POVERTY DYNAMICS FOR MEASUREMENT ERROR

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ABSTRACT

We use latent class models to correct measurement error in estimates of the dynamics of relative income poverty in ten EU countries measured over four waves of the European Community Household Panel. We fit a latent mover-stayer Markov model which gives an acceptable fit to all ten transition tables. We focus in more detail on four countries – Denmark, the Netherlands, Italy and the UK– and show that mobility in poverty transition tables is over-estimated by between 25 and 50 percent if measurement error is ignored. In addition, once error is corrected, poverty rates show less cross-national variation.

Poverty Dynamics Corrected for Measurement Error

1. Introduction

We model poverty dynamics in 10 European countries using ECHP data, but, in contrast to virtually all earlier attempts, we take account of measurement error. We do this by using a model-based approach to measure the degree of stability and change in poverty dynamics. Any use of data to draw conclusions about a phenomenon is based on a model – whether this is recognised or not. In our approach to analyzing poverty dynamics we use an explicit model which, in the conventional way, has two parts: a measurement sub-model, that captures the relationship between the observed data and the underlying reality we seek to measure; and a structural sub-model that refers to processes taking place in that underlying reality. Conclusions about poverty dynamics that are drawn on the basis of observed data (for example, Jarvis and Jenkins 1997) implicitly assume a saturated structural model and a measurement model that posits an exact correspondence between measured poverty and true poverty. But this will almost never be the only model that a set of data will support, and in this paper we show that some simple but plausible models, incorporating both structural and measurement components, provide a very good fit to European poverty data, and are to be preferred to a saturated structural model on the basis of parsimony and, we argue, of plausibility too. In particular, the use of such models allows us to separate the amount of true change in our data from apparent change that is, in fact, the consequence of measurement error.

In contrast to much research that tries to take account of measurement, and other, error, we work with categorical, rather than continuous, variables. The reason for concentrating on categorical variables is that the most influential poverty measurements are simple head-counts, such as the US Census poverty classification or the relative poverty risk measure in the EU social indicators. Qualitative difference is also (implicitly) emphasised in most definitions of poverty, where relative differences in wealth and other resources are assumed to cause an absolute difference in the capability to function or attain some minimum acceptable way of living in the society (Atkinson et al. 2002, 57; Sen 1983; Townsend 1979, 31). For correcting error in head-count poverty measures we draw specifically on latent class models (Van de Pol and Leeuw 1986; Langeheine and Van de Pol 1990). One advantage of such models is that they yield separate estimates of the reliability of measurement of both the poor and non-poor.

We fit these models to data from 10 European countries, and we then focus on four countries – the Netherlands, Denmark, the UK and Italy – in order to show what one can learn from the models about poverty dynamics. In all four cases, correcting for error leads us to conclude that there is less movement in and out of poverty than had been thought. And we argue that the between-country differences we uncover are more plausible than those that we might have arrived at through a simple examination of the observed data.

2. Previous studies of poverty dynamics and the problem of measurement error

Since the influential article of Bane and Ellwood (1986) it has been accepted that analysing poverty as a longitudinal phenomenon is essential both to our understanding of it and to the development of social policy. Eurostat has recently started to publish persistent poverty risk rates alongside measures of the cross-sectional poverty rates in EU countries, and it seems that far fewer people live in persistent poverty than are in poverty at any given time (see Atkinson et al. 2002). This means that there is high mobility in and out of poverty and a much larger part of the population has experienced poverty than cross-sectional figures indicate. According to the study of 11 EU countries by Layte and Whelan (2003), only about half of those living in poverty at a point in time were in the same situation a year earlier. However they also found that the incidence of poverty tends to be concentrated in the same part of the population, showing an unequal distribution of the risk of becoming poor.

These two aspects of poverty dynamics – the high rate of poverty mobility associated with a majority of experiences of poverty being short-lived and the fact that only a minority of the poor are living in uninterrupted long-term poverty – seem to surface in one form or another in most studies of poverty dynamics (see Bane and Ellwood 1986; Duncan et al. 1993; Leisering and Leibfried 1999; Whelan, et al. 2000). However, many researchers have expressed their concern about the possibility of measurement error in longitudinal poverty studies and the consequent risk of over-estimating poverty mobility (e.g. Duncan 2000; Rendtel et al. 1998). In fact, measurement error is likely to have significant effects in at least three areas: (i) cross-sectional estimates of poverty rates; (ii) between country comparisons of such rates; and, (iii) the dynamics of poverty. Goldberg (1973) presents results relevant to the first two of these.

Let p_{jt} be the true poverty rate in country j and time t, let r be the proportion of the truly poor who are observed as poor and s be the proportion of the non-poor who are observed as such: r and s can therefore be interpreted as the reliabilities of the measures of observed poverty and non-poverty. From this it follows that the observed cross-sectional poverty rate is

$$E(p'_{jt}) = p_{jt} r + (1 - p_{jt})(1 - s)$$

Given that $p_{jt} < ½$ then, if poverty and non-poverty were equally well measured (i.e. $r=s<1$), measurement error would lead the rate to be overstated. But if (as we generally find in our analyses) $r < s$ (i.e. the poor are harder to identify than the non-poor) then measurement error will make the observed poverty rate lower than the true rate provided that

$$p > \frac{1-s}{1-s+1-r}$$

Concerning comparisons of poverty between countries, Goldberg (1973) shows that

$$E(p'_{2t} - p'_{1t}) = p_{2t}(r_2 + s_2 - 1) - p_{1t}(r_1 + s_1 - 1) + s_1 - s_2$$

and in this case the bias induced by measurement error could lead to apparent differences between countries that were greater or smaller than the true difference, though if the reliabilities are the same in each country ($r_1 = r_2 < 1$ and $s_1 = s_2 < 1$) the difference is always understated. To the best of our knowledge there are no analytical results concerning the effects of measurement error on the dynamics of categorical variables, but Chua and Fuller (1987) find that response error attenuates the diagonal elements in two-wave panel data.

