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# ABSTRACT

## From No Pay to Low Pay and Back Again? A Multi-State Model of Low Pay Dynamics*

This study analyzes the mobility between three labor market states: working in low paid jobs, working in higher paid jobs and not working. Using German panel data I estimate dynamic multinomial logit panel data models with random effects taking the initial conditions problem and potential endogeneity of panel attrition into account. In line with results from other countries, this first study on Germany finds true state dependence in low pay jobs and confirms previous results of state dependence in non-employment. Moreover, I find evidence for a "low pay no pay cycle", i.e. being low paid or not employed itself increases the probability of being in one of these states in the next year. However, compared to non working, being low paid does not have adverse effects on future employment prospects: the employment probability increases with low pay employment and the probability of being high paid seems to be higher for previously low paid workers. I find no evidence for endogenous panel attrition.

JEL Classification: J64, J62, J31, C33, C35

Keywords: low pay dynamics, unemployment dynamics, dynamic random effects models, state dependence, panel attrition, unobserved heterogeneity

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# 1 Introduction

Unskilled and low-skilled individuals have a relatively high risk of unemployment. In this context low pay employment is discussed controversially. In Germany, characterized by an almost continuously rising unemployment rate in the last decades, it is often argued that rising employment rates in the low pay sector could be one solution to overcome the high unemployment rate among low skilled workers. On the other hand low paid jobs are often associated with unstable working careers and a high risk of unemployment. According to this the ongoing public debate in Germany ranges from discussions of the introduction of a minimum wage to the implementation of workfare programs. In this context it is important to know whether low paid jobs are transitory experiences of the working career and stepping stones to better jobs or whether there exists a “low pay - no pay cycle”.

In this paper, I analyze low pay and non-employment dynamics of men in west Germany. The focus lies on the extent of true or genuine state dependence in low pay and non-employment. True state dependence describes the fact that being low paid or not employed in one period itself increases the probability of being low paid or not employed in the next period. The knowledge of the state dependence allows to evaluate in how far the employment prospects of low paid individuals differ from not employed and high paid individuals.

The existence of state dependence in employment dynamics can be explained by several factors. Past unemployment may alter preferences, prices or constraints and therefore increase the probability of future unemployment, see e.g. Heckman and Borjas (1980) and Prowse (2005). For example, non-employment may prevent human capital accumulation and lead to a loss of work experience or firms may use unemployment spells as a proxy for unobserved components of ability in their hiring decisions. These effects may be the same for low wage jobs. Being low paid could lead to non-accumulation and deterioration of human capital. Moreover, McCormick (1990) argues that low paid jobs are low-quality jobs and the type of job may be used by firms as an indicator about worker quality. Hence, being low paid could stigmatize employees and may be used as a screening device of employers (Stewart, 2006). The aim of this paper is to examine the extent of true state dependence and to analyze whether low wage jobs have the same or even higher adverse effects on future employment prospects compared to non-employment.

Studies comparing the extent of a low wage sector across countries indicate that there exist wide variations, with the highest incidence of low pay in western Europe measured in the UK and an average incidence in Germany (e.g. European Commission, 2004). Numerous studies exist on low pay dynamics in Europe, e.g. the edited volume of Asplund, Sloane, and Theodossiu (1998) contains several analyses. Descriptive studies about the low pay dynamics indicate that the low pay dynamics have been decreasing in Germany over the last two decades (Rhein, Gartner, and Krug, 2005) and that Germany has the lowest exit probability from low pay to high pay in western Europe (European Commission, 2004). Stewart and Swaffield (1999) have shown that models without potential endogeneity of the initial wage state may lead to biased parameter estimates. This endogeneity of the initial wage state is taken into account only in some of the existing studies (Stewart and Swaffield (1999), Cappellari (2002) and Sousa-Poza (2004), among others). Cappellari and Jenkins (2004) additionally allow for potentially endogenous selection into employment and panel attrition. They conclude that 'economic' selection is more important than 'survey' selection. So far, for Germany, there exists no study on low pay dynamics accounting for the endogeneity of the initial state, but several studies on unemployment dynamics. Flaig, Licht, and Steiner (1993) and Mühleisen and Zimmermann (1994) find evidence for state dependence in unemployment and Haan (2005) reports state dependence in employment for married women. These results correspond to the results for other countries. For example Arulampalam, Booth, and Taylor (2000) find state dependence in unemployment for British men, Hyslop (1999) and Michaud and Tatsiramos (2005) find state dependence in employment for married women in the US and in several European countries, respectively, and Prowse (2005) reports state dependence in part- and full-time employment for women in Britain.

As far as I know only two studies investigate the relation between the three labor market states low pay, high pay and unemployment and taking the initial condition problem into account: Cappellari and Jenkins (2004) and Stewart (2006), both using the British Household Panel (BHPS). Cappellari and Jenkins (2004) estimate a multivariate probit model with several endogenous selection processes and find evidence for state dependence and a higher probability of becoming unemployed for low paid and of becoming low paid for unemployed individuals. Stewart (2006) analyzes the transitions into unemployment and takes the previous labor market state into account. In contrast to Cappellari and Jenkins (2004) he makes use of the panel structure of his data set by estimating several dynamic random and fixed effects models including models with autocorrelated error terms, bivariate random effects and GMM estimators. His results do not differ qualitatively between the various methods and are in line with the results of Cappellari and Jenkins.

I extend the approaches of Stewart (2006) and Cappellari and Jenkins (2004) and estimate a dynamic multinomial logit model with random effects. In this model, it is possible to differentiate three initial and three destination states instead of two destination states in binary probit models. Therefore, I can model 'economic' selection with respect to non-employment as a mutually exclusive state directly in the multinomial model. In addition to that I take the 'survey' selection into account by simultaneously modeling the panel attrition similar to Cappellari and Jenkins (2004). In contrast to them I make use of the panel structure of the data and allow for random effects.

Low pay is defined as a relative concept and the models are estimated with two alternative thresholds defined as two-thirds of the median hourly gross wage and the first quintile of the hourly gross wage distribution. All wages above the corresponding threshold are labeled as "high paid". In my analysis I use data from the German Socio-Economic Panel Study (SOEP) for men aged between 20 and 55.

The results indicate that there exists strong true state dependence in low pay as well as in non-employment. In addition to that there exists a strong link between low pay and no pay. Compared to high paid workers not employed individuals have a higher probability to be low paid in the future and vice versa. Despite this clear evidence for a "low pay - no pay cycle", compared to non-employment low-wage jobs increase the probability of being employed in the future and low pay seems to lead to higher paid jobs. Thus, there is some evidence that low paid jobs are stepping stones to better jobs and no evidence that being low paid does have any adverse effects on future employment prospects if it is compared with non-employment. However, being low paid goes along with a higher risk of non-employment and a higher probability of being low paid in the future if it is compared to high paid jobs. I find no evidence for the endogeneity of panel attrition. The corresponding correlation coefficients are insignificant and the results do not change compared to the simpler model.

Section 2 gives a short description of the data, the low pay definitions and descriptive statistics of the transition probabilities. Section 3 outlines the econometric approach, Section 4 presents empirical results and section 5 concludes.

## 2 Data and Descriptive Statistics

This study uses data from the German Socio-Economic Panel Study (SOEP). The annual survey started in 1984 in west Germany and was extended to include east Germany in 1990. In all panel waves, the head of the household provides information about the household and every household member aged 16 or older provides additional individual information. For a detailed description see Haisken-DeNew and Frick (2005).

Monthly payments may vary due to short-time or overtime working and bonus payments (Sloane and Theodossiu, 1998). Therefore, I measure earnings on an hourly basis accounting for overtime working and excluding bonus-payments, and include full-time, part-time as well as marginal employment. This information is given for the month previous to the interview, hence the labor market information refers to one month in the year.

I define low pay as a relative concept. Individuals whose wage does not exceed a certain relative position in the wage distribution are defined as being low paid. In the literature different low pay cutoffs are used. Stewart and Swaffield (1999) use two thresholds and define low paid employees as persons whose earnings are less than half of the median and whose earnings are less than two-thirds of the median, respectively. Cappellari (2002) uses the first quintile and the third decile to differentiate between low paid and high paid. In this study two alternative thresholds are applied: individuals with a gross wage lower (i) than two thirds of the current median hourly earnings and (ii) the first quintile of the wage distribution are defined to be low paid, respectively. In Table 1 the hourly low-pay thresholds are presented for the different years in 2000 prices. These low pay thresholds are calculated on an annual basis and refer to all individuals, men and women, not being self-employed, living in west Germany, reporting their working hours and their last monthly wage in the SOEP. The 2/3 median threshold lies in every year below the first quintile threshold and is almost continuously rising, reflecting a real wage growth of the median wage over time. For the first quintile threshold, no clear trend can be observed.

