Low-wage jobs - stepping stones or just bad signals? *

Alexander Mosthaf†

Alexander Mosthaf

March 2011

Abstract

This study investigates how the effects of low-wage employment and non-employment on wage prospects vary depending on qualification. We apply dynamic nonlinear models with random effects and include interactions of the lagged labor market state with qualification to estimate heterogeneity in state dependence. We find that low-wage jobs are stepping stones to high-paid jobs for low qualified workers. In contrast, the chances of workers with a university degree to obtain a high-paid job are the same when being low-paid or non-employed (whereas their risk of non-employment falls when having a low-paid job). Furthermore, our results suggest that for workers with university degree low-wage jobs are associated with negative signals.

Keywords: low-pay dynamics, state dependence, dynamic multinomial logit model, partial effect, nonlinear models, interaction term, unobserved heterogeneity

New JEL-Classification: J30, J60, C33

*Preliminary version! Please do not quote!

†Institute for Employment Research (IAB) and University of Mainz; Regensburger Str. 104, 90478 Nuremberg; alexander.mosthaf@iab.de

1 Introduction

Recent studies have investigated the scarring effects of non-employment and low-wage employment in order to assess whether taking up a low-paid interim job improves the labor market prospects of not employed individuals (Buddelmeyer, Lee and Wooden, 2009; Cappellari and Jenkins, 2008; Mosthaf, Schank and Schnabel, 2009; Stewart, 2007; Uhlendorff, 2006).[1] So far, the heterogeneity in these effects has been given scant attention although it is important to know if taking up a low-paid interim job is advisable for everyone or only for specific subgroups of the population. This paper investigates how the effects of low-wage employment and non-employment on future labor market outcomes vary depending on qualification.

The current economic crisis in several OECD-countries lends a special interest to the question whether it is beneficial to take up a low-paid interim job. Ljungqvist and Sargent (1998) argue that European labor markets are more vulnerable to recessions than the US because generous unemployment benefits reduce incentives for laid-off workers to quickly accept jobs with lower wages than those of their previous jobs. In times of economic crisis the number of "good jobs" with high wages is limited and high reservation wages of laid-off workers lead to long-term unemployment, a factor producing a significant loss of human capital. By taking up a low-paid job instead of waiting for a "good job", unemployed individuals could shorten unemployment duration and thereby averting scarring effects associated with unemployment. On the other hand Burdett (1979) and Marimon and Zilibotti (1999) point out that searching for the right job match during unemployment may have positive returns.

Since the German government reduced the generosity of the unemployment benefit system (Caliendo, 2009), there has been a lively political discussion about policy instruments such as unemployment benefits, minimum wages and employment subsidies. Given the growing low-wage sector there is the concern that individuals accepting "bad jobs" might become trapped in low-wage employment and in doing

[1] McCormick (1990, p. 300) focusses in his study on interim jobs and defines them as jobs which are "*acceptable by certain workers as an interim position while searching on-the-job for a preferred, but costly to locate, job type.*"

so might further increase their unemployment risk (so that that there is a low-pay-no-pay cycle).

Non-employment may lead to a loss of human capital (Phelps, 1972) or to negative signalling effects (Lockwood, 1991) and therefore enhance the probability of facing unemployment or low-wage employment in the future. In addition, job mobility will be hampered by transaction costs (like costs of job search) reducing the likelihood that workers will take up a new job (Burdett, 1978). The incidence of non-employment may also alter preferences. Individuals who experience an episode of non-employment in presence may ascribe a higher utility to leisure and a lower utility to wages and consumption than in the past. As a consequence, individuals could reduce labor supply and raise reservation wages (Hotz, Kydland and Sedlacek, 1988). As stated for instance by Layard, Nickell and Jackman (1991), signalling effects of low-wage jobs could be even worse than those of unemployment. It is a reasonable assumption that this may also be true for human capital depreciation and costs of job search.[2]

Thus, it appears that labor market history affects current labor market success, a phenomenon referred to as state dependence in the literature. Due to the effect of time-constant unobserved variables on labor market outcomes and by virtue of the fact that the individuals labor market history is often not observed from its beginning, difficulties in measuring state dependence arise from the separation of genuine state dependence from spurious state dependence as well as from the problem of initial conditions. These issues have been addressed in a number of papers (see e. g. Heckman (1981*a*); Heckman (1981*b*); Honoré and Kyriazidou (2000); Wooldridge (2005)).

To our knowledge, genuine state dependence in low-wage work and non-employment has been analyzed jointly before in studies for the UK, Australia and Germany. Cappellari and Jenkins (2008) investigate yearly transitions between low-wage employment, high-wage employment and unemployment in the UK. The study

[2]The existence of human capital depreciation in low-wage employment is consistent with theories of labor market segmentation (Taubman and Wachter, 1986).

finds strong evidence for a low-pay-no-pay cycle. That is, being low-paid instead of being high-paid in period $t-1$ increases the probability to be unemployed in period t and vice versa. Stewart (2007) comes to similar conclusions. His results suggest that a low-paid job has the same negative effect on the probability to be employed in the future as an episode of unemployment. Stewart reasons that low-wage jobs are a conduit to repeat unemployment in the UK.

In a study for Australia, Buddelmeyer, Lee and Wooden (2009) find considerable differences in the effects between men and women. For men they show that the negative effect of a low-paid job on the employment probability is rather small. Low-wage work only leads to a higher unemployment risk when the preceding employment spell is an episode of unemployment. Women having a low-paid job, however, have in general a much larger probability of experiencing unemployment in future than women having a high-paid job.

Uhlendorff (2006) shows for German men that low-wage jobs reduce the probability to get a high-wage job and increase the risk of non-employment in the future but that employment prospects of low-wage earners are still better than the prospects of not employed individuals. He concludes that low-wage jobs are stepping stones to better jobs. Mosthaf, Schank and Schnabel (2009) investigate labor market dynamics of western German women and come to the result that future labor market success is better for low-paid women than for unemployed and inactive women, especially when having full-time jobs.

How does state dependence vary with qualification? Studies estimating the upward mobility of low-wage workers point to a positive impact of qualification on the probability to get high-paid jobs. Schank, Schnabel and Stephani (2009), Mosthaf, Schnabel and Stephani (2011) and Grün, Mahringer and Rhein (2011) show with German administrative datasets which stem from the same sources as our dataset that transitions from low-pay to high-pay are more likely for well qualified individuals. Cappellari (2007) investigates low-pay dynamics of Italian workers and finds a positive but insignificant effect of qualification on upward mobility. Pavlopoulus and Fourarge (2010) use the British BHPS and the German SOEP and come to the result that in Germany qualification has positive effects on the probability to get high-paid while in Great Britain qualification has positive effects only for those with unfavorable unobserved characteristics. Studies which examine transitions from non-employment to employment usually find a positive impact of qualification on the transition probability (Fitzenberger and Wilke, 2010, e. g.). These findings support the hypothesis that state dependence in low-wage employment and non-employment is lower for high qualified individuals because they should have a higher job offer arrival rate and therefore lower costs of job search.

Nevertheless, while upward mobility seems to be larger for high qualified workers, the penalty of entering low-wage employment or non-employment concerning future employment prospects may be stronger for individuals with good qualifications than for low qualified workers. First, human capital depreciation should be higher for well qualified workers as technological change is more important in occupations which are associated with complex tasks. Another argument stems from theories on signalling effects. McCormick (1990) introduced the idea that taking up an interim job is associated with negative signalling effects, as employers may interpret the job search behavior of workers as a signal for their future productivity. In his model high-productive individuals are able to move faster from job to job and it is only profitable for low-productive individuals to take up an interim job and hence taking up such a job incurs negative signals.

We argue that negative signalling effects of low-paid jobs are likely to be stronger for high qualified individuals than for medium and low qualified individuals, as episodes of low-wage employment are uncommon for high qualified individuals and hence employers might assume that high qualified individuals with low-wage jobs represent an adverse selection with respect to unobserved characteristics. Accordingly, state dependence in low-wage employment should be higher for well-educated workers. These arguments could also be true for episodes of non-employment. However, episodes of non-employment are not as rare for high qualified individuals as episodes of low-wage employment.

While there is some evidence that non-employment is associated with negative signalling effects (Gibbons and Katz, 1991; Oberholzer-Gee, 2008; Omori, 1997; Biewen and Steffes, 2010) we are not aware of studies which show the importance of signals for state dependence in low-wage work. This study uses a rich German administrative dataset and applies dynamic multinomial logit models with random effects which control for the problem of initial conditions and include interaction terms of the lagged labor market state. Thereby, we measure heterogeneity in state dependence in low-wage employment and non-employment with respect to qualification. We show that low-wage jobs are associated with negative signals for high qualified workers. Furthermore, we find that low-wage jobs clearly incur weaker scarring effects than non-employment for low qualified workers. For high qualified workers, however, low-wage employment reduces the chances to get a high-paid job in the future as much as non-employment.

The rest of this paper is organized as follows: section 2 introduces the empirical specification while section 3 describes the institutional background and the data. Section 4 shows descriptive statistics. The econometric results are presented in section 5 and section 6 concludes.

2 Empirical specification

We are interested in a model for the propensity of individual i to be in state j (high-wage employment, low-wage employment, non-employment, absorbing state) in time period $t = s, \ldots, T$ (2001-2006). We therefore specify the following conditional density of y_{ijt}:

$$\prod_{t=s}^{T} f(y_{ijt}|\mathbf{y}_{it-1}, \mathbf{q}_i, \mathbf{x}_{it}, \alpha_{ij}) \tag{1}$$

where $i = 1, \ldots, N$; $j = 1, \ldots, 4$. $\mathbf{y}_{it-1}$ is a vector of dummy variables representing the lagged employment state. $\mathbf{q}_i$ indicates the individuals qualification level. $\mathbf{x}_i$ is a vector of observed explanatory variables and α_{ij} are person specific random effects. The exclusion of $\mathbf{q}_i$, $\mathbf{x}_i$ and α_{ij} in this model would lead to the measurement of spurious state dependence. We include them, so that the coefficients belonging to $\mathbf{y}_{it-1}$ measure genuine state dependence.

