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How real is mobility between low pay, high pay and non-employment?

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Abstract

The aim of this paper is to investigate the effect of measurement error on low-pay transition probabilities. Our approach combines the virtues of panel regression and Latent Class models, while it does not require the use of validation or re-interview data. Using British, German and Dutch panel data, we show that the true estimated low-pay transition probability is much lower that what previous research has found. This implies that almost half of the observed transitions can be attributed to measurement error. The highest low-pay transition probabilities are found in Germany and the lowest in the Netherlands. When applying this correction for measurement error in a multivariate model of low-pay transitions, the results indicate that measurement error attenuates considerably the effects of the main covariates, such as training, job change, change in the employment contract type and shift from part-time to full-time employment.

Keywords: Low pay, measurement error, markov model, panel data.
JEL-code: C23,J31.

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1 Introduction

The issue of low-pay mobility is receiving increasing interest in economic and political debate (Organization for Economic Cooperation and Development, 1996, 1997, 2003; Acemoglu, 2003b, 2003a). The increase in wage inequality along with the increase in the number of workers with wages below the low-wage threshold has raised equity and efficiency concerns. Low-pay mobility may have an equalizing effect on the earnings of these workers. The higher the level of upward low-wage mobility, the greater the chances low-paid workers have to improve the level of their earnings. Previous research, using data from household surveys, suggests that there is substantial year-to-year mobility, especially at the bottom of the wage distribution. Using data from the British Household Panel Survey (BHPS), Stewart and Swaffield (1999) find that, depending on the low-pay threshold used, between 29% and 48% of the British low paid move to a higher earnings state within one year. Cappellari and Jenkins (2004b) conclude from their analysis that the fraction of the British low-paid workers that make a transition to higher pay reaches 42.3% if we take into account non-response and attrition. Similar percentages are found in several other studies and for several other countries (see, for example, Sloane & Theodossiou, 1996, 1998; Cappellari, 2002). These studies show that although there is a considerable state dependence in low pay, the average transition probabilities are much higher than common sense would suggest.

A possible methodological explanation for these rather unexpected findings is that panel surveys contain measurement error. Survey respondents may misreport their income and interviewers do not always record the responses correctly, which can produce a substantial amount of error in wage measurement. Using the SIPP dataset, Gottschalk (2005) argues that two-thirds of the observed downward adjustments of nominal wages without a job change are due to measurement error. Pischke (1995), using the PSID validation study, suggests that measurement error overstates annual earnings' fluctuation by 20%-45%. When, as in the majority of economic studies on wages, hourly wages are derived from yearly or monthly earnings, measurement error may be even larger as it is introduced via two sources: earnings and hours of work (Rodgers et al., 1993). In an investigation of the effect of measurement error on poverty transitions in the German Socio-Economic Panel (GSOEP), Rendtel et al. (1998) conclude that approximately half of the observed transitions are due to measurement error. Lollivier and Daniel (2005) corroborate this result for the European Community Household Panel (ECHP). Despite the enormous bias that measurement error can cause in the estimation of wage dynamics, most relevant studies ignore this phenomenon.

In the incomplete literature on measurement error in transition models, two approaches are used. The first approach to estimate measurement error uses either validation or reinterview data and assumes that this data is error free. In a validation study, the survey information on the labour market status and income is compared to the same information from administrative sources. A reinterview implies that respondents are asked to provide the same information as in the original survey a second time, typically under more favourable conditions (better interviewer, more expanded questions, etc.). Poterba and

Summers (1986, 1995) use the reinterview data from the Current Population Survey to study the impact of measurement error on the estimated number of labour market transitions. Magnac and Visser (1999) use prospective and retrospective data for the same time period to study labour mobility of French workers with the Labour Force Survey. The prospective data is treated as error-free.

The assumption that administrative and reinterview data are error-free is questioned by several studies. The way administrative data are constructed and the definition of earnings in these data may also introduce error (Nordberg, Rendtel, & Basic, 2004). Abowd and Stinson (2005) study measurement error in the Survey of Income and Program Participation (SIPP) and in the Detailed Earnings Records (DER). The size of measurement error is even higher in the administrative DER dataset (20%-27%) than in SIPP (13%-15%). Kapteyn and Ypma (2007) suggest that the use of administrative data may lead to a severe bias of results. The reason for this bias may be either measurement error or a failed operationalization of the concept of earnings.

The second approach to correct for measurement error in transition models is applied when no auxiliary (error-free) information is available. Rendtel et al. (1998) use such an approach. More specifically, they use a Latent Markov model with two measurements of income to correct for measurement error in the German Socio-Economic Panel (GSOEP). Bassi et al. (2000) study labour market transitions of American workers using the SIPP dataset without the use of auxiliary data. This approach is found in several studies dealing with classification error in categorical variables (van de Pol & Langeheine, 1990; Vermunt et al., 1999; Paas et al., 2007). Regardless of the approach, most of these studies assume that the errors made at two subsequent time periods are conditionally independent given the true states. This is referred to as the assumption of the Independent Classification Errors (ICE).

The aim of this paper is to investigate the bias that measurement error causes on low-wage transitions. For this purpose, we develop a panel regression model for low-pay transitions that corrects for measurement error. To correct for measurement error we use a Mixed Latent Markov model, advancing the approach of Rendtel et al. (1998). While Rendtel et al control for measurement error in aggregate transition probabilities, we also correct for observed and unobserved heterogeneity and moreover work with a much longer time series. In this way, we relax the unattractive property of population homogeneity that is assumed in most of the studies using Markov models on labour market transitions. The ICE assumption is mostly retained in this paper as we only use prospective and not retrospective data. However, we perform some sensitivity analysis on the validity of this assumption. Using three panel surveys (BHPS, GSOEP, SEP) we determine which proportion of the observed low-pay transitions is spurious. Furthermore, we examine how much bias ignoring measurement error causes in the effects of certain determinants of wage mobility in a panel regression model. We choose to focus on those determinants that can account for a considerable upward or downward change in the wage, and can therefore cause a worker to move from low pay to high pay or vice versa. Such determinants include labour market events, such as a job change, a change of the employment contract type, or a considerable change in working hours. We expect the effect of these determinants to be considerably underestimated by measurement error. In our analysis, we distinguish between two earnings states, low-paid and higher-paid, as well as the state of non-employment. For low pay, we apply the most common definition: a low-paid worker is someone who earns less than two-thirds of the median wage (Organization for Economic Cooperation and Development, 1996). Moreover, we test the sensitivity of our results to alternative definitions of low pay.

Another novel aspect of this paper is that it investigates low-pay transitions in a cross-country comparative perspective. Labour market institutions are believed to account for differences in the opportunities and the risks that individuals face in the various labour markets in Europe (Freeman & Katz, 1995; Blau & Kahn, 1996). In liberal-unregulated labour markets, such as the UK, there is a much higher level of job and wage mobility than in regulated labour markets, such as Germany. Countries combining a high protection of employment security with a high level of flexibility in the labour market in terms of regulations enhancing job mobility, such as the Netherlands, occupy an intermediate position. Investigating low-pay transitions that are corrected for measurement error may be more informative concerning the real extent of cross-country differences in low-pay mobility and hence of the impact of labour market institutions on this mobility than by simply looking at observed transitions.

The rest of the paper is organized as follows: Section 2 discusses further the implications of measurement error on wage mobility. Section 3 elaborates on the model we apply. The three datasets we use are presented in section 4. In section 5, we discuss the results of our data analysis. These results consist of a descriptive part, where the aggregate amount of measurement error is estimated as well as an part where we discuss the effect of measurement error in low-pay transitions on the parameter estimation of a multivariate panel regression model.

2 The implications of measurement error

The implications of measurement error on earnings have been studied with the use of validation studies. The main finding of the literature are that although there is a high level of misreporting earnings at the individual level, the error in the average estimate of earnings is rather small (Duncan & Hill, 1985; Pischke, 1995; Bound et al., 2001). Evidence also shows that measurement error in earnings is mean reverted. This means that the measurement error is negatively correlated with the true value of earnings (Bound & Krueger, 1991; Bound et al., 1994, 2001). Pischke (1995) suggests that the reason of this negative correlation is that respondents typically underreport the transitory fluctuations of their earnings.

In the case of a categorical variable - such as in our study - the properties of measurement error are similar with the case of earnings. The measurement error in a categorical variable is always mean reverting (for a simple illustration, see, Bound et al., 2001). For this paper, what matters more is measurement error in the estimation of year-to-year transition matrices. Hagenaars (1990, 1994) shows that even small amounts of classification error can lead to considerable bias in the estimation of such matrices. As a simple illustration, let us assume a fictitious transition matrix for a discrete variable X with two categories and between two time points. We further assume that there is error in the observation of the variable X. Instead of X_1 and X_2, we rather observe the states Y_1 and Y_2. The model for the joint distribution of Y_1 and Y_2 has the form of a Latent Class model for two time points. More specifically, the joint distribution of the observed states Y_1 and Y_2 can be expressed as follows:

$$\begin{aligned} P(Y_1 = y_1, Y_2 = y_2) \quad &= \quad \sum_{x_1, x_2} [P(X_1 = x_1) P(X_2 = x_2 | X_1 = x_1) \\ & \qquad P(Y_1 = y_1 | X_1 = x_1) P(Y_2 = y_2 | X_2 = x_2)] \, . \end{aligned} \tag{1}$$

In the above probability expression $P(X_1 = x_1)$ denotes the probability of being in the latent (true) state x_1 at the first time point and $P(X_2 = x_2|X_1 = x_1)$ the probability of being in the latent state x_2 at the second time point, conditional on being in the latent state x_1 at the first time point. The other two terms refer to the relationship between the latent and observed states, and represent the measurement error component. $P(Y_1 = y_1|X_1 = x_1)$ denotes the probability of observing the state y_1 conditional on being in the latent (true) state x_1. The expected observed transition probability is:

$$P(Y_2 = y_2 | Y_1 = y_1) = \frac{P(Y_1 = y_1, Y_2 = y_2)}{P(Y_1 = y_1)} = \frac{P(Y_1 = y_1, Y_2 = y_2)}{\sum_{y_2} P(Y_1 = y_1, Y_2 = y_2)} \quad . \tag{2}$$

To illustrate the impact of measurement error, assume that $P(X_2 = x_2|X_1 = x_1) = .05$ for $x_1 \neq x_2$ and that $P(Y_1 = y_1|X_1 = x_1) = P(Y_2 = y_1|X_2 = x_2) = .05$ for $y_1 \neq x_1$ and $y_2 \neq x_2$. Using equations (1) and (2) one can easily verify that the probability $P(Y_2 = y_2|Y_1 = y_1)$ for $y_1 \neq y_2$ equals .136 . In other words, even a small amount of classification error (5%) results in a large increase in the number of the observed transitions, here by a factor of 2.72 (13.6% observed versus 5% real transitions).

