The British Low-Wage Sector and the Employment Prospects of the Unemployed

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Abstract Are low wages an instrument for the unemployed to switch to high-paying jobs within a medium-term period? Using data from the British Household Panel Survey (BHPS), the labor market dynamics of men are analyzed up to six years after entering unemployment. An alternative econometric approach is presented that allows for correlated random effects between the three labor market states (high-paid employed, low-paid employed and unemployed). The results show that low wages help to significantly reduce the risk of future unemployment. Indications of a "springboard effect" of low wages are found, especially for men without post-secondary education. However, the calculated probability of obtaining a high-paying job is noticeably influenced by the monetary level of the low-wage threshold.

Keywords: low-pay dynamics, simulated correlated multivariate random effects probit model, state dependence, unobserved heterogeneity

JEL Classification Numbers: J64, J62, J31

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1 Introduction

In Great Britain, there exist several public strategies for the activation and labor market integration of the unemployed (an overview can be found in the study by Tergeist and Grubb 2006); however, their impact is controversial (e.g., Card et al. 2010, Kluve 2010). In this study, the hypothesis of whether low-wage employment could work within a medium-term time frame as an instrument for improving the labor market prospects of the unemployed is tested: do low-paying jobs make it easier to find better-paid employment compared to remaining unemployed?[1] In total, approximately one-fifth of the employed in Great Britain are affected by low wages (OECD 2012). In the political discussion, the concern is that low wages might push workers into a low pay-no pay cycle (OECD 1997, European Commission 2003). Several studies (e.g., Stewart and Swaffield 1999, Stewart 2007, Cappellari and Jenkins 2008, Clark and Kanellopoulos 2013) confirm these concerns and illustrate a particularly negative picture of the employment prospects of low-paid workers in Great Britain. For example, Stewart (2007) concludes that being employed in the low-wage sector has "almost as large an adverse effect as unemployment on future prospects" [p. 511]. Whether this general negative picture of low wages also holds for the subsample of initially unemployed workers is examined in this study.

In most empirical studies (e.g., Stewart and Swaffield 1999, Stewart 2007, Clark and Kanellopoulos 2013, Knabe and Plum 2013), the labor market effect of low wages is estimated on the basis of the total labor force (within a certain age frame). The derived predictions and partial effects are calculated under the hypothesis that an individual was unemployed, low-paid, or high-paid employed in the previous period, given that all other characteristics remain constant. One shortcoming of this strategy is that the sample might contain individuals that are heterogeneous with respect to their labor market expectations: a worker might be employed in the low-wage sector for a longer period by choice because the position he holds maximizes his utility under the constraint of his productivity. Hence, the sample of low-paid workers could consist of individuals who do not want to leave their labor market positions, and therefore, the estimated effect of low wages on their employment prospects could be biased. The same could be true for someone who is voluntarily unemployed. To address these aspects, I apply a different identification strategy: only the time span after an individual became unemployed is considered. Applying this strategy ensures that the observed individual who works in

[1]In the literature, this effect is also called the "stepping stone effect" (see for instance Uhlendorff 2006) or "springboard effect" (see for instance Knabe and Plum 2013).

the low-wage sector does so to escape unemployment. Furthermore, only the first six years after an individual enters unemployment are considered, assuming that his persistence in the respective labor market position might be influenced by the duration of the respective spell length and have a negative effect on the amount of labor market transitions.[2]

From a theoretical perspective, the effect of a low-paying job on one's employment prospects is unclear. In general, finding a job might be helpful to increase the level of human capital or, in the case of foregoing unemployment, at least stop its deterioration. However, the positive impact of low-wage employment on the level of human capital could be doubted if the job is associated with a low social class, e.g., monotonic manual work, which might have almost no significant effect on the manual or intellectual abilities of the worker.[3] Moreover, due to the lack of complete information in labor markets, signals might play an important role and might not be in favor for low-paid work. Because the true productivity of an applicant is unknown to an employer, the employer has to evaluate the applicant using the information available to him, for example, by looking at the applicant's education or work experience. However, if the applicant has picked up a low-paying job in the past, this might cause a negative signal in future terms: the employer could interpret this (falsely) as poor productivity. This might be especially relevant for people who are highly educated because the gap between their formal qualifications and their employment record is more noticeable. Layard et al. (1991, p. 249) summarized this aspect in the following phrase: "While unemployment is a bad signal, being in a low-quality job may well be a worse one".

