability of being poor at a point in time of just under 12 percent, and an expected spell of 1.9 years in poverty were he to fall in it. The expected length of time between poverty spells was 15 years. By contrast, a non-working lone mother (with otherwise similar characteristics) had a much higher predicted poverty persistence rate (0.549) and much higher predicted poverty entry rate (0.184). These rates imply a probability of being poor at a point in time of 29 percent, an expected poverty spell length of 2.2 years, and expected time between poverty spells of 5.4 years.

Looking at all the predictions together, we observed that there was greater variation in poverty entry rates across individuals of different types than there was variation in poverty persistence rates. To put things another way, the large differences in the chances of being poor that were associated with differences in characteristics (such as the number of workers, household type and so on) appeared to be related more to differences in the lengths of time spent out of poverty, than to differences in the lengths of time spent in poverty. This finding is of policy relevance. In Britain most of the Labour government's anti-poverty policies, introduced from 1997 onwards, have aimed primarily to get poor people out of poverty, rather than to keep them out of poverty once they have left it (or from falling into poverty in the first place). Our findings suggest the relevance of policies also directed at the latter.

Further results concern the extent to which current poverty depends on past poverty, separately from the effect of personal characteristics (observed and unobserved). Our estimates indicate that this 'state dependence' accounts for a substantial share (60 percent) of overall persistence of low income, with the remainder attributable to differences between individuals ('heterogeneity'). Thus the sheer fact of having been poor last year can affect your chances of being poor this year, regardless of what your characteristics are. Although we did not investigate the causes of state dependence, these findings about its size reinforce our conclusions about the need for policies that prevent individuals from falling into poverty.

1. Introduction

The specification of models of income dynamics raises issues of interest to econometricians, and the estimates from such models provide useful information for policy makers and their advisers. In this paper we aim to contribute some new methods and some new findings. We propose an extension of a first-order Markov model for low income transitions – in econometric terms, a type of endogeneous switching regression model with a binary dependent variable (poverty status). We fit the model using British Household Panel Survey data about working age adults, use it to show who is most likely to stay poor or enter poverty, and derive measures of state dependence in low income.

Two types of model have mainly been used to describe the poverty dynamics of individuals (Jenkins, 2000). The most commonly-estimated models have been hazard regression models of poverty exit rates and re-entry rates. Rarer have been models fitting a stochastic time-series structure to income itself, from which the implications for poverty have been derived. Lillard and Willis (1978) were pioneers of such 'covariance structure' models. For an up-to-date illustration of the two types of model and a comparison of their predictive capacities, see Stevens (1999) based on US Panel Study of Income Dynamics data. For a recent application also comparing both models, but using British panel data, see Devicienti (2001b).

We propose a third type of model, a first order Markov model of poverty transitions. Our particular contribution is the modelling of initial poverty status and non-random attrition in addition to the modelling of the poverty transition, thereby providing a generalisation of the oft-cited model of Boskin and Nold (1975). We take account of the fact that the set of individuals at risk of exiting poverty, or the set at risk of entering poverty, may not be a random sample of the population, an example of an 'initial conditions' problem (Heckman, 1981a). Moreover, data on household income at two consecutive annual interviews (at waves t–1 and t) are not available for individuals who leave the panel altogether between t–1 and t, or for those are respondents at t but live in a household in which at least one other household member did not respond (so aggregate household income, and thence poverty status can not be determined). Our estimates of poverty transitions control for potentially non-random selection into the sub-sample of individuals for whom two consecutive household incomes are observed.

Our Markovian model is a complement to hazard and covariance structure models. On the one hand the intrinsic dynamics in our model are not as sophisticated as those of the other two types. But, on the other hand, we account for income attrition and initial conditions, issues that have received little attention in the context of the other models. For example most applications of hazard models – single spell models – have assumed that unobserved effects are independent of entry to the state (so left-censored spells can be safely ignored).[1] Attrition has typically been ignored in estimation of both types of model.[2] In addition covariance structure models assume that the same income dynamics process applies to all persons, rich or poor, which is implausible to some commentators (e.g. Stevens, 1999). Our models, like hazard models, introduce non-linearities by distinguishing between rich and poor. Indeed, in one version of our model, we distinguish five income classes from which transitions are made. One advantageous feature of first-order Markov models is that simple closed-form expressions are available to summarise the distribution of poverty and non-poverty spell lengths (see below).

First-order Markov models have also been applied to transitions into and out of low earnings (rather than low income). Stewart and Swaffield (1999), for example, modelled transitions controlling for the endogeneity of initial conditions and provided estimates of the degree of state dependence in low pay in Britain. Bingley et al. (1995) and Cappellari (2001) controlled for endogeneity in attrition as well as initial conditions in studies of earnings mobility in Denmark and Italy. Similar models for poverty do not exist, that we are aware of.[3]

We treat membership of the base year income category and sample retention as issues of multiple endogenous selection.[4] The simultaneous estimation of the probability of the two selection mechanisms together with the probability of low income transitions poses a computational problem due to the need to evaluate multivariate normal integrals. We deal with this by applying simulated maximum likelihood (SML). Additional issues arise because an individual's poverty status depends on the income of the household to which he or she belongs: an individual is judged to be poor if household income is below the relevant poverty line. Thus within each multi-person household there are repeated sample observations on poverty status and household characteristics. We control for this by using a pseudo maximum likelihood estimator drawing on ideas from the survey statistics literature. This device is also used to control for the fact that we pool poverty transitions from our panel (which introduces

[1] The assumption need not be made – see e.g. Devicienti (2001b) for an exception – but it is the typical practice.
[2] Respondents that attrit could be assumed to contribute right censored spells to hazard model data sets. But if attrition is non-random, then this would conflict with the independent censoring assumption typically employed when estimating hazard regression models.
[3] A brief summary of early estimates from our model is provided in Cappellari and Jenkins (2002).

repeated observations on the same individual). The joint treatment of the two issues yields a pseudo simulated maximum likelihood (PSML) estimator.

Multivariate models of poverty transitions in Britain are rare, of any type, partly because suitable panel data have not been available until recently. However the British Household Panel Survey (BHPS), which we also use, has data for up to nine waves.[5] Otherwise most British research on poverty dynamics has simply documented low income transition rates for different groups and used bivariate 'trigger event' methods to investigate poverty determinants (see for example Jarvis and Jenkins, 1997; Jenkins, 2000; Jenkins and Rigg, 2001). There is also a related literature that has modelled transitions onto or off receipt of social assistance benefit rather than low income itself. See for example Böheim *et al.* (1999) or Noble *et al.* (1998), but neither paper accounted for the endogeneity of attrition or of initial conditions. State dependence in low income – the extent to which the experience of low income one year raises the risk of having low income in the following year, while controlling for differences in observed and unobserved characteristics between individuals ('heterogeneity') – has not been studied before for Britain.[6]

Our results have relevance to a national welfare state policy environment that has increasingly embraced a longitudinal perspectives rather than cross-sectional ones. The philosophy of anti-poverty policy in Britain has – as in the US before it – shifted away from income supplementation of those currently poor and towards providing routes out of poverty and preventing falls into poverty. The motivation is that '[s]napshot data can lead people to focus on the symptoms of the problem rather than addressing the underlying processes which lead people to have or be denied opportunities.' (Treasury, 1999, p. 5.) If one takes the dynamic perspective, the salient research questions change from 'who is most likely to be poor at the moment?', to 'who is most likely to remain poor and who is most at risk of becoming poor?'. Our models help provide answers to these questions.

Several of the issues that we shall address are illustrated by an examination of the raw poverty transition matrix for the data set that we use (definitions are explained in detail later): see Table 1. Panel (a) shows the transition matrix constructed using data for all adults with two consecutive observations on income. This suggests that a substantial proportion, about four in ten, of those who were poor one year were no longer poor the following year. But

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[4] See Tunali (1986) for a discussion of multiple selectivity in the context of earnings equations estimation.
[5] Devicienti (2001b) and Jenkins and Rigg (2001) used these data to estimate hazard and covariance structure models of poverty dynamics.

clearly the chances of being poor in a given year differed substantially depending on poverty status in the previous year. The poverty rate among those poor in the previous year was some 54 percentage points higher than the poverty rate among those non-poor in the previous year. This measure of 'aggregate' state dependence does not of course control for individual heterogeneity, observed or unobserved, and we shall develop a measure of 'genuine' state dependence that does.

<Table 1 near here>

The high rates of persistence in the same state also raise questions about whether they arose simply because of an endogenous selection mechanism over time – the high rates might have arisen because persons likely to remain poor were over-represented among those who were poor at a point in time (year t–1 here). And similarly for the non-poor. We address this problem by controlling for the observed and unobserved determinants of initial poverty status. Another possible reason for the high rates of persistence in the same state – with potential knock-on effects for the estimates of state dependence – might be the dichotomisation of a continuous variable (income). We addressed this issue in two ways, investigating the effect on our results of varying the value of the poverty line, and considering a model in which there were five income classes at t–1.

Panel (b) of Table 1 draws attention to the issue of endogeneity of income retention. Observe the extra 'Missing' column on the right hand side of the table. The problem is not so much that a non-trivial proportion of the sample were not retained from one year to the next, but that the retention rates differed by poverty status at t–1: 13.3 per cent for the poor and 10.6 per cent for the non-poor.[7] We account for non-random income retention in our modelling, jointly with the initial conditions and poverty transition processes. In effect our model is a means of modelling poverty transitions while using sample data with observations of six different types – one corresponding to each of the six cells of Table 1 panel (b) – and also incorporates individual heterogeneity.

We find that the two selection mechanisms (initial conditions and sample retention) are endogenous to the estimation of low income transitions. As far as the substantive findings are concerned, our estimates of measures of state dependence indicate that, once observed and unobserved individual heterogeneity are controlled for, there remains substantial 'genuine'

[6] Hill (1981) is one US application.
[7] The 10.9 per cent attrition rate arose in roughly equal measure from non-response by the individual concerned (5.6 per cent) and non-reponse by someone else in the individual's household (5.3 per cent).

state dependence. We demonstrate how differences in poverty rates at a point in time are related to differences in poverty entry and poverty persistence rates.

The remainder of the paper is set out as follows. In Section 2, we describe our econometric model and the estimation method. In Section 3, we discuss the BHPS data that we use, the definitions of the dependent and explanatory variables, and our identification assumptions. Our main results are presented in Section 4. Section 5 demonstrates that the results are robust to using alternative definitions of the poverty line and to summarising the base year income distribution using five income bands rather than two. Concluding remarks are presented in Section 6. Supplementary tables are provided in the Appendix.

2. An econometric model of poverty transitions

To model poverty transitions between two consecutive years, t–1 and t, we used a trivariate probit model. There are four parts to the model: the determination of poverty status in period t–1 (to account for the initial conditions problem), the determination of whether incomes are observed at both t–1 and t (income retention), the determination of poverty status in period t, and the correlations between the unobservables affecting these processes. The combination of these four components characterises the determinants of poverty persistence and poverty entry rates. We discuss each of the four processes in turn, thereby presenting a binary response model with multiple endogeneous switching.

Assume that in period t–1, individuals can be characterised by a latent poverty propensity p^*_{it-1} of the following form:

$$p^*_{it-1} = \beta' x_{it-1} + \mu_i + \delta_{it-1} \tag{1}$$

where $i = 1,\ldots N$ indexes individuals, x_{it-1} is a vector of explanatory variables describing individual i and her household, β is a vector of parameters, and error term $u_{it\text{-}1}$ is the sum of an individual-specific effect plus an orthogonal white noise error: $u_{it\text{-}1} = \mu_i + \delta_{it-1}$. We assume that $u_{it\text{-}1}$ follows the standard Normal distribution: $u_{it\text{-}1} \sim N(0,1)$. Our specification is equivalent to assuming a model of income, in which an arbitrary monotonic transformation of income is a linear function of personal characteristics plus an error term that has the standard Normal distribution (Stewart and Swaffield, 1999). If individual i's poverty propensity exceeds some unobserved value (which can be set equal to zero without loss of generality), then she is observed to be poor. Define a variable $P_{it-1} = 1$ if $p^*_{it-1} > 0$ and zero otherwise.