In this paper, the categorical dependent variable X - the true earnings state - can be seen as resulting from discretizing a continuous variable ξ that represents earnings from paid employment. Assume that there are two states and that the cutoff is at 0:

$X = 1$ if $\xi > 0$

and $X = 0$ if $\xi < 0$.

However, the observed earnings that are used to derive the observed state Y contain measurement error υ, which means that:

$Y = 1$ if $\xi + \upsilon > 0$

and $Y = 0$ if $\xi + \upsilon < 0$.

This means that the implication of the discretization is that the classification error probabilities $P(Y = 1|X = 0)$ and $P(Y = 0|X = 1)$ are in fact averages of $P(\xi + \upsilon > 0|\xi < 0)$ and $P(\xi + \upsilon < 0|\xi > 0)$ across $\xi < 0$ and $\xi > 0$, respectively.

Measurement error does not only result in an overestimation of the aggregate number of transitions, but may also have severe implications when trying to explain earnings dynamics. When failing to control for classification errors, the dependent variable in an earnings transition model contains noise which is independent of the covariates. As a result, the effects of covariates will typically be underestimated even if covariates themselves are error-free (Bollinger, 1996; Abrevaya & Hausman, 1997; Hausman et al., 2009).

Following Bound et al. (2001), let us assume a simple regression $y = z\beta + \epsilon$, with y measured with error v ($y = y^* + v$, where y^* is the true value of the dependent variable) and $v = \delta y + v^*$, where v^* is uncorrelated to z and ϵ. Then even if z is measured without error, there is bias in the estimation of β, which is proportional to δ. Empirical findings, however, are scarce and contradictory. Rodgers et al. (1993) and Bound et al. (1994) suggest that since measurement error in earnings is mean reverting, the coefficients of all explanatory variables in a wage regression are biased towards zero by approximately 20%. They also do not find any consistent pattern of a relationship between the covariates and the error in earnings. Using the PSID validation study, Duncan and Hill (1985) find that measurement error in log earnings attenuates the effect of tenure by 30% in a wage regression. However, they do not find a significant effect on the coefficient for education and labour market experience. It should be noted here that the PSID validation study does not refer to the same individuals as in the original survey. It was in fact conducted on a sample of employees from a large firm. Comparing data from the Current Population Survey and the Social Security records, Bound and Krueger (1991) fail to find any significant bias in the effects of education, experience, age or other covariates on log earnings. Mellow and Sider (1983) suggest that the use of survey or employer data does not affect significantly the structure of a wage equation. The detection of this particular type of bias, however, is difficult since, in practice, these covariates are never error-free. The error in these covariates can be correlated with the error in earnings causing either an increase or decrease of the bias in the wage-regression coefficients.

3 A Mixed Latent Markov model

Specification of the model

Our aim is to control for measurement error in the year-to-year transitions from and to low pay. This can be achieved with a Latent Markov model (van de Pol & Langeheine, 1990) as depicted in Figure 1. According to this model, the true state X_{it} of an individual i at a time point t cannot be observed; it is a latent state. We rather observe state Y_{it}, which might differ from the true (latent) state X_{it}. Y_{it} and X_{it} are probabilistically related. The observed states at different time points are mutually independent, conditional on the true latent states. In other words, we assume that measurement error is not serially correlated in any way. This means that the independent classification error (ICE) assumption is made.

The true state X_{it} follows a Markov process. Thus, the state of an individual i at time point t, X_{it}, is independent of the state at time point t', $X_{it'}$, where $t' < t-1$, conditionally on the state at $t-1$, $X_{i(t-1)}$. An arrow indicates a direct effect, for example of the state at one time point on the state at the next time point. In our study, X_{it} and Y_{it} are the

$$
\begin{tikzcd}
\cdots \mathrm{X(t\ -\ 1)} \arrow[r] \arrow[d] & \mathrm{X(t)} \arrow[r] \arrow[d] & \mathrm{X(t\ +\ 1)} \cdots \arrow[d] \\
\cdots \mathrm{Y(t\ -\ 1)} & \mathrm{Y(t)} & \mathrm{Y(t\ +\ 1)} \cdots
\end{tikzcd}
$$

Figure 1: Path diagram for the Latent Markov model

true and observed earnings state, respectively, that are assumed to take on three values: low-paid, higher-paid and non-employed. It is obvious that our definition of earnings states includes a state where the individual has no income from paid employment, the 'other' or non-employment state. For reasons of simplicity, however, we will refer to these states as 'earnings states'.

The joint probability of following a certain path over the $T + 1$ time points can be specified as:

$$
\begin{aligned}
P(\mathbf{Y}_i = \mathbf{y}_i) \quad = \quad & \sum_{x_0=1}^{3} \sum_{x_1=1}^{3} ... \sum_{x_T=1}^{3} P(X_{i0} = x_0) \\
& \prod_{t=1}^{T} \left[P\left(X_{it} = x_t | X_{i(t-1)} \ = x_{t-1} \ \right) \right] \prod_{t=0}^{T} P(Y_{it} = y_{it} | X_{it} = x_t) \ , \qquad (3)
\end{aligned}
$$

where $i = 1, ..., I$ is the index for the individual, and $t = 0, ..., T$ represents the time points.

The probability $P(Y_{it} = y_{it}|X_{it} = x_t)$ represents the measurement error. The identification of this model requires the assumption that either the measurement error probabilities or the latent transition probabilities are time homogeneous. In the current application we assume that the measurement error parameters are time constant. More specifically, we restrict the probability of observing a state Y_{it} conditional on the true state X_{it} to be constant over time, so $P(Y_{i(t-1)} = s|X_{i(t-1)} = r) = P(Y_{it} = s|X_{it} = r)$ for every t. With these restrictions, the model is identified with at least three time points (Vermunt et al., 1999).

Since controlling for heterogeneity in Markov models for income mobility is necessary (Shorrocks, 1976), we control for observed time-constant and time-varying characteristics in our Latent Markov model following the approach suggested by Vermunt et al. (1999). Specifically, we allow the covariates $\mathbf{Z}_{it}$ to affect the latent transition probabilities between latent states $X_{i(t-1)}, X_{it}$.

The transition probabilities between earnings states may also be affected by unobserved personal characteristics, such as ability and motivation. Failing to control for such unobservables may result in an overstatement of the effect of the observed covariates. In the framework of Markov models, this is usually tackled in a non-parametric way by assuming that individuals belong to different Markov chains. The simplest form of these models is the mover-stayer model of Blumen et al. (1966), which assumes that the population can be split into two groups with different Markov chains. In one chain (the 'movers' chain'), transitions are unrestricted, while in the 'stayers' chain' the transition probability from state j in time point $t-1$ to the state k in time point t is 1 if $j = k$ and 0 otherwise. Other, more complicated Mixed Markov models assume the existence of more than two chains and may even allow for turnover between the chains (for an overview of these studies, see, van de Pol & Langeheine, 1990).

We prefer to adopt a parametric approach of correcting for unobserved heterogeneity, which makes our model similar to a random-effects panel regression. Specifically, we introduce an individual-specific unobserved variable F_{1i} that captures time-invariant individual effects.

The problem of 'initial conditions' is tackled in a similar way. The sample of individuals being in state x at the first time point may not be random and this may affect the transition probabilities. For example, previous experiences of low pay may affect the low-pay transition probability (Stewart & Swaffield, 1999; Cappellari & Jenkins, 2004b). We assume that the joint distribution of the individual effects affecting the transition probability F_{1i} and the individual effects affecting the initial state F_{2i} follows a bivariate normal distribution. The joint distribution is characterized by one free correlation and two variances to be estimated:

$$\rho = corr(F_{1i}, F_{2i})$$

$$\sigma_1 = var(F_{1i})$$

$$\sigma_2 = var(F_{2i})$$

The joint probability of having a particular state path conditional on covariate values can be expressed as:

$$\begin{aligned} P(\mathbf{Y}_i = \mathbf{y}_i|\mathbf{Z}_i) \;\; = \;\; & \int\int \sum_{x_0=1}^{3}\sum_{x_1=1}^{3} ... \sum_{x_T=1}^{3} P(X_{i0} = x_0|\mathbf{Z}_{i1}, F_{2i}) \\ & \prod_{t=1}^{T} \left[P\left(X_{it} = x_t | X_{i(t-1)} \; = x_{t-1}, \; \mathbf{Z}_{it}, F_{1i} \right) \right] \\ & \prod_{t=0}^{T} P(Y_{it} = y_{it}|X_{it} = x_t) f(F_{1i}, F_{2i}) \mathrm{d}F_{1i} \mathrm{d}F_{2i} \;, \end{aligned} \tag{4}$$

where $f(F_{1i}, F_{2i})$ is the joint density function for the individual effects F_{1i} and F_{2i}.

For the issue of the identification of initial conditions, we should stress that we use a random effects approach for dealing with possibly correlated unobserved heterogeneity in the initial state and the transition probabilities. The unobserved heterogeneity in transition probabilities is assumed to be time-constant and is based on T measurements per individual. The unobserved heterogeneity component in the initial state concerns a single measurement occasion ($t = 0$) and it is less obvious that it can be identified. However, the logit model for the initial state contains predictors which are not identical to the ones in the model for the transitions (all time-varying predictors are different for at least a part of the sample), which makes it possible to identify the heterogeneity component in the initial state.

The Mixed Latent Markov model assumes a first-order Markov process for the true states conditionally on the individual's covariate values and the time-constant unobserved individual effects. However, it should be noted that after marginalizing over the covariates and individual effects the model does not assume a first-order Markov process for the true state. Moreover, as already mentioned, the model does not assume a first-order Markov process for the observed state.