Coleman (1968) showed that we can estimate true stability and measurement error if we have panel data from three or more waves. Heise (1969) and Wiley and Wiley (1970) presented path analytic methods for estimating true stability and error from test-retest correlations. However, the path analytic, and other structural equation models based on the covariance or correlation matrix are not suitable for nominal level measurements, in particular because the mean and variance are not independent (Henry 1973). Lazarsfeld and Henry (1968) had developed the latent structure model in the 1950s and 1960s and they defined these models as measurement models that relate, in a probabilistic way, a discrete or continuous latent variable to the discrete scores or categories of manifest variables. Their work was later developed by Goodman (see, especially, Goodman 1974a and 1974b). An early application of latent class methods to correct for binary classification errors is Ekholm and Palmgren (1982) and, later, Van de Pol and de Leeuw (1986) estimated error in repeated nominal measurements by applying latent structure analysis. To our knowledge only Rendtel et al. (1998) have used a latent structure analysis to separate true poverty mobility from measurement error. Using a latent Markov model, originally introduced for this purpose by Langeheine and van de Pol (1990), they arrived at the striking finding that almost half of the observed poverty mobility in their German Socio-Economic Panel data might be due to measurement error. Their study dealt only with Germany, but we can expect that, if we do not correct the measurement error in poverty transition tables, poverty mobility will be over-estimated in other countries as well.

3. Modelling poverty transition tables with Markov and latent Markov models

The panel data used here come from the four first waves from the European Community Household Panel (ECHP). The ECHP is based on annual household surveys conducted between 1994 and 2001 and carried out by national statistical offices or national research institutes in all EU member states. Eurostat is responsible for gathering and standardising the data for comparative use (Eurostat 1999). At the time of writing, five annual waves (1994 to 1998) have been prepared for research purposes. Since the information on incomes in the ECHP refers to the previous year, while information on household size and composition refers to the current year, only four waves, i.e. 1994-1997, could be used in this analysis and these four waves were available for 10 countries. Poverty transition tables were constructed using the relative poverty risk threshold, set at 60% of median individual equivalised (using the modified OECD scale: Atkinson et al. 2002) net incomes. Those below this threshold were classified as poor. Of course, since any definition of poverty requires the categorization of the population into the poor and not-poor, the approach we present can equally be applied to poverty measures based on deprivation, access to resources, subjective indicators, and so on.

Four repeated measurements yield a transition table of 16 cells, and some descriptive figures are presented in Table 1. The first four columns present poverty rates in each wave, the next five the percentages of the population classed as poor zero, one, two, three or four times over the four waves, and the last three columns present the poverty risk in the second, third and fourth wave conditional on having been recorded as poor in the first wave. There seem to be no major changes in poverty rates in any country across the four waves, except in Portugal, where the rate declines by three percentage points and in Denmark, where it increases by almost five percentage points between the third and fourth waves. There has been a rise in the poverty rates in Denmark during the late 1990's (see Eurostat 2003), but, nevertheless, such a large and rapid increase as is observed in our balanced panel is suggestive of error. Otherwise poverty rates vary between ten (Denmark and the Netherlands) and 22 percent (Spain, Portugal and the UK). The unweighted mean across countries is 18 percent and this is constant across all four waves. The proportion of the population who have experienced poverty at least once is around twice the size of the cross-sectional poverty rate. In the Netherlands, for example, the poverty rate is 11 per cent and 23 per cent of the population has some experience of poverty. This 'double-ratio' between poverty rates and the proportion of the population that has experienced poverty at least once in the four waves seems to hold in all ten countries. The proportions experiencing multiple spells of poverty decrease sharply when the number of spells increases. So, for example, only two percent are classified as poor in all four waves in Denmark. The proportions are higher in other countries, but the percentage in long-term and interrupted poverty is always a small fraction of the cross-sectional poverty rate. If poverty spells seem to be mainly of short duration, the risk that poverty recurs seems to be quite persistent. When observing the risks P(i|1) to be in poverty again after a year, two years or three years, we can see that it does not decrease much. Even in Denmark, where long poverty spells are very rare, we can see that being in poverty in 1994 is associated with a .44 probability of being poor in 1995, and this elevated risk is maintained even after three years. The risk that income poverty will recur is higher in other countries, but the pattern is the same.

Table 1 here

We can now sketch a rough picture of poverty dynamics as having the following characteristics: (1) there is high inflow and outflow from poverty; (2) only a small group suffers long and uninterrupted poverty; (3) even a single incidence of poverty is associated with a high risk that poverty will recur.