[Table 1 about here]

Earning and participation dynamics may differ between men and women and have to be analyzed separately. Therefore I exclude women from the analysis. In addition to that individuals younger than 20 and older than 54 years are excluded from the sample. The first age restriction is motivated by the schooling schemes and the second one by the retirement schemes in Germany. The sample focuses on west Germany. The reason for this is given by the differences in the wage distributions between east and west Germany. Calculating joint thresholds would imply a very small share of low paid individuals in west Germany.[1] Furthermore, east and west German labor markets still exhibit large differences which would draw attention away from the major research topic of this paper. Moreover individuals who are at no interview date during the observation period employed or registered as unemployed are excluded because these individuals have a high probability to be out of the labor force.

I use the SOEP waves 1998 to 2003 for the analysis. An individual enters the sample if the person is within the age restrictions, has finished education, civilian or military service and is not self-employed or in "disabled employment" at any interview date. There exist two possible entry dates: 1998, the first year of observation and the year of the introduction of the "refreshment" sample and 2000, the year of the introduction of the "innovation" sample in the SOEP. Around 45% of all interviewed individuals in 2000 belong to the "innovation" sample.[2] In the regression analysis, described in the next chapter, I control for the entry date 1998 and 2000, respectively, to capture potential differences between the two samples with respect to labor market transition processes.[3] An individual leaves the sample in the first year in which it is not possible to observe one of the variables used in the econometric analysis. This could happen by panel attrition or by missing values in the dependent or independent variables. This leads to an unbalanced panel data set with continuously observed years for each individual.

The share of low paid men in west Germany in 1998 is around 6.9% and was increasing to 9.2% in 2003 with respect to the first threshold (2/3 median). The corresponding shares evaluated by the first quintile of the wage distribution are with 16.9% in 1998 and 17.5% in 2003 more stable. Compared to the United Kingdom this is a relatively low rate of low paid employees. For example Stewart and Swaffield (1999) report around 22% of working British men to be low paid in the

[1]For the wage gap between east and west Germany and its development over time see e.g. Görzig, Gornig, and Werwatz (2005).

[2]Both, the refreshment and the innovation samples are supplementary random samples with the aim to stabilize the number of cases in the SOEP (Schupp and Wagner, 2002).

[3]Differences between these two cohorts could exist because the 1998 sample mainly consists of individuals who have been taking part in the SOEP for several waves, i.e. the share of individuals with a low probability of attrition is relatively high compared to the 2000 sample.

years 1991-1995 with respect to the first threshold.

Table 2 presents the probabilities of being low or high paid in period $t$, conditional on the pay state in the previous period $t-1$. The unweighted sample consists of pooled year to year transitions between 1998 and 2003 and is restricted to men being employed and reporting wages in at least two waves. The probability of being low paid is much higher for those who have been low paid in the previous year. For the first threshold (2/3 median) around 43% of the low paid individuals stay low paid if they are still employed and less than two percent of the previously high paid individuals are low paid in the next period. The second threshold (first quintile) goes along with a higher state dependence in low paid jobs (47%) and a slightly higher transition probability from high paid to low paid jobs (2.1%).

[Tables 2 and 3 about here]

In Table 3 non-employment is additionally taken into account. The pooled sample is restricted to those being not employed or employed with observed wages. Taking the non-employment into account, we still observe a much higher probability of being low paid for those who have been low paid in the previous period compared to previously high paid individuals. The probability of being not employed in year $t$ is around 15% and 13% and thus clearly higher for those who were low paid in $t-1$ than for previously high paid individuals with 2.4% and 2.2%, respectively. In addition to that, previously not employed individuals clearly have a higher probability of being low paid than previously high paid individuals. These descriptive statistics suggest that there may exist state dependence in all the three analyzed labor market states as well as a "low pay no pay cycle", independent of the threshold definition. These main results do not change fundamentally if attrition is additionally taken into account. However, not employed individuals leave the sample with the highest (8.6%) and high paid individuals with the lowest probability (5.4%), see Table 4. Attrition in this context means a drop out from the SOEP. The share of panel attrition is relatively low and underestimates the real panel attrition because the individuals have to be observed for two subsequent waves for entering the sample for estimation reasons, i.e. panel attrition in this context refers to drop out in the third or one of the following years of observation in my sample.

[Table 4 about here]

In Table 5 descriptive statistics of the observed characteristics are reported, conditioned on the labor market state in the first year of observation. Higher paid employees are on average better educated than non working and low paid individuals. The difference in education between non working and low paid individuals is relatively small. Moreover, low paid individuals are younger, are less often married and have fewer children than high paid and non working persons. The share of immigrants is higher among the low paid and not employed and the average local unemployment rate is higher among not employed individuals but the differences between the three groups are small. These results are quite similar for both thresholds.

[Table 5 about here]

The different aggregate transition probabilities for individuals in low and high paid jobs or in non-employment reported above could derive from observed and unobserved heterogeneity as well as from true state dependence, i.e. the fact that being low paid in one period itself increases the probability of being low paid in the next period (Stewart and Swaffield, 1999). If certain observable or unobservable individual characteristics go along with low transition probabilities into higher paid jobs, such as education or age, this will create aggregate state dependence although there does not need to be true state dependence. I will distinguish the different sources of the observed different transition probabilities in the econometric part of this paper and analyze whether and to which extent one can observe true state dependence in the three labour market states.

# 3 Modeling Transition Probabilities

This study analyzes the mobility between high pay ($j = 1$) and low pay employment ($j = 2$) on the one hand and non-employment ($j = 3$) on the other hand. Earnings are classified into two discrete ranges, low pay and high pay. I estimate the transition probabilities $P$ between the three states from period $t-1$ to $t$. The transition matrix $TM$ corresponds to

$$TM = \begin{pmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{pmatrix}. \tag{1}$$

I assume a first-order Markov process. The latent propensity $E^*$ of individual $i$ to be in state $j$ in period $t$ can be written as

$$E^*_{i,j,t} = X_{it}\beta_j + Z_{it-1}\gamma_j + \alpha_{ij} + \epsilon_{ijt}. \tag{2}$$

$X_{it}$ contains individual observed characteristics in period $t$ and $Z_{it-1}$ contains the lagged labor market state, consisting of two dummy variables which indicate the state in period $t-1$ with high paid employment as the base category. Vector $\alpha_i = \{\alpha_{i1}, \alpha_{i2}, \alpha_{i3}\}$ describes the individual specific unobserved heterogeneity and $\epsilon_{ijt}$ is the error term. The error term is assumed to be independent from observable and unobservable individual characteristics and to follow a Type I extreme value distribution. The labor market state $Z_{it}$ with the highest propensity $E^*_{i,j,t}$ is realized ($Z_{it} = j$ if $E^*_{i,j,t} > E^*_{i,l,t}$ for any $l \neq j$). This ends up in a multinomial logit panel data model with random effects with three states. Alternatively one could model the propensities to be employed and to be high or low paid simultaneously with two probit models ((Cappellari and Jenkins, 2004)). However, a disadvantage of this approach is that exclusion restrictions are required. Therefore, and because the three labor market states are mutually exclusive I choose a multinomial logit model. For other studies applying a multinomial logit model in the context of low pay dynamics see e.g. (Cappellari and Jenkins, 2004). Applying a standard multinomial logit model would imply the restrictive and often unrealistic assumption of independence of irrelevant alternatives (IIA), see e.g. Cameron and Trivedi (2005). With the introduction of random effects this assumption is relaxed as the random effects have to be integrated out and the denominators of the logit formula are inside the integral and therefore do not cancel out when calculating the probability ratio of two alternatives (Train, 2003). For a given unobserved heterogeneity the probability of individual $i$ to be in state $j$ in period $t$ corresponds to

$$P(Z_{it} = j | X_{it}, Z_{it-1}, \alpha_i) = \frac{exp(X_{it}\beta_j + Z_{it-1}\gamma_j + \alpha_{ij})}{\Sigma^3_{k=1} exp(X_{it}\beta_k + Z_{it-1}\gamma_k + \alpha_{ik})}. \tag{3}$$

The coefficient vectors $\beta_1$ and $\gamma_1$ and the unobserved heterogeneity term $\alpha_{i1}$ of the base category are set to 0 for identification of the model.