Now consider the chances that those individuals with incomes observed in period t–1 also have incomes observed at period t. Let r^*_{it} be i's latent propensity of retention between t–1 and t be summarised by the relationship:

$$r^*_{it} = \psi' w_{it-1} + \eta_i + \xi_{it} \tag{2}$$

where the error term v_{it} is the sum of an individual-specific effect (η_i) plus an orthogonal white noise error (ξ_{it}) with $v_{it} \sim N(0,1)$, and ψ and w_{it-1} are column vectors. If i's latent retention propensity is lower than some critical threshold (again normalised to 0), then her income is not observed in period t, and hence her poverty transition status is also not observed. Let R_{it} be a binary indicator of the income retention outcome for each individual, where $R_{it} = 1$ if $r^*_{it} > 0$ and zero otherwise.

The third component of the model is the specification for poverty status in period t. Let the latent propensity of poverty be characterised by

$$p^*_{it} = [(P_{it-1})\gamma_1' + (1-P_{it-1})\gamma_2']z_{it-1} + \tau_i + \zeta_{it} \tag{3}$$

where γ_1, γ_2, and z_{it-1} are column vectors, and the error term ε_{it} is the sum of an individual-specific effect (τ_i) plus an orthogonal white noise error (ζ_{it}), with $\varepsilon_{it} \sim N(0,1)$.[8] Define a variable $P_{it} = 1$ if $p^*_{it} > 0$ and zero otherwise. (Of course P_{it} is only observed if $R_{it} = 1$.) The specification allows the impact of explanatory variables on current poverty to differ according to poverty status in the last period. Thus we describe (3) as the equation for conditional current poverty status though, for brevity's sake, we sometimes refer to it as the equation for poverty transitions.

We assume that the joint distribution of the error terms u_{it-1}, v_{it}, and ε_{it} is trivariate standard Normal, and is characterised by three free (and estimable) correlations. Given our assumptions, we may write them as:

$$\begin{aligned} \rho_1 &\equiv \text{corr}(u_{it-1}, v_{it}) = \text{cov}(\mu_i, \eta_i) \\ \rho_2 &\equiv \text{corr}(u_{it-1}, \varepsilon_{it}) = \text{cov}(\mu_i, \tau_i) \\ \rho_3 &\equiv \text{corr}(v_{it-1}, \varepsilon_{it}) = \text{cov}(\eta_i, \tau_i). \end{aligned} \tag{4}$$

Thus the distribution of unobserved heterogeneity is parameterised (apart from necessary normalisations) via the cross-equation correlations. The correlation ρ_1 summarises the association between unobservable individual-specific factors determining base year poverty status and income retention. A positive (resp. negative) sign indicates that individuals

[8] Observed attributes are measured using last period's values in order to avoid simultaneity between changes in attributes and changes in poverty status. Since equation (3) refers to poverty status conditional on lagged poverty and attrition, the error term differs from the error term in the expression for unconditional poverty status (1).

who were more likely to be initially poor are more (resp. less) likely to remain into the income distribution of the subsequent year compared to the non-poor. The ρ_2 is the correlation between unobservable individual-specific factors determining base year poverty status and poverty transitions (i.e. conditional current poverty status, $P_{it}|P_{it-1}$). A positive (resp. negative) sign indicates that individuals who were more likely to be initially poor were more (resp. less) likely to remain poor compared to the non-poor. The correlation ρ_3 summarises the association between unobservable individual-specific factors determining retention propensities and those determining conditional current poverty status. A positive (resp. negative) sign indicates that individuals with incomes observed in two successive periods were more (resp. less) likely to remain poor or to fall into poverty compared to individuals more likely to attrit.

If $\rho_1 = \rho_3 = 0$, then the income retention process is ignorable and the model reduces to a bivariate probit model with endogenous selection of the type used by Stewart and Swaffield (1999) in their study of low earnings. If $\rho_1 = \rho_2 = 0$, then there is no initial conditions problem: poverty status at t–1 may be treated as exogenous. And if $\rho_1 = \rho_2 = \rho_3 = 0$, then poverty entry and exit equations may be estimated using simple univariate probit models. (See Sloane and Theodossiou, 1996, for a related example.) We estimate the general model with free correlations and test whether income retention and initial conditions are exogenous.

Poverty transition probabilities

Of particular interest are the transition probabilities implied by the model: the probability of being poor at t, conditional on being poor at t–1 (the poverty persistence rate), and the probability of being poor at t, conditional on being non-poor at t–1 (the poverty entry rate). These are given, respectively, by:

$$s_{it} \equiv \Pr(P_{it} = 1 | P_{it-1} = 1) = \frac{\Phi_2(\gamma_1' z_{it-1}, \beta' x_{it-1}; \rho_2)}{\Phi(\beta' x_{it-1})} \tag{5}$$

and

$$e_{it} \equiv \Pr(P_{it} = 1 | P_{it-1} = 0) = \frac{\Phi_2(\gamma_2' z_{it-1}, -\beta' x_{it-1}; -\rho_2)}{\Phi(-\beta' x_{it-1})} \tag{6}$$

where $\Phi(.)$ and $\Phi_2(.)$ are the cumulative density functions of the univariate and bivariate standard Normal distributions.

In our empirical work, expressions for transition probabilities were derived by replacing population parameters by their sample estimates. Observe that, since explanatory variables are measured at t–1, transition probabilities can be predicted also for the attritor subsample (individuals with R_{it} = 0), using estimates that are robust to non-random retention. Thus we were able to predict what poverty persistence and entry rates would have been, had the subsample with R_{it} = 0 been observed in the income distribution at year t. By contrast the aggregate transition rates in Table 1(a) only refer to the subsample with R_{it} = 1.

Implications of the model for poverty spell durations, etc.

A notable advantage of the first-order Markov model is that simple closed form expressions are available to describe the distributions of spells of poverty and non-poverty (Boskin and Nold, 1975). Assuming a stationary environment, so that all rates have reached steady-state values, then the mean duration of a poverty spell is $1/(1–s_i)$, and the median duration is $\log(0.5)/\log(s_i)$, where the poverty persistence rate s_i is defined in (5). The mean duration of a spell of non-poverty is $1/(e_i)$, and the median duration is $\log(0.5)/\log(1–e_i)$, where the poverty entry e_i is defined in (6). The unconditional (state) probability of being poor is $e_i/(e_i + 1 - s_i)$. In Section 4 we provide estimates of these statistics for individuals of different types.

Testing for and measuring state dependence

The endogenous switching structure of the model allows us to investigate the issue of state dependence. We distinguish between aggregate state dependence (ASD) and genuine state dependence (GSD). ASD is the simple difference between the probability of being poor for those who were poor last period and the probability of being poor for those who were not poor (as discussed in the context of Table 1(a)). This takes no account of individual heterogeneity. A straightforward measure of ASD is thus:

$$\text{ASD} = \left(\frac{\sum_{i \in \{P_{it-1}=1\}} \Pr(P_{it}=1 \mid P_{it-1}=1)}{\sum_i P_{it-1}} \right) - \left(\frac{\sum_{i \in \{P_{it-1}=0\}} \Pr(P_{it}=1 \mid P_{it-1}=0)}{\sum_i (1-P_{it-1})} \right). \qquad (7)$$

Genuine state dependence arises when the chances of being poor this period depend on poverty status in the previous period, controlling for individual heterogeneity (observed and unobserved). For example, the experience of poverty itself might induce a loss of motivation, lowering the chances that individuals with given attributes escape poverty in the future. The null hypothesis of a test for the absence of GSD can be formulated, given our model, as H_0: γ_1

$= \gamma_2$.[9] Our measure of the degree of GSD is derived by calculating for each individual the difference between the predicted probability of being poor conditional on being poor last period and the predicted probability of being poor conditional on being non-poor last period, and then taking the average across all *N* individuals:

$$\text{GSD} = (1/N)\sum_{i=1}^{N} \Pr(P_{it} = 1 | P_{it\text{-}1} = 1) - \Pr(P_{it} = 1 | P_{it\text{-}1} = 0) \qquad (8)$$

The calculation of individual-specific probability differences (which are then averaged) ensures that individual heterogeneity is controlled for. Observe that ASD and GSD can be computed for the whole sample (including individuals that attrit between t–1 and t).[10]

In Section 4, we generalise the GSD measure to the case where are five income classes at t–1 rather than two.

Sample likelihood and the PSML estimator

In the observed data, each individual may fall into one of six regimes (cf. Table 1(b)). If incomes are observed for two consecutive periods ($R_{it} = 1$), then there are four possible outcomes depending on poverty status at each of period t–1 and t. And if individuals are not retained in the sample, then all that is observed is whether they were poor or non-poor at t–1 (two outcomes).

The sample likelihood contributions are given by expressions summarising the probability that an individual is observed in each of the six data regimes. For example, the probability of being poor for two consecutive years and having an income observed in each of these years is:

$$\Pr(P_{it} = 1, P_{it-1} = 1, R_{it} = 1) = \Phi_3(\gamma_1' z_{it-1}, \psi' w_{it-1}, \beta' x_{it-1}; \rho_3, \rho_2, \rho_1) \qquad (9)$$

where $\Phi_3(.)$ is the trivariate Normal cdf. Similarly, the probability of moving into poverty between t–1 and t and having an income observed in each of these years is:

$$\Pr(P_{it} = 1, P_{it-1} = 0, R_{it} = 1) = \Phi_3(\gamma_2' z_{it-1}, \psi' w_{it-1}, -\beta' x_{it-1}; \rho_3, -\rho_2, -\rho_1). \qquad (10)$$

[9] Tests for GSD have been formulated differently in the context of different types of econometric model. For example, Arulampalam *et al*. (2000) used a dynamic random effects probit model of unemployment in which a binary variable summarising unemployment status last period was used as a regressor. Their test for GSD in unemployment was based on whether the coefficient on lagged unemployment status was equal to zero. The GSD test proposed in this paper generalises the Arulampalam *et al*. test because the whole parameter vector associated with personal characteristics differs according to status in the previous period.

[10] The discussion of aggregate state dependence in the Introduction referred only to averaging over individuals with $R_{it} = 1$.

The probability of observing someone to be poor at t–1 and with unknown poverty status at t is:

$$\Pr(P_{it-1} = 1, R_{it} = 0) = \Phi_2(-\psi' w_{it-1}, -\beta' x_{it-1}; \rho_1). \tag{11}$$

And so on for the other three regimes.

In sum, the contribution to the sample log-likelihood for each individual i with poverty status observed in period t–1, is:

$$\begin{aligned} \log L_i = \quad & P_{it-1}R_{it}\log[\Phi_3(k_i\gamma_1' z_{it-1}, m_i\psi' w_{it-1}, q_i\beta' x_{it-1}; k_i m_i\rho_3, k_i q_i\rho_2, m_i q_i\rho_1)] \\ + \quad & (1-P_{it-1})R_{it}\log[\Phi_3(k_i\gamma_2' z_{it-1}, m_i\psi' w_{it-1}, q_i\beta' x_{it-1}; k_i m_i\rho_3, k_i q_i\rho_2, m_i q_i\rho_1)] \\ + \quad & (1-R_{it})\log[\Phi_2(m_i\psi' w_{it-1}, q_i\beta' x_{it-1}; m_i q_i\rho_1)] \end{aligned} \tag{12}$$

where $k_i \equiv 2P_{it} - 1$, $m_i \equiv 2R_{it-1} - 1$, $q_i \equiv 2P_{it-1} - 1$.