Markov models are widely used for modelling the stochastic process underlying categorical panel data. A first-order Markov process (or simple Markov chain model) assumes that the state occupied at time *t* depends only on the state occupied at time *t-1* and thus, conditional on the state occupied at *t-1*, there is independence between the states occupied at *t* and *t-j*, for *j>1*. The simple Markov model, however, rarely fits the data. This can be for one or both of two reasons: the model assumes a homogeneous population, and it does not allow for measurement error. The solution to the first problem is to increase the number of chains and, in this way, allow heterogeneity in the population: such a model is usually referred to as a mixed Markov model.[1] The second problem can be tackled by constructing a measurement model that describes the relationships between the observed and true values (Langeheine and van de Pol 1990).

We address both these issues by fitting latent class models of three types. The first group contains simple and mixed Markov models that make no allowance for error; the second contains latent class models that allow for error but no true change: in other words, they test the assumption that all observed mobility is error. The third group comprises models that combine a measurement and structural model – i.e. that hypothesise both true change and error.

The simple Markov model can be formulated as

[1] $$F_{ijkl} = N\delta_i \tau_{j|i} \tau_{k|j} \tau_{l|k}$$

where the expected frequency F in the i, j, k, l^{th} cell of the four-way transition table is presented as a function of the sample size N, initial probabilities δ and transition probabilities τ. Subscript i=1,...,I (I=2 in this case) indexes the states of poor and not poor at the first wave, j=1,..,J, k=1,...,K and l=1,…,L index the states at the later waves. The δ 's indicate the initial distribution over states (probabilities of being in the i=1,...,I categories) and the τ's indicate the transition probabilities into a state at *t+1* given membership of one or other state at *t*. The time-homogenous simple Markov model constrains these latter parameters to be invariant with respect to time.

[1] In an early study, McCall (1971), found that a Mixed Markov model was better than a simple Markov model in explaining low-income dynamics in the US between 1957and 1966.

The mixed Markov model can be presented in a similar way as

[2] $$F_{ijkl} = N\sum_{s=1}^{S}\pi_s\delta_{si}\tau_{s,j|i}\tau_{s,k|j}\tau_{s,l|k}$$

This specifies several Markov processes or chains (indicated by s=1,...,S). The expected frequency is now a sum over these processes, and the new parameter, π_s, indicates the proportions of the sample in each of the S chains. The simple Markov model arises when S=1, but for S >1 the membership of the different chains is defined by latent classes. Another important special case of this model arises when S=2 and, for one of the processes, $\tau_{j|i} = 1$ if state j = state i, 0 otherwise, and similarly for all the other transition probabilities. This is the mover-stayer model, in which there is a fraction of the population who never change state.

Measurement error can be captured through a latent class formulation by assuming that to each observation of the states (manifest variable) there corresponds a latent variable which measures the true distribution over the states. These latent variables are completely specified by the size of the latent classes and the probabilities of being observed in a given manifest class conditional on being in a given latent class. This model can be written

[3] $$F_{ijkl} = N\sum_{a=1}^{A}\sum_{b=1}^{B}\sum_{c=1}^{C}\sum_{d=1}^{D}\delta_a\rho_{i|a}\rho_{j|b}\rho_{k|c}\rho_{l|d}$$

The latent variables are denoted a=1,...,A, b=1,...,B, c=1,...,C and d=1,…,D. The distribution in the first latent variable is given by δ and the relationship between the observed variables *I*, *J*, *K* and *L* and their latent counterparts, *A*, *B*, *C* and *D* is described by the conditional response probabilities ρ. The closer the response probability matrix is to an identity matrix (i.e. $\rho_{manifest|latent}$ =1 when the latent and manifest states are the same, 0 otherwise) the smaller is the measurement error of the variable. These ρ parameters can thus be interpreted as measures of reliability.

This measurement model can be embedded in a simple Markov model as follows:

$$[4] \qquad F_{ijkl} = N\sum_{a=1}^{A}\sum_{b=1}^{B}\sum_{c=1}^{C}\sum_{d=1}^{D}\delta_a \tau_{b|a}\tau_{c|b}\tau_{d|c}\rho_{i|a}\rho_{j|b}\rho_{k|c}\rho_{l|d}$$

where the τ's now indicate the transition probabilities between the latent variables. So this latent Markov model contains the structural model (simple Markov chain) and a measurement model that describes how the manifest and latent variables are related. Model (3) can be derived from (4) by imposing the constraint that the matrices of τ parameters are all identity matrices.

Lastly, the latent mixed Markov model combines the mixed Markov structural model with the same measurement model:

$$[5] \qquad F_{ijkl} = N\sum_{s=1}^{S}\sum_{a=1}^{A}\sum_{b=1}^{B}\sum_{c=1}^{C}\sum_{d=1}^{D}\pi_s \delta_{sa}\tau_{s,b|a}\tau_{s,c|b}\tau_{s,d|c}\rho_{s,i|a}\rho_{s,j|b}\rho_{s,k|c}\rho_{s,l|d}$$

The latent mixed Markov model is a group of latent Markov processes indexed by s=1,...,S, each of which can have its own measurement model. An example is the latent mover-stayer model in which the reliability of measurement differs between movers and stayers. Maximum likelihood estimates of models 1 to 5 can be found using the EM algorithm (Dempster et. al. 1977). However, many latent class models will not be identified because they will require more parameters than there are degrees of freedom, and, even when this is not the case, identification may be a problem. For example, for any latent Markov chain over three or more waves, the reliabilities (i.e. the ρ matrices mapping the latent into the observed classes) of the first and last waves will not be identified without some equality constraints among the reliability matrices (Van de Pol and de Leeuw 1986: 126). Goodman (1974b) provides a rank test for the identifiability of latent class models.[2]