We consider the absorbing state to account for the possible endogeneity of panel retention. In our sample we cannot identify whether individuals who after leaving employment do not register as unemployed or do not return to employment covered by social security are actually searching for a job, inactive or working as civil servants or as self-employed. Van den Berg, Lindeboom and Ridder (1994) and Van den Berg and Lindeboom (1998) show that ignoring transitions to panel retention may lead to inconsistent estimates if these transitions are driven by the same unobserved characteristics as the transitions of interest.[3]

The estimation of dynamic models with lagged dependent variables goes along with the initial conditions problem (Heckman, 1981*a*). Typically, the first observed employment state of an individual is not random, but determined by the individuals prior labor market history and his observed and unobserved characteristics.

$$f(y_{ijs-1} | \mathbf{y}_{i1} \ldots \mathbf{y}_{is-2}, \mathbf{q}_i, \mathbf{x}_{i1} \ldots \mathbf{x}_{is-1}, \alpha_{ij}) \tag{2}$$

The latter violates the standard assumption of random effects models, namely the assumption that there is no correlation between the random effects ($\boldsymbol{\alpha}_i$) and the observed variables on the right side of the equation ($\mathbf{y}_{it-1}$, $\mathbf{q}_i$, $\mathbf{x}_i$). Wooldridge (2005) proposes to account for the correlation of $\boldsymbol{\alpha}_i$ with $\mathbf{y}_{is-1}$, $\mathbf{q}_i$ and $\mathbf{x}_i$ by explicitly modeling the following distribution:

$$f(\alpha_{ij} | \mathbf{y}_{is-1}, \mathbf{q}_i, \bar{\mathbf{x}}_i, \eta_{ij}) \tag{3}$$

[3]Van den Berg, Lindeboom and Ridder (1994) and Van den Berg and Lindeboom (1998) apply multivariate duration models with random effects but their point also holds for dynamic multinomial logit models.

where $\bar{\mathbf{x}}_i$ are individual specific means of $\mathbf{x}$ over time. η_{ij} are random effects which are orthogonal to other explanatory variables of the model.

Equation 2 shows the dependence of the outcome variable and the individuals pre-sample labor market history. Our administrative dataset allows us to control for the labor market history of all sampled individuals. We therefore specify the density of y_{ijt} conditional on $\mathbf{h}_i$ - a vector of variables representing the individuals prior labor market history.[4] By including $\mathbf{h}_i$ we intent to control more precisely for the impact of the prior labor market history than it would be done by the common Wooldridge-approach. In our model we take into account that workers could have a higher probability to be in the state of low-wage employment or non-employment because of the occurrence of events of low-wage employment or non-employment in the period between 1995 and 2000.[5] In addition, workers who are in one of both sectors in our analyzed period could be an adverse selection with respect to time-invariant variables not observed in the data. In this case $\mathbf{h}_i$ could catch up these unobserved characteristics.[6] An alternative way of including the effect of the labor market history in the period between 1995 and 2000 would be to run our estimations for all the periods between 1995 and 2006. However, our definition of non-employment relies on information about job-search and participation in active labor market programs which is only available since 1999 (see chapter 3 for details of the definitions of non-employment).

In this study we want to measure how state dependence varies with respect to qualification. For this purpose, we include interaction terms of $\mathbf{y}_{it-1}$ and $\mathbf{q}_i$. As suggested by Wooldridge (2005), possible correlation of $\mathbf{y}_{is-1} * \mathbf{q}_i$ is accounted for

[4] $\mathbf{h}_i$ is a vector of variables representing the number of spells of non-employment and low-wage employment in the period between 1995 and 2000 broken down by the duration of these episodes. Additionally, it contains the cumulated duration of episodes of non-employment and episodes of low-wage employment in the period between 1998 and 2000. See Table 2 for an overview of these variables.

[5] For a definition of occurrence dependence see Heckman and Borjas (1980).

[6] Heckman (1981*a*) proposes an alternative estimator to solve the problem of initial conditions. He suggested to include as much information of the prior labor market history as possible.

by an additional term $\mathbf{y}_{is-1} * \mathbf{q}_i$.

$$\prod_{t=s}^{T} f(\mathbf{y}_{ijt}|\mathbf{y}_{it-1}, \mathbf{y}_{it-1} * \mathbf{q}_i, \mathbf{q}_i, \mathbf{x}_{it}, \mathbf{y}_{is-1}, \mathbf{h}_i, \bar{\mathbf{x}}_i, \mathbf{y}_{is-1} * q_i, \eta_{ij}) \tag{4}$$

We assume that the function in 4 has a Type I extreme value distribution and obtain a multinomial logit model with random effects for the probability to be high-wage employed, low-wage employed, not employed or in the absorbing state. High-wage employment serves as reference category. Concerning the random effects we have to make assumptions about their distribution. Therefore, we compare models with the assumption of normal distributed random effects and models assuming a discrete distribution with an a priori unknown number of mass points. For the model of the normal random effects specification we estimate the parameters of the variance-covariance-matrix and integrate the distribution by applying adaptive quadrature.

$$L_i = \int_{-\infty}^{\infty} \prod_{t=s}^{T} \prod_{j=2}^{4} \frac{exp(\mathbf{y}_{ij-1}\gamma_j + \mathbf{y}_{it-1} * \mathbf{q}_i\boldsymbol{\tau}_j + \mathbf{q}_i\boldsymbol{\kappa}_j + \mathbf{x}_{it}\boldsymbol{\beta}_j + \mathbf{y}_{is-1}\boldsymbol{\varphi} + \mathbf{h}_i\boldsymbol{\omega}_j + \bar{\mathbf{x}}_i\varepsilon_j + \mathbf{y}_{is-1} * \mathbf{q}_i\boldsymbol{\xi}_j + \eta_{ij})}{1 + \sum_{k=2}^{4} exp(\mathbf{y}_{ij-1}\gamma_j + \mathbf{y}_{it-1} * \mathbf{q}_i\boldsymbol{\tau}_j + \mathbf{q}_i\boldsymbol{\kappa}_j + \mathbf{x}_{it}\boldsymbol{\beta}_j + \mathbf{y}_{is-1}\boldsymbol{\varphi} + \mathbf{h}_i\boldsymbol{\omega}_j + \bar{\mathbf{x}}_i\varepsilon_j + \mathbf{y}_{is-1} * \mathbf{q}_i\boldsymbol{\xi}_j + \eta_{ij})}^{d_{ijt}} f(\boldsymbol{\eta})d(\boldsymbol{\eta}) \tag{5}$$

, where d_{ijt} is one if individual i is in state j at period t and zero otherwise. For the model with the discrete distribution of the random effects, we begin with estimating a model with one mass point and raise the number of mass points until the Akaike Information Criterion (AIC) does not improve. This model is referred to as nonparametric maximum likelihood estimator (Heckman and Singer, 1984).[7]

$$L_i = \sum_{m=1}^{M} p_m \prod_{t=s}^{T} \prod_{j=2}^{4} \frac{exp(\mathbf{y}_{ij-1}\gamma_j + \mathbf{y}_{it-1} * \mathbf{q}_i\boldsymbol{\tau}_j + \mathbf{q}_i\boldsymbol{\kappa}_j + \mathbf{x}_{it}\boldsymbol{\beta}_j + \mathbf{y}_{is-1}\boldsymbol{\varphi} + \mathbf{h}_i\boldsymbol{\omega}_j + \bar{\mathbf{x}}_i\varepsilon_j + \mathbf{y}_{is-1} * \mathbf{q}_i\boldsymbol{\xi}_j + v_{mj})}{1 + \sum_{k=2}^{4} exp(\mathbf{y}_{ij-1}\gamma_j + \mathbf{y}_{it-1} * \mathbf{q}_i\boldsymbol{\tau}_j + \mathbf{q}_i\boldsymbol{\kappa}_j + \mathbf{x}_{it}\boldsymbol{\beta}_j + \mathbf{y}_{is-1}\boldsymbol{\varphi} + \mathbf{h}_i\boldsymbol{\omega}_j + \bar{\mathbf{x}}_i\varepsilon_j + \mathbf{y}_{is-1} * \mathbf{q}_i\boldsymbol{\xi}_j + v_{mj})}^{d_{ijt}} \tag{6}$$

, p_m is the probability of the mass point $\mathbf{v}_m$. Both are parameters to be estimated.

[7] All models in this paper are estimated using the Stata-ado-file GLLAMM by Rabe-Hesketh and Skrondal (2005).