Maximisation of the sample log-likelihood requires evaluation of trivariate standard Normal distribution functions, $\Phi_3(.)$. We solved this computational problem using simulated maximum likelihood (SML) methods, and $\Phi_3(.)$ was replaced by its simulated counterpart. We used the Geweke-Hajivassiliou-Keane (GHK) simulator.[11]

Estimation also took account of the fact that our sample data consisted of repeated observations on individuals from the same household at each t, and repeated observations on the same individual across successive pairs of periods because we pooled transitions from our panel (see later). These repeated observations mean that the i.i.d. assumption is violated. To account for this, we used a Pseudo Simulated Maximum Likelihood (PSML) estimator, as follows. The complex survey statistics literature has developed methods for adjusting the estimates of the parameter covariance matrix to account for sample clustering, using formulae that allow for arbitrary correlations between observations within the same sample cluster. See *inter alia* Huber (1967) and Binder (1983) and, for an independent derivation in the econometrics literature, White (1982). We defined each cluster to consist of all the individuals that were members of the same household unit in wave 1 of the BHPS.[12] The sample log-likelihood is a ‘pseudo-likelihood’ in this case (Gourieroux and Monfort, 1996), from which can be derived a ‘robust’ variance estimator of the parameter estimates using

[11] See Hajivassiliou and Ruud (1994) and Gourieroux and Monfort (1996, 93–107) for discussions of simulation methods and their application to maximum likelihood estimation of multivariate limited dependent variable models. Bivariate cdfs were evaluated using the numerical function in our software package rather than the GHK simulator.

[12] Hence adult respondents living in a different household in wave 2 or subsequently than their wave 1 household (e.g. because of divorce or separation) were allocated to the same cluster. Adults who joined the panel after wave 1 (typically by marriage to a respondent) were allocated to the same cluster as that of their household head.

Taylor-series linearisation. Our estimator is a PSML estimator because the pseudo-likelihood was evaluated using the GHK simulator.

3. Data, variable definitions, and identification

We used data from waves 1–9 (1991–9) of the British Household Panel Survey (see Taylor *et al.*, 2001, for details). Pairs of consecutive waves were used to identify low income transitions, and estimation was based on a sample that pooled these transitions. The estimation sample was restricted to individuals aged 20–59 years in year t–1 who were not in full-time education; our focus is on poverty among adults of working age rather than child poverty or pensioner poverty.

Each individual's poverty status was measured using data about the income of the household to which he or she belonged. We used a definition of income that is employed in the official British low income statistics (Department of Social Security, 2000): post-tax post-transfer current household income, adjusted for differences in household needs using the McClements equivalence scale, in August 2000 prices (and without deducting housing costs). An individual was defined to be poor at t if he or she had an income below 60% of median income at t, a poverty line that is widely used.[13] (Variations were also considered: see Section 5.)

We followed previous literature when choosing covariates: they were mostly variables summarising the demographic composition and labour market attachment of the household in which the individual lived. All covariates in the poverty transition equation (3) were measured using the values pertaining at the interview in the base year (wave t–1) and, again in common with virtually all the poverty modelling literature, were assumed to be pre-determined. (These form the elements of z_{it-1}.) Because poverty status was measured using a household-level income variable, most of the covariates were also measured at the household level. More specifically, the covariates referred to the individual (age, sex), to the household head (age, sex, employment status, ethnic group), and to the household itself (several

Children turning 16 and being and interviewed as respondents in their own right were allocated to the same cluster as their parents.

[13] The poverty lines for the nine waves were, in pounds per week (August 2000 prices): 149, 152, 156, 160, 166, 17, 172, 176. This represents an increase in real terms of 19 per cent between 1991 and 1999.

variables summarising household composition, housing tenure, and the number of workers).[14] We also included year dummies in all equations.

In order to identify the model, and if functional form is not relied on, exclusion restrictions are needed in terms of variables affecting either initial poverty or retention but, conditional on these, with no effect on poverty transition (i.e. variables entering the x_{it-1} or w_{it-1} vectors but not the z_{it-1} one). Heckman (1981b) suggested that when modelling labour market outcomes, initial conditions could be instrumented by using information prior to labour market entry. Our model is of adult life poverty transitions, and the instruments used for base year poverty status were variables summarising parental socio-economic status measured when the respondents were aged 14. We created a set of binary variables to summarise each respondent's parents' occupation, including variables to indicate missing information on the items of interest.[15] I.e. the vector x_{it-1} in (1) included all the variables in z_{it-1}, plus the parental background indicators. As an instrument for sample retention, we used a dummy variable indicating whether the individual was a BHPS original sample member (OSM). BHPS respondents can be classified into OSMs or joiners. The former group have been in the panel since the first wave (1991); the latter joined the survey later by moving into an OSM's household.[16] Our identifying restriction assumes that OSMs are more stable survey members compared to joiners and that sample membership status is orthogonal to poverty transition propensity.[17] I.e. in terms of (2) and (3) Thus the vector w_{it-1} included all the variables in z_{it-1}, plus the OSM indicator.

In order to test the validity of identifying restrictions we exploited assumptions about the distribution of error terms. We used functional form as an identifying restriction, so that exclusion restrictions about parental background and sample membership status were over-identifying and testable. We report results from tests of the significance of instruments in both the selection and transition equations.

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[14] Each individual's characteristics may play a role in addition to and separately from the characteristics of their household. For example it is well-known that divorced and separated women have lower living standards than divorced and separated women after a household split (Jarvis and Jenkins, 1999) so, other things equal, one might expect the poverty (re-)entry risks for husband and wife from the same household to differ, and the risks might also vary by age.

[15] These instruments for initial conditions are similar to those used by Stewart and Swaffield (1999) in their analysis of low pay transitions based on BHPS data.

[16] Children in an OSM's household are also classified as OSMs.

[17] In principle, other information could have served as instruments. We experimented with the share of household respondents classified by the interviewer as 'very good co-operators' in the interview, and with a dummy variable for change of interviewer between t–2 and t–1. Validity of these variables as instruments was rejected by the test described in the next paragraph. Parameter estimates were robust to changes in the set of instruments.

4. Results

We discuss the results in two stages. First we present the estimates of the correlations between unobservables and the associated tests of the exogeneity of initial conditions and sample retention. Second we discuss the estimated impact of each explanatory variable on the poverty status, and draw out the implications of the model for poverty transition probabilities and state dependence.

Testing the exogeneity of initial conditions and sample retention, and instrument validity

In order to assess the exogeneity of the two selection mechanisms we tested for the separate and joint significance of the correlation coefficients associated with each of the two selection equations. Consider first the estimates of the correlations *per se*: see the top panel of Table 2. The correlation between unobservables affecting initial poverty and income retention (ρ_1) was negative and statistically significant, indicating a lower retention propensity among the initially poor compared to the non-poor (as we found in Table 1(b)). The correlation between unobservables affecting initial poverty and conditional current poverty (ρ_2) was also negative and statistically significant. Since this measures the correlation between unobservables affecting initial poverty status and conditional current poverty status – poverty transition propensity, in other words – the negative sign can be interpreted as an example of Galtonian regression towards the mean (Stewart and Swaffield, 1999). Finally, the correlation between unobservables affecting income retention and poverty transition (ρ_3) was not precisely estimated.

<Table 2 near here>

The exogeneity tests are reported in the bottom panel of Table 2. Exogeneity of initial conditions would imply that ρ_1 and ρ_2 were jointly zero but such a hypothesis was strongly rejected ($p < 0.000$). Exogeneity of income retention, on the other hand, can be tested by testing the joint significance of ρ_1 and ρ_3. Again, the data rejected the null hypothesis, although rejection was less evident than in the previous case – which is unsurprising given that ρ_3 was imprecisely estimated – but still with a level of joint significance of 1 per cent. The result indicates that retention was endogenous for poverty transitions, whereas the point estimates of the correlation coefficients indicate that endogeneity operated via a correlation with initial conditions, rather than directly affecting transition probabilities. Finally, the test for the joint significance of the three correlation coefficients indicates that they were jointly significant with a *p*-value of less than 1 per cent. In sum, the tests on correlations of the unobservables indicate that initial conditions and income retention were endogenous.

Regarding the validity of the instruments, the estimates shown in the bottom panel of Table 2 indicate that parental background indicators and the sample membership dummy could be excluded from the transition equation, both separately and simultaneously, with excludability more evident in the case of sample membership status. (The *p*-values for the separate tests were 0.27 and 0.62, and 0.30 for the joint test.) Note too that these variables were found to be statistically significant in the two selection equations (*p*-values of 0.04 and 0.00). In sum, the validity of the proposed instruments was supported by the data.

The impacts of the explanatory variables on transition probabilities

The impacts of explanatory variables on poverty transitions (equation 3) are summarised in Table 3. (The corresponding estimates for initial poverty status and retention are provided in Table A1 in the Appendix.) There are two sets of estimates, depending on poverty status at $t-1$. The middle column of each set shows the coefficient estimates (γ_1, γ_2) and associated asymptotic *t*-ratios. The first column of each set, and the focus of our discussion, shows the marginal effect of a change in each explanatory variable on the probability of poverty persistence and on the probability of poverty entry (s_{it} and e_{it} in equations 5 and 6).

To define the marginal effects, observe that a change in an element of z_{it-1} also implies a change in the corresponding element of the x_{it-1} vector (they have many common elements). This changes not only the conditional probability of current poverty (the numerator of the relevant expression in equation 5 or 6), but also the conditioning state (the denominator, summarising the base year poverty probability). In order to hold conditioning events constant, we first computed predicted probabilities for base year poverty status (using parameter vector β estimated from the trivariate probit, the x_{it-1} vector and univariate Normal cdfs), and averaged them over the relevant samples (i.e. separately for those respondents who were poor and those who were not poor in the base year). Next we computed the arguments of these average predicted probabilities and substituted them into (5) and (6), thus holding the probabilities of the conditioning events fixed. Finally, each marginal effect was calculated as the change in conditional current poverty probability implied by a *ceteris paribus* change in characteristics relative to the characteristics of a reference person. The reference person was defined by setting the continuous covariates, age and household head's age, equal to the sample median values (37 and 41), and all the remaining binary variables to zero. For age-related variables, the estimated marginal effect is the change induced when the relevant age variable was changed from the median to the sample 75th percentile value. For all other variables, the marginal effect shows the impact of having changed its value from zero to one.

<Table 3 near here>

Consider first the estimates conditioning on being poor at *t*–1 (γ_1). The predicted probability of current poverty for this group was 0.67 if averaged over all observations present at *t*–1, or 0.59 if calculated only for the subsample present at *t*–1 and *t* (as in Table 1(a)). If evaluated at the values for the reference person, the corresponding predictions were 0.62 and 0.54. In other words, excluding attritors leads to an under-estimate of average poverty persistence.

We found that there were few covariates with statistically significant effects at the five per cent level or better.[18] Having a household head with A-levels was associated with a conditional poverty probability some six percentage points lower. Ethnic group effects are often hard to identify in the BHPS because of small cell sizes, but it was apparent nonetheless that individuals with household heads of Pakistani or Bangladeshi ethnic origin had much higher probabilities than those of European origin: the marginal effect was 14 percentage points. Having more children aged 3–4 years or 5–11 years was associated with conditional poverty risks seven and eight percentage points higher. Finally living in a multi-family household was associated with a large decrease in conditional poverty risk: the probability was 18 percentage points lower than for those in single-family households.

Consider now the estimates conditioning on being non-poor at *t*–1 (γ_2). The predicted probability of current poverty for this group was 0.054 if averaged over all observations present at *t*–1, or 0.058 if calculated for those present at *t*–1 and *t* (as in Table 1(a)). If

[18] This may surprise some readers, but recall that the equation is for conditional poverty status. In the equation for initial poverty status, there are many more statistically significant effects, and all with the expected signs (Appendix Table 1). For example, lower risks of initial poverty were associated *inter alia* with being male, having a head of household with higher educational qualifications, working full-time, not of Pakistani or Bangladeshi origin, not living in social housing, and with fewer children present. To put things another way, observe that when we estimated a transition equation ignoring initial conditions, then some characteristics such as educational qualifications and the number of household workers are more strongly statistically significant. This suggests that we can then ascribe the weaker effects observed in our transition model to the effects of endogeneity being accounted for. Arguably the weaker statistical significance of the persistence coefficients relative to that of the entry coefficients is because the number of persons poor (at risk of poverty persistence) is much smaller than the number of non-poor persons (at risk of poverty entry). But the former number is in the thousands nonetheless.

evaluated at the values for the reference person, the corresponding predictions were each 0.09. In other words, excluding attritors leads to a small or negligible over-estimate of average poverty entry propensity.