Table 2 reports the fit of the models to the poverty transition tables.[3] Models are fitted separately for each country and for each we report the degrees of freedom, the likelihood-ratio chi-squared statistic, G^2, and the index of dissimilarity, Δ. The table is divided into three parts corresponding to the three types of model outlined above. So, the first three models assume no

[2] See also Kuha and Skinner 1997: 659-60 for further discussion of identifiability.
[3] The analyses were conducted using Jeroen Vermunt's LEM program (Vermunt 1997).

error. Models 1 and 2 are realisations of equation [1] above: model 1 is a simple Markov model with time homogenous transition probabilities and model 2 relaxes this constraint. Model 3 is the mover-stayer specification of equation [2] with the mover transition probabilities allowed to vary over time.[4]

The simple time-homogenous Markov model is quite a poor fit in every country. The best fit is found in the Dutch table, with a G^2 value of 708.2 on 12 degrees of freedom and six per cent of cases misclassified. The G^2 value is lower in the Danish table, 565.7, but the index of dissimilarity is higher, eight per cent. Since the tables have very different Ns, and G^2 is sensitive to sample size, we rely more on Δ than G^2 when comparing the fit of models across countries. The largest mismatch is found in the Spanish table where the G^2 value is 2685.6 and 14 per cent of cases are wrongly classified. Removing the stationarity restriction takes four degrees of freedom, but it improves the goodness of fit only slightly, again fitting best in the Dutch (G^2=660.1; Δ=5.5) and Danish (G^2=771.0, Δ=5.6) tables and most poorly in the Spanish (G^2=2566.1; Δ=13.8). Allowing population heterogeneity, by using the mover-stayer model, brings about a large improvement in model fit. This model has six degrees of freedom and the best fit is once again found in the Dutch table, where G^2 is 64.4 and Δ is 1.2 percent. In the rest of the countries, the model misclassifies around 2 percent of all cases.

Table 2 here

It appears, then, that one possible reason for the poor fit of the simple Markov models is population heterogeneity. The other possibility is error, and so in the next two models we isolate the error and test a hypothesis that there is no true change and all observed transitions are simply error. For this purpose we draw on equation [3]. The stationary latent class model (in which all the reliabilities are constant over time) has 12 degrees of freedom and the model is not a particularly good fit to the data of any country: in most cases the misclassifications vary around four or five percent. The unrestricted latent class model (where the ρs can vary between transitions) has 6 degrees of freedom and fits much better. The best fit is found in

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[4] The time-homogenous Markov model is fitted here because it is a standard and much used specification, but on grounds of plausibility we should not expect too much from it. A model that allows some or all transition probabilities to vary over time is more plausible given that we should expect overall poverty risks to vary according to the state of the economy and labour market. McCall (1971) found time-heterogeneous transition probabilities in the movers' chain of his Mover Stayer model.

Denmark, where $G^2 = 76.4$ and the dissimilarity index is less than two percent. Bearing in mind the rather extreme hypothesis that these models represent, the goodness of fit of the unrestricted latent class model is strikingly good.

Finally we move to equations [4] and [5] and we estimate three models, 7 through 9, that are the direct counterparts of models 1 to 3, except that we now allow for measurement error. In all cases we set the reliabilities to be time-homogenous. The latent Markov model, where the latent transitions are stationary, has 10 degrees of freedom. The model fits the Dutch data best (G^2=120.3; Δ=2.1). But, considering all 10 countries and comparing the misclassifications of this model with those from the simple Markov model (model 1), we see that, taking into account measurement error, we can improve the goodness of fit by between 24 and 79 percent, depending on the country. Furthermore, the time-heterogeneous latent Markov model decreases the misclassifications to a fraction of those produced by the simple Markov model. These results strongly confirm our suspicion that measurement error plays a large part in generating the observed transition rates. Nevertheless, taking into account measurement error alone is not enough to achieve an adequate model fit. Models 1 to 3 suggested that the population is heterogeneous, so, in the final model, we allow both error and population heterogeneity. This is the latent mover-stayer model, where the movers' chain is time-heterogeneous, the stayers are assumed to be measured without error, and the reliabilities for the movers are time homogenous. In other words, the model allows constant error when estimating the movers' states, but assumes that the stayers are measured perfectly.[5] This model has 4 degrees of freedom and yields a good fit to most countries' data. Δ is everywhere two per cent or less (except in Spain where it is 2.1) and in the Dutch, French, Italian and British tables, less than one per cent. Although the G^2 values indicate that there are statistically significant differences (at the .05 level) between the estimated and observed frequencies (except in the Netherlands), taking into account the sample size and the nature of our frequency tables, this degree of goodness of fit seems satisfactory. We therefore conclude that poverty dynamics seem to follow a process that can be described by the time-heterogeneous mover-stayer model that allows error in the measurement of the movers' states. Using the measurement error corrected estimates of the model we can now calculate the true change and stability in the poverty transition tables.

[5] This latter is not a necessary assumption and later we relax when modelling dynamics in the four countries on which concentrate.