The ICE assumption

The ICE assumption is retained in all aforementioned versions of our model. This implies that the errors made at different time points are uncorrelated conditional on the true state. This assumption is plausible as there is no obvious process that could lead to an error correlation. A direct serial correlation of the error typically emerges when using retrospective data (Magnac & Visser, 1999; Bassi et al., 2000). Even in the case of prospective data studies find some degree of serial correlation. Bound and Krueger (1991) and Kristensen and Westergård-Nielsen (2006) find a serial correlation of 0.3 - 0.4 in measurement error. However, this serial correlation is mostly an effect of the type and level of income as well as of some personal characteristics of the respondent. Nordberg et al. (2004) suggest that income from self-employment and income transfers are more prone to error and that this error is larger for respondents younger than 30 and older than 55. Bound and Krueger (1991) and Bollinger (1998) suggest that the size and the structure of measurement error are different between men and women. Kristensen and Westergård-Nielsen (2006) suggest that measurement error is higher for the low incomes. These issues are largely taken care of in our study as we restrict our sample to male, prime-age wage earners (see section 4) and we condition the measurement error on the true pay level of the respondent. According to the survey of Bound et al. (2001), in such a sample, there is no consistent evidence of a correlation of measurement error with demographic or human capital characteristics.

Another source of serial correlation may emerge from the tendency of respondents to round up numbers. Using the Finnish sample of the European Community Household Panel (ECHP), Hanisch (2005) finds that almost one third of all gross earnings are rounded after the first digit while almost half after the second digit. In the Danish ECHP sample, this percentage rises to 79% (Kristensen & Westergård-Nielsen, 2006). This appears to be much less of a problem in our data where less than 2% of all earnings are rounded after the first digit and less than 7% after the second digit.

Despite the aforementioned arguments, some sources of violation of the ICE assumption may still exist. The working hours are used to construct the pay status of the respondent (see section 4). The error in the reported working hours may be serially correlated, especially towards the direction of over-reporting (Mellow & Sider, 1983). For this reason, we also perform a sensitivity analysis where we relax the ICE assumption. For this purpose, we use a variable that may affect the measurement error but is unrelated to low-pay mobility. Specifically, in some household surveys, respondents are asked to show their pay slip to the interviewer. If the ICE assumption is not valid, introducing this variable as a predictor of measurement error should reduce considerably the size of the measurement error and give a different picture on the latent transition probabilities. If we had multiple indicators for the earnings state (i.e. indicators coming from different measures of the wage), we could relax the ICE assumption in a more 'direct' way, by assuming that the measurement error is serially correlated. However, our data do not allow such an approach.

Parameter estimation

The estimates for the parameters of our model are obtained by means of maximum likelihood. Specifically, we use a variant of the well-known Expected Maximization (EM) algorithm (Dempster et al., 1977), which switches between an E step and a M step until it achieves convergence. The E-step of the EM algorithm involves computing the expected value of the complete data log-likelihood or, more intuitively, filling in the missing data (here the unobserved class memberships and the unobserved random effects) with their expected values given the current parameter values and the observed data. In the M step, standard estimation methods are used to update the model parameter such that the expected complete data log-likelihood is maximized. In our case the M step involves estimating logistic regression models for the initial state, the transition, and the measurement error probabilities using the marginal posteriors obtained in the E step as weights. The E and M steps cycle until a certain converge criterion is reached.

The relevant variant of EM, which is called the forward-backward or Baum-Welch algorithm, is implemented in the recent syntax version of the statistical software LatentGOLD (Vermunt & Magidson, 2008). The standard EM algorithm cannot be applied for Latent Markov models for many time points T, as the time and storage needed for computation increases exponentially with T (Vermunt et al., 1999). The extended version of the forward-backward algorithm we applied supports multivariate analysis and control for unobserved heterogeneity, features that are required for our analysis.

The log-likelihood function that is maximized is based on the probability density provided in equation 4. Taking the log of this density and summing over all individuals gives the log-likelihood function that is maximized:

$$logL = \sum_{i=1}^{N} \ln P(\mathbf{Y}_i = \mathbf{y}_i | \mathbf{Z}_i) \tag{5}$$

Thus, in fact, it is assumed that the joint response vector of an individual (Y_i) follows a multinomial distribution conditional on the predictor values ($\mathbf{Z}_i$). No additional assumptions other than the ones implied by the model need to be made for parameter estimation by maximum likelihood. Parameter estimation is presented in detail in Appendix B (see, also, Vermunt et al., 2008).

4 Data and main concepts

The study uses data for the period 1991-2004 from three national panel datasets. For the UK, we use waves 1 to 14 of the British Household Panel Survey (BHPS) (Taylor et al., 2006), covering the years 1991-2004. For Germany, we make use of 14 waves of the German Socio-Economic Panel (GSOEP) (Wagner et al., 2007), which cover the period 1991-2004. For the Netherlands, our data come from the Socio-Economic Panel (SEP) (CBS, 1991). We make use of the last 12 waves of the panel, covering the years 1991-2002. The information from the three datasets has been made highly comparable for the purpose of this study.The BHPS data were made available by the Data Archive at Essex University. The GSOEP was provided by the German Institute for Economic Research. The SEP was made accessible by Statistics Netherlands. The full list of the variables included in our analysis is presented in detail in Appendix A.

In the light of the discussion in section 3, we compare these three countries with respect to the amount of 'true' low-pay transitions. In the liberal-unregulated labour market of the UK, individuals are supposed to experience a higher level of wage mobility than in both the semi-regulated Dutch labour market and the highly regulated German labour market. A model that does not control for measurement error may over- or underestimate cross-country differences due to possible differences in the amount and type of error between the three national datasets.

Since we focus on earnings transitions of employed individuals, our sample consists of prime age males (aged 25-55). Women are not included in our sample as they tend to have much more heterogeneous career paths than men. The main reason for this is that childbirth is a major event that affects their labour supply decision (Dex et al., 1998). Moreover, the country's institutional support for mothers affects decisively this decision (Uunk et al., 2005) as well as the joint decision of the couple for labour supply (Powell, 2002). Especially in the Netherlands, the decision of women about their labour supply has implications for the number of hours they work (Paull, 2008). Therefore, to adequately investigate the mobility patterns of female workers we would have to control for childbirth and to add part-time employment in the possible destination states of our model. These aspects fall beyond the scope of this paper.

Our main economic variable is the earnings state of the individual, defined as the level of the hourly wage. Since there is no direct information available on an individual's hourly wage, this is computed by dividing the total gross annual earnings from paid employment by the total amount of the annual hours worked. As in the SEP and the GSOEP, only retrospective wage information is available, the wage in t is derived from wave $t+1$. We define two real earnings states, low paid and higher paid, as well as an 'other' (non-employment) state.

Only individuals reporting paid employment as their main employment status are classified in one of the two earnings states. The self-employed are clustered in the 'other' state (non-employment state). Individuals who are in education or in apprenticeship - especially relevant for Germany - are also classified as non-employed. This 'other' state is very heterogeneous implying that transitions to and from 'other' cannot be expected to have a clear interpretation. However, the inclusion of such a state in our dependent variable is important from both a substantial and methodological point of view. Several studies, such as Cappellari and Jenkins (2004a) and Stewart (2007) show that being in non-employment is a possible cause of moving to a low-paid job and vice versa. Moreover, ignoring the non-employment state would make it impossible to define a Latent Markov model as the latent states should not only be mutually exclusive but also exhaustive.

Each individual is included in the analysis from the time point he first enters the survey. Using maximum likelihood estimation with missing data, we deal with the fact that at some occasions information for the earnings state of the individual may be missing, due to non-response or temporary attrition. This approach does not cause any bias as long as non-response is random conditionally on the observed wage and covariate information, that is, as long as the missing data is missing at random (MAR). Missing values in covariates were imputed by interpolation when possible. For example if the individual reported 'higher education' in $t-1$ and $t+1$, and the value for education was missing for t we imputed the value for education in t as being 'higher education'. Interpolation is a practical way to keep individuals with missing values on time-varying predictors in the analysis. As typically done in statistical models with predictors that are estimated by Maximum Likelihood, our likelihood function is constructed conditional on the predictors (see equation 4). This means that modeling the covariate distribution under a missing at random assumption is not an option. Other, more sophisticated (multiple) imputation strategies are possible. However, they fall outside the scope of the current paper. The remaining missing values were imputed by the mean of the relevant variable.

5 Measurement error and its effect

Descriptive part

In total, we applied ten versions of the model described by equations (3) and (4); namely, a standard Markov model (Model 1), a Latent Markov model (Model 2), a Markov model with covariates (Model 3), a Latent Markov model with covariates (Model 4), three Markov models with covariates controlling for unobservables (Mixed Markov models - Models 5, 7 and 9) and three Mixed Latent Markov models correcting for both measurement error and for observed and unobserved heterogeneity (Models 6, 8 and 10). In Models 5 and 6, initial conditions are treated as exogenous. In Models 7 and 8, we assume perfect correlation between the unobservables affecting the initial state and the latent transition probability. In Models 9 and 10, the aforementioned assumption is relaxed and different individual effects are allowed to affect the initial state and the transition probability.

Table 1: Model comparison

	UK		Netherlands		Germany	
	LL	BIC (LL)	LL	BIC (LL)	LL	BIC (LL)
1. Markov	**-21,937.6**	**43,947.0**	**-9,553.9**	**19,175.6**	**-23,803.8**	**47,680.3**
2. Latent Markov	**-21,211.3**	**42,548.2**	**-9,125.6**	**18,469.9**	**-22,988.5**	**46,104.2**
3. Markov with covariates	**-22,882.0**	**46,535.6**	**-9,182.8**	**19,044.0**	**-19,250.9**	**39,337.3**
4. Latent Markov with covariates	**-20,080.9**	**40,987.2**	**-8,878.4**	**18,486.2**	**-16,693.0**	**34,276.0**
5. Mixed Markov with covariates 1	**-20,670.8**	**42,131.1**	**-9,145.7**	**18,986.7**	**-19,165.8**	**39,185.3**
6. Mixed Latent Markov with covariates 1	**-20,138.9**	**41,121.2**	**-8,876.4**	**18,499.0**	**-16,580.0**	**34,068.3**
7. Mixed Markov with covariates 2	**-20,353.1**	**41,513.7**	**-8,910.5**	**18,533.4**	**-18,941.3**	**38,754.5**
8. Mixed Latent Markov with covariates 2	**-19,955.0**	**40,771.4**	**-8,842.1**	**18,447.3**	**-16,527.8**	**33,982.0**
9. Mixed Markov with covariates 3	**-19,851.8**	**40,645.8**	**-8,910.5**	**18,541.9**	**-16,501.6**	**34,102.2**
10. Mixed Latent Markov with covariates 3	**-19,456.8**	**39,909.5**	**-8,842.1**	**18,455.8**	**-13,127.0**	**27,407.4**

NOTE: In Models 5 and 6, initial conditions are treated as exogenous. In Models 7 and 8, we assume perfect correlation between the unobservables affecting the initial state and the latent transition probability. In Models 9 and 10, the two unobserved effects are allowed to vary freely.