In this part of the model, there were many statistically significant associations. For instance, higher risks of poverty were associated with being older, and having a household head that was older, was male, had educational qualifications below A-levels, and who did not work or worked part-time. Ethnic origin had large effects. Compared to individuals with a household head of European origin, having a household head of Pakistani/Bangleshi or Chinese ethnic origin meant a poverty risk about 18 and 36 percentage points higher respectively. Poverty risks were also higher for individuals living in lone parent families and multi-family households (marginal effects of some 3–4 percentage points), those living in social housing (10 percentage points) and having fewer workers in the household (4 percentage points). In addition, the presence of individuals aged 60+ lowered poverty risks, whereas the presence of dependent children aged 0–15 raised them.

Predicted poverty transition probabilities and poverty spell lengths

An alternative, and perhaps more intuitive, way of exploring the implications of the estimates is to examine the predicted probabilities of poverty entry and exit that they imply for persons with different combinations of characteristics. With the additional assumption that all relevant processes are in a stationary equilibrium, then one can also derive what these poverty transition rates imply for the state probability of being poor and the average lengths of time spent poor for those beginning a spell and the average poverty recurrence time for those ending a poverty spell (Section 2). By construction, the estimates control for the selection biases associated with initial poverty status and retention.

The various predictions are summarised in Table 4, and were derived using the point estimates of the parameters shown in Table 3 and the formulae in (5), (6).[19] Our reference person, case 1, was a man aged 40, working full-time, whose household head had no A-levels and was of European origin, living in a single-family single earner household comprising a married couple with one child aged 5–11, with no adults aged 60+ present, and who were not living in social housing. His predicted poverty persistence rate was just under one half (0.480) and his predicted poverty entry rate was about one in fifteen (0.068). Under the stationarity

[19] Since a number of estimated coefficients were not statistically significant, we have considered changes in characteristics associated with coefficients that were significant.

assumption, these rates imply a probability of being poor of just over one in ten (0.115), and a mean poverty spell length of 1.9 years and mean time between poverty spells of 14.7 years. The estimates of median spell lengths are smaller than the corresponding means, as expected, but the magnitude of the differential between mean and median indicates a wide dispersion in spell lengths even among individuals sharing the same characteristics.

<Table 4 near here>

Having A-level or higher educational qualifications (case 2) lowered the poverty persistence rate and the poverty entry rate compared to the reference person, to 0.42 and 0.05 respectively, implying shorter poverty spells (the median fell to 0.79 years from 0.94) and longer median recurrence times (up to 14.2 years from 9.9). By contrast, having a household head of Pakistani or Bangladeshi ethnic origin (case 3) implied a much higher persistence rate (0.64) and a much higher entry rate (0.22). The predicted state probability was 0.38, the median poverty spell length 1.6 years and median recurrence time only 2.7 years. Having an extra young child in the household had an even larger impact (case 5): the persistence rate became 0.56 and the entry rate, 0.10, implying a median poverty spell length of 2.3 years and a median recurrence time of 1.9 years. The predicted state probability was almost one fifth (0.19). Living in social housing (case 4) provided estimates in between those for the reference man and these two cases. Having no children (case 6) or an additional worker in the household (case 7) had a clearly beneficial effect – predicted spell lengths were shorter and recurrence times were longer than for the reference person – and of much the same magnitude. For example the state probabilities of poverty were roughly halved, to 0.06 and 0.07 respectively.

The non-working lone mother described in cases 8–10 had, as expected, a much higher poverty persistence rate and a higher poverty rate than the corresponding reference married man in full-time work. For example the state probability of being poor for the reference lone mother (case 8) was more than double that of the reference man (case 1): 0.29 compared to 0.12. This adverse differential persists across the other lone mother cases. If she had an additional child aged 3–4 (case 9), then the state probability of being poor rose to 0.40 (compared to 0.19 for case 5), the predicted median poverty spell length was 1.5 years (compared to 1.2 years) and the median recurrence time 2.4 years (6.3 years). Even if the lone mother were in full-time work (case 11), the state probability of being poor was still relatively high (0.16).

One general lesson from Table 4 is that there is greater individual heterogeneity in poverty entry rates than in poverty persistence rates. To put things another way, the large differences in predicted state probabilities of being poor appear related more to differences in the lengths of time spent out of poverty rather than to differences in the lengths of time spent in poverty. (And this in turns arises from the fact that coefficients in the poverty persistence equation are smaller and less significant than those in the entry equation.) This finding is of policy relevance. In Britain most of the Labour government's anti-poverty policies, introduced from 1997 onwards, have been aimed at getting poor people out of poverty (i.e. lowering persistence) and relatively little at keeping them out of poverty once out (or from falling into poverty in the first place). Our findings suggest the relevance of policies also directed at the latter.

Predicted transition rates also provide information about the consequences of ignoring the endogeneity of initial poverty status and of retention. To examine this issue, we estimated three variations on our model: (a) one treating initial poverty status as exogeneous and retention as endogeneous, (b) one treating retention as endogeneous and initial poverty status as exogeneous, and (c) one treating both processes as exogeneous. Model (a) led to under-estimates of both poverty persistence rates and poverty entry rates (relative to the corresponding ones shown in Table 4), whereas models (b) and (c) each led to over-estimates. For example, for the reference person, our preferred model implied a poverty persistence rate of 0.480 and a poverty entry rate of 0.068 (Table 4, row 1). By contrast, for model (a), the corresponding estimates were 0.465 and 0.066; for model (b), they were 0.569 and 0.079 and, for model (c), 0.532 and 0.073.[20] Model (a) provided predicted rates that were the least biased, which suggests that neglecting to control for endogeneity of initial poverty status is more problematic than neglecting to control for endogeneity of retention. Consistent with this observation, recall that the estimated correlation between base year poverty status and conditional current poverty status (ρ_2) was much larger the magnitude than the other two correlations.

[20] The predicted state probabilities were 0.110, 0.154, 0.136 for models (a)–(c) respectively, and the predicted mean poverty spell durations were 1.87, 2.32, and 2.14 years. I.e. they were substantially different from the corresponding estimates in Table 4, especially for model (b).

State dependence in low income

The results displayed in Table 3 suggest that observed characteristics had different impacts on poverty propensities, depending on whether an individual was already or poor – a finding consistent with the existence of genuine state dependence (GSD) in low income. A formal test for the absence of GSD, formulated using the null hypothesis H_0: $\gamma_1 = \gamma_2$, led to a test statistic of 332.470 (d.f. = 36) with $p < 0.0000$. The null hypothesis was therefore overwhelmingly rejected.

We also calculated measures of Aggregate State Dependence (ASD) and GSD using the formulae shown in (7) and (8). We estimated that ASD = 0.610 when calculated using all sample respondents present at t–1, and 0.527 when calculated for those present at t–1 and t (as in Table 1). By constrast, we estimated that GSD = 0.477 when calculated using all sample respondents present at t–1, and 0.312 when calculated for those present at t–1 and t. (That state dependence was lower if attriters were excluded from computations reflects the fact mentioned earlier, that attritors had above-average poverty persistence rates.)

Our estimates indicate that GSD constituted a substantial proportion of ASD, some 80 per cent when calculated using sample respondents present at t–1 (60 per cent if attritors are excluded). This fraction is in line with the estimates of ASD and GSD reported by Stewart and Swaffield (1999), albeit for for low pay, rather than for income as in this paper. While the degree of ASD found here is similar to that reported by Hill (1981) for the USA in the 1970s, our estimate of the extent of GSD is rather larger than hers, though she did not control for initial conditions or differential retention as we have.

In sum, the GSD test result and the high proportion of ASD accounted for by GSD indicates that a non-trivial part of poverty persistence may be ascribed to past poverty experiences. The labour market is the most obvious source of state dependence effects and is the one most researched so far in Britain: see for example Stewart and Swaffield (1999), Arulampalam *et al*. (2000), and the papers in the November 2001 *Economic Journal* (Arulampulam *et al.*, 2001).

5. Sensitivity analysis

In this section we report on our checks of the robustness of our results to variations in some of the assumptions underlying the model of Section 2. First we considered what happened when we used alternative definitions of the poverty line, and second we extended the econometric model to incorporate five income bands to summarise the base year income distribution rather than just two (above and below the poverty line).

Were findings robust to the choice of the definition of the poverty line?

The definition of the poverty line that was utilised so far was inspired by definitions used in Britain's official low income statistics and much academic research. Nonetheless its choice is arbitrary in essence (Atkinson, 1987). This motivated us to re-estimate the model using three alternative definitions of the poverty line: 50 per cent of contemporary median income, 70 per cent of contemporary median income, and 60 per cent of 1991 median income. The first two thresholds provide bounds to the 60-per-cent of median line used earlier. The third cut off is an absolute poverty line, fixed in real terms over time, whereas all the other lines are relative ones (whose generosity increases over time with secular income growth).

Table 5 shows the aggregate sample poverty entry rates and persistence rates implied by the three alternative poverty line definitions, using both the sample with two consecutive income observations and the sample that also included attritors. Estimates based on poverty lines based on contemporary median incomes, and comparisons with corresponding figures in Table 1, suggest that persistence and entry rates rise monotonically as the low income cut-off approaches the median of the distribution – consistent with fact that the chance of being poor at any point in time is higher, the higher the cut-off.[21] This pattern was present for both of the samples. Transition rates computed using the poverty line fixed at 60 per cent of median 1991 income were remarkably similar to those based on 60 per cent of contemporary median income (Table 1). This is because the shape of the British income distribution changed relatively little over the sample period (1991–9).

<Table 5 near here>

Table 6 reports estimates of the model correlations and the parameters of the conditional current poverty equations. (The estimates for initial poverty status and retention are provided in Table A2 in the Appendix.) We summarise the impact of observed characteristics in terms of their marginal effects. For brevity's sake, we show the asymptotic t-ratios of the underlying PSML coefficient estimates, but not the coefficients themselves.

<Table 6 near here>

[21] The same pattern was reported by Stewart and Swaffield (1999) for the earnings distribution.

Estimated cross-equation correlations were similar in magnitude to those reported in Table 2, and the tests of their significance also indicated that initial poverty status and retention were endogenous (the test statistics and *p*-values are reported at the bottom of Table 6). There was also a high degree of cross-model consistency in the sets of covariates that had statistically significant associations with conditional current poverty status. Perhaps the most notable differences between the estimates were that for the least generous poverty line (50 per cent of median income) and in the equation for those poor at t–1, coefficients on covariates measuring whether the respondent was female and whether the head of household was female were statistically significant, and the coefficient on the covariates measuring whether the household head had A-level or higher educational qualifications was not statistically significant. In other words female-headed households appear to have had more marked poverty persistence risk when the low income cut-off was relatively low. The magnitude of the covariate effects is broadly similar across models too – in so far as they can be compared.[22]

We also found that, for each poverty line, the inclusion of attriters led to substantially larger rates of poverty persistence: compare the predicted probabilities for the full and balanced samples shown towards the bottom of Table 6. Finally, the measures of ASD and GSD support previous our findings about the importance of GSD. In particular, when the lowest poverty line threshold was used, GSD was estimated to be even larger than ASD (albeit only slightly). An explanation for this is that, at the very bottom of the distribution heterogeneity is not relevant: when the poverty line is low, individuals with incomes just above the lowest poverty line may be very similar to those with incomes below the line.