4. Error corrected estimates of poverty dynamics

To interpret the latent mover-stayer model we now focus on four of our countries – Denmark, the Netherlands, Italy and the UK. Before discussing our results, however, it may be useful to set out the differences that we should expect to find between these countries. To do this we focus on two dimensions – the degree of income inequality in each country and the flexibility of the labour market. Together these two should shape, at least partially, the patterns of flows into and out of poverty. Income inequality will, we suggest, mainly influence the distribution of those who are and are not at risk of falling into, or escaping from poverty (the proportions of movers and stayers, in other words), while the flexibility of the labour market will be an important factor in determining how easy it is for those at risk of moving between poverty and non-poverty to do so.[6] On the first dimension, then, the major contrast is between Denmark and the Netherlands, on the one hand, (where income inequality is low) and the UK and Italy, on the other, (where it is high).[7] On the second dimension, the Netherlands and Italy have relatively inflexible labour markets while Denmark, and particularly the UK, have flexible ones.[8] On this basis, then, we might expect that poverty risks will be most equally distributed in Denmark. In the UK and in Italy there should be a distinction between those at risk of poverty and those who have no risk, but, among those at risk, we should expect a difference between these countries. In the UK there should be much greater flows among the movers than in Italy. Finally, in the Netherlands we should expect a relatively equal distribution of risks (as in Denmark) and rather little movement in and out of poverty (as in Italy).

Table 3 presents the estimated parameter values from the model. The first column presents the π coefficients that indicate the proportions of movers and stayers. There is a clear contrast here between Denmark and the Netherlands, on the one hand, where the proportion of movers is large, and Italy and the UK, on the other hand, where it is much smaller. The initial probabilities, δ, show that, among the stayers, over 90 per cent are in the non-poor class, except in the Netherlands. By multiplying the proportion of stayers (π) with the initial

[6] Of course this is an over-simplified description of the roles played by these factors in shaping poverty dynamics. Not least one can argue that flexibility will also go some way to determining the shares of movers and stayers.

[7] Own ECHP based calculations on the ratio between the highest/lowest income quintiles (S80/S20). See also Structural Indicators of Eurostat (2003).

probabilities (δ), we get the proportions of the population that are either never in poverty or always in poverty. In Italy and the UK there is a large proportion of the population who will never be observed in poverty, 45 per cent in Italy and 46 per cent in the UK, compared with 18 per cent in Denmark and 14 per cent in the Netherlands. The percentage who will always be observed as poor is highest in the UK at 3.3 three per cent and lowest in Denmark, 1.1 per cent (and around 2.5 per cent in the Netherlands and in Italy). So this finding accords with our expectations.

Table 3 here

The latent transition probabilities (τ) for the movers, show that rates of transition out of poverty are distinctively low in Italy but relatively high in the Netherlands and highest in the UK. Transition rates into poverty are also highest in the UK. These high transition rates suggest that the UK has the largest turnover in poverty among movers. This provides partial support for our expectations. The UK is the most fluid country (among movers), and Italy the least, but Denmark, rather surprisingly, also displays very little movement in and out of poverty. Perhaps a clearer picture from which to draw comparisons is provided by panel A of Table 4 which reports overall latent transition rates for the four countries. These are calculated as a weighted sum (using the πs as weights) of the transition rates of both movers and stayers. This clearly shows that the Netherlands and UK have the largest proportions of individuals moving between poverty states, while Denmark has less and Italy has remarkably few people moving in and out of poverty. The lack of much movement in Italy accords with our expectations but the relative lack of movement in Denmark does not.

Table 4 here

Finally the response probabilities (ρ) relate the manifest to the latent variables. The modal response probabilities in the diagonal of the ρ matrix can be treated as reliabilities, and the non-modal as error. It is perhaps not surprising that there seems to be more measurement error among those classified as poor (except in the UK where the reliabilities are the same). In

[8] Based on the OECD's measure of 'Overall strictness of protection against dismissals' published in the June 1998 *Employment Outlook.* The substantial labour market reforms (flexicurity) of 1996 have made the Dutch labour market more flexible (Visser and Hemerijck 1997), but our data are mainly gathered before these changes.

Denmark we estimate that 37.9 percent of those who are classified as poor in the latent variable are observed to be not in poverty: in the Dutch table the proportion is 32.3 percent and in the Italian 21.7 percent. In the UK the figure is 6.4 percent. On the other hand, the proportion of the latent non-poor who appears to be poor is 1.9 per cent in Denmark, 0.7 per cent in the Netherlands, 10.5 per cent in Italy and 6.9 per cent in the UK. These results suggest that measurement error in poverty dynamics is mainly associated with a failure accurately to identify the poor.

This point is reinforced when we turn to Table 4 and compare the latent transitions rates in panel A with observed transition rates shown in panel B. This comparison yields a striking result: in general, the latent probabilities of moving into poverty are slightly lower than the observed probabilities, but, in all four countries, the latent probabilities of escaping poverty are much lower than the observed. In other words, because the state of poverty is poorly measured, much of what appears to be change is, in fact, error in classifying respondents.