The Log-Likelihood values and the BIC values for the estimated models are reported in Table 1. This Table shows that Model 2 fits the data considerable better than Model 1, Model 4 better than Model 3, Model 6 better than Model 5, Model 8 than Model 7 and Model 10 than Model 9. This indicates that correcting for measurement error is important, regardless of whether we control for observed and unobserved heterogeneity.

Also controlling for observed characteristics improves the fit of the model in the UK and in Germany, as can be seen by comparing the fit of either Models 1 and 3 or Models 2 and 4. In these two countries, correcting for unobservables improves further the fit of the model (comparison of Model 3 with Models 5, 7 and 9, and Model 4 with Models 6, 8 and 10). For the Netherlands, however, controlling for observed and unobserved heterogeneity or for initial conditions does not improve significantly the fit of the model.

Controlling for initial conditions appears also to be important for our analysis, in the UK and in Germany. A comparison of the fit values for the models that assume exogeneity of initial conditions (Models 5 and 6) with the models that relax this assumption (Models 7 and 9 as well as Models 8 and 10, respectively) indicates that this assumption is not plausible. Even the assumption of perfect correlation between the the unobservables affecting the initial state and the latent transition probability is rather strong; when this assumption is relaxed the fit of the model is further improved (comparison of Models 7 and 8 with Models 9 and 10, respectively). The importance of controlling for initial conditions is analyzed further in the discussion of the estimates for the correlations of the unobserved effects. From here on, if not otherwise indicated, our results will be based on Models 9 and 10.

A question we tackle here is how much classification error exists in earnings states. The amount of measurement error can be derived from the estimated values for the probabilities $P(Y_{it} = y_{it}|X_{it} = x_t)$ that are presented in Table 2. These estimates indicate that there is a large amount of classification error for the low-paid workers in all three countries.

Table 2: The size of the measurement error according to Model 10

		UK				Germany		
		Observed state				**Observed state**		
		low	**high**	**other**		**low**	**higher**	**other**
	low	**0.658**	**0.259**	**0.083**	**low**	**0.684**	**0.272**	**0.044**
		(0.013)	(0.012)	(0.008)		(0.012)	(0.001)	(0.001)
Latent	**higher**	**0.013**	**0.972**	**0.016**	**higher**	**0.006**	**0.994**	**0.000**
state		(0.002)	(0.012)	(0.002)		(0.001)	(0.001)	(0.001)
	other	**0.009**	**0.007**	**0.984**	**other**	**0.000**	**0.001**	**0.999**
		(0.001)	(0.002)	(0.013)		(0.000)	(0.002)	(0.003)

		Netherlands		
		Observed state		
		low	**higher**	**other**
	low	**0.705**	**0.294**	**0.001**
		(0.019)	(0.018)	(0.001)
Latent	**higher**	**0.006**	**0.989**	**0.005**
state		0.001)	(0.001)	(0.001)
	other	**0.003**	**0.009**	**0.988**
		(0.002)	(0.003)	(0.004)

NOTE: Standard errors are reported in parentheses.

In the Netherlands, 29.5% (29.4% plus 0.10%) of the low-paid workers are misclassified into another state, while in the UK this figure is 34.2%, and in Germany 31.6%. In all three countries, the misclassification of low-paid workers is more likely to be into the higher earnings state than into the other (non-employment) state, which shows that many workers that are truly low paid are observed to have earnings above the low-pay threshold.

Measurement error for workers who are truly in the higher-paid and non-employment states is considerably lower than in the low-paid state. In the three countries under scrutiny, it ranges between 0.6% and 2.9% for the higher paid and between 0.1% and 1.6% for the non-employed.

It is important to stress the fact that the size of measurement error is not sensitive to the specification of the model. The estimates for the error do not differ more than 2%

between Models 2, 4, 6, 8 and 10 as defined in Table 1.

Table 3: Observed and latent transitions

		Observed transitions				**Latent transitions**		
		United Kingdom						
		State in t				**State in t**		
		low	higher	other		low	higher	other
	low	**0.519**	**0.382**	**0.099**	low	**0.722**	**0.186**	**0.092**
		(0.009)	(0.009)	(0.005)		(0.010)	(0.009)	(0.005)
State	higher	**0.052**	**0.899**	**0.049**	higher	**0.016**	**0.949**	**0.035**
in $t-1$		(0.002)	(0.002)	(0.002)		(0.001)	(0.002)	(0.001)
	other	**0.057**	**0.090**	**0.853**	other	**0.069**	**0.055**	**0.876**
		(0.002)	(0.003)	(0.003)		(0.003)	(0.003)	(0.003)
		Netherlands						
		State in t				**State in t**		
		low	higher	other		low	higher	other
	low	**0.463**	**0.416**	**0.121**	low	**0.680**	**0.165**	**0.154**
		(0.014)	(0.013)	(0.011)		(0.015)	(0.013)	(0.009)
State	higher	**0.027**	**0.948**	**0.025**	other	**0.011**	**0.976**	**0.013**
in $t-1$		(0.001)	(0.003)	(0.002)		(0.001)	(0.001)	(0.001)
	other	**0.067**	**0.092**	**0.841**	other	**0.085**	**0.049**	**0.866**
		(0.004)	(0.006)	(0.006)		(0.005)	(0.004)	(0.006)
		Germany						
		State in t				**State in t**		
		low	higher	other		low	higher	other
	low	**0.402**	**0.420**	**0.178**	low	**0.614**	**0.203**	**0.183**
		(0.010)	(0.010)	(0.007)		(0.012)	(0.010)	(0.008)
State	higher	**0.028**	**0.904**	**0.068**	higher	**0.012**	**0.931**	**0.058**
in $t-1$		(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
	other	**0.074**	**0.143**	**0.782**	other	**0.161**	**0.136**	**0.703**
		(0.003)	(0.003)	(0.004)		(0.004)	(0.003)	(0.004)

NOTE: Standard errors are reported in parentheses. The observed transitions are estimated with the first-order Markov model. The latent transitions are estimated with the MLM model. The reference person in the MLM model is a person having the 'average' characteristics. The covariates included in the MLM model are calendar time, age, education, labour market experience (not available in the Netherlands) and the Gini coefficient.

The implication of controlling for possible classification errors on the estimates of the transition probabilities between earnings states is illustrated in Table 3. The left panel of the table shows the average transition probabilities without controlling for measurement error, while the right panel shows the true (i.e. latent) average transition probabilities. 'Observed transitions' represent the estimated transitions from Model 9, and 'latent transitions' denote the estimated transitions from Model 10. The former are thus transitions that are 'contaminated' by measurement error while the latter are 'error-free'. To perform cross-country comparisons in low-wage transition probabilities, we need to account for the different structure of the wage distribution in different countries. This is accounted for by using the Gini coefficient for wage inequality as a control variable. The full list of the control variables is presented in the next section.

Verifying the findings of previous research, we show that low-pay transitions are considerably less than originally thought. More specifically, we find that observed transitions from low to higher pay are overestimated by a factor of 2.1 - 2.5. Without controlling for measurement error, 38.2% of British low-paid workers increase their earnings above the low-pay threshold in a one-year period. This fraction of year-to-year movers drops to 18.6% when we control for measurement error. Results for the other two countries are similar. The 'true' amount of transitions from low to higher pay in Germany is 20.3% and not 42% as the 'error-contaminated' model suggests. In the Netherlands, the true low-to-high pay transitions are even less frequent: 16.5% compared to 41.6% as estimated by the model that does not correct for measurement error.

In all three countries, the transitions from higher to low pay are also severely overestimated. Although the transition probabilities are much lower than those from low pay, the fraction of spurious transitions is equally large. More specifically, in the UK, these transitions are overestimated by a factor of 2.7, in the Netherlands by 2.5, and in Germany by 2.3.

Interesting cross-country differences emerge from Table 3. In accordance with Pavlopoulos and Fouarge (2010), the smallest low-to-higher pay transition probability among the three countries under scrutiny is found for the Netherlands. Although, this country is the most egalitarian in terms of wage inequality, it presents the largest persistence in low pay. The highest transition probability from low to higher pay is found in Germany.

Sensitivity analysis: the ICE assumption

So far, the ICE assumption has been retained. In other words, we have assumed that, conditional on the true status, there is no serial correlation in measurement error. In the light of the discussion in section 3, in this section, we relax this assumption. More specifically, we estimate again Model 6 by assuming that the measurement error also depends on the variable indicating whether the interviewer has seen the pay slip of the respondent. As this information is only collected by the BHPS, we restrict our analysis in the UK. Table 4 compares the model fit measures, the size of the measurement error and the amount of transitions from low pay between 3 models: Models 5 and 6 are similar to the relevant Models that are presented in Table 1 and Model 6a, which is the model that relaxes the ICE assumption. However, Models 5 and 6 are estimated with a a smaller set of covariates than in Table 1. This explains the difference in the values of the model fit measures between Table 4 and and Table 1. Due to the complexity of the model, this sensitivity analysis could not be performed with Models 7-10 that also control for unobserved heterogeneity.