The observation period of transition probabilities does not coincide with the start of the stochastic process generating individual's employment dynamics. Therefore, when modelling transition probabilities the initial condition problem has to be taken into account, see e.g. Heckman (1981a).

To take the problem of initial condition into account, I follow Gong, van Soest, and Villagomez (2004) and estimate a static multinomial logit model for the initial labor market state ($t = 0$) without lagged labor market states and different slope parameters similar to Heckman (1981b) estimating dynamic binary choice models.

The probability of individual $i$ to be in state $j$ in the initial period $t = 0$ corresponds to

$$P(Z_{it} = j|X_{it}, \nu_i) = \frac{exp(X_{it}\delta_j + \nu_{ij})}{\Sigma_{k=1}^{J} exp(X_{it}\delta_k + \nu_{ik})} \tag{4}$$

with the unobserved heterogeneity $\nu_i = \{\nu_{i1}, \nu_{i2}, \nu_{i3}\}$ and the state specific coefficient vector $\delta_j$. Being high paid ($j = 1$) is the base category and the coefficient vector $\delta_1$ and the unobserved heterogeneity term $\nu_{i1}$ are set to 0.

The unobserved heterogeneity or random effects $\nu_i = \{\nu_{i2}, \nu_{i3}\}$ are functions of the unobserved heterogeneity $\alpha_i$. Similar to Gong, van Soest, and Villagomez (2004) I assume that $\nu_i = C\alpha_i$, where $C$ is a lower triangular matrix and has to be estimated.

$$C = \begin{pmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{pmatrix} \tag{5}$$

The unobserved heterogeneity $\alpha_i = \{\alpha_{i2}, \alpha_{i3}\}$ is unknown and has to be integrated out when calculating the likelihood function. In a model without attrition the individual likelihood contribution can be written as

$$\begin{aligned} L_i = \int_{-\infty}^{\infty} & \prod_{t=1}^{T} \frac{exp(X_{it}\beta_2 + Z_{it-1}\gamma_2 + \alpha_2)^{l_t} exp(X_{it}\beta_3 + Z_{it-1}\gamma_3 + \alpha_3)^{n_t}}{1 + \Sigma_{k=2}^{3} exp(X_{it}\beta_k + Z_{it-1}\gamma_k + \alpha_k)} \\ & \frac{exp(X_{it}\delta_2 + \nu_2)^{l_0} exp(X_{it}\delta_3 + \nu_3)^{n_0}}{1 + \Sigma_{k=2}^{3} exp(X_{it}\delta_k + \nu_k)} f(\alpha) d\alpha \end{aligned} \tag{6}$$

with $l_t = 1$ ($n_t = 1$) if the individual is low paid (not employed) in $t$, $l_t = 0$ ($n_t = 0$) if not and $l_0 = 1$ ($n_0 = 1$) if the individual is low paid (not employed) in the initial period and $l_0 = 0$ ($n_0 = 0$) if not.[4]

In general, panel attrition is not taken into account in studies dealing with employment dynamics. As long as the unobserved individual heterogeneity influencing the employment dynamics is not correlated with the unobserved term influencing the attrition process, no problem occurs. But a correlation of these terms could lead to biased estimates. In my data set, non-employment and low paid jobs go along with

[4]An alternative estimator for dynamic discrete choice models is given by Wooldridge (2005) who propose to estimate the distribution conditional on the initial state and time invariant variables instead of jointly modeling all outcome variables. This ends up in less complex estimation methods. For an application in the context of dynamic multinomial discrete choice models see Haan (2005). However, for this approach a balanced panel is needed.

a higher probability of attrition, see Table 4. Therefore I take potential endogeneous sample attrition into account by estimating the employment transitions and the attrition process simultaneously. The latent attrition propensity $D_t^*$ is assumed to be a linear function of the in the previous period observed characteristics $A_{it-1}$ and unobserved characteristics $\alpha_{i4}$. Attrition is present if the latent propensity $D_t^*$ is positive.

$$D_t^* = A_{it-1}\xi_{+}\alpha_{i4} + \kappa_{it} > 0 \tag{7}$$

The error terms $\kappa_{it}$ are assumed to be independent from observed and unobserved characteristics and to follow a logistic distribution. This ends up in a logit model for the attrition equation. The indicator variable $a_t$ takes on the value 1 if the individual is not interviewed in year $t$ and 0 if no attrition occurs. For an individual with $T$ observed years and the observation period ending before 2003 the corresponding likelihood contribution is given by

$$L_i = \int_{-\infty}^{\infty} \prod_{t=1}^{T} \frac{exp(X_{it}\beta_2 + Z_{it-1}\gamma_2 + \alpha_2)^{l_t} exp(X_{it}\beta_3 + Z_{it-1}\gamma_3 + \alpha_3)^{n_t}}{1 + \Sigma_{k=2}^{3} exp(X_{it}\beta_k + Z_{it-1}\gamma_k + \alpha_k)} \tag{8}$$
$$\frac{exp(X_{it}\delta_2 + \nu_2)^{l_0} exp(X_{it}\delta_3 + \nu_3)^{n_0}}{1 + \Sigma_{k=2}^{3} exp(X_{it}\delta_k + \nu_k)} \prod_{t=2}^{T+1} \Big(\frac{exp(A_{it-1}\xi + \alpha_4)^{a_t}}{1 + (A_{it-1}\xi + \alpha_4)}\Big) f(\alpha) d\alpha$$

For an individual with the last observation in 2003 no panel attrition occurs after entering into the sample. In this case the likelihood contribution can be written as

$$L_i = \int_{-\infty}^{\infty} \prod_{t=1}^{T} \Big(\frac{exp(X_{it}\beta_2 + Z_{it-1}\gamma_2 + \alpha_2)^{l_t} exp(X_{it}\beta_3 + Z_{it-1}\gamma_3 + \alpha_3)^{n_t}}{1 + \Sigma_{k=2}^{3} exp(X_{it}\beta_k + Z_{it-1}\gamma_k + \alpha_k)}\Big) \tag{9}$$
$$\frac{exp(X_{it}\delta_2 + \nu_2)^{l_0} exp(X_{it}\delta_3 + \nu_3)^{n_0}}{1 + \Sigma_{k=2}^{3} exp(X_{it}\delta_k + \nu_k)} \prod_{t=2}^{T} \Big(\frac{1}{1 + (A_{it-1}\xi + \alpha_4)}\Big) f(\alpha) d\alpha$$

For the estimation of the selection process into panel attrition, an identification restriction is needed. Therefore, $A_{it-1}$ includes the same variables as $X_{it-1}$ and $Z_{it-1}$ and as the exclusion restriction a dummy variable indicating an interviewer change between $t-1$ and $t$. Interviewer changes are potentially endogenous with respect to wage mobility. For individuals moving due to a new job, one will probably observe an interviewer change. Therefore, I define an interviewer change only if the interviewer of the last year drops out of the SOEP interviewer sample, i.e. we do not observe any interviews of this interviewer in period $t$. An interviewer change defined in this way should be exogenous with respect to employment dynamics but should have a positive influence on the attrition probability. This influence should arise because the first meeting with an interviewer should go along with a relatively high tendency to refuse participation and subsequent contacts should increase trust. For a similar argument in the context of item nonresponse see Schräpler (2004).

I estimate a model with free correlations. The correlation coefficient $\rho_1$ measures the correlation between unobservable individual specific characteristics influencing the probability of being low paid and not employed in $t$ while the correlations $\rho_2$ and $\rho_3$ describe the association between unobservables determining the attrition process and the probability of being low paid ($\rho_2$) and not employed ($\rho_3$). If $\rho_2 = \rho_3 = 0$, the attrition process can be assumed to be exogenous and the model reduces to a dynamic multinomal logit model as suggested by Gong, van Soest, and Villagomez (2004).

It is assumed that the individual specific random intercepts $\alpha_i = \{\alpha_{i2}, \alpha_{i3}, \alpha_{i4}\}$ follow a multivariate normal distribution. The likelihood contribution involves a 3 dimensional integration. I estimate the models with a Maximum Simulated Likelihood (MSL) approach. In this approach simulated probabilities are used instead of exact probabilities, see Gourieroux and Monfort (1993) or Hajivassiliou and Ruud (1994) for the properties of MSL.