Lastly, we can decompose the observed change and stability in the four countries into true and error components. In labelling these we follow the terminology of Langeheine and van de Pol (1990). The results are shown in Table 5, together with the observed proportion of stable cases (OBS) and of change (OBC). [9] 'Perfect stability' is simply the proportion of the sample in the stayer latent class. The total proportion of stability (TOS) is then the number of movers remaining in their original state throughout the observation period, expressed as a proportion of the total sample. TRS, or 'true stability' is then TOS corrected for measurement error. It can be thought of as that proportion of the true stability which is observed. The difference between TOS and TRS is error. The formulae for these are

[6] $$TOS = \pi_{s=1} \sum_{a=1}^{A} \delta_a \tau_{b|a} \tau_{c|b} \tau_{d|c}$$

[7] $$TRS = \sum_{a=1}^{A} \sum_{b=1}^{B} \sum_{c=1}^{C} \sum_{d=1}^{D} \pi_{s=1} \delta_a \tau_{b|a} \tau_{c|b} \tau_{d|c} \left(\rho_{i|a}\right)^4$$

(i=a, j=b, k=c, l=d, a=b=c=d in 6 and 7)

Change itself can be decomposed in a similar way. Total change, TOC, is 1- perfect stability - TOS, and this can be partitioned into true change, TRC and error. Here true change is the proportion of latent change which is observed as such:

[8] $$TRC = \sum_{a=1}^{A} \sum_{b=1}^{B} \sum_{c=1}^{C} \sum_{d=1}^{D} \pi_{s=1} \delta_a \tau_{b|a} \tau_{c|b} \tau_{d|c} \left(\rho_{i|a}\right)^4$$

(i=a, j=b, k=c, l=d, not a=b=c=d)

Perfect stability is measured without error because we have assumed that the states occupied by the stayers are measured perfectly. The observed proportion stable in Italy and the UK is equal to perfect stability plus TRS and the proportion who change is equal to TRC plus the two error components. In other words, all the error appears as change. In Denmark and the Netherlands this is not so: here most of the error is counted as change but some of it appears as stability. The reason for this is that, compared with Italy and the UK, in these two countries the mover class is much larger and so is the probability of a poor respondent being classed as non-poor. This means that a respondent who, for example, is poor in only one of the four waves, has a much greater probability in Denmark or the Netherlands of being erroneously considered to have remained outside poverty in all waves.

Table 5 here

In the latent or true poverty indicators, stability is equal to perfect stability plus TOS and change is equal to TOC. We therefore see that the observed data understate true stability and overstate change. As a percentage of the total sample this effect varies between two per cent in Denmark and 17 per cent in Italy. Expressed as a percentage of observed change, we see that 10 per cent of observed change is error in the Netherlands, 20 per cent in Denmark and the UK and 63 per cent in Italy. This gives rise to a very striking change in the relative position of Italy on a ranking of poverty dynamics. Whereas in the observed data is appears to have the largest proportion of respondents who move between poverty and non-poverty, under the

[9] The fitted values of the latent mover-stayer model reproduced these values exactly.

latent Markov model it has the least. This latter result is, we argue, much more consistent with what one would have expected, given knowledge of the Italian labour market and of Italy's rather high level of income inequality.

Error affects not only comparisons of poverty dynamics, but also cross-sectional poverty estimates, such as the poverty rate and the persistent poverty rate. For example, comparing the observed poverty rate in 1994 (shown in the first column of Table 1) with the latent rates (calculated from the πs and δs in Table 3), the latent rates for Denmark and Netherlands (11 and 14.4 per cent, respectively) are higher than the observed rates, whereas the opposite is true of Italy and the UK (18.2 and 19.7 per cent compared with observed rates of 18.7 and 21 per cent). The cross-sectional latent poverty rate shows less difference between countries than does the observed poverty rate. The latent persistent poverty rate[10], on the other hand, is somewhat higher in all four countries than the observed rate, reflecting the under-estimation of the persistence of poverty. In Denmark, the observed rate of persistent poverty is 3.7 per cent, but the corrected rate is 7.3 per cent. In the Netherlands, the observed rate is 6.0 per cent, while the latent rate is 10.8 per cent. In Italy the observed rate is 10.7 per cent, the latent rate is 13.8. The under-estimation is lower in the UK: 13.2 compared to 13.4 per cent. So, if we ignore error, we are not only likely to over-estimate poverty mobility: we also under-estimate the persistence of poverty and have unreliable estimates of cross-sectional poverty rates.

5. Conclusion

We have fitted a latent mover-stayer model to poverty transition data with the aim of correcting for classification errors. Although we argued that this is an improvement on the normal practice of examining observed poverty transition matrices, the model contains a number of assumptions and, as with any assumptions, it is important to ask how much the results we obtained owe to them, or, equivalently, how robust the results are to changes in the assumptions. In the structural model we assume (i) that there are two classes of respondent; and (ii) these are movers and stayers. In the measurement model we assume (iii) stayers are measured without error; and (iv) errors are independent (that is, there is no association between the errors are waves t and t+1). Unfortunately, not all these assumptions can be tested. The last assumption cannot be tested with our data since it would require multiple

[10] The persistent poverty rate is the proportion of those currently poor who have been in the same situation in at least two out of the preceding three years (see Atkinson et al. 2002).

measures at each wave (Rendtel *et al* 1998). Assumption (i) could be tested by allowing for a third chain in the model and (ii) could be tested by relaxing the assumption that the transition matrix in one of the chains is the identity matrix. However, given that the latent mover-stayer model has only four degrees of freedom, these assumptions could be relaxed only if we introduced others. For example, a two-chain latent Markov model will have two more parameters than there are degrees of freedom if we allow all the transition probabilities (two τs for each chain) to vary over waves, and a three-chain model must constrain the τs in at least two of its chains to be time-homogenous and, even then, in the absence of any other constraint (such as forcing one chain to be made up of stayers), the model will have exactly as many parameters as degrees of freedom.