The first part of Table 4 shows that by relaxing the ICE assumption, the model fit

Table 4: Sensitivity of low-pay transitions to the ICE assumption - the UK

Model fit			
	Log Likelihood	BIC (LL)	
5. Mixed Markov with covariates 1	**-22.882.0**	**46.535.6**	
6. Mixed Latent Markov with covariates 1	**-20.080.9**	**40.987.2**	
6a. Mixed Latent Markov with covariates 1a	**-19.548.9**	**39.990.8**	
Measurement error			
	low	higher	other
6. Mixed Latent Markov with covariates 1	**0.668**	**0.258**	**0.074**
6a. Mixed Latent Markov with covariates 1a	**0.681**	**0.205**	**0.114**
Transitions			
	low	higher	other
5. Mixed Markov with covariates 1	**0.540**	**0.326**	**0.134**
6. Mixed Latent Markov with covariates 1	**0.654**	**0.205**	**0.142**
6a. Mixed Latent Markov with covariates 1a	**0.724**	**0.189**	**0.087**

NOTE: Models 5 and 6 have a similar specification to the one in Table 1. The difference is only that a smaller set of covariates was used. This explains the difference in the values of the model fit measures between this Table and and Table 1. Model 6a is similar to Model 6. The difference is that the measurement error in this model depends also on whether the interviewer has seen the pay slip of the respondent. Only transitions from low pay are presented here.

is improved. However, the second and third part of this table show that the differences between the model that retains the ICE assumption (Model 6) and the model that relaxes it (Model 6a) are not dramatic. More specifically, the overall size of the measurement error slightly reduces (1.3%) when we relax the ICE assumption. Although the overall difference is small, the distribution of the measurement error to the different observed states differs between Models 6 and 6a. According to Model 6a, respondents that in reality are low paid report mistakenly much less that they are in higher pay and much more that they are in non-employment than Model 6 suggests.

Comparing the amount of the transitions out of the low pay status between Models 6 and 6a shows that a larger pay stability emerges when the ICE assumption is relaxed. However, this larger pay stability is due to the much lower amount of latent transitions from low pay to non-employment. Transitions from low pay to higher pay decrease only by 1.6% when we move from Model 6 to Model 6a.

All in all, the results of this sensitivity analysis indicate that although the relaxation of the ICE assumption improves the model fit, the main conclusions of our research are not seriously affected by the ICE assumption.

Sensitivity analysis: definitions of low pay

The analysis we performed until now was based on a low-pay threshold equal to two-thirds of the median wage. However, Organization for Economic Cooperation and Development (1996) suggests that both the incidence of low pay within a country and the ranking

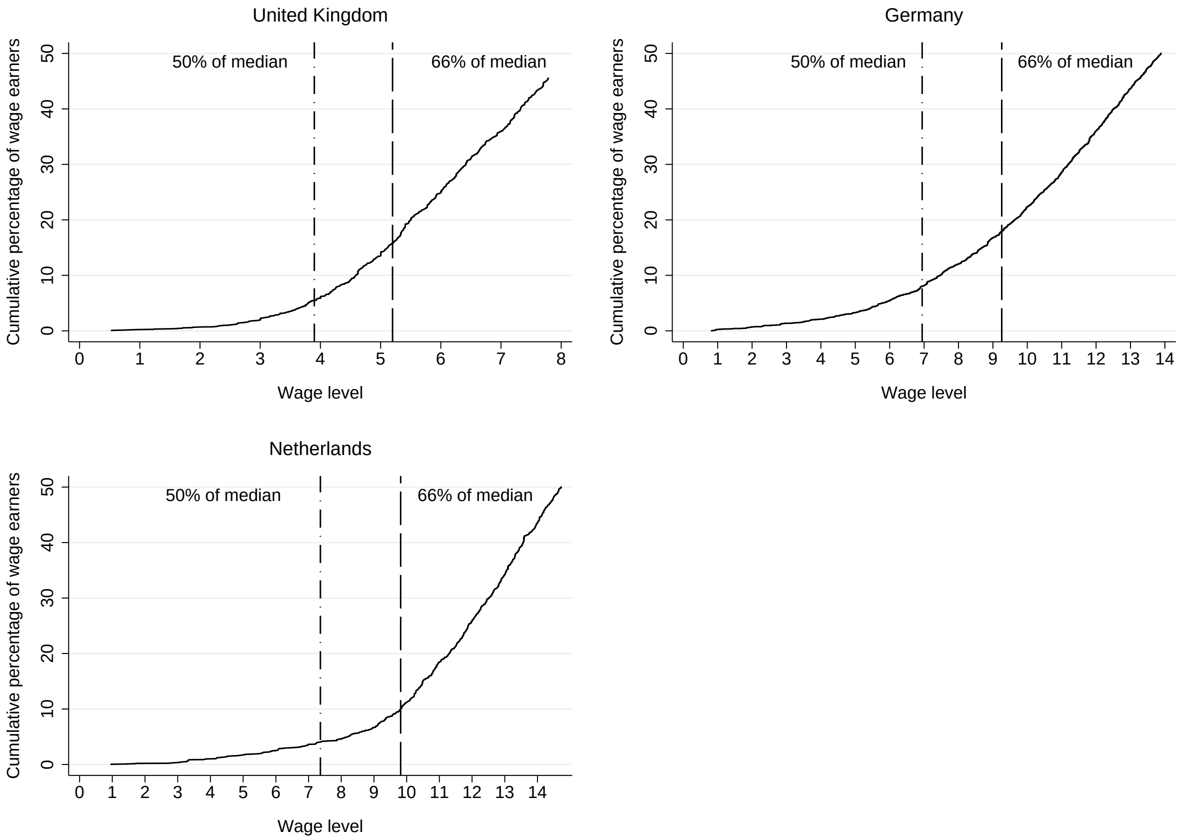

Figure 2: Distribution of the hourly wage for male workers aged 16-55 and for the year 2000.

of countries with respect to low-pay incidence are sensitive to the choice of the low-pay threshold. To check whether our results are also sensitive to this choice, we repeat the same analysis with different low-pay thresholds. We restrict our tests to relative measures of low pay as these are more appropriate for cross-country comparisons than absolute measures (Förster, 1994). More specifically, instead of two-thirds of the median wage as the low-pay threshold, we use 50% and 40% of the median hourly wage. The 50% of the median is a measure used often by EUROSTAT, while the 40% of the median is a level close to the UK poverty line derived from the Supplementary Benefit scale in the 1990's. Figure 2 shows that changing the low-pay definition from two-thirds of the median to 50% of the median results in a considerable reduction in the proportion of the low paid in all three countries. The elasticity of the proportion of low paid with respect to the percentage of the median at which the low-paid threshold is set equals 1.095 in the UK, 0.845 in Germany and 0.595 in the Netherlands. This means that the percentage of low-paid workers is most sensitive to the low-pay threshold in the UK, and least sensitive in the Netherlands. Please note that these elasticities are calculated for values close to two thirds of the median.

Table 5: Sensitivity of low-pay transitions to the low-pay threshold

	UK			**Netherlands**			**Germany**		
	low	higher	other	low	higher	other	low	higher	other
2/3 of the	**0.722**	**0.186**	**0.092**	**0.680**	**0.165**	**0.154**	**0.614**	**0.203**	**0.183**
median	(0.010)	(0.009)	(0.005)	(0.056)	(0.036)	(0.037)	(0.012)	(0.010)	(0.008)
50% of the	**0.604**	**0.260**	**0.136**	**0.511**	**0.203**	**0.286**	**0.550**	**0.253**	**0.197**
median	(0.037)	(0.017)	(0.026)	(0.052)	(0.038)	(0.035)	(0.018)	(0.015)	(0.005)
40% of the	**0.459**	**0.354**	**0.187**	**0.494**	**0.238**	**0.268**	**0.427**	**0.348**	**0.224**
median	(0.044)	(0.016)	(0.041)	(0.057)	(0.082)	(0.054)	(0.023)	(0.020)	(0.006)

NOTE: These transition probabilities are estimated using separate Mixed Latent Markov models (Model 10), each time by using a different low pay threshold. Here we only present the transition probabilities from low pay.

Table 5 presents the main findings from the analysis using each of these alternative definitions of low pay, where we concentrate on transitions from low pay. As can be seen, the lower the percentage of the median at which the threshold is set, the higher the transition rate out of low pay. The ranking of countries with respect to the low-pay transition probability remains unchanged when we consider the aggregate transition probability from low pay. However, if we focus on transitions from low to higher pay, the transition probability is the highest in the UK when we apply the thresholds of 40% or 50% of the median, whereas it is highest for Germany with the higher threshold. It seems, therefore, that in the liberal British labour market slightly higher mobility rates are observed at the very low end of the wage distribution than is the case for in the highly regulated German labour market. Since the wage distribution of the UK is more left-skewed than the German distribution, the average distance from the low-pay threshold is much larger in the UK than in Germany, which makes crossing the threshold much more difficult for the British low-paid workers than for the German ones. When we apply a lower threshold, the average distance from the threshold in the UK is decreased and low-pay transition probabilities increase considerably. Again, the lowest low-to-high pay transition probabilities are found in the Netherlands.

Discussion of the results

Before discussing the parameter estimates for our main covariates, it is worth elaborating on the correlation structure of our unobservables. Table 6 presents the variances and correlations of the individual effects from Models 9 and 10 for all three countries. This Table shows clearly that initial conditions are endogenous. The correlation of the individual effects affecting the initial state and the transition equation is strongly significant in all three countries. Moreover, it is significant in both the 'error-contaminated' and in the 'error-free' model (Models 9 and 10, respectively). This finding means that being truly in low pay at the first year of observation increases the likelihood of being in low pay in the years thereafter. Our results here are in accordance to previous research on the effect of initial conditions on low-wage mobility (Stewart & Swaffield, 1999; Cappellari & Jenkins, 2004b).

Table 6: Variances and covariances of the individual effects

	UK		**Netherlands**		**Germany**	
	Model 9	Model 10	Model 9	Model 10	Model 9	Model 10
σ_1	**0.477*****	**0.399*****	**0.315*****	**0.237*****	**0.740*****	**0.515*****
σ_2	**0.951**	**3.237****	**0.245****	**1.842**	**0.880*****	**0.450*****
ρ	**0.604*****	**0.893*****	**0.278*****	**0.486*****	**0.807*****	**0.481*****

* significant at 10%; ** significant at 5%; *** significant at 1%

As a next step in our analysis, we assess the impact of classification errors in the earnings state on the estimated covariate effects of our panel-regression model. For this purpose, in Table 7, we compare the estimates from Model 9 and Model 10. The main variables of interest are labour market events that can potentially account for a considerable wage change, and can therefore cause a transition from low to higher pay or vice versa. These event variables are a job change, an occurrence of formal training, a transition from a temporary employment contract to a permanent one, or vice versa, and a transition from part-time employment to full-time employment, or vice versa. Our control variables are the Gini coefficient, calendar time, education, labour market experience, changes in marital status and, in Germany, also apprenticeship. For the Netherlands, as experience is not available we use age as a proxy.