In this MSL approach the integral in equation (8) is replaced by

$$L_i = \frac{1}{R}\sum_{d=1}^{R} \quad \prod_{t=1}^{T}\Big(\frac{exp(X_{it}\beta_2 + Z_{it-1}\gamma_2 + \alpha_2^d)^{l_t} exp(X_{it}\beta_3 + Z_{it-1}\gamma_3 + \alpha_3^d)^{n_t}}{1 + \Sigma_{k=2}^{3} exp(X_{it}\beta_k + Z_{it-1}\gamma_k + \alpha_k^d)}\Big) \tag{10}$$
$$\frac{exp(X_{it}\delta_2 + \nu_{i2})^{l_0} exp(X_{it}\delta_3 + \nu_{i3})^{n_0}}{1 + \Sigma_{k=2}^{3} exp(X_{it}\delta_k + \nu_{ik})} \prod_{t=2}^{T+1}\Big(\frac{exp(A_{it-1}\xi_4 + \alpha_4^d)^{a_t}}{1 + (A_{it-1}\xi_4 + \alpha_4^d)}\Big)$$

For equation (9) the integral is replaced in the same way. In general independent random draws from mixing distributions are used in simulation approaches. In this paper I apply Halton Sequences as an alternative method, for details see e.g. Train (2003). The superior coverage compared to random draws and the negative correlation over the observations lead to a significant reduction in estimation time. For example Train (2000) and Bhat (2001) find in their studies that the results of mixed logit models are more precise with 100 Halton draws than with 1000 random draws. In this paper I use $r = 200$ Halton draws per individual. The models are programmed in Stata Version 8.2. For a description of the applied simulation procedure in the context of random effects multinomial logit models see Haan and Uhlendorff (2006).

**Extent of State Dependence**

The magnitudes of the estimated coefficients provide little information about the extent of true state dependence. State dependence describes the effect of being in one state compared to another state in $t-1$ on the probability of being in state $j$ in period $t$. Therefore and due to the nonlinearity of the model, the measure of true state dependence $SD$ is derived by calculating the average of pairwise individual differences between the predicted probabilities of being in state $j$ conditional on two of the three labor market states. For example, the effect of being low paid ($j=2$) compared to being high paid ($j=1$) in $t-1$ on the probability of being low paid in $t$ can be written as

$$SD = \frac{1}{N}\sum_{i=1}^{N}(P_i(j=2|j=2) - P_i(j=2|j=1)). \tag{11}$$

In order to derive the individual specific probabilities for each category given observed and unobserved characteristics it is necessary to assign individual values to the random intercepts. An individual value is given by the mean of the individual specific posterior distribution of unobserved heterogeneity. The posterior distribution depends on the prior (estimated) distribution of unobserved heterogeneity and the observed individual sequence of labor market states. This way of assigning values to latent variables is sometimes referred to as *Empirical Bayes* prediction (Skrondal and Rabe-Hesketh, 2004).[5]

I follow Train (2003) and take $r$ draws of $\alpha$ from the population distribution and calculate the individually weighted averages of these draws. The weight for each draw $d$ is proportional to the probability of the observed sequence of labor market states $P(y_i|x_i,\alpha_d)$. The simulated individual mean $\tilde{\alpha}_i$ is given by:

$$\tilde{\alpha}_i = \sum_{d=1}^{R} w^d \alpha^d \tag{12}$$

The higher the probability of the chosen sequence given the unobserved heterogeneity the higher the weight $w^d$ assigned to the draw:

$$w^d = \frac{P(y_i|x_i,\alpha_d)}{\sum_{d=1}^{R} P(y_i|x_i,\alpha_d)}$$

Given the unobserved and observed heterogeneity, individual transition probabilities between the three states can be calculated. The standard errors of average transition

[5] Alternatively one could use the expected value 0 of the unobserved heterogeneity for all individuals. However, in this study the extent of state dependence of different groups, e.g. the initially low paid individuals in my sample, is of interest and the average latent values probably vary with the initial state which may have a relevant influence on the predictions.

probabilities and of extents of true state dependence are computed using parametric bootstrap.

# 4 Results

I estimate dynamic multinomial logit panel data models with random effects and potential endogenous panel attrition for two different low pay thresholds. The results of the dynamic equations and the distributions of the unobserved heterogeneity are reported in Tables 6 and 7, the results of the static multinomial logit model and the attrition process are reported in the Appendix, Tables A1 and A2. For both thresholds I estimate the process with (model 2) and without unobserved heterogeneity (model 1). In the following I compare the different models and evaluate the endogeneity of the initial state and the attrition process. Second, I report the coefficients of the models and third I discuss the extent of true state dependence.

[Tables 6 and 7 about here]

## 4.1 Endogeneity of Initial State and Attrition

Both correlation coefficients describing the unobserved heterogeneity of the attrition process and the probability of being low paid and the probability of non-employment, respectively, are not significantly different from 0. This indicates that panel attrition is exogenous with respect to low pay and non-employment dynamics and the employment dynamics and the attrition process can be estimated separately. According to that, the results of a dynamic multinomial logit model without simultanous estimation of the attrition process are very similar to the one of the full model, see Table A3 in the Appendix.

Compared to a simple multinomial logit model (model 1) the inclusion of unobserved heterogeneity and the modeling of the initial condition (model 2) significantly increase the log-likelihood and clearly reduces the coefficients of the lagged labor market state variables. These results confirm previous research on low pay and unemployment dynamics and emphasize the importance of the initial condition problem within dynamic panel data models. For both thresholds the correlation coefficient $\rho_{12}$ is around 0.7, indicating that unobserved characteristics which lead to low pay employment and non-employment are similar but different from unobserved characteristics of high paid individuals. The estimated variances of all random intercepts are significant and the point estimates of the variances in the dynamic equation (4.81 and 8.37 for the threshold 1 and 4.95 and 8.14 for the threshold 2) indicate that both random intercepts contribute more to the state probability than the idiosyncratic errors with a normalized variance of $\pi^2/6$.

## 4.2 Model Estimates

Several covariables are included in the regressions. The results indicate that immigrants have a higher probability of being low paid or not employed, while married men are more often in high paid jobs. The existence of children in the household goes along with a higher probability of being not employed, while the coefficient of having children is not significantly different from zero with respect to the probability of being low-paid. The age has a U-shaped influence on the probability of being low paid and not employed: The younger and the older persons have a lower probability of being in a higher paid job. A higher education goes along with a higher probability of being in a high paid job. The comparison group of the three categories "apprenticeship", "further vocational training" and "university" consists of individuals with no vocational training at all. Moreover, individuals with a handicap have a higher risk of non-employment or being low paid and a higher local unemployment decreases the probability of being high paid.

The coefficients of the lagged labor market states indicate that there exists true state dependence in low pay as well as in non-employment in west Germany for men for both thresholds (see Tables 6 and 7). Being low paid in year $t-1$ increases the probability of being low paid compared to the probability of being high paid in year $t$. Being not employed in year $t-1$ increases the probability of being not employed compared to the probability of being high paid in year $t$.

In addition to that there exists a strong relation between low pay and no pay. Being low paid in year $t-1$ increases the probability of non working compared to the probability of being high paid in year $t$. Being not employed in year $t-1$ increases the probability of being low paid compared to the probability of being high paid.

## 4.3 Extent of True State Dependence

As mentioned above, the coefficients provide little information about the extent of true state dependence. Table 8 contains the transition matrices between the three states for both thresholds, based on averaged transition probabilities across all individuals. Independent of the previous labor market state, the average probability to be high paid in the next period is above 80%. This result holds for both thresholds and can be explained by the influence of observable and unobservable characteristics shifting the main share of individuals into relatively high paid jobs, independent of their employment state in the last year. However, the probability of being high paid is with 93% and 92%, respectively, the highest for individuals who have been high paid in the previous period. Previous non-employment goes along with a probability of 84% (80%) and previous low payment with a probability of 89% (86%) to be high paid in $t$.

Table 9 contains the transition probabilities for three groups defined by their initially observed state. Compared to Table 8 the results change and are similar to the descriptive transition matrices. For example more than 65% of the sample consisting of initially not employed individuals are not employed in the subsequent period, conditional on non-employment in the previous period, and the predicted probability of staying low paid is around 40% for the group of initially low paid individuals.

[Tables 8 and 9 about here]

The differences in the state probabilities can be attributed to the different previous labor market states and therefore provide information about true state dependence. Because the extent of state dependence may differ with respect to observed and unobserved heterogeneity, I calculated the $SD$ of four different groups separately: all men, initially not employed, low paid and high paid men. The results are presented in Table 10.