The main variable of interest in our paper is the interaction term of the lagged employment state with qualification $\mathbf{y}_{it-1} * \mathbf{q}_i$ which measures the heterogeneity in state dependence with respect to qualification. The coefficients in multinomial logit models cannot be interpreted with respect to economic significance. Ai and Norton (2003) point out that the calculation of partial effects of interaction terms in nonlinear models is not as straightforward as in linear models. In our context, the partial effect of $\mathbf{y}_{it-1} * \mathbf{q}_i$ of the multinomial model in equation 5 would be (Greene, 2010):[8]

$$
\begin{aligned}
&\frac{\Delta^2 E[\mathbf{y}_{ijt}|\mathbf{y}_{it-1}, \mathbf{y}_{it-1} * \mathbf{q}_i, \mathbf{q}_i, \mathbf{x}_{it}, \mathbf{y}_{is-1}, \mathbf{h}_i, \bar{\mathbf{x}}_i, \mathbf{y}_{is-1} * \mathbf{q}_i, \eta_{ij}]}{\Delta y_{lt-1}\Delta q_e} = \\
&[f(\gamma_{lj} + \tau_{lej} + \kappa_{ej} + \mathbf{x}_{it}\boldsymbol{\beta}_j + \mathbf{y}_{is-1}\boldsymbol{\varphi} + \mathbf{h}_i\boldsymbol{\omega}_j + \bar{\mathbf{x}}_i\boldsymbol{\varepsilon}_j + \mathbf{y}_{is-1} * \mathbf{q}_i\boldsymbol{\xi}_j + \eta_{ij}) - \\
&f(\kappa_{ej} + \mathbf{x}_{it}\boldsymbol{\beta}_j + \mathbf{y}_{is-1}\boldsymbol{\varphi} + \mathbf{h}_i\boldsymbol{\omega}_j + \bar{\mathbf{x}}_i\boldsymbol{\varepsilon}_j + \mathbf{y}_{is-1} * \mathbf{q}_i\boldsymbol{\xi}_j + \eta_{ij})] - \\
&[f(\gamma_{lj} + \mathbf{x}_{it}\boldsymbol{\beta}_j + \mathbf{y}_{is-1}\boldsymbol{\varphi} + \mathbf{h}_i\boldsymbol{\omega}_j + \bar{\mathbf{x}}_i\boldsymbol{\varepsilon}_j + \mathbf{y}_{is-1} * \mathbf{q}_i\boldsymbol{\xi}_j + \eta_{ij}) - \\
&f(\mathbf{x}_{it}\boldsymbol{\beta}_j + \mathbf{y}_{is-1}\boldsymbol{\varphi} + \mathbf{h}_i\boldsymbol{\omega}_j + \bar{\mathbf{x}}_i\boldsymbol{\varepsilon}_j + \mathbf{y}_{is-1} * \mathbf{q}_i\boldsymbol{\xi}_j + \eta_{ij})]
\end{aligned}
\tag{7}
$$

, with $l = 2, 3$ and $e = 2, 3, 4$. For identification $\boldsymbol{\gamma}_1$, $\boldsymbol{\tau}_{l1}$ and $\boldsymbol{\kappa}_1$ are set to zero.[9]

However, this partial effect is not interesting if one wants to draw conclusions about genuine state dependence. The cross difference in 7 consists of subtrahends with and without the coefficient of qualification κ. As described earlier, κ represents spurious state dependence and hence the partial effect of the interaction term mixes up genuine state dependence and spurious state dependence. To determine genuine state dependence κ should be fix. Here, one can refer to Greene (2010, p. 293) who states that "*one can test the hypothesis that the interaction effect is zero ... It is unclear, however, what this hypothesis means*".

Rather than calculating the partial effect of the interaction term, we calculate transition matrices separated for each group of qualification to draw conclusions

[8]For simplicity we ignore $\mathbf{y}_{is-1}$ and $\mathbf{y}_{is-1} * \mathbf{q}_i$ when derivating the function. Our point, however, also applies when we consider these terms in the derivation.

[9]γ_{1j} is the effect of high-pay, $t-1$ on the probability to be in state j. γ_{2j} the effect of low-pay, $t-1$ and γ_{3j} the effect of non-employment, $t-1$. Individuals who entered the absorbing state ($j = 4$) leave the dataset. κ_{1j} represents the effect of low qualification, κ_{2j} of lower middle qualification, κ_{3j} the effect of middle qualification and κ_{4j} the effect of high qualification.

about heterogeneity in genuine state dependence. Therefore, we calculate individual predictions of y_{ijt} for each individual i at period t conditional on the lagged labor market state and qualification:

$$P_i(y_{ijt} = 1|y_{ilt-1} = 1, q_e = 1) =$$
$$f(\gamma_{lj} + \tau_{lej} + \kappa_{ej} + \mathbf{x}_{it}\boldsymbol{\beta}_j + \mathbf{y}_{is-1}\boldsymbol{\varphi} + \mathbf{h}_i\boldsymbol{\omega}_j + \bar{\mathbf{x}}_i\boldsymbol{\varepsilon}_j + \mathbf{y}_{is-1} * \mathbf{q}_i\boldsymbol{\xi}_j + \eta_{ij}) \quad (8)$$

Other explanatory variables than the lagged labor market state and qualification are fixed at the true sample values. We use empirical Bayes methods to assign values of the random effects to the sampled individuals. Here, information about the prior distribution of $\boldsymbol{\eta}$ and the observed dependent and explanatory variables is used together with the empirical parameters estimated. The posterior distribution is obtained using Bayes theorem.[10] See Skrondal and Rabe-Hesketh (2004, chapter 7) for details of this approach. To calculate the confidence intervals of the predictions, we apply a Stata-ado-file by Skrondal and Rabe-Hesketh. The simulation-based confidence intervals are obtained by 1000 times drawing values from the estimated distribution of the random effects and calculating predictions. After obtaining predictions and confidence intervals for each individual i in period t, average transition probabilities of the sample are calculated. State dependence in low-wage employment with respect to the probability to be high-paid for a high qualified individual averaged over the sample is then:

$$\frac{1}{N}\sum_{n=1}^{N} P_i(y_{i1t} = 1|y_{i2t-1} = 1, q_{i4} = 1) - \frac{1}{N}\sum_{n=1}^{N} P_i(y_{i1t} = 1|y_{i1t-1} = 1, q_{i4} = 1) \quad (9)$$

State dependence is equivalent to the partial effect of $\mathbf{y}_{it-1}$. Due to the nonlinear functional form of multinomial logit models, state dependence varies by individual and moreover varies systematically with predicted probability.[11] Since our paper is focussed on the question whether low-wage jobs can be stepping stones out of non-

[10] $g(\boldsymbol{\eta}|\mathbf{y}, \mathbf{x}; \hat{\boldsymbol{\theta}}) = \frac{P(\mathbf{y},\boldsymbol{\eta}|\mathbf{x};\hat{\boldsymbol{\theta}})}{P(\mathbf{y}|\mathbf{x};\hat{\boldsymbol{\theta}})}$. Here, $\mathbf{y}$ is the vector of dependent and $\mathbf{x}$ the vector of explanatory variables. $\hat{\boldsymbol{\theta}}$ is a vector of parameter estimates.

[11] Ai and Norton (2003) illustrate the variance of partial effects of interaction terms.

employment, we estimate transition matrices for the group of workers who were not employed in period $s-1$.

3 Institutional background and data

The German educational system differs from those of Anglo-Saxon and most European countries. Therefore we briefly give an overview of the German educational system before describing our sample. At the age of ten pupils leave the elementary school and are allocated into three school tracks: *Hauptschule* (basic school), *Realschule* (middle school) and *Gymnasium* (advanced school). While *Hauptschule* and *Realschule* qualify pupils for vocational training, the *Gymnasium* is meant to educate pupils for studies in universities and provides the school leaving certificate which enables absolvents to enter university (*Abitur*). Apart from theory-orientated universities, there are polytechnical universities (technical colleges), which rather prepare students for practice. See Riphahn and Schieferdecker (2010) for further details. Besides universities, Germany has an apprenticeship system where apprentices obtain on-the-job training in establishments and formal education by the state (von Wachter and Bender, 2006). For simplicity, we will use in the following the terminology presented in Table 1.

We use data from the German Integrated Employment Biographies Sample (IEBS). The administrative dataset includes information on employment, unemployment benefits, job search, and participation in active labor market programs on a daily basis. It is available at the Research Data Center of the German Federal Employment Agency (FEA) at the Institute for Employment Research (IAB) (see Jacobebbinghaus and Seth (2007)).

We restrict our analysis to western Germany, as labor market conditions still vary considerably between western and eastern Germany. Similarly, we exclude women from our analysis. In our dataset, we cannot observe the search intensity of not employed individuals. As women are much more often inactive on the labor market than men, one should apply different definitions of non-employment for both sexes.

For our study, we build a panel dataset with yearly observations at the reference day June 30 for the period between 2000 and 2006. We analyze yearly transitions between three mutually exclusive states: high-wage employment, low-wage employment and non-employment. An individual is in the state of non-employment, if he is not employed in a job liable to social security and (a) is registered as unemployed, (b) participates in a program of active labor market policy or (c) if he is in a period between two employment periods and is registered as unemployed or participating in a program of active labor market policy for at least one day in this period. Since information on employment stems from notifications to social security bodies, we cannot rule out that individuals defined as not employed are working as as civil servants or are self-employed. Earlier studies did not have access to information on job search and participation in labor market programs and used information on unemployment benefit receipt for the definition of non-employment. For the analysis of employment dynamics of low-wage workers our definition is more appropiate since only individuals who have been employed for at least twelve months qualify for the receipt of unemployment benefits. If we used unemployment benefit receipt for the definition of non-employment instead of job search, we would loose those low-wage workers with unstable working careers who are of special interest in our analyis.

We follow a large part of the literature on low-wage employment and define an individual as low-paid if he earns less than two thirds of the median gross wage of all full-time employed individuals in western Germany liable to social security.

Although part-time jobs could be an important alternative for individuals searching for an interim job we only consider full-time jobs here. First, working hours are only crudely measured in our dataset and it would be impossible to assess if part-time workers are low-paid or high-paid. Second, including part-time work would force us to define more employment states which would require a huge computational effort.

The econometric models applied in this study are computationally very intensive.

Therefore we run our estimations on a random sample of 15 000 individuals of the IEBS who are full-time employed or in the non-employment state in the year 2000. We define an absorbing state for individuals leaving the panel. Individuals enter the absorbing state, when they are working part-time at the reference day, when they cannot be classified as low-paid, high-paid or not employed or when there is a missing value in one of the variables needed in the econometric analysis.[12] Afterwards, they are not considered anymore.

When there is a gap between two episodes of employment at the same establishment that is equal or shorter than 32 days, we combine both job spells. Job spells shorter than two weeks are not considered in our analysis. This is because we want to avoid to include single payments. In our econometric analysis we will use information of the prior labor market history between 1995 until 2000. For this period, information about job search and participation in active labor market programs is not available. Therefore, episodes of non-employment simply are defined as gaps between two spells of part-time or full-time employment liable to social security. We suppose that individuals who had no full-time job between 1995 and 2000 have been out of the labor force and do not consider them in our analysis. In order to omit transitions from education to work and from work to retirement, we focus on individuals older than 30 in 2000 and younger than 59 in 2006. Moreover, we exclude individuals, who during the observation period work as trainees, interns, working students, are in partial retirement, live outside western Germany and individuals who are handicapped.