Table 7: Results from the Mixed Latent Markov model

	Origin state	Destination state	The UK: no ME correction	The UK: with ME correction	The UK: Difference	The Netherlands: no ME correction	The Netherlands: with ME correction	The Netherlands: Difference	Germany: no ME correction	Germany: with ME correction	Germany: Difference
Training	Low	Higher	0.194***	0.476***	59.3%***	0.616**	0.710**	13.2%***	-0.741***	0.379	
	Low	Other	-0.342*	-0.254		0.261	-0.259		1.098***	1.191*	7.8%**
	Higher	Low	-0.308***	-0.521***	40.8%***	-0.157	-0.698		1.007***	0.569*	-77.1%
Job change	Low	Higher	-0.049	0.003					-0.021	-0.126	83.7%***
	Low	Other	-	-	-	-	-	-	-	-	
	Higher	Low	0.710***	1.008***	29.6%***				0.648***	1.116***	42.0%***
Temporary to permanent contract	Low	Higher	0.273	-0.146		-0.355	0.011		0.261	0.607**	57.0%***
	Low	Other	-	-	-	-	-	-	-	-	
	Higher	Low	0.459	0.683		-0.071	-4.208		-0.203**	-1.124**	82.0%***
Permanent to temporary contract	Low	Higher	0.092***	0.344		-0.107	-0.124		-0.446	0.136	
	Low	Other	-	-	-	-	-	-	-	-	
	Higher	Low	0.175	1.139		0.792**	1.906***	58.4%***	0.930***	1.526***	39.0%***
Full to part time work	Low	Higher	0.254	-0.497		0.811***	0.548***	-47.9%***	-0.416	-0.465	
	Low	Other	-	-	-	-	-	-	-	-	
	Higher	Low	-0.335	-0.667		-0.407	-0.866		0.787***	1.374***	42.7%***
Part to full time work	Low	Higher	-0.487	0.319		0.068	-0.397		-0.068	0.423*	
	Low	Other	-	-	-	-	-	-	-	-	
	Higher	Low	1.043***	2.186***	52.3%***	0.757**	2.294***	67.0%***	1.288***	2.283***	
Unobserved heterogeneity	Higher		-1.206***	0.544***	321.7%***	-2.037***	0.738**	375.9%***	-0.654***	0.523***	225.2%***
	Other		0.206*	-1.544***	113.3%***	1.037***	-1.738***	159.7%***	-0.346***	-1.523***	77.3%***

* significant at 10%; ** significant at 5%; *** significant at 1%

NOTE: The dependent variable is the earnings state. It takes three values: low pay, higher pay and other. Transitions between all states are modelled. However, here we only present the estimates on the transitions from low to higher pay, from low to the 'other' state and from higher to low pay. The control variables are calendar time, education, labour market experience (age in the Netherlands), apprenticeship (only in Germany) and the Gini coefficient. The column with title 'Difference' presents the difference between the estimates of the models presented in the two previous columns. The significance of the difference is estimated with a Hausman test. The difference is reported only when coefficients from both models are significant.

One commonly-used specification is to allow covariates to affect the probability of being in a certain state at a time point t. We use another more flexible specification in which covariates have an effect on making a particular type of transition. For example, our model estimates the effect of a job change on making a transition from low pay to higher pay rather than 'just' estimating the effect of this covariate on being in low pay. The statistical significance of the difference between the estimate of each covariate effect in the 'error-contaminated' model (Model 9) and the 'error-free' model (Model 10) is assessed using a Hausman test (Hausman, 1978).

We first discuss the estimates from Model 10, the 'error-free' model. Job-related training seems to be an important determinant of low-wage mobility. Training has a positive effect on the probability of a low-to-higher pay transition in the UK and in the Netherlands, while it has no effect in Germany. We should stress here that our variable for training does not include apprenticeship. In Germany, apprenticeship is included as a control variable. Our results - not presented here - show that having apprenticeship qualifications increases the probability of a low-paid to higher-paid transition. Moreover, the definition of the training variable is not uniform across countries. See Appendix A for details. In both the UK and in Germany, a job change increases the probability for a higher-to-low pay transition. For the Netherlands we were unable to include a job change variable due to an artifact in the data.

Changes in the employment contract type present some differences across countries. A shift from a temporary to a permanent contract has no effect in the UK or in the

Netherlands. On the contrary, in Germany, such a shift increases the probability of a low- to higher-pay transition and decreases the probability of a higher-paid to low-paid transition. The reverse shift, from a permanent to a temporary contract, has no significant effect on the low-wage transition probabilities in any of the three countries. In the Netherlands and in Germany, however, it increases the probability for a higher-to-low wage transition.

The lack of any significant finding concerning employment contract changes for the UK is not surprising. Since in the British labour market, job protection for both permanent and temporary workers is low, both types of workers have the same status with respect to pay, promotion opportunities and job quality. In the same line of reasoning, temporary employment in Germany holds a much lower status than in the UK. The German labour market is a typical 'insiders' labour market, where 'core' workers in the primary segment enjoy a high level of job protection and higher wages, while their counterparts in the secondary segment are much less protected and much more exposed to low pay (Blossfeld, 2001). A shift from temporary to permanent employment is likely to represent a move from the secondary into the primary segment of the labour market. For the Netherlands, we expected the relevant estimates to be in between the British and the German estimates, as the Dutch labour market is featured strong job protection but rather a lenient regulation with respect to temporary contracts (Muffels & Luijkx, 2006). However, the results show no significant wage effect of a shift from a temporary to a permanent contract. A possible explanation for this finding is that, in the Netherlands, changes of the employment contract and shifts from part-time to full-time employment, or vice versa, may also have captured the effects of a job change. That means that the contract change may also involve a change of job on the internal or external labour market involving a different pay scheme.

A shift from full-time to part-time employment or vice versa is also an important determinant of low-pay transitions. The shift from full-time to part-time work increases the probability for a low-to-higher wage mobility in the Netherlands and the probability for a higher-to-low pay transition in Germany. The reverse shift, from part-time to full-time employment increases the probability of a transition from low to higher pay in Germany (the estimate is significant only at the 10% level) but remarkably also the likelihood of a move from higher to low pay in all three countries to more or less the same extent.

The interpretation of these results involves 2 processes. The first process suggests that a involuntary decrease of working hours without an employer change may be accompanied by a demotion or a shift to a job that is less important for the firm. Such a shift leads probably to a lower wage. The opposite should happen for an increase of working hours without an employer change. We would expect these effects to be stronger in countries such as Germany and the UK, where due to occupational segregation part-time jobs are relatively 'bad' jobs in terms of pay and promotion chances, than in countries such as the Netherlands, where part-time jobs are widespread and have an increased level of job quality (Fouarge & Muffels, 2010). This explains the relevant finding for Germany and the Netherlands but not the insignificant result for the UK.

The second process may explain the positive effect of a shift from part-time to full-time employment on the higher-to-low pay probability in all three countries. This process suggests individual preferences for the total earnings matter more than preferences for the hourly wage. The male beholder of these jobs may prefer to work longer hours with lower hourly pay over fewer hours with a higher hourly pay. Hence, when workers increase their working hours, they may accept a lower hourly wage in order to receive higher monthly earnings. The positive effect we observe in all countries of a shift from part-time to full-time employment on the higher-to-low pay probability is probably explained by this preference shifting process.

Although results from the coefficient estimation are plausible, two words of caution should be added. The first issue involves a possible correlation in the measurement error of the dependent and the independent variable. Working hours is used both for the construction of our dependent variable (i.e. the earnings state) and for the definition of the dummies for a full-time to part-time shift and the part-time to full-time shift. Therefore, any error in the measurement of the number of working hours affects both variables. This correlation between the errors in the dependent and in the independent variable may cause some bias in the estimation of the coefficient of the shifts between full-time and part-time work.

The second issue involves the underlying assumption of our model that all predictors are strictly exogenous, i.e. that the error term is uncorrelated to the past, current and future realizations of the predictors. It can be expected that this assumption does not hold to a certain extend when low-paid workers have more chances than higher-paid workers to change contract or number of working hours. This issue has been investigated for the case of employment participation and household composition as predictors of poverty (Biewen, 2009). However, the bias resulting from the possible violation of this assumption is likely to be rather small and correcting for it in this context is left for further scrutiny.

As far as the expected impact of correcting for measurement error is concerned, the findings in Table 7 confirm our expectations. Comparing the estimates of Models 9 and 10 shows that many covariate effects are attenuated by measurement error. For example, the effect of job change on the transition from higher to low paid in the UK is underestimated by 29.6%. The effect of training on the transition from low to higher pay in the Netherlands is underestimated by 13.2%. However, in some cases covariate effects are overestimated due to measurement error. The effect of a shift from full-time to part-time work on the transition from low to higher pay in the Netherlands in overestimated by 47.9%. We should remember here that the difference in the sizes of the covariate effects between Models 9 and 10 may also represent processes other than just correction for measurement error in the dependent variable. If there is error in the measurement of the covariates, then this error might be correlated with the error in the dependent variable. In this case, what is being measured is a combination of two processes: the attenuation of the effect of the covariate due to the classification error in the earnings state, and the ambiguous effect of the correlation of the errors in the dependent and the independent variable.

In most cases, however, the effect of the covariates is strengthened when correcting for measurement error. Therefore, controlling for classification error in the earnings state is necessary in order to obtain correct (or at least more correct) estimates of the covariates.

An extension of this study may concern distinguishing further the effect of measurement error. Several studies, such as Shorrocks (1976) and Lillard and Willis (1978), suggest that higher order processes determine income mobility. According to these studies, these higher order processes are caused by heterogeneity and unobserved serial correlation. In this paper, we have controlled for observed and unobserved heterogeneity. Nevertheless, as our model does not make use of validation data, some true second-order process is classified as measurement error. This may happen because our model derives from the longitudinal information for all individuals a pattern of 'regular transition behaviour' for individuals belonging to state x (Vermunt, 2004). The obvious result of this is that our model, as well as other similar models, may slightly overestimate the amount of measurement error. From a policy perspective, however, this is not necessarily bad. Our model does not only filter out measurement error but may also remove the transitory moves from the earnings states. Thus, the 'true' transitions we estimate are the transitions between the states x_j and x_k when accompanied by a change in transition 'behavior'; from the transition 'behaviour' corresponding to individuals in state x_j to the transition 'behaviour' of individuals in state x_k.