A model with five income bands to describe the base year income distribution

The models utilised so far indicate that the magnitude of GSD is substantial. The principal aim in this subsection is to explore the extent to which that result was contingent on the use of only two income bands to describe the base year income distribution. The GSD measure characterised in (12) is based on the difference in the parameters indexing transition probabilities, γ_1 and γ_2. Since γ_2 was estimated using all individuals with a base year income above the poverty line, then arguably our GSD finding might simply reflect substantial

[22] Some differences in marginal effects are likely purely because the calculations were based on different samples in each model. Recall the earlier discussion about how the derivations involve accounting for the conditioning on base year poverty status.

heterogeneity among the individuals who were initially not poor. In order to assess the robustness of our earlier result, we tested for and measured GSD using a greater number of categories of base year income in order to differentiate among the non-poor. Specifically, while continuing to define the poverty line as 60 per cent of median income, we partitioned the non-poor into four groups by introducing three additional income thresholds: 80 per cent, 100 per cent, and 150 per cent of the median.

Aggregate poverty transition rates based on this five income band classification are reported in Table 7. Differences in poverty entry rates across the base year distribution are clear. Among those who had incomes between 60 per cent and 80 per cent of median income at t–1, the probability of falling into poverty the next year was 21 per cent, whereas for those with an income greater than 150 per cent of the median, the probability was only 1.5 per cent. Moving from lower to higher incomes, the probability of entering poverty declined monotonically, with a considerable drop (14 percentage points) occurring between the poorest and second poorest of the non-poor income groups. Table 7 also reports (in panel b) transition probabilities obtained when income attrition was included as a destination state. Differences in retention rates across the four groups of non-poor individuals were negligible.

<Table 7 near here>

We allowed for heterogeneity among the initially non-poor by specifying the initial condition equation as an ordered probit for the five income classes defined earlier. We introduced three additional thresholds in the support of p^*_{it-1}, and our discrete indicator of initial income became polychotomous:

$$P^{\circ}_{it\text{-}1} = \begin{cases} 1 & \text{if} \quad p^*_{it\text{-}1} > 0 \\ 0 & \text{if} \quad 0 \geq p^*_{it\text{-}1} > \tau_1 \\ -1 & \text{if} \quad \tau_1 \geq p^*_{it\text{-}1} > \tau_2 \\ -2 & \text{if} \quad \tau_2 \geq p^*_{it\text{-}1} > \tau_3 \\ -3 & \text{if} \quad \tau_3 \geq p^*_{it\text{-}1} \end{cases} \tag{13}$$

where $0 > \tau_1 > \tau_2 > \tau_3$.

Accordingly, the period t poverty equation had five regimes:

$$\Pr(P_{it} = 1) = \Phi(\gamma_j' z_{it-1}) \text{ if } P^{\circ}_{it-1} = j \text{ and } R_{it} = 1, \tag{14}$$

where j = –3, –2, –1, 0, 1.

The rest of the model (retention equation and error distribution) was specified as in Section 2. The absence of GSD was tested by testing the difference between γ_1 and each of the other vectors of coefficients indexing transition probabilities. To measure ASD and GSD in this context, we extended the definition proposed earlier to take account of multiple base year income bands. Since ASD and GSD are computed by comparing conditional poverty probabilities between the initially poor and non-poor, one can now compute as many indicators of ASD and GSD as there are non-poverty states in the base year. For initial non-poor income class *j*, we propose that ASD be computed as the difference between the predicted probability of persistence (averaged over the initially poor) and the weighted average of predicted entry probabilities taken over the initially non-poor in all classes up to the *j*-th, with the weights being the proportion of respondents falling into each of the non-poor income classes:

$$\text{ASD}j = \left[\frac{\sum_{i\in\{P^{o}_{it-1}=1\}} \Pr(P_{it}-1 \mid P^{o}_{it-1}=1)}{\sum_{i} I(P^{o}_{it-1}=1)}\right] - \sum_{k=0}^{|j|} w_k^j \left[\frac{\sum_{i\in\{P^{o}_{it-1}=-k\}} \Pr(P_{it}=1 \mid P^{o}_{it-1}=-k)}{\sum_{i} I(P_{it-1}=-k)}\right] \qquad (15)$$

for $j = -3, -2, -1, 0$, where w^j_k are the weights and $I(.)$ is an indicator function taking value 1 when its argument holds and 0 otherwise.[23] Similarly, we propose that the GSD measure for initial non-poor income class *j* be obtained by computing, for each individual in *j*, the difference between the conditional poverty probability for each individual *i* were she poor in the base year and the weighted average of the poverty probabilities conditional on membership of all non-poor income classes up to and including *j*:

$$\text{GSD}_{ij} = \Pr(P_{it}=1 \mid P^{o}_{it-1}=1) - \sum_{k=0}^{|j|} w_k^j \Pr(P_{it}=1 \mid P_{it-1}=-k) \qquad (16)$$

for $j = -3, -2, -1, 0$. The summary measure of GSD for class *j* was obtained by averaging this expression over all individuals.

Estimates of the poverty transition equation with the five-class distribution in year *t*–1 are reported in Table 8. (The estimates for initial poverty status and retention are provided in Table A2 in the Appendix.) The bottom panel of the table reports predicted conditional poverty probabilities averaged over the members of *t*–1 income classes. When the subsample

[23] Weights were normalised to sum to unity, i.e. we used different set of weights for the four ASD indices that can be computed.

with two consecutive income observations was used, model predictions replicated the aggregate figures shown in Table 7. Table 8 also reports predicted probabilities for persons with average sample characteristics or with ‘reference’ characteristics (defined in the table note). Although these predictions tended to be lower than the sample averages for low income classes, the opposite was true for high income classes.

<Table 8 near here>

Tests for the absence of GSD confirmed our previous findings, always rejecting this hypothesis with p-values < 0.0000 (see the foot of Table 8). Thus, even for individuals with base year incomes just above the poverty line, the impact of observed characteristics on poverty transition propensities differed from the impact for those who were initially poor. This finding indicates that our earlier results are robust to the categorisation of the base year income distribution. Estimates of state dependence based on the measures defined in (15) and (16) indicated that GSD was relevant even if we focussed only on the lower range of the year t–1 income distribution. Comparisons of the conditional poverty probabilities for the initially poor and those with an income between the poverty line (60 per cent of median income) and 80 per cent of the median showed that 65 per cent of ASD was accounted for by GSD. In other words, our earlier results about the importance of GSD were not driven by neglect of heterogeneity among the non-poor. When we looked at the ASD and GSD measures for the richer base year income classes, the estimates tended to mimic the ones reported from the model of Section 2.

A second set of findings from the five-income-class model concerns the significance of correlations between unobservables of the three equations. Our estimates show that these parameters were imprecisely estimated; in fact they were not statistically different from zero. The loss of significance for correlation involving retention is consistent with the summary evidence presented in Table 7. This showed that attrition rates were similar for all base year income classes excluding the poorest one. The non-significance for correlations involving initial conditions might reflect the introduction into the model of additional base-year-contingent parameters to index transition probabilities: allowance for greater heterogeneity via observed variables may have reduced extent of estimated unobserved heterogeneity. Some support for this argument is adduced by comparisons of corresponding marginal effects across the four pairs of columns on the right hand side of Table 8 – suggesting differences across groups – but conclusions were constrained by the fact that many coefficient estimates were no longer statistically significant. This in turn was likely to reflect the smaller sample sizes within income bands when more bands were used.

Overall the evidence about the sensitivity of conclusions is somewhat more mixed than for the poverty line variation case. Nonetheless we would emphasise that our specific motivation for the extended model was to check the earlier conclusions about state dependence, and these appear relatively robust.

6. Concluding remarks

In the Introduction we stated that our aim was to contribute some new methods and some new findings. We have shown that there is a useful role for first-order Markov models in the analysis of poverty dynamics alongside the more common hazard regression and covariance structure models. Markovian models can account for the potential endogeneity of both initial poverty status and sample retention and straightforwardly provide estimates of useful statistics about the distributions of poverty and non-poverty. In particular, using British panel data for the 1990s, we confirmed that initial conditions and sample retention issues were indeed endogenous in the estimation of poverty transition equations (though this did depend on the number of income bands used to specify the base year income distribution).

There appears to be substantial heterogeneity in the rates of movement into and out of poverty. For example married couples had both lower poverty entry rates and lower poverty persistence rates than lone mothers, which corresponded to longer spells of poverty and shorter spells of non-poverty for the latter group. These relativities are of course exactly what one would expect; the strength of the model is that it could also provide a large number of much more specific predictions for individuals from a range of household types. Finally we have also shown that, notwithstanding the substantial differences in poverty propensities associated with individual heterogeneity, there appears also to be non-trivial state dependence in low income in Britain. Pinpointing the sources of this is an important topic for further research on poverty. On the methodological side there is also scope for development of Markovian models. For example, in current research, we are building a second-order Markov model.

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Table 1. Annual poverty inflow and outflow rates (row %), with and without missing income data

Poverty status, year t–1	Poverty status, year t		
	Not poor	Poor	Missing
(a) Sample with non-missing income at t			
Not poor	94.2	5.8	
Poor	41.5	58.5	
All	*87.9*	*12.1*	
(b) All individuals			
Not poor	84.3	5.2	10.6
Poor	36.3	50.8	13.3
All	*78.3*	*10.8*	*10.9*

Pooled transitions from British Household Panel Survey, waves 1–9. Sample size (panel b) = 44,772. Adults aged 20–59, excluding full-time students. The poverty line is 60% of median contemporary equivalised real net household income. Missing income data at t arise from either sample attrition or incomplete response within a respondent's household. See text for further details.

Table 2. PSML estimates of model correlations, and model test statistics (exogeneity of initial conditions and sample retention, instrument validity, no state dependence)

Correlations between unobservables affecting:	Estimate	|t-ratio|
Base year poverty status and retention (ρ_1)	–0.061	(2.980)
Base year poverty status and conditional current poverty status (ρ_2)	–0.265	(2.980)
Retention and conditional current poverty status (ρ_3)	–0.029	(0.250)

Null hypotheses for tests	Test statistic	*p*-value
$\rho_1 = \rho_2 = 0$	17.55	0.0002
$\rho_1 = \rho_3 = 0$	8.98	0.0112
$\rho_1 = \rho_2 = \rho_3 = 0$	17.66	0.0005
Exclusion of parental background from transition equation (d.f. = 28)	32.15	0.2686
Exclusion of sample membership status from transition equation (d.f. = 2)	0.96	0.6190
Exclusion of parental background and sample membership status from transition equation (d.f. = 30)	33.51	0.3007
Inclusion of parental background in initial conditions equation (d.f. = 14)	24.87	0.0359
Inclusion of sample membership status in retention equation (d.f. = 1)	466.68	0.0000
$\gamma_1 = \gamma_2$ (d.f. = 36)	332.47	0.0000

GHK simulated pseudo maximum likelihood estimation with 250 random draws. Asymptotic standard errors are robust for the presence of repeated income observations within households and on the same individual.