[Table 10 about here]

For the whole sample being not employed increases the probability of being not employed in the future by 6.63% for threshold 1 and 7.44% for threshold 2. This state dependence is higher compared to the state dependence in low paid jobs (2.52% and 3.94%, respectively). Moreover, low paid jobs increase the probability to be not employed by 1.90% and 2.12%, while not employed individuals have a higher probability to be low paid in the next period (2.37% and 4.59%, respectively). There is evidence for a "low pay no pay cycle", but the individuals seem to be better off if they have a low paid job than no job at all. This can also be seen in Table 8, indicating that low pay employment leads with a significantly higher probability (88.79%) to higher paid jobs than non-employment (84.22%).

The extent of the state dependence varies between the groups. The initially high paid men are characterized by the lowest marginal effects of the lagged states, while initially low paid and not employed men have relatively strong effects of state dependence in low pay and non-employment. For example the extent of state dependence in low paid jobs (SD LP) for initially not employed men is 6.89% (8.52%) and the corresponding effect in non-employment is 29.96% (12.76%).

Although there exists evidence for a "low pay - no pay cycle", the estimated effect of previous non-employment on the probability of non-employment is significantly higher for all groups and both thresholds than the effect of being previously low paid, see Tables 8 and 9. Moreover the point estimates to be high paid are always higher for previous low payment, although this difference is not always significantly different from zero. However, for the whole sample the confidence bands do not overlap, see Table 8.

I find some evidence that low paid jobs are stepping stones to better jobs in west Germany and the results indicate that being low paid does not have any adverse effects on future employment prospects if it is compared with non-employment. Thus, these results are not consistent with the hypothesis that a low-wage job does not augment a person's human capital more than unemployment. The results allow a more positive evaluation of low wage employment than the results of Stewart (2006) who does not estimate different effects of previous unemployment and previous low paid jobs on the probability of unemployment. But in comparison to high paid jobs being low paid goes along with a higher risk of non-employment and a higher probability of being low paid in the future.

# 5 Conclusion

This paper examines the low pay and non-employment dynamics of men in west Germany. I estimate a dynamic multinomial logit model with random effects and take the the initial condition problem into account. In addition to that I take potential endogeneity of panel attrition into account by estimating the processes of panel attrition and employment dynamics simultaneously. There is no evidence of endogeneous panel attrition, the corresponding correlation coefficients are insignificant and the results do not change compared to the simpler model.

This first study on low pay dynamics in Germany indicates that there exists strong true state dependence in low pay as well as in non-employment for men in west Germany. In addition to that there is a strong link between low pay and no pay. Despite this evidence for a "low pay no pay cycle", compared to non-employment low-wage jobs increase the probability of being employed in the future. Moreover, low paid jobs seem to lead to a higher paid job in the future.

This study finds some evidence that low paid jobs are stepping stones to better jobs in west Germany and no evidence that being low paid does have any adverse effects on future employment prospects if it is compared with non-employment. However, in comparison to high paid jobs being low paid goes along with a higher risk of non-employment and a higher probability of being low paid in the future.

Table 1: Low Pay Thresholds 1998-2003 in prices of 2000, Euro

| | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 |
|---|---|---|---|---|---|---|
| 2/3 median | 8.27 | 8.75 | 8.88 | 8.87 | 8.97 | 9.23 |
| First quintile | 10.47 | 10.25 | 10.57 | 10.58 | 10.44 | 11.04 |

*Source:* SOEP, weigthed yearly observations

Table 2: Transition Matrix: Low Pay and High Pay

| | Threshold 1 | | | Threshold 2 | | |
|---|---|---|---|---|---|---|
| | Low paid, t | High paid, t | Total | Low paid, t | High paid, t | Total |
| Low paid, t-1 | 43.1 | 57.0 | 3.5 | 47.1 | 53.0 | 6.0 |
| High paid, t-1 | 1.6 | 98.4 | 96.5 | 2.1 | 97.9 | 94.0 |
| Total | 3.0 | 97.0 | 100 | 4.8 | 95.3 | 100 |

*Source:* SOEP, unweighted pooled sample 1998-2003, n=8,483
Threshold 1: 2/3 of the median, Threshold 2: First quintile

Table 3: Transition Matrix: Low Pay, High Pay and Non-Employment

| | Threshold 1 | | | |
|---|---|---|---|---|
| | Non-employment, t | Low paid, t | High paid, t | Total |
| Non-employment, t-1 | 72.2 | 9.3 | 18.5 | 7.4 |
| Low paid, t-1 | 15.2 | 36.5 | 48.3 | 3.7 |
| High paid, t-1 | 2.4 | 1.5 | 96.0 | 88.9 |
| Total | 8.1 | 3.4 | 88.5 | 100 |
| | Threshold 2 | | | |
| | Non-employment, t | Low paid, t | High paid, t | Total |
| Non-employment, t-1 | 72.2 | 12.1 | 15.7 | 7.4 |
| Low paid, t-1 | 13.3 | 40.8 | 45.9 | 6.2 |
| High paid, t-1 | 2.2 | 2.0 | 95.8 | 86.4 |
| Total | 8.1 | 5.2 | 86.8 | 100 |

*Source:* SOEP, unweighted pooled sample 1998-2003, n=9,441
Threshold 1: 2/3 of the median, Threshold 2: First quintile

Table 4: Transition Matrix: Low Pay, High Pay, Non-Employment and Attrition

| | Threshold 1 | | | | |
|---|---|---|---|---|---|
| | Non-employment, t | Low paid, t | High paid, t | Attrition, t | Total |
| Non-employment, t-1 | 66.0 | 8.5 | 16.7 | 8.6 | 7.7 |
| Low paid, t-1 | 14.1 | 33.9 | 44.8 | 7.2 | 3.8 |
| High paid, t-1 | 2.3 | 1.4 | 90.9 | 5.4 | 88.6 |
| Total | 7.6 | 3.2 | 83.5 | 5.7 | 100 |
| | Threshold 1 | | | | |
| | Non-employment, t | Low paid, t | High paid, t | Attrition, t | Total |
| Non-employment, t-1 | 66.0 | 11.1 | 14.3 | 8.6 | 7.7 |
| Low paid, t-1 | 12.4 | 38.0 | 42.8 | 6.8 | 6.3 |
| High paid, t-1 | 2.1 | 1.9 | 90.7 | 5.3 | 86.1 |
| Total | 7.6 | 4.9 | 81.8 | 5.7 | 100 |

*Source:* SOEP, unweighted pooled sample 1998-2003, n=10,010
Threshold 1: 2/3 of the median, Threshold 2: First quintile

Table 5: Descriptive Statistics

| | | Threshold 1 | | Threshold 2 | |
|---|---|---|---|---|---|
| | Non-employment | Low paid | High paid | Low paid | High paid |
| Age | 36.71 (9.47) | 31.28 (8.85) | 38.11 (8.01) | 31.99 (8.58) | 38.36 (7.92) |
| Handicap | 0.16 | 0.07 | 0.05 | 0.07 | 0.05 |
| Married | 0.51 | 0.37 | 0.70 | 0.44 | 0.70 |
| Immigrant | 0.39 | 0.31 | 0.19 | 0.31 | 0.19 |
| Apprenticeship | 0.43 | 0.55 | 0.46 | 0.60 | 0.45 |
| Vocational training | 0.15 | 0.10 | 0.24 | 0.11 | 0.24 |
| University | 0.09 | 0.11 | 0.21 | 0.09 | 0.21 |
| Children | 0.81 | 0.59 | 0.83 | 0.61 | 0.84 |
| Local unemployment rate | 10.10 (2.61) | 9.64 (2.60) | 9.43 (2.33) | 9.64 (2.38) | 9.42 (2.34) |
| Year of entry 2000 | 0.43 | 0.51 | 0.46 | 0.49 | 0.46 |
| Number of observations | 243 | 138 | 2585 | 255 | 2468 |

*Source:* SOEP, descriptives with respect to the year of entry, standard deviations in pharentheses, n=2,966
Threshold 1: 2/3 of the median, Threshold 2: First quintile