Appendix A: Description of the variables

Calendar time: We use dummies for every year. For the UK, this varies between 1991 and 2004, for Germany between 1991 and 2004 and for the Netherlands between 1991 and 2002.

Gini coefficient: This is the Gini coefficient for the male hourly wages. It is calculated on a yearly basis.

Education: This is the highest educational level completed by the individual. It can take three values, lower than high school, high school and higher education.

Training: It takes the value 1 when the individual received formal training during the year prior to the survey and 0 in all other cases. In the UK and in the Netherlands, training refers to both part-time and full-time courses, while in Germany, it refers only to full-time courses.

Labour market experience: Measured in months. This is available only for the UK and for Germany. It is constructed by combining data from the yearly files and the employment history files of BHPS and GSOEP.

Age: Measured in years.

Job change: It takes the value 1 when the individual changed an employer during the year prior to the survey and 0 in all other cases. It also takes the value 0 when the individual moves from or to non-employment as well as when he remains in non-employment. This variable was not included for the Netherlands.

Temporary to permanent: It takes the value 1 when the individual reported being employed with a temporary contract in $t-1$ and being employed with a permanent contract in t and 0 in all other cases. It also takes the value 0 when the individual moves from or to non-employment as well as when he remains in non-employment.

Permanent to temporary: It takes the value 1 when the individual reported being employed with a permanent contract in $t-1$ and being employed with a temporary contract in t and 0 in all other cases. It also takes the value 0 when the individual moves from or to non-employment as well as when he remains in non-employment.

Part-time to full-time: It takes the value 1 when the individual reported being employed part-time in $t-1$ and being employed full-time in t and 0 in all other cases. It also takes the value 0 when the individual moves from or to non-employment as well as when he remains in non-employment.

Full-time to part-time: It takes the value 1 when the individual reported being employed part-time in $t-1$ and being employed full-time in t and 0 in all other cases. It also takes the value 0 when the individual moves from or to non-employment as well as when he remains in non-employment.

Appendix B: The parameter estimation

The estimates for the parameters of our model are obtained by means of maximum likelihood, where the likelihood contribution of individual i equals the density given in equation (4). We solve the integral using Gauss-Hermite numerical integration, which means that the integrals are replaced by a sum over L quadrature nodes. Below, we will refer to a particular node by w, to its location by $\mathbf{F}_w$ and to its weight by π_w.

The numerically integrated log-likelihood function is maximized using a special variant of the Expected Maximization (EM) algorithm (Dempster et al., 1977) called the forward-backward or Baum-Welch algorithm (Baum et al., 1970). Below we present an expanded version of this algorithm for the situation in which the latent Markov model contains random effects. The EM algorithm is a general iterative procedure for maximum likelihood estimation in the presence of latent variables or other types of missing data. It switches between an E-step and an M-step till convergence. The E-step computes the expected value of the complete log-likelihood or, more intuitively, estimates the missing data (here the unobserved class memberships and random effects). For this, the algorithm employs the expected value given the current parameter values and the observed data. For the mixed latent Markov model described in equation (4), contribution of case i to the expected complete-data log-likelihood, $E(\log L_i)$, is as follows:

$$\begin{aligned} E(\log L_i) = & \sum_{w=1}^{L}\sum_{x_0=1}^{3} \pi_{iwx_0} \log P(X_{i0} = x_0|\mathbf{Z}_{i0}, \mathbf{F}_w) \\ & + \sum_{t=1}^{T}\sum_{w=1}^{L}\sum_{x_{t-1}=1}^{3}\sum_{x_t=1}^{3} \pi_{iwx_{t-1}x_t} \log P(X_{it} = x_t|X_{i(t-1)} = x_{t-1}, \mathbf{Z}_{it}, \mathbf{F}_w) \\ & + \sum_{t=0}^{T}\sum_{x_t=1}^{3} \pi_{ix_t} \log P(Y_{it} = y_{it}|X_{it} = x_t), \end{aligned}$$

The E-step requires updating the marginal posterior probabilities π_{iwx_0}, $\pi_{iwx_{t-1}x_t}$, and π_{ix_t}, which are defined as:

$$\begin{aligned}
\pi_{iwx_0} &= P(w, x_0|\mathbf{y}_i, \mathbf{Z}_i), \\
\pi_{iwx_{t-1}x_t} &= P(w, x_{t-1}, x_t|\mathbf{y}_i, \mathbf{Z}_i), \\
\pi_{ix_t} &= P(x_t|\mathbf{y}_i, \mathbf{Z}_i).
\end{aligned}$$

The forward-backward algorithm obtains them by a recursive scheme and once found they are used in the above equation for the next M-step.

The two key components of the Baum-Welch algorithm are the forward probabilities α_{iwx_t} and the backward probabilities β_{iwx_t}. These two quantities are defined as follows:

$$\begin{aligned}
\alpha_{iwx_t} &= P(w, x_t, y_{i0}...y_{it}|\mathbf{Z}_i), \\
\beta_{iwx_t} &= P(y_{i(t+1)}...y_{iT}|w, x_t, \mathbf{Z}_i).
\end{aligned}$$

Thus, the forward probability α_{iwx_t} refers to having the observed set of responses, i.e. observed states, up to time point t, being in latent state x_t at t, and having random effects corresponding to node w, conditional on covariate values and model parameters. The backward probability β_{iwx_t} is the probability of having the observed set of responses after time point t, conditional on being in latent class x_t at t, the random effects corresponding to node w, covariate values and model parameters. Using α_{iwx_t}, and β_{iwx_t}, one can obtain the relevant marginal posteriors as follows:

$$
\begin{aligned}
\pi_{iwx_0} &= \frac{\alpha_{iwx_0}\beta_{iwx_0}}{P(\mathbf{y}_i|\mathbf{Z}_i)}, \\
\pi_{iwx_{t-1}x_t} &= \frac{\alpha_{iwx_{t-1}}P\left(x_t|x_{t-1},\mathbf{Z}_{it},\mathbf{F}_w\right)P(y_{it}|x_t,\mathbf{Z}_{it},\mathbf{F}_w)\,\beta_{iwx_t}}{P(\mathbf{y}_i|\mathbf{Z}_i)} \\
\pi_{ix_t} &= \sum_{w=1}^{L}\frac{\alpha_{iwx_t}\beta_{iwx_t}}{P(\mathbf{y}_i|\mathbf{Z}_i)},
\end{aligned}
$$

where $P(\mathbf{y}_i|\mathbf{Z}_i) = \sum_{w=1}^{L}\sum_{x_t=1}^{3}\alpha_{iwx_t}\beta_{iwx_t}$ for any t, and $P\left(x_t|x_{t-1},\mathbf{Z}_{it},\mathbf{F}_w\right)$ and $P(y_{it}|x_t,\mathbf{Z}_{it},\mathbf{F}_w)$ are model probabilities from the previous M-step.

The key element of the forward-backward algorithm is that $T+1$ sets of α_{iwx_t} and β_{iwx_t} terms are computed using recursive schemes. The forward recursion scheme for α_{iwx_t} is:

$$
\begin{aligned}
\alpha_{iwx_0} &= \pi_w\,P(X_{i0}=x_0|\mathbf{Z}_{i0},w)P(y_{i0}|X_{i0}=x_0,\mathbf{Z}_{i0},\mathbf{F}_w), \\
\alpha_{iwx_t} &= \left\{\sum_{x_{t-1}=1}^{K}\alpha_{iwx_{t-1}}P\left(X_{it}=x_t|X_{i(t-1)}=x_{t-1},\mathbf{Z}_{it}\mathbf{F}_w\right)\right\}P(y_{it}|X_{it}=x_t,\mathbf{Z}_{it},\mathbf{F}_w)\,,
\end{aligned}
$$

for $t=1$ up to $t=T$. The backward recursion scheme for β_{iwx_t} is:

$$
\begin{aligned}
\beta_{iwx_T} &= 1, \\
\beta_{iwx_t} &= \sum_{x_{t+1}=1}^{K}\beta_{iwx_{t+1}}P\left(x_{t+1}|x_t,\mathbf{Z}_{it},\mathbf{F}_w\right)P(y_{it+1}|x_{t+1},\mathbf{Z}_{it},\mathbf{F}_w)\,,
\end{aligned}
$$

for$t=T-1$ down to $t=0$. So, we obtain α_{iwx_t} and β_{iwx_t} for all time points using the model probabilities from the previous M step and use these to obtain the posterior probabilities π_{iwx_0}, $\pi_{iwx_{t-1}x_t}$, and π_{ix_t}.

The M-step uses standard estimation methods to update the model parameters, such that the expected complete-data log-likelihood is maximized or increased. Here, the M-step involves using the filled-in expected values as if they were observed data in logistic regression analysis. The E- and M-step cycle till a certain convergence criterion has been reached.

References

Abowd, J. M., & Stinson, M. H. (2005). Estimating measurement error in SIPP annual job earnings: A comparison of census survey and ssa administrative data. *Technical Paper, U.S. Census Bureau.*

Abrevaya, J., & Hausman, J. A. (1997). *Semiparametric estimation with mismeasured dependent variables: an application to panel data on unemployment spells.* Mimeo, University of Chicago, Graduate School of Business and MIT, Department of Economics.

Acemoglu, D. (2003a). Cross-country inequality trends. *Economic Journal*, *113*, 121-149.

Acemoglu, D. (2003b). Patterns of skill premia. *Review of Economic Studies*, *70*(2), 199-230.

Bassi, F., Hagenaars, J. A., Croon, M. A., & Vermunt, J. K. (2000). Estimating true changes when categorical panel data are affected by uncorrelated and correlated classification errors. *Sociological Methods and Research*, *29*(2), 230-268.

Baum, L. E., Petrie, T., Soules, G., & Weiss, N. (1970). A maximization technique occuring in the statistical analysis of probabilistic functions of markov chains. *The Annals of Mathematical Statistics*, *41*(1), 164-171.

Biewen, M. (2009). Measuring state dependence in individual poverty histories when there is feedback to employment status and household composition. *Journal of Applied Econometrics*, *24*(7), 1095-1116.