We tested assumption (iii) in two ways: first by making no distinction in the measurement error for movers and stayers, and, secondly, by allowing the errors to be distinct but imposing no constraint on the stayers' reliabilities. The former led to poorer fitting models and the latter did not improve on the latent mover stayer model.[11] A partial exception is Italy, however, where a model with common reliabilities for movers and stayers yielded a slightly better G^2 of 20.72 with 4 df (compared with 22.8 and the same df for the latent mover stayer model) but a slightly poorer Δ (0.8 per cent compared with 0.7 per cent).[12] Given that, in the Italian case, there is so little to choose between these two models, it is of interest whether or not they lead to the same conclusions. The model with common reliabilities for movers and stayers places a larger percentage – 76 per cent – in the stayer category, but the off-diagonal transition probabilities for the movers are then much larger (between .3 and .4). So there are fewer movers but more mobility among them. Overall this model indicates that the rate of true change is 17 per cent, as compared with 10 per cent in our preferred model and an observed rate of 27 per cent. The figure of 17 per cent places Italy on a par with Denmark (16 per cent) and the Netherlands (17 per cent). Thus, although the overall conclusion that we would draw does not change when we re-specify the model, the details certainly do. Given these two possible accounts of the Italian data the choice between them can be resolved only with further information. Alternatively, of course, we might resolve the issue by specifying a third

[11] The detailed results are available from the authors on request.
[12] In Italy the model allowing different and unconstrained reliabilities for movers and stayers reduces G^2 by exactly one for the loss of two df compared with the model of common reliabilities.

model that provides a better fit to the data than either, though we were unable to find such a model.

Our results show that not only does correcting for measurement error influence conclusions we might draw regarding any single country but also, because these errors operate with differential effect in the various countries, they lead us to different conclusions about country comparisons. So we have seen that, once error is corrected, poverty rates show less cross-national variation and the ordering of countries in terms of the size of their flows into and out of poverty can also change. Perhaps the simplest message that comes from our measurement model is that, in the ECHP, the poor (when poverty is defined as relative income poverty) are usually rather badly identified, and certainly much less accurately measured than the non-poor. Much of what appears to be exits from poverty is actually measurement error.

The use of the mover-stayer formulation led us to findings that are not evident from the observed data – the most obvious of which is the distinction between movers and stayers. The differences in the distribution of movers and stayers between the four countries on which we focused are as we hypothesised. On the basis of the model we also showed that the main difference between countries lies in the proportion of those never at risk of poverty. There is, conversely, very little difference in the proportion of permanently poor, which varies from one per cent in Denmark to just over three per cent in the UK.

The use of the mover-stayer formulation for our structural model should not be thought to imply that more developed structural models cannot be used in this context. We can allow the dynamic relationship between latent indicators to depend on measured characteristics of the respondents. Taking educational level as an example, one approach would be to replace the existing 2^4 table with a $2^4 \times M$ table (where there are M educational levels, membership of which is assumed to be invariant over time) and then allow the τ parameters to be functions of educational level. This is an approach that we hope to employ in subsequent research on poverty dynamics. Finally, the latent class approach might also be used to address problems of sample attrition. By defining a third manifest state that includes all those for whom information is missing at a given wave, it may be possible to assign to this category probabilities of being in one or other latent state.

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Table 1. Descriptive figures for poverty dynamics

	Poverty rates (%) in each wave				Proportion classed as poor *i* times out four measurement times					Risk that poverty recurs after 1, 2 or 3 years		
COUNTRY	wave 1	wave 2	wave 3	wave 4	0 out 4	1 out 4	2 out 4	3 out 4	4 out 4	P(1|2)	P(1|3)	P(1|4)
Denmark	8.9	6.9	7.9	13.6	77.7	22.3	8.5	4.4	2.0	.44	.48	.44
Netherlands	11.0	12.4	11.0	11.5	77.2	22.8	12.6	7.1	3.6	.59	.51	.45
Belgium	18.0	18.8	16.8	17.5	68.9	31.1	19.6	13.2	7.2	.70	.63	.53
France	17.1	16.6	16.2	17.1	71.7	28.3	18.1	12.5	8.1	.71	.64	.62
Ireland	17.6	18.4	19.1	18.2	66.4	33.6	21.0	12.5	6.3	.65	.63	.47
Italy	18.7	18.3	17.4	17.4	66.7	33.3	19.7	12.4	6.5	.62	.53	.54
Greece	21.4	21.7	24.0	21.7	61.6	38.4	24.9	16.8	8.7	.67	.67	.57
Spain	19.5	17.2	18.3	20.5	62.9	37.1	22.9	10.9	4.6	.46	.47	.57
Portugal	23.9	21.4	22.6	20.6	63.5	36.5	23.9	17.0	11.0	.70	.65	.59
UK	21.0	21.1	22.1	22.4	62.3	37.7	24.5	15.9	8.5	.66	.62	.54
Total	18.4	17.9	18.2	18.4	67.0	33.0	20.4	12.7	6.9	.63	.59	.55