4 Descriptive statistics

Table 2 shows some descriptive statistics of our pooled sample broken down by labor market state. 85 percent of the observations in the pooled sample are high-paid, 4 percent are low-paid and 9 percent are in the state of non-employment. 2 percent

[12]Missing values are rare in our administrative dataset. One exception is the variable on education. For this variable, we applied the IPI imputation rule by Fitzenberger, Osikominu and Völter (2006).

enter the absorbing state in one of the years between 2001 and 2005 and fall out of the panel.

There is a very low share of individuals with low qualification in the high-wage sector, whereas their share under the low-paid is high. In contrast, the share of individuals with high qualification is extremely small under the low-paid. Moreover, they have a relatively low probability to be not employed. We do not observe that the probability to enter the absorbing state follows a strong systematic pattern with respect to qualification. Germans are less often low-paid or not employed than foreigners and the mean local unemployment rate is lower for high-paid individuals than for the low-paid or not employed.

We now turn to the variables describing the prior labor market history of the individuals in our sample. Sample means of these variables indicate that individuals who have experienced episodes of low-wage employment or non-employment in the past are more likely to be in one of these employment states in the observation period. For instance, the mean cumulated duration of episodes of non-employment between 1998 and 2000 is highest among the non-working individuals (228 days) and lowest among the high-paid individuals. Similarly, the mean cumulated duration of episodes of low-wage employment is highest among the low-paid and smallest among the high-paid. What is more, individuals who enter the absorbing-state on average have a higher number of episodes of non-employment and episodes of low-wage employment between 1995 and 2000.

The interrelation between past labor market experience and current labor market outcomes is also highlighted in Table 3. Only 13.77 percent of the individuals who were low-paid in period $t-1$ in our sample achieved to get a high-paid job in the following period. 64.19 percent of them remained low-paid. 16.81 percent lost their job, while 5.23 entered the absorbing-state. In contrast, most individuals who where high-paid in $t-1$ also were high-paid in t (95.46 percent). Only a minor part changed to low-wage employment, non-employment or to the absorbing-state. Like low-wage workers, individuals who were not working in period $t-1$ were more likely to be not employed or low-paid than previously high-paid individuals. This pattern is in line with results by Uhlendorff (2006) with data of the GSOEP. The probability of entering the absorbing state is largest for low-paid individuals and smallest for the high-paid.

Note that aggregate transition probabilities vary by qualification. Transition rates to high-wage employment typically are larger for individuals with better qualifications, although the difference between preciously low-paid individuals with lower middle qualification, middle qualification and high qualification is only marginal. 15.57 percent of the low-paid individuals with university or technical college degree obtained a high-paid job in the following period, while only 9.05 percent of the low-wage workers with low qualification moved up the job ladder. The variation of upward mobility from non-employment to high-wage employment varies more dramatically. 23.50 percent of the best qualified workers reach the high-wage sector and only 4.94 percent of the individuals with the lowest qualification get a high-paid job in the next year.

With respect to the average values of our descriptive transition matrix, low-paid workers seem to be better off than those without a job. While the average transition rate to high-wage employment is around 14 percent for both employment states, the transition rate to non-employment is clearly lower for low-wage workers (16.81 percent) than for the non-employed (74.59 percent). Breaking down the transition rates by qualification we get a more differentiated picture. For low-wage workers with low qualification, the transition rate to better jobs is higher, when being low-paid instead of not being employed and hence, low-wage jobs seem to be stepping stones out of non-employment. For the best qualified, however, the transition rate from non-employment to high-wage employment is higher than the transition rate from low-pay to high-pay. This suggests that for individuals with university or technical college degree, low-wage jobs are rather dead-ends regarding future wage prospects.

The statistics presented in this chapter are descriptive and do not allow us to draw conclusions about genuine state dependence in low-pay-no-pay dynamics.

Therefor, we apply the econometric model presented in chapter 2.

5 Econometric results

We first consider the distribution of unobserved heterogeneity. Table 4 shows the estimated coefficients of a dynamic multinomial logit model which models dynamics between three employment states: high-pay, low-pay and non-employment.[13] Concerning the dependent variables, high-pay serves as reference category. The random effects are assumed to follow a bivariate discrete distribution with five mass points. The Akaike information criterion (AIC) has a value of 34211.5. We also tried to estimate a model with six mass points. The estimation was stopped at iteration 23. Until then the AIC did not improve considerably. Table 5 shows the model estimated with the assumption of normally distributed random effects. The AIC is lower (34184.5) which points to the better fit of the normal random effects specification. In the further analysis we will rely on the assumption of normally distributed unobserved heterogeneity.

We now turn to the estimated coefficients of the variance-covariance matrix of the model presented in Table 5. The variances (η_2 and η_3) of the variance-covariance matrix are clearly significant at the one percent level as well as the covariance η_{23}. Accordingly, it was indeed important to control for unobserved heterogeneity and to estimate the probability of being high-paid, low-paid or not employed jointly.

The coefficients of the labor market states in period $s-1$ (year 2000) are highly significant with respect to the probabilities to be low-paid or not employed, respectively, versus the probability of having a high-paid job. This indicates that initial conditions are endogenous and controlling for the initial conditions problem is indispensable. The labor market experience before the year 2000 is highly correlated with the propensity of being in one of the three labor market states in the years

[13] We also estimated a model which estimates transitions accounting for all four labor market states described in section 4 including the absorbing state. The impact of unobserved heterogeneity on the probability to leave the panel is very low and the coefficients for the probabilities to be low-paid or non-employed are similar to the ones of the model accounting only for three employment states. In the following, we will present models which ignore panel retention.

between 2001 and 2006. The higher the number of episodes of non-employment between 1995 and 2000 and the cumulated durations of non-employment and low-wage employment between 1998 and 2000, the higher is the propensity to be low-paid or not employed in the period between 2001 and 2006. Yet, our model does not allow us to conclude if these correlations stem from true occurrence or duration dependence or if these variables rather serve as proxies for unobserved heterogeneity (Heckman and Borjas, 1980).

The coefficients representing the qualification of the individuals in our sample indicate that better qualification leads to a lower probability of being low-paid or not employed in comparison with the probability of being high-paid. This is in line with the results of studies estimating the upward mobility of low-wage earners.[14] One has to note, however, that these coefficients are likely to be correlated with unobserved heterogeneity and hence cannot be interpreted as causal effects.[15] We do not detect large statistical effects of age with our model. Only the coefficients of the dummy variables Age: 35-39 and Age: 55-59 are statistically different from the reference category Age: 31-34. Though, there is a high multicolinearity with the individual specific means over time of the age variables. While Turkish nationality does not seem to be associated with a higher probability of being low-paid or not-employed, individuals with nationalities other than German or Turkish are both more often low-paid or not-employed in our sample. Furthermore, the higher the local unemployment rate, the higher is the probability of not being employed in comparison with the probability of being high-paid.

We now turn to the coefficients representing genuine state dependence. The coefficient of low-pay in $t-1$ is statistically different from the reference category high-pay in $t-1$ on the probability of being low-paid at the one percent level. That is, individuals who experienced an episode of low-wage employment in the prior period

[14] e. g. Schank, Schnabel and Stephani (2009), Mosthaf, Schnabel and Stephani (2011), Grün, Mahringer and Rhein (2011), Pavlopoulus and Fourarge (2010).

[15] The Wooldridge-method is only able to measure causal effects of time-varying variables. This is a minor problem as the time-invariant variables representing qualification are not central in our analysis.

have a higher probability of being low-paid again rather than getting a high-paid job. The same applies to individuals who were not employed in $t-1$. Regarding the probability of not being employed in comparison with the probability of being high-paid in period t, the coefficients indicate that both, the occurrence of low-wage employment and of non-employment in the foregoing period enhance the probability of not being employed.

Table 6 presents the results of the central model in our paper where we interacted the lagged endogenous variables with the variables concerning qualification. The coefficients of the control variables as well as the coefficients representing the labor market states in period $s-1$ and the prior labor market history largely remained unchanged. As a matter of course, the variables concerning state dependence and qualification changed. Again, high-wage employment in period t is the reference category of the dependent variables. High-wage in period $t-1$ serves as the reference category for the variables low-pay, $t-1$ and non-employment, $t-1$. These variables in turn serve as reference category for the corresponding interactions with qualification and hence have to be interpreted with respect to individuals with low qualification.

That is, the dummy low-pay, t-1 on the probability of being low-paid indicates that the worst-educated who experienced an episode of low-pay in the preceding period have a higher probability of being low-paid again rather than being high-paid in period t. For formerly low-paid individuals with lower middle qualification, the probability of being low-paid is lower than for those with low qualification. The coefficient of the interaction of the lagged labor market state with middle qualification is not statistically different from zero at the 10 percent level. However, individuals who experienced an episode of low-pay in $t-1$ and who have a high qualification have a higher probability of being repeatedly low-paid than those with low qualification.

Non-employment in $t-1$ also leads to a higher probability of low-pay in period t in comparison with the probability of high-pay in period t. This effect, however, declines with better qualification. All interaction terms of non-employment, $t-1$

are negative in sign, although the coefficient of non-employment$*$high qualification is not statistically different from zero.

With respect to the probability of non-employment in t the coefficients of the lagged endogenous variables without interactions point to the same direction as those of the model without interactions. Although not statistically different from zero in every case, the results indicate that better qualified individuals have a higher probability of being high-paid instead of not being employed. This pattern is most pronounced regarding the transitions out of non-employment.