Table 6: Dynamic Multinomial Logit Model, Threshold 1, joint estimation with the Attrition Process

| | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
|---|---|---|---|---|---|---|---|---|
| | Model 1 | | | | Model 2 | | | |
| | Low Paid | | Non-employment | | Low Paid | | Non-employment | |
| Low paid, t-1 | 3.37** | 0.16 | 2.23** | 0.18 | 1.17** | 0.29 | 0.93** | 0.35 |
| Non Employment, t-1 | 3.14** | 0.18 | 4.73** | 0.13 | 1.49** | 0.30 | 2.31** | 0.28 |
| Year 2000 | -0.12 | 0.23 | 0.20 | 0.21 | -0.05 | 0.26 | 0.13 | 0.24 |
| Year 2001 | 0.08 | 0.20 | 0.39* | 0.18 | 0.13 | 0.23 | 0.34 | 0.23 |
| Year 2002 | 0.52** | 0.20 | 0.71** | 0.18 | 0.61** | 0.23 | 0.73** | 0.23 |
| Year 2003 | 0.07 | 0.22 | 0.80** | 0.18 | 0.24 | 0.25 | 0.96** | 0.24 |
| Age | -0.18** | 0.07 | -0.15* | 0.06 | -0.49** | 0.11 | -0.43** | 0.11 |
| Age squared $*10^{-2}$ | 0.22* | 0.09 | 0.22** | 0.08 | 0.58** | 0.14 | 0.57** | 0.14 |
| Apprenticeship | -0.27 | 0.17 | -0.73** | 0.14 | -0.79** | 0.28 | -1.84** | 0.32 |
| Vocational training | -0.90** | 0.24 | -1.05** | 0.18 | -1.68** | 0.36 | -2.51** | 0.39 |
| University | -1.23** | 0.27 | -1.54** | 0.21 | -2.29** | 0.41 | -3.39** | 0.47 |
| Non German | 0.58 | 0.15 | 0.67** | 0.13 | 1.12** | 0.24 | 1.57** | 0.28 |
| Married | -0.53** | 0.16 | -0.70** | 0.14 | -0.90** | 0.23 | -1.34** | 0.24 |
| Children | 0.02 | 0.08 | 0.16* | 0.06 | 0.10 | 0.10 | 0.27* | 0.10 |
| Handicap | 0.43 | 0.24 | 1.09** | 0.16 | 1.03** | 0.33 | 2.12** | 0.31 |
| Local unemp. rate | 0.12** | 0.02 | 0.06** | 0.02 | 0.21** | 0.04 | 0.17** | 0.04 |
| Constant | -0.98 | 1.25 | -1.58 | 1.17 | 3.94* | 1.94 | 2.31 | 2.11 |
| | | | | | | Coef. | Std. Err. | |
| $\sigma_1^2$ | | - | - | | | 4.81** | 1.20 | |
| $\sigma_2^2$ | | - | - | | | 8.37** | 2.03 | |
| $\sigma_3^2$ | | - | - | | | 3.50** | 1.29 | |
| $\rho_{12}$ | | - | - | | | 0.70** | 0.09 | |
| $\rho_{23}$ | | - | - | | | -0.01 | 0.10 | |
| $\rho_{33}$ | | - | - | | | -0.12 | 0.15 | |
| Log-Likelihood | -5,668.57 | | | | -5,408.37 | | | |

The unobserved heterogeneity is assumed to follow a multivariate normal distribution. The equations of the initial state and the attrition process are reported in the Appendix. Observations: 2,966 individuals.

Model 1: No unobserved heterogeneity; Model 2: Jointly distributed unobserved heterogeneity.

Threshold 1: 2/3 of the median wage; Threshold 2: first quintile of the wage distribution.

*: statistically significant at least at the 5% level; **: statistically significant at least at the 1% level.

Table 7: Dynamic Multinomial Logit Model, Threshold 2, joint estimation with the Attrition Process

| | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
|---|---|---|---|---|---|---|---|---|
| | Model 1 | | | | Model 2 | | | |
| | Low Paid | | Non-employment | | Low Paid | | Non-employment | |
| Low paid, t-1 | 3.38** | 0.13 | 2.35** | 0.16 | 1.25** | 0.24 | 1.11** | 0.30 |
| Non Employment, t-1 | 3.34** | 0.17 | 5.02** | 0.14 | 1.76** | 0.28 | 2.62** | 0.29 |
| Year 2000 | 0.07 | 0.19 | 0.27 | 0.21 | 0.05 | 0.22 | 0.19 | 0.25 |
| Year 2001 | 0.14 | 0.16 | 0.41* | 0.18 | 0.13 | 0.20 | 0.38 | 0.23 |
| Year 2002 | 0.43* | 0.17 | 0.76** | 0.18 | 0.33 | 0.20 | 0.76** | 0.24 |
| Year 2003 | -0.02 | 0.19 | 0.84** | 0.18 | -0.08 | 0.22 | 0.98** | 0.24 |
| Age | -0.06 | 0.06 | -0.12 | 0.06 | -0.34** | 0.10 | -0.39** | 0.11 |
| Age squared $*10^{-2}$ | 0.07 | 0.08 | 0.18* | 0.08 | 0.39** | 0.12 | 0.52** | 0.14 |
| Apprenticeship | -0.26 | 0.15 | -0.75** | 0.14 | -0.77** | 0.25 | -1.85** | 0.32 |
| Vocational training | -0.96** | 0.21 | -1.08** | 0.19 | -1.79* | 0.32 | -2.53** | 0.40 |
| University | -1.18** | 0.23 | -1.58** | 0.21 | -2.39** | 0.38 | -3.42** | 0.47 |
| Non German | 0.51** | 0.13 | 0.66** | 0.13 | 1.13** | 0.22 | 1.57** | 0.27 |
| Married | -0.60** | 0.14 | -0.72** | 0.14 | -1.00** | 0.20 | -1.30** | 0.24 |
| Children | 0.01 | 0.06 | 0.15* | 0.06 | 0.08 | 0.09 | 0.22* | 0.10 |
| Handicap | 0.35 | 0.21 | 1.10** | 0.17 | 0.85** | 0.30 | 2.12** | 0.31 |
| Local unemp. rate | 0.08** | 0.02 | 0.06* | 0.02 | 0.16** | 0.04 | 0.16** | 0.04 |
| Constant | -2.79* | 1.10 | -2.30 | 1.18 | 2.23 | 1.78 | 1.60 | 2.11 |
| | | | | | | Coef. | Std. Err. | |
| $\sigma_1^2$ | | - | - | | | 4.95** | 1.11 | |
| $\sigma_2^2$ | | - | - | | | 8.14** | 2.01 | |
| $\sigma_3^2$ | | - | - | | | 3.31** | 1.32 | |
| $\rho_{12}$ | | - | - | | | 0.68** | 0.08 | |
| $\rho_{23}$ | | - | - | | | -0.12 | 0.10 | |
| $\rho_{33}$ | | - | - | | | -0.05 | 0.18 | |
| Log-Likelihood | -6,206.31 | | | | -5,933.66 | | | |

The unobserved heterogeneity is assumed to follow a multivariate normal distribution. The equations of the initial state and the attrition process are reported in the Appendix. Observations: 2,966 individuals

Model 1: No unobserved heterogeneity; Model 2: Jointly distributed unobserved heterogeneity

Threshold 1: 2/3 of the median wage; Threshold 2: first quintile of the wage distribution.

*: statistically significant at least at the 5% level; **: statistically significant at least at the 1% level.

Table 8: Estimated Transition Matrix: all Men

| All men | Non-employment, t | Low paid, t | High paid, t |
|---|---|---|---|
| | Threshold 1 | | |
| Non-employment, t-1 | 10.98 | 4.80 | 84.22 |
| | (9.41-13.52) | (3.43-6.42) | (81.21-86.33) |
| Low paid, t-1 | 6.26 | 4.95 | 88.79 |
| | (4.55-7.74) | (3.62-6.74) | (86.38-90.70) |
| High paid, t-1 | 4.36 | 2.43 | 93.22 |
| | (3.46-5.25) | (1.77-3.15) | (92.21-94.30) |
| | Threshold 2 | | |
| Non-employment, t-1 | 11.53 | 8.39 | 80.08 |
| | (9.48-14.98) | (6.42-10.82) | (76.16-82.98) |
| Low paid, t-1 | 6.21 | 7.74 | 86.05 |
| | (4.74-7.34) | (6.24-9.75) | (83.99-87.86) |
| High paid, t-1 | 4.09 | 3.80 | 92.11 |
| | (3.14-5.12) | (2.93-4.71) | (90.87-93.34) |

*Source:* SOEP, waves 1998-2003, n=2,966

Threshold 1: 2/3 of the median, Threshold 2: First quintile

The 5th and 95th percentiles are given in parentheses, derived using parametric bootstrap with 200 replications.