Blau, F. D., & Kahn, L. M. (1996). International differences in male wage inequality:

institutions versus market forces. *Journal of Political Economy*, *104*(4), 791-837.

Blossfeld, H.-P. (2001). Globalisation, social inequality and the role of country-specific institutions. Open research questions in a learning society. In H. V. Conceicao & B.-A. Lundvall (Eds.). *Towards a learning society: Innovation and competence building with social cohesion for Europe* Oxford: Oxford University Press.

Blumen, I., Kogan, M., & MacCarthy, P. J. (1966). Probability models for mobility. In P. F. Lasarsfeld & N. W. Henry (Eds.), *Readings in mathematical social science* (p. 318-334). Cambridge, Massachusetts: MIT Press.

Bollinger, C. R. (1996). Bounding mean regressions when a binary regressor is mismeasured. *Journal of Econometrics*, *73*(2), 387-399.

Bollinger, C. R. (1998). Measurement error in the current population survey: A nonparametric look. *Journal of Labor Economics*, *16*(3), 576-594.

Bound, J., Brown, C., Duncan, G. J., & Rodgers, W. L. (1994). Evidence on the validity of cross-sectional and longitudinal labor market data. *Journal of Labor Economics*, *12*(3), 345-368.

Bound, J., Brown, C., & Mathiowetz, N. (2001). Measurement error in survey data. In J. J. Heckman & E. Leamer (Eds.), *Handbook of econometrics* (Vol. 5, p. 3705-3843). Amsterdam: Elsevier.

Bound, J., & Krueger, A. (1991). The extent of measurement error in longitudinal earnings data: Do two wrongs make a right? *Journal of Labor Economics*, *9*(1), 1-24.

Cappellari, L. (2002). Do the 'working poor' stay poor? an analysis of low-pay transitions in Italy. *Oxford Bulletin of Economics and Statistics*, *64*(2), 87-110.

Cappellari, L., & Jenkins, S. P. (2004a). Modelling low income transitions. *Journal of Applied Econometrics*, *19*, 593-610.

Cappellari, L., & Jenkins, S. P. (2004b). *Modelling low pay transition probabilities, accounting for panel attrition, non-response and initial conditions.* Institute for Social and Economic Research, ISER Working Paper Series, nr 2004-08.

CBS. (1991). *Sociaal-economisch panelonderzoek. inhoud, opzet en organisatie.* Voorburg/Heerlen: Centraal Bureau voor de Statistiek.

Dempster, A. P., Laird, N. M., & Rubin, D. B. (1977). Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society, Series B*, *39*(1), 1-38.

Dex, S., Joshi, H., & Macran, S. (1998). Women's employment transitions around childbearing. *Oxford Bulletin of Economics and Statistics*, *60*(1), 79-98.

Duncan, G. J., & Hill, D. H. (1985). An investigation of the extent and consequences of measurement error in labor-economic survey data. *Journal of Labor Economics*, *3*(3), 508-522.

Förster, M. F. (1994). *Measurement of low income and poverty in a perspective of international comparisons.* Labour Market and Social Policy Occasional Papers, No. 14, OECD, Paris.

Fouarge, D., & Muffels, R. (2010). Working part-time in the British, German and Dutch labour market: scarring for the wage career? *Journal of Applied Social Science Studies*, *129*, 85-100.

Freeman, R. B., & Katz, L. F. (1995). *Differences and changes in wage structures.* University of Chicago Press.

Gottschalk, P. (2005). Downward nominal-wage flexibility: Real or measurement error. *Review of Economics and Statistics*, *87*(3), 556-568.

Hagenaars, J. A. (1990). *Categorical longitudinal data log-linear panel, trend and cohort analysis.* Newbury Park, CA: Sage Publications.

Hagenaars, J. A. (1994). Latent variables in log-linear models of repeated observations. In A. von Eye & C. C. Clogg (Eds.), *Latent variable analysis: Applications for developmental research* (p. 329-352). Thousand Oaks, CA: Sage Publications.

Hanisch, J. U. (2005). Rounded responses to income questions. *Allgemeines Statistisches Archiv*, *89*(1), 39-49.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica*, *6*(46), 1251-1271.

Hausman, J. A., Abrevaya, J., & Scott-Morton, F. (2009). Misclassification of the dependent variable in a dicrete response setting. *Journal of Econometrics*, *2*(87), 239-269.

Kapteyn, A., & Ypma, J. Y. (2007). Measurement error and misclassification: A comparison of survey and register data. *Journal of Labor Economics*, *25*(3), 513-551.

Kristensen, N., & Westergård-Nielsen, N. (2006). A large-scale validation study of measurement errors in longitudinal survey data. *Institute for the Study of Labor, IZA Discussion Paper*, *2329*.

Lillard, L. A., & Willis, R. J. (1978). Dynamic aspects of earning mobility. *Econometrica*, *46*(5), 985-1012.

Lollivier, S., & Daniel, V. (2005). Trois apports des donnés longitudinales à l' analyse de la pauvreté. *Economie et Statistique*, *383-384-385*, 245-282.

Magnac, T., & Visser, M. (1999). Transition models with measurement errors. *Review of Economics and Statistics*, *81*(3), 466-474.

Mellow, W., & Sider, H. (1983). Accuracy of response in labor market surveys: Evidence and implications. *Journal of Labor Economics*, *4*(1), 331-344.

Muffels, R. J. A., & Luijkx, R. (2006). Globalisation and male job mobility in European welfare states. In H. P. Blossfeld, M. Mills, & F. Bernardi (Eds.). *Globalization, uncertainty and men's careers.* Cheltenham, UK/Northampton, MA, USA: Edward Elgar.

Nordberg, L., Rendtel, U., & Basic, E. (2004). Measurement error of survey and register income. In M. Ehling & U. Rendtel (Eds.), *Harmonisation of panel surveys and data quality* (p. 65-88). Wiesbaden: Statistisches Bundesamt.

Organization for Economic Cooperation and Development. (1996). *Employment Outlook 1996.* Paris: Organization for Economic Cooperation and Development.

Organization for Economic Cooperation and Development. (1997). Earnings mobility: Taking a longer-run view. In *Employment Outlook 1997* p. 27-61. Paris: Organization for Economic Cooperation and Development.

Organization for Economic Cooperation and Development. (2003). *Employment Outlook 2003.* Paris: Organization for Economic Cooperation and Development.

Paas, L. J., Bijmolt, T. H., & Vermunt, J. K. (2007). Latent class markov modeling for assessing and predicting household acquisitions of financial products. *Journal of Economic Psychology*, *28*(2), 229-241.

Paull, G. (2008). Children and women's hours of work. *Economic Journal*, *118*, F8 - F27.

Pavlopoulos, D., & Fouarge, D. (2010). Escaping low pay: Do male labour market entrants stand a chance? *International Journal of Manpower*, *31*(8), 908-927.

Pischke, J.-S. (1995). Measurement error and earnings dynamics: Some estimates from the PSID validation study. *Journal of Business and Economic Statistics*, *13*(3), 305-314.

Poterba, J. M., & Summers, L. H. (1986). Reporting errors and labor market dynamics. *Econometrica*, *54*(6), 1319-1338.

Poterba, J. M., & Summers, L. H. (1995). Unemployment benefits and labor market transitions: A multinomial logit model with errors in classification. *Review of Economics and Statistics*, *77*(2), 207-216.

Powell, L. M. (2002). Joint labor supply and childcare choice decisions of married mothers. *Journal of Human Resources*, *37*(1), 106-128.

Rendtel, U., Langeheine, R., & Berntsen, R. (1998). The estimation of poverty dynamics using different measurements of household income. *Review of Income and Wealth*, *44*(1), 81-98.

Rodgers, W. L., Brown, C., & Duncan, G. J. (1993). Errors in survey reports of earnings, hours worked, and hourly wages. *Journal of the American Statistical Association*, *88*(3), 345-368.

Shorrocks, A. F. (1976). Income mobility and the markov assumption. *Economic Journal*, *86*, 566-578.

Sloane, P. J., & Theodossiou, I. (1996). Earnings mobility, family income and low pay. *Economic Journal*, *106*, 657-666.

Sloane, P. J., & Theodossiou, I. (1998). An econometric analysis of low pay and earnings mobility in Britain. In R. Asplund & P. J. Sloane (Eds.), *Low pay and earnings mobility in Europe* (p. 103-115). Cheltenham [etc.] : Edward Elgar Publishing.

Stewart, M. B. (2007). The inter-related dynamics of unemployment and low-wage employment. *Journal of Applied Econometrics*, *22*(3), 511-531.

Stewart, M. B., & Swaffield, J. K. (1999). Low pay dynamics and transition probabilities. *Economica*, *66*(127), 23-42.

Taylor, M. F. e., Brice, J., Buck, N., & Prentice-Lane, E. (2006). *British Household Panel Survey User Manual volume A: Introduction, technical report and appendices.* Colchester: University of Essex.

Uunk, W., Kalmijn, M., & Muffels, R. (2005). The impact of young children on women's labour supply: A reassessment of institutional effects in Europe. *Acta Sociologica*, *48*(1), 41-62.

van de Pol, F., & Langeheine, R. (1990). Mixed markov latent class models. *Sociological Methodology*, *20*, 213-247.

Vermunt, J. K. (2004). Comment on: An analysis of classification error for the revised current population survey employment questions. *Survey Methodology*, *30*, 141-144.

Vermunt, J. K., Langeheine, R., & Böckenholt, U. (1999). Discrete-time discrete-state latent markov models with time-constant and time-varying covariates. *Journal of Educational and Behavioral Statistics*, *24*, 178-205.

Vermunt, J. K., & Magidson, J. (2008). *LG - Syntax user's guide: Manual for Latent GOLD 4.5 syntax module.* Belmont Massachussetts: Statistical Innovations Inc.

Vermunt, J. K., Tran, B., & Magidson, J. (2008). Latent class models in longitudinal research. In S. Menard (Ed.), *Handbook of longitudinal research: Design, measurement, and analysis* (p. 373-385). Burlington, MA: Elsevier.

Wagner, G. G., Frick, J. R., & Schupp, J. (2007). The German Socio-Economic Panel Study (SOEP) - scope, evolution and enhancements. *Schmollers Jahrbuch: Journal of Applied Social Science Studies*, *127*(1), 429-433.