To sum up, both the experience of low-wage employment and non-employment in the past enhances the probability of being low-paid or not-paid in presence. While state dependence in non-employment diminishes with better qualification the same is only true for low-wage employment regarding the probability of not being employed in comparison with the probability of being high-paid. Regarding the probability of being low-paid rather than high-paid, workers with lower middle qualification and (although the effect is not statistically different from zero) workers with middle qualification have a lower probability of being low-paid again than those with low qualification. Formerly low-paid workers with high qualification face higher state dependence than those with low qualification and especially than those with lower middle qualification. In section 1, we discussed the different sources of state dependence in low-wage employment. In the following we will argue that the described pattern points to the importance of negative signalling effects for low-wage workers with technical college or university degree.

Human capital accumulation cannot explain our results as human capital accumulation is very likely to be lower when not being employed than when being low-paid. Similarly, there is no explanation why transaction costs like costs of job search should be higher for individuals with university degree than for individuals with worse qualification. Last but not least we do not believe that changes in preferences like habit formation concerning preferences between consumption and leisure should be higher when being low-paid instead of not being employed.

As coefficients of multinomial logit models are difficult to interpret with respect to the size of the effect, we calculated average transition probabilities using the parameters of model three. The Tables 7 to ten show average transition probabilities for those individuals who were not employed in the year 2000 broken down by qualification. Transition matrices calculated for other subgroups in our sample are presented in the Appendix. The conclusion by Uhlendorff (2006) for western German men that low-wage employment goes along with a higher probability of changing to high-wage employment and a lower probability of getting not employed than non-employment is clearly confirmed for those with the worst qualification in our sample (Table 7). The probability of being high-paid is 0.137 for those who were low-paid in $t-1$. This estimate is not in the 5 percent confidence interval of the probability of being high-paid for those who were not employed in $t-1$ (0.037 and 0.092 respectively). The risk of not being employed in t is also lower when being low-paid. The point estimates of the probability of not being employed in t are 0.537 for those who were low-paid and 0.851 for those not employed in $t-1$. The confidence intervals do not overlap.

The same pattern applies for those who have a lower middle qualification level. However, looking at the probabilities of those with middle qualification the picture becomes unclear. The point estimates of the probability of being high-paid for those who were low-paid in $t-1$ lies in the confidence interval of the probability for those who were not employed in the preceding period. Yet, their risk of not being employed is still lower.

We now turn to the transition probabilities of individuals with high qualification. Those with the best qualification have the highest probability of being high-paid and the lowest probability of not being employed. However, with respect to the probability of being high-paid, the probability for those who were low-paid is almost the same in comparison with those who were not paid in $t-1$. State dependence in low-wage work regarding the probability of being high-paid is 34.7 percent points (0.637-0.290) while state dependence for those with low qualification is 31.5 and state dependence for those with lower middle qualification is 23.6. Again, concerning the risk of non-employment low-wage workers are still better off than those not employed.

In sum, our results suggest that low-wage work incurs negative signals for workers with technical college or university degree. While those with low qualification have better labor market prospects when being low-paid instead of not being employed, for individuals with high qualification, this is only true when one considers the risk of non-employment. Regarding the chances to get a high-paid job, low-wage jobs go along with the same transition probabilities as non-employment.

6 Conclusions

In this paper, we examined transitions between high-wage employment, low-wage employment and non-employment using dynamic multinomial logit models which control for unobserved heterogeneity and the problem of initial conditions. Using a rich German administrative dataset, we focussed on the heterogeneity in state dependence in both low-wage employment and non-employment with respect to qualification by including interaction terms of the lagged labor market states.

We showed that results of earlier studies that low-wage jobs serve as stepping stones to better-paid jobs still hold for individuals without vocational training and for individuals with apprenticeship and without *Abitur*. However, for individuals with technical college or university degree state dependence in low-wage employment with respect to the probability of getting a high-paid job has about the same size like state dependence in non-employment. Looking at the risk of non-employment low-wage workers are better off than those not employed regardless of the qualification level.

State dependence in low-wage employment regarding the transition to high-wage employment is strongest for those with the highest qualification level. We conclude that low-wage jobs indeed go along with negative signals for high qualified workers. This result is important for labor market policy. If low human capital accumulation was the most important source of state dependence in low-wage work, high qualified low-wage workers could prevent scarring effects by participating in further training measures. This, however, would not lead to lower state dependence if signalling effects were the main origin of state dependence. In this case, policy makers could weaken employment protection in order to reduce the employers costs of screening workers. Further research should investigate the distinct sources of state dependence and determine their impacts on transition probabilities.

References

Ai, C. and Norton, E. (2003), ‘Interaction terms in logit and probit models’, *Economics Letters* **80**, 123–129.

Biewen, M. and Steffes, S. (2010), ‘Unemployment persistence: Is there evidence for stigma effects?’, *Econmics Letters* **106**(3), 188–190.

Buddelmeyer, H., Lee, W.-S. and Wooden, M. (2009), Low-Paid Employment and Unemployment Dynamics in Australia, Melbourne Institute Working Paper Series, Working Paper No. 06/09, University of Melbourne, Melbourne.

Burdett, K. (1978), ‘A theory of employee job search and quit rates’, *The American Economic Review* **68**(1), 212–220.

Burdett, K. (1979), ‘Unemployment insurance payments as a search subsidy: A theoritical analysis’, *Economic Inquiry* **17**(3), 333–343.

Caliendo, M. (2009), Income support systems, labor market policies and labor supply: The German experience, IZA Discussion Paper No. 4665, Institute for the Study of Labor, Bonn.

Cappellari, L. (2007), ‘Earnings mobility among Italian low-paid workers’, *Journal of Population Economics* **20**(3), 465–482.

Cappellari, L. and Jenkins, P. (2008), Transistions between unemployment and low pay, *in* ‘Research in Labor Economics’, Solomon W. Polachek and Konstantinos Tatsiramos, pp. 57–79.

Fitzenberger, B., Osikominu, A. and Völter, R. (2006), ‘Imputation rules to improve the education variable in the iab employment subsample.’, *Journal of Applied Social Science Studies* **126**(3), 405–436.

Fitzenberger, B. and Wilke, R. (2010), ‘New insights into unemployment duration and post unemployment earnings in Germany’, *Oxford Bulletin of Economics and Statistics* **72**(6), 794–826.

Gibbons, R. and Katz, L. F. (1991), 'Layoffs and lemons', *Journal of Labor Economics* **9**(4), 351–380.

Greene, W. (2010), 'Testing hypothesis about interaction terms in nonlinear models', *Economics Letters* **107**, 291–296.

Grün, C., Mahringer, H. and Rhein, T. (2011), Low-wage jobs: A means for employment integration for the unemployed?, IAB Discussion Paper No. 1/2011, Institute for Employment Research, Nuremberg.

Heckman, J. J. (1981*a*), The incidental parameters problem and the problem of initial conditions in estimating a discrete time-discrete data stochastic process, *in* C. F. Manski and D. McFadden, eds, 'Structural analysis of discrete data with econometric applictions', The MIT Press, Cambridge, pp. 179–195.

Heckman, J. J. (1981*b*), Statistical models for discrete panel data, *in* C. F. Manski and D. McFadden, eds, 'Structural analysis of discrete data with econometric applications', The MIT Press, Cambridge, pp. 114–178.

Heckman, J. J. and Borjas, G. J. (1980), 'Does unemployment cause future employment? Definitions, questions and answers from a continuous time model of heterogeneity and state dependence', *Economica* **47**, 247–283.

Heckman, J. J. and Singer, B. (1984), 'A method for minimizing the impact of distributional assumptions in econometric models for duration data', *Econometrica* **52**(2), 271–320.

Honoré, B. E. and Kyriazidou, E. (2000), 'Panel data discrete choice models with lagged dependent variables', *Econometrica* **68**(4), 839–874.

Hotz, V. J., Kydland, F. E. and Sedlacek, G. L. (1988), 'Intertemporal preferences and labor supply', *Econometrica* **56**(2), 335–360.

Jacobebbinghaus, P. and Seth, S. (2007), 'The german integrated employment biographies sample', *Journal of Applied Social Sciences Studies* **127**(2), 335–342.

Layard, R., Nickell, S. and Jackman, R. (1991), *Unemployment. Macroeconomic performance and the labour market*, Oxford University Press, Oxford.

Ljungqvist, L. and Sargent, T. J. (1998), 'The European unemployment dilemma', *The Journal of Political Economy* **106**, 514–550.

Lockwood, B. (1991), 'Information externalities in the labour market and the duration of unemployment', *Review of Economic Studies* **58**, 733–753.

Marimon, R. and Zilibotti, F. (1999), 'Unemployment vs. mismatch of talents: reconsidering unemployment benefits', *The Economic Journal* **109**(455), 266–291.

McCormick, B. (1990), 'A theory of signalling during job search, employment efficiency and "stigmatised" jobs', *Review of Economic Studies* **57**(2), 299–313.

Mosthaf, A., Schank, T. and Schnabel, C. (2009), Low-wage employment versus unemployment: Which one provides better prospects for women?, Discussion Paper No. 65, Friedrich-Alexander-University Erlangen-Nuremberg, Chair of Labour and Regional Economics, Nuremberg.

Mosthaf, A., Schnabel, C. and Stephani, J. (2011), 'Low-wage Careers: Are there dead-end firms and dead-end jobs?', *Zeitschrift für Arbeitsmarktforschung* **43**(3), 231–249.

Oberholzer-Gee, F. (2008), 'Nonemployment stigma as rational herding: A field experiment', *Journal of Economic Behavior & Organisation* **65**(30-40).

Omori, Y. (1997), 'Stigma effects of nonemployment', *Economic Inquiry* **35**, 394–416.

Pavlopoulus, D. and Fourarge, D. (2010), 'Escaping low pay: do male labour market entrants stand a chance?', *International Journal of Human Manpower* **31**(8), 908–927.

Phelps, E. S. (1972), *Inflation policy and unemployment theory. The cost-benefit approach to monetary planning*, MacMillan, London (u. a.).

Rabe-Hesketh, S. and Skrondal, A. (2005), *Multilevel and longitudinal modeling using Stata*, 1 edn, Stata Press, College Station, Texas.