Table 2. Markov and Latent Markov models for poverty dynamics

		DK		NL		B		F		IRL		I		EL		E		P		UK	
Model	df	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta
(1)Markov	12	565.7	7.9	708.2	6.0	854.2	9.2	1566.5	8.8	935.5	8.3	1993.1	10.7	1124.6	9.8	2685.6	14.0	1718.5	11.5	765.8	7.3
(2) Markov*	8	371.0	5.6	660.1	5.5	804.6	9.0	1524.7	9.0	926.4	8.4	1983.6	10.6	1059.1	9.8	2566.1	13.8	1637.8	11.3	701.4	7.6
(3)Move-stay	6	111.0	2.6	64.4	1.2	146.2	2.6	88.2	1.4	210.1	3.0	214.6	2.5	168.6	2.9	144.9	2.5	178.9	2.3	57.8	1.5
(4)Latent Class	12	373.5	5.9	349.8	3.8	336.8	5.2	613.7	4.8	555.6	5.7	459.3	4.0	519.1	4.7	579.9	4.5	712.8	5.6	786.6	6.9
(5)Latent Class*	6	76.4	1.8	175.2	2.2	213.8	3.9	474.0	3.8	395.6	4.3	390.8	3.3	336.2	3.8	477.5	3.9	505.5	4.7	424.4	4.5
(6)Lat. Markov	10	262.1	4.6	120.3	2.1	175.8	3.2	287.5	3.1	213.1	2.6	159.8	2.3	166.8	2.5	570.9	4.2	238.6	3.5	206.0	3.0
(7)Lat. Markov*	6	46.5	1.3	83.5	1.8	157.2	2.9	245.0	2.6	191.0	2.6	122.6	1.8	128.5	2.1	529.3	3.7	219.7	3.2	145.3	2.6
(8)Lat. move-st.	4	34.7	1.1	7.0	0.5	56.6	1.9	25.4	0.7	130.1	2.0	22.8	0.7	69.3	1.5	126.0	2.1	68.7	1.5	17.1	0.8

* The (latent) transition/conditional probabilities are not set equal between waves

Table 3. Estimated Parameter Values for Partially Latent Movers-Stayers Model

	Chain proportion		Initial proportion		Latent Transition Probabilities t to t+1						Responce probabilities	
Country	**Chain**	π	**Class**	δ	Non-poor	Poor	Non-poor	Poor	Non-poor	Poor	Non-poor	Poor
DK	Movers	0,805	Non-poor	0.878	1.000	0.000	0.969	0.031	0.860	0.140	0.981	0.019
			Poor	0.122	0.236	0.764	0.067	0.841	0.067	0.933	0.379	0.621
	Stayers	0,195	Non-poor	0.942	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
			Poor	0.058	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000
NL	Movers	0,831	Non-poor	0.857	0.926	0.075	0.979	0.021	0.953	0.047	0.993	0.007
			Poor	0.143	0.280	0.720	0.231	0.765	0.231	0.769	0.323	0.677
	Stayers	0,169	Non-poor	0.854	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
			Poor	0.146	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000
I	Movers	0,523	Non-poor	0.702	0.854	0.146	0.807	0.194	0.923	0.077	0.895	0.105
			Poor	0.298	0.044	0.956	0.024	0.951	0.024	0.976	0.217	0.783
	Stayers	0,477	Non-poor	0.945	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
			Poor	0.055	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000
UK	Movers	0,507	Non-poor	0.677	0.845	0.155	0.883	0.117	0.820	0.180	0.931	0.069
			Poor	0.323	0.312	0.688	0.318	0.816	0.318	0.683	0.064	0.936
	Stayers	0,493	Non-poor	0.933	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
			Poor	0.067	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000

Table 4: Latent and Observed Transition Probabilities

	Panel A: Latent transition probabilities						Panel B: Observed transition probabilities					
	t+1=1995		t+1=1996		t+1=1997		t+1=1995		t+1=1996		t+1=1997	
State at t ↓	Not poor	Poor	Not poor	Poor	Not poor	Poor	Not poor	Poor	Not poor	Poor	Not poor	Poor
Denmark												
Not poor	1.00	.00	.98	.02	.89	.11	.97	.03	.95	.05	.90	.10
Poor	.19	.81	.13	.87	.05	.95	.56	.44	.52	.48	.42	.58
Netherlands												
Not poor	.94	.06	.98	.02	.96	.04	.93	.07	.96	.04	.95	.05
Poor	.23	.77	.20	.80	.19	.81	.41	.59	.41	.59	.40	.60
Italy												
Not poor	.92	.08	.90	.10	.96	.04	.92	.08	.92	.08	.92	.08
Poor	.02	.98	.03	.97	.01	.99	.37	.62	.41	.59	.38	.62
United Kingdom												
Not poor	.92	.08	.94	.06	.91	.09	.91	.09	.92	.08	.90	.10
Poor	.16	.84	.09	.91	.16	.84	.34	.66	.25	.75	.34	.66

Table 5. Estimated proportions of true stability and change in the poverty transition tables

	DK	NL	I	UK
OBS	0,80	0,81	0,73	0,71
OBC	0,20	0,19	0,27	0,29
Perf.Stab.	0,20	0,17	0,48	0,49
TOS	0,65	0,66	0,42	0,27
TRS	0,55	0,61	0,25	0,21
error	0,09	0,06	0,18	0,07
TOC	0,16	0,17	0,10	0,23
TRC	0,08	0,08	0,05	0,18
error	0,07	0,08	0,05	0,06