Table 3. PSML estimates of poverty status at *t*, conditional on poverty status at *t*–1

Covariate (measured at *t*–1)	Poor at *t*–1			Non-poor at *t*–1		
	Marginal effect	Coefficent	|t-ratio|	Marginal effect	Coefficient	|t-ratio|
Individual characteristics						
Age	0.004	0.006	(0.34)	0.028	–0.042	(3.62)
Age squared		–0.0001	(0.27)		0.001	(3.83)
Female	–0.014	–0.037	(1.43)	0.008	0.049	(3.41)
Household head's characteristics						
Age	0.054	0.019	(1.02)	0.003	–0.034	(2.82)
Age squared		–0.0001	(0.47)		0.0004	(2.55)
Female	0.038	0.102	(1.56)	–0.015	–0.099	(2.49)
Has A-levels or higher educational qualification	–0.059	–0.150	(1.97)	–0.026	–0.176	(4.70)
Works full–time	0.010	0.027	(0.30)	–0.025	–0.167	(3.02)
Works part–time	0.020	0.053	(0.53)	0.035	0.185	(2.75)
Ethnic group						
Black Caribbean	0.120	0.338	(1.50)	–0.058	–0.484	(1.77)
Black African	–0.013	–0.034	(0.10)	–0.009	–0.058	(0.30)
Black Other	0.036	0.096	(0.39)	0.024	0.131	(0.45)
Indian	0.064	0.174	(0.57)	0.027	0.148	(0.85)
Pakistani or Bangladeshi	0.143	0.409	(2.10)	0.183	0.725	(2.17)
Chinese	–0.147	–0.371	(0.88)	0.367	1.220	(3.98)
Other ethnic origin	0.136	0.387	(1.21)	–0.044	–0.334	(1.80)
Household characteristics						
Lone parent household	0.008	0.020	(0.25)	0.041	0.213	(3.21)
Other household type	0.059	0.160	(1.06)	–0.002	–0.012	(0.14)
Presence in household of						
adult aged 60–75	–0.043	–0.111	(0.70)	–0.029	–0.195	(2.20)
adult aged 76+	–0.102	–0.259	(0.78)	–0.066	–0.602	(2.99)
children aged 0–2	0.040	0.107	(1.45)	0.027	0.149	(2.90)
children aged 3–4	0.071	0.193	(2.83)	0.045	0.234	(4.71)
children aged 5–11	0.085	0.232	(3.53)	0.045	0.234	(5.97)
children aged 12–15	0.020	0.052	(0.71)	0.042	0.219	(4.62)
children aged 16–18	0.049	0.132	(0.90)	0.012	0.071	(0.78)
Number of workers	–0.045	–0.115	(1.39)	–0.036	–0.257	(7.81)
Lives in social housing	0.031	0.081	(1.32)	0.098	0.446	(9.94)
Multi-family household	–0.182	–0.461	(3.32)	0.037	0.195	(2.62)
Intercept		–0.393	(1.03)		0.257	(0.95)
Log-likelihood	–34,832					
Model chi-square (d.f. = 155)	5,830 ($p < 0.000$)					
Number of observations (persons)	9,279					
Number of observations (person-waves	44,602					

Notes: GHK simulated pseudo-maximum likelihood with 250 random draws. Asymptotic t-ratios for coefficients, in parentheses, are robust for the presence of repeated income observations within households and on the same individual. Marginal effects defined in text. Regressions also included year dummies. Reference categories for dummy variables: male, male household head with no A-levels, not working and of European ethnic origin, married couple household with no elderly or children, not living in social housing and single family, base year is 1991.

Table 4. Predicted poverty transition probabilities, and steady-state state probabilities and spell durations

Characteristics		Poverty persistence rate (s_{it})	Poverty entry rate (e_{it})	Pr(poor)	Poverty spell duration (years)		Non-poverty spell duration (years)	
					mean	median	mean	median
1.	Man aged 40, working full-time; household head has no A-levels, of European origin, one worker in household, single-family household, married couple with one child aged 5–11, no adults aged 60+ present, not living in social housing	0.480	0.068	0.115	1.92	0.94	14.73	9.86
2.	As (1), except household head has A-levels	0.417	0.048	0.075	1.71	0.79	21.01	14.21
3.	As (1), except household head of Pakistani or Bangladeshi origin	0.643	0.223	0.384	2.80	1.57	4.49	2.75
4.	As (1), except lives in social housing	0.511	0.148	0.233	2.05	1.03	6.74	4.31
5.	As (1), except also has child aged 3–4	0.557	0.104	0.191	2.26	1.18	9.58	6.29
6.	As (1), except no children present	0.384	0.042	0.064	1.62	0.72	23.72	16.09
7.	As (1), except one additional worker	0.431	0.040	0.066	1.76	0.82	24.94	16.94
8.	As (1), except woman, not working; no workers in household	0.549	0.184	0.290	2.22	1.16	5.44	3.41
9.	As (8), except lives in social housing	0.582	0.326	0.438	2.39	1.28	3.07	1.76
10.	As (8), except also has child aged 3–4	0.626	0.253	0.403	2.68	1.48	3.96	2.38
11.	As (8), except head works full-time	0.513	0.092	0.159	2.05	1.04	10.84	7.16

Predicted persistence rates and entry rates derived from (5), (6) and the point estimates reported in Table 3. Remaining estimates derived assuming steady-state equilibrium (see Section 2 for the formulae).

Table 5. Annual poverty inflow and outflow rates, with and without missing income data, by poverty line definition (row %)

Poverty status, year *t*–1	Poverty status, year *t*		
	Not poor	Poor	Missing
Poverty line = 50% of median income			
(a) Sample with non-missing income at *t*			
Not poor	95.6	4.4	
Poor	52.8	47.2	
All	*92.5*	*7.5*	
(b) All individuals			
Not poor	85.4	3.9	10.7
Poor	45.4	40.6	14.1
All	*82.4*	*6.7*	*10.9*
Poverty line = 70% of median income			
(a) Sample with non-missing income at *t*			
Not poor	92.5	7.5	
Poor	34.5	65.5	
All	*82.5*	*17.6*	
(b) All individuals			
Not poor	82.7	6.7	10.6
Poor	30.2	57.3	12.5
All	*73.5*	*15.6*	*10.9*
Poverty line = 60% of 1991 median income			
(a) Sample with non-missing income at *t*			
Not poor	95.1	4.9	
Poor	47.1	52.9	
All	*90.2*	*9.8*	
(b) All individuals			
Not poor	85.1	4.4	10.6
Poor	40.6	45.5	13.9
All	*80.4*	*8.7*	*10.9*

Pooled transitions from British Household Panel Survey, waves 1–9. Adults aged 20–59, excluding full-time students. Missing income data at *t* arise from either sample attrition or incomplete response within a respondent's household. See text for further details. Compare patterns with those in Table 1, based on a poverty line equal to 60 per cent of median income.

Table 6. PSML estimates of conditional current poverty probability, by poverty line definition

Covariate (measured at *t*–1)	Poverty line = 50% median				Poverty line = 70% median				Poverty line = 60% of 1991 median			
	Poor		Non-poor		Poor		Non-poor		Poor		Non-poor	
	M.E.	|t-ratio|	M.E.	|t-ratio|	M.E.	|t-ratio|	M.E.	|t-ratio|	M.E.	|t-ratio|	M.E.	|t-ratio|
Individual characteristics												
Age	0.034	(0.19)	0.014	(2.74)	–0.003	(0.95)	0.044	(5.27)	0.015	(0.50)	0.021	(3.16)
Age squared		(0.38)		(2.73)		(0.84)		(5.51)		(0.34)		(3.28)
Female	–0.028	(2.29)	0.004	(1.77)	0.007	(0.97)	0.009	(3.63)	–0.013	(1.19)	0.005	(2.00)
Household head characteristics												
Age	0.038	(1.47)	0.001	(1.53)	0.031	(0.94)	0.001	(1.96)	0.061	(0.41)	0.004	(2.45)
Age squared		(1.05)		(1.35)		(0.46)		(1.69)		(0.08)		(2.25)
Female	0.083	(3.02)	–0.018	(3.09)	0.010	(0.52)	–0.015	(2.23)	0.043	(1.68)	–0.014	(2.33)
Has A-levels or higher ed. Qualification	–0.004	(0.13)	–0.017	(3.13)	–0.053	(2.30)	–0.035	(6.13)	–0.033	(1.04)	–0.020	(3.47)
Works full-time	0.058	(1.38)	–0.020	(2.68)	0.007	(0.28)	–0.022	(2.49)	0.029	(0.79)	–0.023	(2.96)
Works part-time	–0.008	(0.18)	0.028	(2.47)	0.049	(1.80)	0.031	(2.30)	0.010	(0.25)	0.033	(2.77)
Ethnic group												
Black Caribbean	0.249	(3.61)	–0.031	(1.05)	0.013	(0.18)	–0.059	(1.39)	0.193	(2.61)	–0.053	(1.51)
Black African	–0.299	(1.45)	0.026	(0.91)	–0.119	(1.24)	0.039	(0.86)	–0.117	(1.18)	0.023	(0.64)
Black Other	–0.009	(0.16)	0.065	(1.58)	0.107	(1.30)	0.034	(0.70)	–0.058	(0.62)	0.050	(1.04)
Indian	0.147	(1.04)	0.010	(0.38)	0.043	(0.55)	0.031	(0.87)	0.084	(0.62)	0.033	(1.10)
Pakistani or Bangladeshi	0.142	(2.29)	0.153	(2.83)	0.168	(2.24)	0.152	(1.42)	0.144	(2.23)	0.172	(2.68)
Chinese	–0.593	(12.41)	0.205	(3.19)	–0.250	(1.40)	0.314	(3.03)	0.076	(1.69)	0.348	(3.36)
Other ethnic origin	–0.008	(0.08)	–0.006	(0.21)	0.041	(0.42)	–0.001	(0.05)	0.129	(0.88)	–0.026	(0.90)
Household characteristics												
Lone parent household	0.001	(0.02)	0.020	(1.94)	0.008	(0.34)	0.066	(4.19)	–0.003	(0.08)	0.034	(2.80)
Other household type	0.065	(1.10)	0.002	(0.16)	0.037	(0.97)	–0.009	(0.70)	0.057	(1.11)	–0.004	(0.32)
Presence of												
adult aged 60–75	0.023	(0.31)	–0.031	(2.39)	–0.018	(0.43)	–0.013	(0.79)	–0.078	(1.09)	–0.037	(2.78)
adult aged 76+	–0.073	(0.58)	–0.044	(1.75)	–0.066	(0.68)	–0.054	(1.62)	–0.164	(1.06)	–0.064	(2.92)
children aged 0–2	0.003	(0.10)	0.023	(2.77)	0.015	(0.72)	0.052	(5.12)	0.034	(1.20)	0.026	(2.88)
children aged 3–4	0.028	(0.96)	0.030	(3.65)	0.049	(2.41)	0.043	(4.23)	0.076	(2.74)	0.037	(3.95)
children aged 5–11	0.068	(2.32)	0.030	(4.69)	0.078	(4.24)	0.065	(7.25)	0.071	(2.67)	0.038	(5.15)
children aged 12–15	–0.002	(0.05)	0.025	(3.04)	0.031	(1.46)	0.047	(4.75)	0.032	(1.12)	0.030	(3.43)
children aged 16–18	–0.010	(0.16)	0.035	(2.37)	–0.013	(0.32)	0.009	(0.53)	0.041	(0.67)	0.026	(1.70)
Number of workers	0.047	(1.30)	–0.036	(8.94)	–0.075	(3.34)	–0.034	(6.64)	–0.008	(0.23)	–0.036	(8.06)
Lives in social housing	–0.013	(0.53)	0.054	(6.97)	0.072	(3.95)	0.089	(7.90)	0.014	(0.56)	0.078	(8.78)
Multi-family household	–0.212	(3.89)	0.027	(1.95)	–0.132	(3.55)	0.056	(3.72)	–0.222	(4.53)	0.046	(3.10)

Intercept	–0.496	(1.02)	–0.276	(1.02)	–0.161	(0.49)	0.427	(1.51)	–0.329	(0.77)	0.061	(0.22)
ρ_1	–0.056	(2.52)			–0.034	(1.82)			–0.061	(2.93)		
ρ_2	–0.474	(5.20)			–0.239	(2.91)			–0.332	(3.54)		
ρ_3	–0.094	(0.90)			–0.047	(0.42)			0.002	(0.02)		
Log-likelihood	-30,281				-39,892				-32,898			
Model chi2 (d.f.=155)	5,148		$p < 0.0000$		6,959		$p < 0.0000$		4,319		$p < 0.0000$	
Number of observations (person-waves)	44,602				44,602				44,602			
Predicted probability: sample averages	0.687	[0.471]	0.037	[0.044]	0.740	[0.655]	0.075	[0.075]	0.641	[0.527]	0.043	[0.049]
Predicted probability: reference person	0.593	[0.381]	0.083	[0.079]	0.707	[0.643]	0.106	[0.107]	0.592	[0.485]	0.090	[0.091]
Measures of state dependence	ASD=0.650 [0.427]		GSD=0.665 [0.281]		ASD=0.665 [0.58]		GSD=0.503 [0.35]		ASD=0.598 [0.478]		GSD=0.519 [0.292]	
Null hypothesis of test	*Test statistic*		*p-value*		*Test statistic*		*p-value*		*Test statistic*		*p-value*	
$\rho_1 = \rho_2 = 0$	34.30		0.0000		11.92		0.0026		20.67		0.0000	
$\rho_1 = \rho_3 = 0$	7.62		0.0222		3.55		0.1693		8.62		0.0134	
$\rho_1 = \rho_2 = \rho_3 =0$	40.28		0.0000		12.32		0.0064		20.76		0.0001	
$\gamma_1 = \gamma_2$ (d.f.=36)	548.41		0.0000		408.24		0.0000		295.64		0.0000	

Notes: GHK simulated pseudo-maximum likelihood with 250 random draws. 'M.E.' = marginal effect (defined in text). Asymptotic *t*-ratios for coefficients, in parentheses, are robust for the presence of repeated income observations within households and on the same individual. Equations include year dummies. Figures in square brackets are computed for the balanced income sample between *t*–1 and *t*. Reference categories for dummy variables: male, male household head with no A-levels, not working and of European ethnic origin, married couple household with no adults aged 60+ or children present, not living in social housing and single-family household, 1991–92 transition.