Riphahn, R. T. and Schieferdecker, F. (2010), The transition to tertiary education and parental background over time, forthcoming in Journal of Population Economics, University of Erlangen-Nuremberg, Nuremberg.

Schank, T., Schnabel, C. and Stephani, J. (2009), 'Geringverdiener. Wem und wie gelingt der Aufstieg?', *Jahrbücher für Nationalökonomie und Statistik* **229**(5), 584–614.

Skrondal, A. and Rabe-Hesketh, S. (2004), *Generalized Latent Variable Modeling*, Chapman & Hall/CRC, Boca Raton.

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

Taubman, P. and Wachter, M. L. (1986), Segmented labor markets, *in* O. C. Ashenfelter and R. Layard, eds, 'Handbook of Labor Economics', Vol. 2, Elsevier, Amsterdam, chapter 21, pp. 1183–1217.

Uhlendorff, A. (2006), From no pay to low pay and back again? A multi-state model of low pay dynamics, IZA Discussion Paper No. 2482, Institute for the Study of Labor, Bonn.

Van den Berg, G. J. and Lindeboom, M. (1998), 'Attrition in panel survey data and the estimation of multi-state labor market models', *The Journal of Human Resources* **33**(2), 458–478.

Van den Berg, G. J., Lindeboom, M. and Ridder, G. (1994), 'Attrition in longitudinal panel data and the empirical analysis of dynamic labour market behaviour', *Journal of Applied Econometrics* **9**(4), 421–435.

von Wachter, T. and Bender, S. (2006), 'In the right place at the wrong time: The role of firms and luck in young workers careers', *American Economic Review* **96**(5), 1679–1705.

Wooldridge, J. M. (2005), 'Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogenity', *Journal of Applied Econometrics* **20**(1), 39–54.

Table 1: Terminology

no vocational training	low qualification
vocational training, no *Abitur*	lower middle qualification
vocational training, *Abitur*	middle qualification
technical college or university degree	high qualification

Table 2: Variable means by labor market state

	High-pay	Low-pay	Non-employment	Absorbing-state
Low qualification (dummy)	0.09	0.18	0.15	0.12
Lower middle qualification (dummy)	0.68	0.74	0.71	0.66
Middle qualification (dummy)	0.06	0.05	0.06	0.07
High qualification (dummy)	0.17	0.04	0.08	0.16
Age: 30-34 (dummy)	0.08	0.10	0.09	0.10
Age: 35-39 (dummy)	0.25	0.28	0.25	0.27
Age: 40-44 (dummy)	0.26	0.23	0.23	0.25
Age: 45-49 (dummy)	0.21	0.19	0.21	0.20
Age: 50-54 (dummy)	0.15	0.15	0.15	0.14
Age: 55-59 (dummy)	0.05	0.06	0.07	0.04
Nationality: German (dummy)	0.93	0.81	0.84	0.87
Nationality: Turkish (dummy)	0.02	0.05	0.06	0.04
Nationality: other (dummy)	0.04	0.13	0.10	0.10
Local unemployment rate	8.23	8.94	9.24	7.90
Number of low-pay episodes with tenure > 0 / <= 180 days	0.07	0.61	0.53	0.29
Number of low-pay episodes with tenure > 180 / <= 365 days	0.03	0.31	0.19	0.11
Number of low-pay episodes with tenure > 365 / <= 545 days	0.01	0.11	0.06	0.04
Number of low-pay episodes with tenure > 545 / <= 730 days	0.01	0.10	0.03	0.03
Number of low-pay episodes with tenure > 730	0.02	0.31	0.06	0.06
Number of non-employment episodes with duration > 0 / <= 180 days	0.34	0.94	0.87	0.56
Number of non-employment episodes with duration > 180 / <= 365 days	0.09	0.29	0.30	0.17
Number of non-employment episodes with duration > 365 / <= 545 days	0.02	0.13	0.13	0.05
Number of non-employment episodes with duration > 545 / <= 730 days	0.01	0.07	0.10	0.04
Number of non-employment episodes with duration > 730	0.03	0.11	0.19	0.08
Cumulated duration of low-wage employment between 1998 and 2000	18.58	304.48	82.98	71.20
Cumulated duration of non-employment between 1998 and 2000	34.44	161.56	228.05	101.95
Share of observations	0.85	0.04	0.09	0.02
Number of observations	71962.00	3367.00	7862.00	1666.00
Number of individuals	15140.00	2926.00	4539.00	1666.00

Source: IEBS (1995-2006); pooled unbalanced sample; 15 000 individuals

Table 3: Descriptive transition matrix by qualification

	High-pay	Low-pay	Non-employment	Absorbing-state	Total
High-pay, t-1	95.46	0.67	2.24	1.63	100
Low-pay, t-1 * low qualification	9.05	68.49	17.32	5.15	100
Low-pay, t-1 * lower middle qualification	14.77	63.58	16.87	4.78	100
Low-pay, t-1 * middle qualification	14.86	59.43	16.57	9.14	100
Low-pay, t-1 * high qualification	15.75	61.42	13.39	9.45	100
Low-pay, t-1 (dummy)	13.77	64.19	16.81	5.23	100
Non-employment * low qualification	4.94	8.11	83.69	3.26	100
Non-employment, t-1 * lower middle qualification	13.66	8.82	74.15	3.36	100
Non-employment, t-1 * middle qualification	18.39	6.13	69.98	5.50	100
Non-employment, t-1 * high qualification	23.50	3.79	66.40	6.31	100
Non-employment, t-1 (dummy)	13.55	8.13	74.59	3.73	100

Source: IEBS (1995-2006); pooled unbalanced sample; 15 000 individuals; Transitions between periods t - 1 and t; figures indicate row percentages

Table 4: Model 1: Multinomial logit model with random effects (discrete distribution, five mass points), model without absorbing-state, no interactions

	Low-pay b/se	Non-employment b/se
High-pay, t-1 (reference group)	-	-
	-	-
Low-pay, t-1 (dummy)	3.251***	1.736***
	(0.114)	(0.108)
Non-employment, t-1 (dummy)	2.530***	3.073***
	(0.102)	(0.075)
Low qualification (reference group)	-	-
	-	-
Lower middle qualification (dummy)	-0.376***	-0.259**
	(0.127)	(0.101)
Middle qualification (dummy)	-0.723***	-0.298*
	(0.214)	(0.153)
High qualification (dummy)	-1.699***	-0.750***
	(0.202)	(0.128)
Age: 31-34 (reference group)	-	-
	-	-
Age: 35-39 (dummy)	0.085	-0.234**
	(0.153)	(0.114)
Age: 40-44 (dummy)	0.086	-0.259
	(0.240)	(0.177)
Age: 45-49 (dummy)	0.293	-0.125
	(0.328)	(0.240)
Age: 50-54 (dummy)	0.482	0.174
	(0.419)	(0.303)
Age: 55-59 (dummy)	0.921*	0.746**
	(0.519)	(0.372)
Nationality: German (reference group)	-	-
	-	-
Nationality: Turkish (dummy)	0.231	0.289*
	(0.207)	(0.166)

Nationality: other (dummy)	0.403***	0.399***
	(0.144)	(0.122)
Local unemployment rate	-0.006	0.062**
	(0.034)	(0.025)
Individual average of age: 35-39	-0.553	-0.129
	(0.351)	(0.274)
Individual average of age: 40-44	-0.550*	-0.131
	(0.323)	(0.246)
Individual average of age: 45-49	-0.633	0.067
	(0.432)	(0.325)
Individual average of age: 50-54	-0.878*	-0.246
	(0.509)	(0.375)
Individual average of age: 55-59	-0.977	-0.487
	(0.681)	(0.494)
Individual average of local unemployment rate	0.044	-0.003
	(0.036)	(0.027)
High-pay, t=$s-1$ (reference group)	-	-
	-	-
Low-pay, t=$s-1$ (dummy)	3.738***	2.923***
	(0.217)	(0.210)
Non-employment, t=$s-1$ (dummy)	2.863***	3.944***
	(0.228)	(0.182)
Number of low-pay episodes with tenure > 0 / <= 180 days	-0.006	0.117**
	(0.062)	(0.055)
Number of low-pay episodes with tenure > 180 / <= 365 days	-0.027	-0.060
	(0.097)	(0.097)
Number of low-pay episodes with tenure > 365 / <= 545 days	0.045	-0.076
	(0.188)	(0.177)
Number of low-pay episodes with tenure > 545 / <= 730 days	0.039	-0.377
	(0.235)	(0.238)
Number of low-pay episodes with tenure > 730	0.710***	0.183
	(0.239)	(0.239)
Number of non-employment episodes with duration > 0 / <= 180 days	0.323***	0.349***
	(0.040)	(0.032)
Number of non-employment episodes with duration > 180 / <= 365 days	0.412***	0.306***

	(0.094)	(0.078)
Number of non-employment episodes with duration > 365 / <= 545 days	0.859***	0.821***
	(0.152)	(0.131)
Number of non-employment episodes with duration > 545 / <= 730 days	1.026***	0.990***
	(0.202)	(0.169)
Number of non-employment episodes with duration > 730	1.012***	1.296***
	(0.207)	(0.173)
Cumulated duration of low-wage employment between 1998 and 2000	0.003***	0.001***
	(0.000)	(0.000)
Cumulated duration of non-employment between 1998 and 2000	0.001***	0.001**
	(0.000)	(0.000)
Constant	-6.875***	-5.893***
	(0.304)	(0.236)
Observations	249573	
AIC	34211.5	
Log Likelihood	-1.7e+04	

Source: IEBS (1995-2006); 15 000 individuals; year dummies included
Parameters of unobserved heterogeneity are highly significant
Coefficients; Standard errors in parantheses
levels of significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 5: Model 2: Multinomial logit model with random effects (normal distribution), model without absorbing-state, no interactions