Table 9: Estimated Transition Matrices: selected samples with respect to the initial state

| | Non-employment, t | Low paid, t | High paid, t |
|---|---|---|---|
| *Initially not employed* | | Threshold 1 | |
| Non-employment, t-1 | 67.67 | 11.22 | 21.11 |
| | (64.00-71.23) | (8.71-14.13) | (18.16-23.48) |
| Low paid, t-1 | 47.94 | 16.28 | 35.79 |
| | (34.87-56.93) | (10.49-23.46) | (28.34-45.54) |
| High paid, t-1 | 37.71 | 9.39 | 52.91 |
| | (28.08-46.44) | (6.03-13.46) | (44.44-63.24) |
| | | Threshold 2 | |
| Non-employment, t-1 | 67.20 | 15.37 | 17.43 |
| | (63.33-70.76) | (12.64-18.79) | (14.71-19.68) |
| Low paid, t-1 | 46.74 | 20.70 | 32.56 |
| | (36.45-54.72) | (14.44-27.95) | (26.15-41.44) |
| High paid, t-1 | 35.21 | 12.17 | 52.62 |
| | (26.17-44.95) | (8.09-16.71) | (43.29-62.62) |
| *Initially low paid* | | Threshold 1 | |
| Non-employment, t-1 | 21.84 | 40.11 | 38.05 |
| | (14.74-31.04) | (30.73-50.31) | (28.85-46.27) |
| Low paid, t-1 | 10.25 | 40.83 | 48.92 |
| | (7.91-12.63) | (35.57-46.58) | (42.67-54.72) |
| High paid, t-1 | 7.40 | 22.84 | 69.76 |
| | (4.69-10.33) | (15.80-31.24) | (61.01-77.46) |
| | | Threshold 2 | |
| Non-employment, t-1 | 18.51 | 45.96 | 35.53 |
| | (13.10-25.48) | (37.41-54.88) | (26.93-43.05) |
| Low paid, t-1 | 8.57 | 43.08 | 48.35 |
| | (6.74-10.30) | (38.69-47.69) | (43.43-53.03) |
| High paid, t-1 | 5.75 | 23.45 | 70.80 |
| | (3.72-7.82) | (17.57-30.58) | (63.81-76.89) |
| *Initially high paid* | | Threshold 1 | |
| Non-employment, t-1 | 5.07 | 2.30 | 92.63 |
| | (3.63-7.82) | (1.28-3.71) | (89.59-94.73) |
| Low paid, t-1 | 2.12 | 1.96 | 95.91 |
| | (1.30-3.19) | (1.04-3.31) | (93.97-97.26) |
| High paid, t-1 | 1.05 | 0.68 | 98.26 |
| | (0.83-1.26) | (0.52-0.88) | (97.96-98.53) |
| | | Threshold 2 | |
| Non-employment, t-1 | 5.32 | 3.81 | 90.87 |
| | (3.46-8.77) | (2.33-5.76) | (86.97-93.55) |
| Low paid, t-1 | 1.97 | 2.81 | 95.23 |
| | (1.27-2.88) | (1.78-4.38) | (93.34-96.49) |
| High paid, t-1 | 0.85 | 0.95 | 98.20 |
| | (0.66-1.02) | (0.77-1.16) | (97.90-98.46) |

*Source:* SOEP, waves 1998-2003, n=2,966

Threshold 1: 2/3 of the median, Threshold 2: First quintile

The 5th and 95th percentiles are given in parentheses, derived using parametric bootstrap with 200 replications. Transition probabilities are calculated separately for three groups, defined by their initially observed state.

Table 10: Estimated State Dependence (SD)

| | Threshold 1 | | | |
|---|---|---|---|---|
| | All men | Not employed ($t_0$) | Low paid ($t_0$) | High paid ($t_0$) |
| SD LP | 2.52 | 6.89 | 17.99 | 1.28 |
| | (0.97-4.23) | (1.74-12.12) | (9.23-26.37) | (0.44-2.49) |
| SD NP | 6.63 | 29.96 | 14.43 | 4.02 |
| | (4.54-9.97) | (21.51-40.16) | (8.97-21.89) | (2.56-6.81) |
| SD NP-LP | 2.37 | 1.83 | 17.28 | 1.62 |
| | (0.78-4.32) | (-2.54-6.00) | (7.60-27.51) | (0.69-2.96) |
| SD LP-NP | 1.90 | 10.23 | 2.85 | 1.07 |
| | (0.10-3.76) | (-0.59-20.86) | (-0.70-6.10) | (0.26-2.09) |
| | Threshold 2 | | | |
| | All men | Not employed ($t_0$) | Low paid ($t_0$) | High paid ($t_0$) |
| SD LP | 3.94 | 8.52 | 19.63 | 1.86 |
| | (2.06-6.01) | (3.28-13.71) | (12.08-27.04) | (0.85-3.27) |
| SD NP | 7.44 | 31.99 | 12.76 | 4.47 |
| | (4.82-11.65) | (22.07-42.84) | (13.23-32.40) | (2.56-7.93) |
| SD NP-LP | 4.59 | 3.19 | 22.51 | 2.87 |
| | (2.21-7.33) | (-1.72-8.10) | (13.23-32.40) | (1.48-4.74) |
| SD LP-NP | 2.12 | 11.53 | 2.82 | 1.12 |
| | (0.50-3.70) | (2.10-20.42) | (0.29-5.27) | (0.41-1.94) |

*Source:* SOEP, waves 1998-2003, n=2,966

Threshold 1: 2/3 of the median, Threshold 2: First quintile

The 5th and 95th percentiles are given in parentheses, derived using parametric bootstrap with 200 replications.

SD: State Dependence; LP: Low Pay; NP: No Pay;

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# Appendix

Table A1: Dynamic Multinomial Logit Model, Threshold 1: Initial State equation and Attrition Process

| | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Model 1 | | | | | | Model 2 | | | | | |
| | Initial State | | | | Attrition | | Initial State | | | | Attrition | |
| | Low paid | | Non-employment | | | | Low paid | | Non-employment | | | |
| Low paid, t-1 | | | | | 0.20 | 0.21 | - | - | - | - | 0.24 | 0.37 |
| Non-employment, t-1 | | | | | 0.44** | 0.15 | - | - | - | - | 0.94 | 0.51 |
| Year 2000 | 0.51** | 0.19 | 0.26 | 0.15 | - | - | 0.52 | 0.29 | 0.03 | 0.26 | - | - |
| Year 2001 | - | - | - | - | 0.01 | 0.15 | - | - | - | - | 0.39 | 0.21 |
| Year 2002 | - | - | - | - | 1.00** | 0.13 | - | - | - | - | 0.60** | 0.20 |
| Year 2003 | - | - | - | - | 0.69** | 0.14 | - | - | - | - | 0.57* | 0.28 |
| Age | -0.43** | 0.09 | -0.23** | 0.07 | -0.08 | 0.05 | -0.81** | 0.16 | -0.60** | 0.15 | -0.18* | 0.08 |
| Age squared $*10^{-2}$ | 0.49** | 0.12 | 0.30** | 0.09 | 0.09 | 0.07 | 0.93** | 0.21 | 0.74** | 0.20 | 0.20* | 0.10 |
| Apprenticeship | -0.66** | 0.24 | -1.07** | 0.19 | -0.14 | 0.14 | -1.37** | 0.42 | -2.02** | 0.41 | -0.21 | 0.23 |
| Vocational training | -1.34** | 0.35 | -1.39** | 0.23 | -0.04 | 0.16 | -2.73** | 0.58 | -3.06** | 0.53 | -0.04 | 0.25 |
| University | -1.09** | 0.34 | -1.74** | 0.27 | -0.01 | 0.16 | -2.30** | 0.59 | -3.21** | 0.57 | 0.06 | 0.26 |
| Non German | 0.75** | 0.22 | 0.90** | 0.17 | 0.23* | 0.11 | 1.52** | 0.37 | 1.84** | 0.36 | 0.34* | 0.17 |
| Married | -0.93** | 0.24 | -1.04** | 0.18 | -0.12 | 0.11 | -1.46** | 0.37 | -1.63** | 0.34 | -0.16 | 0.16 |
| Children | 0.03 | 0.12 | 0.16* | 0.08 | -0.13* | 0.05 | 0.09 | 0.16 | 0.24 | 0.14 | -0.19* | 0.08 |
| Handicap | 0.82* | 0.38 | 1.42** | 0.22 | -0.12 | 0.19 | 1.64** | 0.57 | 2.41** | 0.48 | -0.29 | 0.28 |
| Local unemp. rate | 0.09* | 0.04 | 0.13** | 0.03 | -0.03 | 0.02 | 0.18** | 0.06 | 0.24** | 0.06 | -0.01 | 0.03 |
| Interviewer Drop out | - | - | - | - | 0.68** | 0.16 | - | - | - | - | 0.86** | 0.22 |
| Constant | 5.65** | 1.54 | 1.73 | 1.32 | -1.27 | 0.97 | 10.82** | 2.65 | 6.23* | 2.64 | 0.13 | 1.50 |
| | | Coef. | Std. Err. | | | | | Coef. | Std. Err. | | | |
| ca | | - | - | | | | | 1.43** | 0.29 | | | |
| cb | | - | - | | | | | 0.65* | 0.27 | | | |
| cc | | - | - | | | | | 0.82** | 0.14 | | | |

Unobserved heterogeneity is assumed to follow a multivariate normal distribution. Observations: 2,966 individuals.