Table 7. Annual transition rates, with and without missing income data, for five-category transition matrix (row %)

Income in year t–1 (as percentage of year t–1 median)	Income in year t (as percentage of year t median)					
	150+	100–150	80–100	60–80	0–60	Missing
(a) Sample with non-missing income at t						
150+	77.5	17.5	2.3	1.2	1.6	
100–150	16.7	62.1	12.8	5.0	3.4	
80–100	4.8	30.7	37.6	19.3	7.6	
60–80	3.9	13.3	23.1	38.3	21.4	
0–60	3.0	7.9	9.0	21.6	58.5	
All	*31.0*	*31.8*	*13.6*	*11.6*	*12.1*	
(b) All individuals						
150+	69.3	15.7	2.1	1.0	1.4	10.6
100–150	14.9	55.5	11.4	4.5	3.1	10.6
80–100	4.3	27.4	33.5	17.2	6.7	10.8
60–80	3.5	11.9	20.8	34.4	19.3	10.2
0–60	2.6	6.9	7.8	18.7	50.8	13.3
All	*27.6*	*28.3*	*12.1*	*10.3*	*10.8*	*10.9*

Pooled transitions from British Household Panel Survey, waves 1–9. Adults aged 20–59, excluding full-time students. Missing income data at t arise from either sample attrition or incomplete response within a respondent's household. See text for further details.

Table 8. PSML estimates of conditional current poverty probability, with five-state categorisation of incomes at *t*-1

Covariate (measured at *t*–1)	Income at *t*-1 (as percentage of year *t*–1 median income)									
	0–60		60–80		80–100		100–150		150+	
	Poor		Non-poor							
	M.E.	|t-ratio|	M.E.	|t-ratio|	M.E.	|t-ratio|	M.E.	|t-ratio|	M.E.	|t-ratio|
Individual characteristics										
Age	0.010	(0.06)	0.015	(0.47)	0.049	(2.52)	0.040	(3.08)	–0.030	(0.24)
Age squared		(0.01)		(0.31)		(2.68)		(3.19)		(0.44)
Female	–0.011	(0.99)	0.021	(2.29)	0.012	(2.07)	0.007	(1.61)	–0.013	(1.52)
Household head's characteristics										
Age	0.045	(0.79)	–0.009	(1.83)	–0.020	(1.83)	0.016	(2.10)	0.030	(1.09)
Age squared		(0.38)		(1.59)		(1.34)		(2.05)		(0.77)
Female	0.019	(0.68)	–0.041	(1.60)	–0.006	(0.36)	–0.014	(1.46)	0.007	(0.34)
Has A-levels or higher ed. qualification	–0.098	(2.70)	–0.046	(1.50)	–0.014	(0.80)	–0.005	(0.43)	–0.040	(2.03)
Works full-time	–0.039	(0.97)	–0.068	(2.07)	–0.044	(2.56)	–0.021	(1.53)	–0.017	(0.57)
Works part-time	0.047	(1.18)	0.039	(1.08)	–0.030	(1.34)	0.042	(1.94)	0.067	(1.39)
Ethnic group										
Black Caribbean	0.124	(1.20)	–0.196	(3.26)	–0.050	(0.85)	–0.047	(1.11)	0.078	(0.50)
Black African	–0.035	(0.24)	–0.077	(0.75)	–0.097	(14.73)	–0.015	(0.24)	0.165	(1.25)
Black Other	0.030	(0.30)	0.367	(1.19)	–0.097	(17.15)	–0.006	(0.09)	0.072	(0.61)
Indian	0.093	(0.71)	0.088	(0.97)	–0.016	(0.27)	0.004	(0.10)	0.051	(0.60)
Pakistani or Bangladeshi	0.224	(2.74)	0.437	(1.58)	0.680	(2.44)	–0.070	(16.06)	0.352	(1.90)
Chinese	–0.084	(0.50)	0.735	(24.84)	–0.097	(12.64)	–0.070	(16.22)	0.839	(3.44)
Other ethnic origin	0.152	(1.08)	0.009	(0.08)	–0.069	(1.61)	–0.070	(31.99)	–0.052	(0.71)
Household characteristics										
Lone parent household	0.010	(0.29)	0.016	(0.48)	0.066	(2.13)	0.087	(3.07)	0.078	(1.35)
Other household type	0.056	(0.88)	0.047	(0.97)	–0.009	(0.32)	–0.014	(0.81)	–0.058	(1.33)
Presence in household of										
adult aged 60–75	–0.076	(1.16)	–0.054	(1.12)	–0.027	(0.95)	–0.035	(1.97)	–0.051	(0.86)
adult aged 76+	–0.131	(0.92)	–0.133	(1.50)	–0.043	(0.72)	–0.063	(2.21)	–0.141	(10.53)
children aged 0–2	0.059	(1.85)	0.042	(1.28)	0.015	(0.71)	0.010	(0.60)	0.025	(0.65)
children aged 3–4	0.099	(3.28)	0.054	(1.67)	0.008	(0.38)	0.046	(2.49)	0.053	(1.31)
children aged 5–11	0.138	(4.18)	0.064	(1.82)	0.011	(0.55)	0.024	(1.51)	0.060	(1.74)
children aged 12–15	0.053	(1.60)	0.042	(1.25)	0.041	(1.74)	0.021	(1.22)	0.035	(0.95)
children aged 16–18	0.098	(1.61)	0.059	(1.04)	–0.052	(1.61)	–0.015	(0.67)	0.020	(0.31)

Number of workers	–0.120	(4.42)	–0.079	(3.43)	–0.016	(1.19)	–0.027	(3.11)	–0.068	(4.40)
Lives in social housing	0.077	(2.32)	0.146	(3.97)	0.068	(2.83)	0.065	(3.31)	0.118	(2.51)
Multi-family household	–0.135	(2.18)	–0.022	(0.48)	0.009	(0.29)	0.054	(2.00)	0.195	(2.93)
Intercept	–0.566	(1.40)	–0.029	(0.06)	1.117	(1.86)	0.870	(1.56)	–2.248	(2.54)
ρ_1	–0.016	(1.23)								
ρ_2	0.095	(0.72)								
ρ_3	–0.017	(0.14)								
Log-likelihood					-79,320					
Model chi2 (d.f.=260)					19,735 ($p < 0.0000$)					
Number of observations					44,602					
Predicted probability: sample averages	0.535	[0.584]	0.220	[0.227]	0.079	[0.079]	0.038	[0.035]	0.022	[0.016]
Predicted probability: reference person	0.485	[0.527]	0.265	[0.214]	0.097	[0.071]	0.070	[0.055]	0.141	[0.120]
Measures of state dependence			ADS=	GSD=	ADS=	GSD=	ADS=	GSD=	ADS=	GSD=
			0.315	0.183	0.414	0.229	0.459	0.252	0.48	0.258
			[0.358]	[0.234]	[0.462]	[0.293]	[0.509]	[0.324]	[0.532]	[0.338]
			Test stat.	*p-value*	*Test stat.*	*p-value*	*Test stat.*	*p-value*	*Test stat.*	*p-value*
Null hypothesis: $\gamma_1 = \gamma_j$ (d.f. = 36)			521.46	0.0000	360.26	0.0000	568.87	0.0000	230.58	0.0000

Notes: GHK simulated pseudo-maximum likelihood with 250 random draws. 'M.E.' = marginal effect (defined in text). Asymptotic t-ratios for coefficients, in parentheses, and are robust for the presence of repeated income observations within households and on the same individual. All equations include year dummies. Figures in square brackets are computed for the balanced income sample between t–1 and t. Reference categories for dummy variables: male, male household head with no A-levels, not working and of European ethnic origin, married couple household with no adults aged 60+ or children present, not living in social housing and single-family household, initial year 1991.

Appendix

Table A1. Coefficient estimates of equations for base year poverty status and retention (Table 3)

Covariate	Initial poverty status $\Pr(P_{t-1} = 1)$		Retention $\Pr(R_t = 1)$	
	Coefficient	|t-ratio|	Coefficient	|t-ratio|
Individual characteristics				
Age	–0.008	(0.62)	0.032	(4.16)
Age squared	0.0001	(0.64)	–0.0004	(3.78)
Female	0.039	(2.42)	0.027	(2.37)
Head of household's characteristics				
Age	–0.012	(1.02)	0.010	(1.26)
Age squared	0.00003	(0.21)	–0.00002	(0.18)
Female	–0.218	(5.05)	0.043	(1.56)
Has A-levels or higher educational qualification	–0.289	(6.12)	0.021	(0.80)
Works full time	–0.441	(8.32)	–0.037	(0.99)
Works part time	0.291	(4.54)	–0.010	(0.19)
Ethnic group				
Black Carribean	–0.057	(0.26)	–0.663	(4.45)
Black African	–0.142	(0.77)	–0.629	(3.95)
Black Other	0.023	(0.10)	–0.322	(1.96)
Indian	0.214	(1.23)	–0.150	(1.32)
Pakistani or Bangladeshi	0.923	(5.23)	–0.459	(2.51)
Chinese	0.533	(3.24)	–0.427	(0.84)
Other ethnic origin	–0.085	(0.31)	–0.156	(1.20)
Household characteristics				
Lone parent household	–0.061	(0.99)	–0.092	(1.84)
Other household type	–0.122	(1.33)	–0.208	(3.79)
Presence in household of				
adult aged 60–75	–0.346	(3.58)	0.026	(0.37)
adult aged 75+	–0.334	(1.52)	0.075	(0.59)
children aged 0–2	0.139	(2.83)	0.233	(5.79)
children aged 3–4	0.163	(3.72)	0.118	(2.87)
children aged 5–11	0.421	(10.14)	–0.032	(1.01)
children aged 12–15	0.310	(6.91)	–0.063	(1.68)
children aged 16–18	0.444	(5.14)	0.005	(0.07)
Number of workers	–0.822	(23.11)	0.075	(3.92)
Lives in social housing	0.378	(8.50)	–0.076	(2.26)
Multi-family household	0.457	(5.94)	–0.339	(6.46)
Mother did not work when respondent aged 14	–0.064	(1.22)		
Father did not work when respondent aged 14	0.002	(0.03)		
Mother deceased or not present	–0.240	(2.02)		
Father deceased or not present	0.058	(0.69)		
Mother in legal, professional or other occupation	–0.195	(2.45)		
Father in legal, professional or other occupation	–0.016	(0.25)		
Mother in non elementary occupation	–0.099	(1.87)		
Father in non elementary occupation	–0.041	(0.78)		
Information on father missing (item non-response)	–0.023	(0.12)		
Information on mother missing (item non-response	–0.247	(1.80)		
Information on parental background proxied	0.118	(0.80)		
Information on parent background not able to be matched	0.068	(0.66)		
Don't know mother's occupation	0.066	(0.62)		
Don't know father's occupation	–0.039	(0.45)		
Original Sample Member (OSM)			0.641	(21.60)
Year dummies				
1992 (wave 2)	–0.072	(1.64)	0.125	(3.17)
1993 (wave 3)	–0.081	(1.77)	0.343	(8.20)
1994 (wave 4)	–0.126	(2.69)	0.275	(6.72)
1995 (wave 5)	–0.165	(3.45)	0.579	(13.20)
1996 (wave 6)	–0.126	(2.62)	0.535	(12.50)
1997 (wave 7)	–0.041	(0.86)	0.474	(11.26)

1998 (wave 8)	–0.045	(0.93)	0.453	(10.64)
Intercept	0.598	(2.33)	–0.573	(3.30)

See Table 3 for estimates of the other parameters of the model.