	Low-pay b/se	Non-employment b/se
High-pay, t-1 (reference group)	-	-
	-	-
Low-pay, t-1 (dummy)	3.217***	1.706***
	(0.115)	(0.109)
Non-employment, t-1 (dummy)	2.509***	2.966***
	(0.107)	(0.076)
Low qualification (reference group)	-	-
	-	-
Lower middle qualification (dummy)	-0.335**	-0.343***
	(0.140)	(0.116)
Middle qualification (dummy)	-0.617***	-0.326*
	(0.221)	(0.172)
High qualification (dummy)	-1.748***	-0.964***
	(0.210)	(0.150)
Age: 31-34 (reference group)	-	-
	-	-
Age: 35-39 (dummy)	0.062	-0.265**
	(0.154)	(0.116)
Age: 40-44 (dummy)	0.068	-0.292
	(0.243)	(0.180)
Age: 45-49 (dummy)	0.290	-0.148
	(0.331)	(0.243)
Age: 50-54 (dummy)	0.455	0.174
	(0.424)	(0.308)
Age: 55-59 (dummy)	0.906*	0.765**
	(0.524)	(0.377)
Nationality: German (reference group)	-	-
	-	-
Nationality: Turkish (dummy)	0.204	0.278
	(0.229)	(0.193)
Nationality: other (dummy)	0.535***	0.420***

	(0.158)	(0.135)
Local unemployment rate	-0.009	0.065**
	(0.034)	(0.026)
Individual average of age: 35-39	-0.614*	-0.159
	(0.364)	(0.296)
Individual average of age: 40-44	-0.575*	-0.074
	(0.332)	(0.258)
Individual average of age: 45-49	-0.696	0.074
	(0.443)	(0.341)
Individual average of age: 50-54	-0.811	-0.214
	(0.521)	(0.391)
Individual average of age: 55-59	-1.006	-0.529
	(0.704)	(0.519)
Individual average of local unemployment rate	0.048	0.001
	(0.037)	(0.028)
High-pay, t=$s-1$ (reference group)	-	-
	-	-
Low-pay, t=$s-1$ (dummy)	3.810***	3.164***
	(0.213)	(0.195)
Non-employment, t=$s-1$ (dummy)	2.960***	4.111***
	(0.201)	(0.180)
Number of low-pay episodes with tenure > 0 / <= 180 days	0.130*	0.265***
	(0.070)	(0.062)
Number of low-pay episodes with tenure > 180 / <= 365 days	0.021	-0.025
	(0.114)	(0.110)
Number of low-pay episodes with tenure > 365 / <= 545 days	0.143	0.238
	(0.222)	(0.203)
Number of low-pay episodes with tenure > 545 / <= 730 days	0.127	-0.361
	(0.278)	(0.266)
Number of low-pay episodes with tenure > 730	0.810***	0.100
	(0.245)	(0.237)
Number of non-employment episodes with duration > 0 / <= 180 days	0.363***	0.377***
	(0.042)	(0.033)
Number of non-employment episodes with duration > 180 / <= 365 days	0.409***	0.344***
	(0.106)	(0.091)

Number of non-employment episodes with duration > 365 / <= 545 days	0.893***	0.913***
	(0.160)	(0.141)
Number of non-employment episodes with duration > 545 / <= 730 days	0.872***	0.962***
	(0.214)	(0.185)
Number of non-employment episodes with duration > 730	1.053***	1.451***
	(0.219)	(0.182)
Cumulated duration of low-wage employment between 1998 and 2000	0.003***	0.001**
	(0.000)	(0.000)
Cumulated duration of non-employment between 1998 and 2000	0.001**	-0.000
	(0.000)	(0.000)
Constant	-6.968***	-5.945***
	(0.313)	(0.251)
Variance η_2	4.692***	
	(0.305)	
Variance η_3	4.715***	
	(0.279)	
Covariance η_{23}	3.584***	
	(0.256)	
Correlation η_{23}	0.762	
Observations	249573	
AIC	34184.5	.
Log Likelihood	-1.7e+04	

Source: IEBS (1995-2006); 15 000 individuals; year dummies included
Coefficients; Standard errors in parantheses
levels of significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 6: Model 3: Multinomial logit model with random effects (normal distribution), model without absorbing-state, with interactions

	Low-pay b/se	Non-employment b/se
High-pay, t-1 (reference group)	-	-
	-	-
Low-pay, t-1 (dummy)	3.664***	2.483***
	(0.322)	(0.311)
Low-pay, t-1 * lower middle qualification	-0.567*	-0.904***
	(0.334)	(0.330)
Low-pay, t-1 * middle qualification	-0.661	-0.722
	(0.541)	(0.541)
Low-pay, t-1 * high qualification	1.010*	-0.286
	(0.612)	(0.608)
Non-employment, t-1 (dummy)	3.269***	4.405***
	(0.306)	(0.244)
Non-employment, t-1 * lower middle qualification	-0.798**	-1.533***
	(0.324)	(0.252)
Non-employment, t-1 * middle qualification	-1.430***	-1.811***
	(0.501)	(0.334)
Non-employment, t-1 * high qualification	-0.418	-1.626***
	(0.512)	(0.306)
Low qualification (reference group)	-	-
	-	-
Lower middle qualification (dummy)	-0.378*	0.125
	(0.195)	(0.145)
Middle qualification (dummy)	-0.714**	0.326
	(0.310)	(0.204)
High qualification (dummy)	-2.340***	-0.393**
	(0.330)	(0.176)
Age: 31-34 (reference group)	-	-
	-	-
Age: 35-39 (dummy)	0.060	-0.263**
	(0.154)	(0.116)
Age: 40-44 (dummy)	0.065	-0.286

	(0.243)	(0.181)
Age: 45-49 (dummy)	0.285	-0.149
	(0.332)	(0.244)
Age: 50-54 (dummy)	0.462	0.168
	(0.424)	(0.309)
Age: 55-59 (dummy)	0.920*	0.768**
	(0.524)	(0.378)
Nationality: German (reference group)	-	-
	-	-
Nationality: Turkish (dummy)	0.218	0.264
	(0.231)	(0.196)
Nationality: other (dummy)	0.530***	0.441***
	(0.159)	(0.136)
Local unemployment rate	-0.007	0.064**
	(0.034)	(0.026)
Individual average of age: 35-39	-0.591	-0.147
	(0.365)	(0.297)
Individual average of age: 40-44	-0.578*	-0.061
	(0.330)	(0.259)
Individual average of age: 45-49	-0.656	0.110
	(0.444)	(0.341)
Individual average of age: 50-54	-0.798	-0.154
	(0.521)	(0.392)
Individual average of age: 55-59	-1.039	-0.523
	(0.705)	(0.522)
Individual average of local unemployment rate	0.047	0.002
	(0.037)	(0.028)
High-pay, t=$s-1$ (reference group)	-	-
	-	-
Low-pay, t=$s-1$ (dummy)	3.693***	3.423***
	(0.442)	(0.411)
Low-pay, t=$s-1$ * lower middle qualification	0.094	-0.267
	(0.432)	(0.414)
Low-pay, t=$s-1$ * middle qualification	0.791	-0.518
	(0.717)	(0.680)

Low-pay, t=$s-1$ * high qualification	0.104	-1.857**
	(0.844)	(0.942)
Non-employment, t=$s-1$ (dummy)	3.158***	4.355***
	(0.441)	(0.386)
Non-employment, t=$s-1$ * lower middle qualification	-0.208	-0.245
	(0.440)	(0.378)
Non-employment, t=$s-1$ * middle qualification	-0.095	-0.943*
	(0.690)	(0.550)
Non-employment, t=$s-1$ * high qualification	-0.386	-0.795*
	(0.642)	(0.478)
Number of low-pay episodes with tenure > 0 / <= 180 days	0.134*	0.262***
	(0.070)	(0.062)
Number of low-pay episodes with tenure > 180 / <= 365 days	0.018	-0.030
	(0.115)	(0.111)
Number of low-pay episodes with tenure > 365 / <= 545 days	0.160	0.211
	(0.222)	(0.205)
Number of low-pay episodes with tenure > 545 / <= 730 days	0.126	-0.368
	(0.275)	(0.261)
Number of low-pay episodes with tenure > 730	0.791***	0.062
	(0.244)	(0.238)
Number of non-employment episodes with duration > 0 / <= 180 days	0.371***	0.385***
	(0.041)	(0.033)
Number of non-employment episodes with duration > 180 / <= 365 days	0.419***	0.354***
	(0.106)	(0.091)
Number of non-employment episodes with duration > 365 / <= 545 days	0.892***	0.921***
	(0.163)	(0.142)
Number of non-employment episodes with duration > 545 / <= 730 days	0.859***	0.945***
	(0.216)	(0.187)
Number of non-employment episodes with duration > 730	1.046***	1.421***
	(0.220)	(0.182)
Cumulated duration of low-wage employment between 1998 and 2000	0.002***	0.001**
	(0.000)	(0.000)
Cumulated duration of non-employment between 1998 and 2000	0.001**	0.000
	(0.000)	(0.000)
Constant	-6.921***	-6.417***

	(0.339)	(0.267)
Observations	249573	
AIC	34126.1	.
Log Likelihood	-1.7e+04	

Source: IEBS (1995-2006); 15 000 individuals; year dummies included
Parameters of unobserved heterogeneity are highly significant and follow the pattern of the model in table 5
Coefficients; Standard errors in parantheses
levels of significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Simulated transition matrices: initially non-employed

Table 7: Simulated transition matrix: low qualification

	High-pay, t			Low-pay, t			Non-employment, t		
High-pay, t-1	0.452	(0.348)	(0.555)	0.106	(0.061)	(0.170)	0.443	(0.341)	(0.545)
Low-pay, t-1	0.137	(0.084)	(0.211)	0.326	(0.230)	(0.435)	0.537	(0.422)	(0.640)
Non-employment, t-1	0.060	(0.037)	(0.092)	0.089	(0.057)	(0.134)	0.851	(0.794)	(0.895)

Source: IEBS (1995-2006); transition matrix simulated with parameters of model 3; five percent confidence intervals in parentheses