Model 1: No unobserved heterogeneity; Model 2: Jointly distributed unobserved heterogeneity.

Threshold 1: 2/3 of the median wage; Threshold 2: first quintile of the wage distribution.

*: statistically significant at least at the 5% level; **: statistically significant at least at the 1% level.

Table A2: Dynamic Multinomial Logit Model, Threshold 2: Initial State equation and Attrition Process

| | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Model 1 | | | | | | Model 2 | | | | | |
| | Initial State | | | | Attrition | | Initial State | | | | Attrition | |
| | Low paid | | Non-employment | | | | Low paid | | Non-employment | | | |
| Low paid, t-1 | - | - | - | - | 0.32 | 0.17 | - | - | - | - | 0.63 | 0.33 |
| Non-employment, t-1 | - | - | - | - | 0.46** | 0.15 | - | - | - | - | 0.78 | 0.55 |
| Year 2000 | 0.43** | 0.15 | 0.28 | 0.15 | - | - | 0.41 | 0.23 | 0.09 | 0.26 | - | - |
| Year 2001 | - | - | - | - | 0.00 | 0.15 | - | - | - | - | 0.37 | 0.21 |
| Year 2002 | - | - | - | - | 1.01** | 0.13 | - | - | - | - | 0.59** | 0.21 |
| Year 2003 | - | - | - | - | 0.69** | 0.14 | - | - | - | - | 0.55 | 0.28 |
| Age | -0.34** | 0.07 | -0.26** | 0.07 | -0.08 | 0.05 | -0.67** | 0.13 | -0.61** | 0.15 | -0.16 | 0.08 |
| Age squared $*10^{-2}$ | 0.36** | 0.10 | 0.32** | 0.10 | 0.00 | 0.00 | 0.73** | 0.17 | 0.74** | 0.19 | 0.00 | 0.00 |
| Apprenticeship | -0.37 | 0.20 | -1.06** | 0.19 | -0.14 | 0.14 | -0.95** | 0.35 | -1.91** | 0.39 | -0.21 | 0.23 |
| Vocational training | -1.18** | 0.26 | -1.43** | 0.23 | -0.03 | 0.16 | -2.34** | 0.45 | -3.03** | 0.50 | -0.03 | 0.25 |
| University | -1.19** | 0.28 | -1.79** | 0.27 | 0.00 | 0.16 | -2.34** | 0.48 | -3.27** | 0.54 | 0.08 | 0.26 |
| Non German | 0.79** | 0.17 | 0.96** | 0.17 | 0.22* | 0.11 | 1.57 | 0.31 | 1.94** | 0.35 | 0.33 | 0.17 |
| Married | -0.61** | 0.18 | -1.05** | 0.18 | -0.12 | 0.11 | -1.01** | 0.28 | -1.50** | 0.31 | -0.14 | 0.16 |
| Children | -0.07 | 0.09 | 0.15 | 0.08 | -0.13* | 0.05 | -0.07 | 0.13 | 0.15 | 0.13 | -0.19* | 0.08 |
| Handicap | 0.82** | 0.29 | 1.47** | 0.22 | -0.13 | 0.19 | 1.68** | 0.46 | 2.57** | 0.46 | -0.24 | 0.28 |
| Local unemp. rate | 0.09** | 0.03 | 0.13** | 0.03 | -0.03 | 0.02 | 0.17** | 0.05 | 0.25** | 0.06 | -0.01 | 0.03 |
| Interviewer Drop out | - | - | - | - | 0.69** | 0.16 | - | - | - | - | 0.85** | 0.22 |
| Constant | 4.77** | 1.25 | 2.27 | 1.33 | -1.41 | 0.97 | 9.80** | 2.24 | 6.89** | 2.58 | -0.13 | 1.47 |
| | | Coef. | Std. Err. | | | | | Coef. | Std. Err. | | | |
| ca | | - | - | | | | | 1.31** | 0.22 | | | |
| cb | | - | - | | | | | 0.61** | 0.23 | | | |
| cc | | - | - | | | | | 0.84** | 0.14 | | | |

Unobserved heterogeneity is assumed to follow a multivariate normal distribution. Observations: 2,966 individuals.

Model 1: No unobserved heterogeneity; Model 2: Jointly distributed unobserved heterogeneity.

Threshold 1: 2/3 of the median wage; Threshold 2: first quintile of the wage distribution.

*: statistically significant at least at the 5% level; **: statistically significant at least at the 1% level.

Table A3: Dynamic Multinomial Logit Model, Estimation with unobserved heterogeneity and without the attrition process

| | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. | Coef. | Std. Err. |
|---|---|---|---|---|---|---|---|---|
| | Threshold 1 | | | | Threshold 2 | | | |
| | Low paid | | Non-employment | | Low paid | | Non-employment | |
| Low paid, t-1 | 1.10** | 0.29 | 1.04** | 0.35 | 1.23** | 0.24 | 1.11** | 0.30 |
| Non-employment, t-1 | 1.67** | 0.33 | 2.41** | 0.28 | 1.80** | 0.28 | 2.60** | 0.29 |
| Year 2000 | -0.03 | 0.26 | 0.16 | 0.24 | 0.06 | 0.22 | 0.20 | 0.25 |
| Year 2001 | 0.15 | 0.23 | 0.38 | 0.22 | 0.16 | 0.20 | 0.40 | 0.22 |
| Year 2002 | 0.64** | 0.23 | 0.78** | 0.22 | 0.37 | 0.20 | 0.78** | 0.23 |
| Year 2003 | 0.26 | 0.25 | 1.02** | 0.23 | -0.04 | 0.22 | 1.00** | 0.23 |
| Age | -0.50** | 0.11 | -0.41** | 0.11 | -0.34** | 0.10 | -0.40** | 0.11 |
| Age squared $*10^{-2}$ | 0.59** | 0.14 | 0.55** | 0.14 | 0.39** | 0.14 | 0.55** | 0.14 |
| Apprenticeship | -0.73** | 0.27 | -1.83** | 0.32 | -0.78** | 0.25 | -1.88** | 0.32 |
| Vocational training | -1.59** | 0.35 | -2.46** | 0.38 | -1.80** | 0.32 | -2.56** | 0.40 |
| University | -2.22** | 0.42 | -3.34** | 0.46 | -2.41** | 0.38 | -3.51** | 0.48 |
| Non German | 1.09** | 0.24 | 1.54** | 0.27 | 1.14** | 0.22 | 1.61** | 0.27 |
| Married | -0.89** | 0.23 | -1.30** | 0.24 | -0.99** | 0.20 | -1.34** | 0.24 |
| Children | 0.12 | 0.10 | 0.23* | 0.10 | 0.08 | 0.09 | 0.23* | 0.10 |
| Handicap | 0.95** | 0.34 | 2.08** | 0.30 | 0.84** | 0.30 | 2.14** | 0.31 |
| Local unemp. rate | 0.20** | 0.04 | 0.16** | 0.04 | 0.15** | 0.04 | 0.16** | 0.04 |
| Constant | 3.98* | 1.97 | 2.04 | 2.10 | 2.24 | 1.78 | 1.75 | 2.11 |
| | | Coef. | Std. Err. | | | Coef. | Std. Err. | |
| $\sigma_1^2$ | | 4.69** | 1.14 | | | 4.90** | 1.07 | |
| $\sigma_2^2$ | | 7.61** | 1.79 | | | 8.26** | 1.96 | |
| $\rho_{12}$ | | 0.60** | 0.11 | | | 0.66** | 0.08 | |
| Log-Likelihood | | -3,442.95 | | | | -3,969.36 | | |

Unobserved heterogeneity is assumed to follow a multivariate normal distribution. Observations: 2,966 individuals.

The estimation results for the initial state are not reported here and are quite similar to the one of the joint estimation with the attrition process.

Threshold 1: 2/3 of the median wage; Threshold 2: first quintile of the wage distribution.

*: statistically significant at least at the 5% level; **: statistically significant at least at the 1% level.