Table A2. Coefficient estimates of equations for base year poverty status and retention (Tables 6 and 8)

Covariate	Alternative poverty lines												Five bands for base year income distribution			
	50% of median				70% of median				60% median (wave 1)							
	Initial Cond.		Retention		Initial Cond.		Retention		Initial Cond.		Retention		Initial Cond.		Retention	
	Coeff.	|t-ratio|	Coeff.	|t-ratio|	Coeff.	|t-ratio|	Coeff.	|t-ratio|	Coeff.	|t-ratio|	Coeff.	|t-ratio|	Coeff.	|t-ratio|	Coeff.	|t-ratio|
Individual characteristics																
Age	0.009	(0.68)	0.032	(4.16)	-0.028	(2.56)	0.032	(4.16)	-0.007	(0.51)	0.032	(4.16)	-0.067	(8.90)	0.032	(4.15)
Age squared	-0.0001	(0.57)	-0.0004	(3.78)	0.0004	(2.61)	-0.0004	(3.78)	0.0001	(0.53)	-0.0004	(3.78)	0.001	(8.58)	-0.0004	(3.78)
Female	0.020	(1.14)	0.027	(2.37)	0.056	(3.91)	0.027	(2.37)	0.025	(1.51)	0.027	(2.38)	0.060	(5.89)	0.027	(2.38)
Head of household's characteristics																
Age	-0.005	(0.35)	0.010	(1.26)	-0.014	(1.30)	0.009	(1.25)	-0.009	(0.74)	0.010	(1.26)	-0.021	(2.59)	0.010	(1.25)
Age squared	-0.00007	(0.46)	-0.00002	(0.18)	0.00004	(0.31)	-0.00002	(0.17)	-0.00001	(0.05)	-0.00002	(0.18)	0.00012	(1.24)	-0.00002	(0.18)
Female	-0.216	(4.64)	0.043	(1.56)	-0.206	(5.16)	0.043	(1.56)	-0.210	(4.72)	0.043	(1.56)	-0.229	(7.52)	0.043	(1.56)
Has A-levels or higher educational qualification	-0.157	(3.02)	0.021	(0.79)	-0.332	(7.79)	0.021	(0.80)	-0.246	(5.00)	0.021	(0.80)	-0.480	(14.86)	0.021	(0.81)
Works full time	-0.465	(8.00)	-0.037	(0.98)	-0.406	(8.25)	-0.037	(0.98)	-0.456	(8.59)	-0.037	(0.99)	-0.460	(12.21)	-0.037	(0.98)
Works part time	0.236	(3.31)	-0.010	(0.18)	0.306	(5.01)	-0.010	(0.18)	0.281	(4.25)	-0.010	(0.19)	0.037	(0.76)	-0.009	(0.18)
Ethnic group																
Black Carribean	0.118	(0.53)	-0.663	(4.45)	-0.089	(0.50)	-0.663	(4.45)	0.088	(0.40)	-0.663	(4.45)	-0.256	(1.60)	-0.663	(4.46)
Black African	-0.066	(0.32)	-0.628	(3.94)	0.198	(0.86)	-0.628	(3.94)	-0.129	(0.72)	-0.629	(3.94)	0.011	(0.05)	-0.627	(3.93)
Black Other	0.070	(0.34)	-0.321	(1.95)	0.050	(0.28)	-0.319	(1.94)	0.107	(0.51)	-0.322	(1.96)	-0.087	(0.36)	-0.320	(1.95)
Indian	0.294	(1.35)	-0.150	(1.32)	0.244	(1.62)	-0.150	(1.32)	0.273	(1.44)	-0.150	(1.32)	0.089	(0.65)	-0.151	(1.33)
Pakistani or Bangladeshi	0.941	(4.41)	-0.460	(2.51)	0.962	(4.37)	-0.459	(2.50)	0.829	(4.45)	-0.459	(2.51)	0.721	(3.83)	-0.459	(2.50)
Chinese	0.097	(0.55)	-0.427	(0.84)	0.523	(2.45)	-0.426	(0.84)	0.278	(1.31)	-0.424	(0.83)	0.792	(4.26)	-0.423	(0.83)
Other ethnic origin	-0.126	(0.50)	-0.157	(1.20)	-0.047	(0.22)	-0.157	(1.20)	-0.028	(0.10)	-0.156	(1.19)	-0.045	(0.28)	-0.156	(1.19)
Household characteristics																
Lone parent household	-0.113	(1.76)	-0.092	(1.86)	0.056	(0.91)	-0.091	(1.83)	-0.131	(2.08)	-0.091	(1.83)	0.257	(4.92)	-0.091	(1.82)
Other household type	-0.073	(0.76)	-0.208	(3.78)	-0.113	(1.42)	-0.208	(3.79)	-0.150	(1.65)	-0.208	(3.79)	-0.055	(1.14)	-0.209	(3.80)
Presence in household of																
adult aged 60–75	-0.319	(2.96)	0.027	(0.39)	-0.197	(2.23)	0.025	(0.36)	-0.401	(4.07)	0.026	(0.38)	-0.135	(2.06)	0.026	(0.38)
adult aged 75+	-0.201	(0.86)	0.075	(0.59)	-0.332	(1.71)	0.074	(0.59)	-0.371	(1.60)	0.074	(0.59)	-0.149	(1.10)	0.075	(0.60)
children aged 0–2	0.113	(2.13)	0.234	(5.80)	0.207	(4.69)	0.234	(5.81)	0.137	(2.79)	0.233	(5.79)	0.244	(7.58)	0.234	(5.80)
children aged 3–4	0.059	(1.24)	0.119	(2.87)	0.221	(5.55)	0.119	(2.88)	0.122	(2.65)	0.118	(2.86)	0.371	(12.40)	0.119	(2.88)
children aged 5–11	0.313	(6.98)	-0.032	(1.01)	0.470	(12.55)	-0.032	(1.00)	0.388	(9.15)	-0.031	(0.99)	0.621	(21.36)	-0.032	(1.01)
children aged 12–15	0.270	(5.55)	-0.063	(1.68)	0.380	(9.05)	-0.063	(1.67)	0.299	(6.69)	-0.063	(1.69)	0.480	(14.88)	-0.063	(1.69)
children aged 16–18	0.374	(3.91)	0.005	(0.07)	0.528	(6.87)	0.004	(0.06)	0.421	(4.85)	0.005	(0.06)	0.557	(11.45)	0.003	(0.05)
Number of workers	-0.778	(19.54)	0.075	(3.92)	-0.754	(22.21)	0.075	(3.93)	-0.816	(22.65)	0.075	(3.92)	-0.479	(23.68)	0.075	(3.94)
Lives in social housing	0.171	(3.48)	-0.076	(2.25)	0.514	(11.64)	-0.076	(2.26)	0.292	(6.47)	-0.076	(2.24)	0.605	(17.71)	-0.076	(2.24)

Multi-family household	0.344	(4.21)	-0.339	(6.48)	0.539	(7.97)	-0.339	(6.46)	0.458	(6.01)	-0.339	(6.47)	0.679	(15.45)	-0.339	(6.48)
Mother did not work when respondent aged 14	-0.031	(0.55)			-0.119	(2.43)			-0.034	(0.63)			-0.100	(2.68)		
Father did not work when respondent aged 14	-0.033	(0.33)			-0.105	(1.23)			0.009	(0.09)			-0.142	(2.13)		
Mother deceased or not present	-0.123	(0.86)			-0.128	(1.20)			-0.124	(1.02)			-0.079	(0.99)		
Father deceased or not present	0.060	(0.71)			0.054	(0.68)			0.077	(0.90)			-0.016	(0.27)		
Mother in legal, professional or other occupation	-0.156	(1.92)			-0.259	(3.53)			-0.159	(1.96)			-0.230	(4.04)		
Father in legal, professional or other occupation	0.013	(0.18)			-0.087	(1.46)			-0.003	(0.05)			-0.249	(5.78)		
Mother in non elementary occupation	-0.040	(0.71)			-0.179	(3.67)			-0.060	(1.11)			-0.140	(3.75)		
Father in non elementary occupation	-0.044	(0.80)			-0.057	(1.17)			-0.038	(0.71)			-0.070	(1.94)		
Information on mother missing (item non-response)	-0.027	(0.13)			-0.208	(1.22)			-0.132	(0.70)			-0.187	(1.38)		
Information on father missing (item non-response)	-0.062	(0.30)			-0.118	(0.70)			-0.039	(0.21)			-0.207	(1.56)		
Information on parental background proxied	0.162	(1.07)			-0.109	(0.78)			0.126	(0.84)			-0.253	(2.40)		
Information on parent background not able to be matched	0.035	(0.31)			-0.120	(1.23)			0.029	(0.28)			-0.252	(3.21)		
Don’t know mother’s occupation	0.014	(0.12)			-0.006	(0.06)			0.044	(0.42)			-0.038	(0.47)		
Don’t know father’s occupation	-0.048	(0.53)			0.027	(0.33)			-0.074	(0.85)			-0.040	(0.65)		
Original Sample Member (OSM)			0.640	(21.58)			0.641	(21.60)			0.640	(21.60)			0.641	(21.58)
Year dummies																
1992 (wave 2)	-0.114	(2.32)	0.125	(3.17)	0.003	(0.07)	0.126	(3.19)	-0.142	(3.25)	0.125	(3.17)	-0.009	(0.42)	0.125	(3.18)
1993 (wave 3)	-0.117	(2.30)	0.342	(8.20)	-0.006	(0.15)	0.343	(8.20)	-0.169	(3.73)	0.342	(8.20)	0.003	(0.12)	0.343	(8.20)
1994 (wave 4)	-0.165	(3.15)	0.275	(6.72)	-0.060	(1.41)	0.275	(6.73)	-0.209	(4.49)	0.275	(6.72)	0.008	(0.33)	0.275	(6.74)
1995 (wave 5)	-0.151	(2.79)	0.579	(13.20)	-0.053	(1.19)	0.579	(13.20)	-0.319	(6.51)	0.578	(13.19)	0.024	(0.98)	0.579	(13.20)
1996 (wave 6)	-0.131	(2.38)	0.535	(12.50)	-0.012	(0.29)	0.535	(12.50)	-0.352	(7.03)	0.535	(12.50)	0.053	(2.12)	0.535	(12.50)
1997 (wave 7)	0.011	(0.20)	0.475	(11.27)	0.051	(1.19)	0.475	(11.26)	-0.250	(4.95)	0.475	(11.26)	0.091	(3.59)	0.475	(11.27)
1998 (wave 8)	-0.050	(0.91)	0.453	(10.64)	0.017	(0.37)	0.453	(10.64)	-0.352	(6.99)	0.453	(10.63)	0.137	(5.40)	0.452	(10.63)
Intercept	-0.186	(0.67)	-0.572	(3.30)	1.163	(4.83)	-0.573	(3.31)	0.540	(2.06)	-0.571	(3.30)	-1.211	(6.49)	-0.572	(3.30)

See Tables 6 and 8 for estimates of the other parameters of the models.