Table 8: Simulated transition matrix: lower middle qualification

	High-pay, t			Low-pay, t			Non-employment, t		
High-pay, t-1	0.447	(0.344)	(0.557)	0.076	(0.041)	(0.127)	0.477	(0.371)	(0.575)
Low-pay, t-1	0.211	(0.140)	(0.300)	0.275	(0.180)	(0.386)	0.514	(0.403)	(0.620)
Non-employment, t-1	0.138	(0.086)	(0.210)	0.095	(0.054)	(0.157)	0.768	(0.675)	(0.836)

Source: IEBS (1995-2006); transition matrix simulated with parameters of model 3; five percent confidence intervals in parentheses

Table 9: Simulated transition matrix: middle qualification

	High-pay, t			Low-pay, t			Non-employment, t		
High-pay, t-1	0.430	(0.321)	(0.545)	0.053	(0.024)	(0.100)	0.518	(0.401)	(0.627)
Low-pay, t-1	0.198	(0.108)	(0.318)	0.182	(0.091)	(0.327)	0.621	(0.445)	(0.756)
Non-employment, t-1	0.150	(0.088)	(0.234)	0.047	(0.020)	(0.102)	0.803	(0.704)	(0.876)

Source: IEBS (1995-2006); transition matrix simulated with parameters of model 3; five percent confidence intervals in parentheses

Table 10: Simulated transition matrix: high qualification

	High-pay, t			Low-pay, t			Non-employment, t		
High-pay, t-1	0.637	(0.535)	(0.726)	0.020	(0.008)	(0.048)	0.343	(0.255)	(0.440)
Low-pay, t-1	0.290	(0.175)	(0.431)	0.238	(0.123)	(0.391)	0.472	(0.308)	(0.628)
Non-employment, t-1	0.277	(0.205)	(0.355)	0.050	(0.026	(0.090)	0.674	(0.589)	(0.748)

Source: IEBS (1995-2006); transition matrix simulated with parameters of model 3; five percent confidence intervals in parentheses

Appendix

Simulated transition matrices: initially low-paid

Table 1: Simulated transition matrix: low qualification

	High-pay, t			Low-pay, t			Non-employment, t		
High-pay, t-1	0.463	(0.356)	(0.574)	0.293	(0.201)	(0.396)	0.244	(0.164)	(0.338)
Low-pay, t-1	0.119	(0.078)	(0.178)	0.641	(0.549)	(0.723)	0.240	(0.172)	(0.318)
Non-employment, t-1	0.078	(0.046)	(0.131)	0.321	(0.231)	(0.420)	0.601	(0.497)	(0.694)

Source: IEBS (1995-2006); transition matrix simulated with parameters of model 3; five percent confidence intervals in parentheses

Table 2: Simulated transition matrix: lower middle qualification

	High-pay, t			Low-pay, t			Non-employment, t		
High-pay, t-1	0.479	(0.367)	(0.588)	0.237	(0.152)	(0.338)	0.284	(0.197)	(0.379)
Low-pay, t-1	0.189	(0.120)	(0.282)	0.573	(0.446)	(0.681)	0.238	(0.156)	(0.338)
Non-employment, t-1	0.165	(0.102)	(0.249)	0.321	(0.217)	(0.434)	0.514	(0.396)	(0.626)

Source: IEBS (1995-2006); transition matrix simulated with parameters of model 3; five percent confidence intervals in parentheses

Table 3: Simulated transition matrix: middle qualification

	High-pay, t			Low-pay, t			Non-employment, t		
High-pay, t-1	0.481	(0.359)	(0.599)	0.186	(0.104)	(0.297)	0.332	(0.229)	(0.446)
Low-pay, t-1	0.200	(0.111)	(0.323)	0.460	(0.298)	(0.625)	0.340	(0.195)	(0.502)
Non-employment, t-1	0.199	(0.119)	(0.304)	0.199	(0.105)	(0.330)	0.602	(0.456)	(0.725)

Source: IEBS (1995-2006); transition matrix simulated with parameters of model 3; five percent confidence intervals in parentheses

Table 4: Simulated transition matrix: high qualification

	High-pay, t			Low-pay, t			Non-employment, t		
High-pay, t-1	0.747	(0.551)	(0.879)	0.139	(0.048)	(0.293)	0.114	(0.037)	(0.262)
Low-pay, t-1	0.251	(0.136)	(0.402)	0.662	(0.482)	(0.797)	0.087	(0.026)	(0.225)
Non-employment, t-1	0.387	(0.215)	(0.581)	0.343	(0.161)	(0.550)	0.270	(0.100)	(0.493)

Source: IEBS (1995-2006); transition matrix simulated with parameters of model 3; five percent confidence intervals in parentheses

Simulated transition matrices: initially high-paid

Table 5: Simulated transition matrix: low qualification

	High-pay, t			Low-pay, t			Non-employment, t		
High-pay, t-1	0.961	(0.948)	(0.970)	0.013	(0.008)	(0.019)	0.026	(0.020)	(0.036)
Low-pay, t-1	0.768	(0.674)	(0.837)	0.129	(0.080)	(0.201)	0.103	(0.067)	(0.150)
Non-employment, t-1	0.630	(0.550)	(0.699)	0.060	(0.037)	(0.096)	0.310	(0.248)	(0.380)

Source: IEBS (1995-2006); transition matrix simulated with parameters of model 3; five percent confidence intervals in parentheses

Table 6: Simulated transition matrix: lower middle qualification

	High-pay, t			Low-pay, t			Non-employment, t		
High-pay, t-1	0.960	(0.951)	(0.968)	0.009	(0.007)	(0.013)	0.031	(0.025)	(0.038)
Low-pay, t-1	0.849	(0.816)	(0.876)	0.078	(0.059)	(0.104)	0.072	(0.057)	(0.091)
Non-employment, t-1	0.789	(0.754)	(0.820)	0.038	(0.028)	(0.051)	0.173	(0.145)	(0.204)

Source: IEBS (1995-2006); transition matrix simulated with parameters of model 3; five percent confidence intervals in parentheses

Table 7: Simulated transition matrix: middle qualification

	High-pay, t			Low-pay, t			Non-employment, t		
High-pay, t-1	0.957	(0.944)	(0.968)	0.007	(0.004)	(0.011)	0.036	(0.027)	(0.048)
Low-pay, t-1	0.846	(0.762)	(0.903)	0.055	(0.029)	(0.098)	0.099	(0.055)	(0.167)
Non-employment, t-1	0.808	(0.752)	(0.855)	0.017	(0.009)	(0.034)	0.174	(0.130)	(0.227)

Source: IEBS (1995-2006); transition matrix simulated with parameters of model 3; five percent confidence intervals in parentheses

Table 8: Simulated transition matrix: high qualification

	High-pay, t			Low-pay, t			Non-employment, t		
High-pay, t-1	0.976	(0.969)	(0.982)	0.002	(0.001)	(0.003)	0.022	(0.017)	(0.029)
Low-pay, t-1	0.859	(0.766)	(0.921)	0.059	(0.030)	(0.108)	0.082	(0.038)	(0.152)
Non-employment, t-1	0.855	(0.811)	(0.890)	0.012	(0.006)	(0.023)	0.133	(0.099)	(0.175)

Source: IEBS (1995-2006); transition matrix simulated with parameters of model 3; five percent confidence intervals in parentheses

Simulated transition matrices: all individuals in the sample, simulated for different levels of qualification

Table 9: Simulated transition matrix: low qualification

	High-pay, t			Low-pay, t			Non-employment, t		
High-pay, t-1	0.86	(0.83)	(0.89)	0.05	(0.03)	(0.07)	0.09	(0.07)	(0.11)
Low-pay, t-1	0.64	(0.55)	(0.71)	0.20	(0.14)	(0.28)	0.16	(0.12)	(0.22)
Non-employment, t-1	0.51	(0.43)	(0.58)	0.09	(0.06)	(0.13)	0.40	(0.33)	(0.48)

Source: IEBS (1995-2006); transition matrix simulated with parameters of model 3; five percent confidence intervals in parentheses

Table 10: Simulated transition matrix: lower middle qualification

	High-pay, t			Low-pay, t			Non-employment, t		
High-pay, t-1	0.90	(0.89)	(0.92)	0.03	(0.02)	(0.03)	0.07	(0.06)	(0.08)
Low-pay, t-1	0.78	(0.74)	(0.81)	0.12	(0.09)	(0.15)	0.11	(0.09)	(0.13)
Non-employment, t-1	0.72	(0.68)	(0.75)	0.06	(0.04)	(0.07)	0.23	(0.20)	(0.26)

Source: IEBS (1995-2006); transition matrix simulated with parameters of model 3; five percent confidence intervals in parentheses

Table 11: Simulated transition matrix: middle qualification

	High-pay, t			Low-pay, t			Non-employment, t		
High-pay, t-1	0.91	(0.88)	(0.93)	0.02	(0.01)	(0.04)	0.07	(0.05)	(0.09)
Low-pay, t-1	0.78	(0.69)	(0.84)	0.09	(0.06)	(0.15)	0.13	(0.08)	(0.21)
Non-employment, t-1	0.74	(0.68)	(0.80)	0.04	(0.02)	(0.06)	0.22	(0.17)	(0.29)

Source: IEBS (1995-2006); transition matrix simulated with parameters of model 3; five percent confidence intervals in parentheses

Table 12: Simulated transition matrix: high qualification

	High-pay, t			Low-pay, t			Non-employment, t		
High-pay, t-1	0.964	(0.952)	(0.973)	0.003	(0.001)	(0.007)	0.033	(0.024)	(0.043)
Low-pay, t-1	0.837	(0.745)	(0.901)	0.068	(0.034)	(0.121)	0.095	(0.049)	(0.170)
Non-employment, t-1	0.834	(0.788)	(0.873)	0.015	(0.008)	(0.028)	0.151	(0.113)	(0.195)

Source: IEBS (1995-2006); transition matrix simulated with parameters of model 3; five percent confidence intervals in parentheses