There exist numerous studies that analyze the labor market transitions of low-wage British workers. Stewart and Swaffield (1999) use data from the British Household Panel Survey (BHPS) and apply a bivariate probit model. They conclude that "the probability of being low-paid depends strongly on low pay in the previous year" [p. 23], and evidence of a low pay-no pay cycle is found. Stewart (2007), also using data from the BHPS, applies a range of dynamic random and fixed effects estimators and finds evidence that low-wage employment has almost as large an adverse effect on the probability of becoming unemployed in the subsequent period as unemployment. The author concludes that "in terms of future employment prospects, low-wage jobs are closer to unemployment than to higher-paid jobs'' (Stewart 2007, p. 529). Cappellari and Jenkins (2008), also using data

[2] For example, in several studies "negative duration dependence" in unemployment was detected (see for instance Kroft et al. 2013).

[3] This might go along with the differentiation into "good" and "bad" jobs (Acemoglu 2001).

from the BHPS, model the transition into and out of low-paid employment. A multivariate probit model is applied that also accounts for panel-dropout, employment retention and the initial conditions problem. Evidence is found that the probability of being low-paid is higher for someone who works in the low-wage sector compared to a high-paid one. Clark and Kanellopoulos (2013), using data from the European Community Household Panel (ECHP), estimate state dependence in low-pay in twelve European countries, including Great Britain. Applying various dynamic random effects probit models, the authors find evidence in Great Britain and other countries of low-pay persistence. Although these studies find indications of low-pay persistence, low wages are not necessarily harmful because remaining unemployed might have a stronger deteriorating effect on an individual's probability of occupational advancement. There exists empirical evidence of "negative duration dependence" in unemployment (see for instance Kroft et al. 2013); hence, the probability of remaining unemployed increases with its duration or, to reverse the above quote by Layard et al. (1991), although working in the low-wage sector may lower one's chances of finding high-paying work, remaining unemployed may make it even more difficult.

The aim of this study is to examine how working for a low wage affects the chances of the currently unemployed to find better-paying work. As shown by Knabe and Plum (2013), labor market transitions could be influenced by job-related and individual characteristics. For example, Knabe and Plum (2013) find evidence that in the German labor market, when a low-paying job is associated with a low social status, the probability of obtaining better-paying work is lower than when the job has a high social status. The findings were similar for those with a college education: while low wages were beneficial for a non-college-educated worker, no positive impact was found for workers with some college education.[4] Following this approach, the effect of low wages is examined according to employment-related characteristics (the social status accorded to the job) and the educational background of the person (whether he has obtained a post-secondary education).

To analyze the labor market transitions in Great Britain, data from the BHPS for the years 1996 to 2008 are used. The crucial assumption in this study is that the labor market position in the previous period has a genuine effect on the current one. To estimate true state dependence, the aspect of unobserved heterogeneity must be allowed for: workers not only differ according to observable characteristics such as educational background but also in unobservable characteristics, such as motivation or ability (Heckman 1981a). Because three different and mutually exclusive labor market positions are considered (having a high-

[4]These results were confirmed by Mosthaf (2014)

paying job, having a low-paying job, and being unemployed), the unobserved characteristics could be correlated between these stages. To address correlated unobserved heterogeneity, correlated random effects parameters are included in the estimation. Furthermore, it must be noted that these unobservable characteristics might be correlated with the labor market position in the first observable period in the sample (Heckman 1981b). In the economics literature, this is also referred to as the “initial conditions problem”.

For the estimation, a modified version of the bivariate random effects probit model as proposed by Stewart (2007) is applied. Based on simulated multivariate normal probabilities (Cappellari and Jenkins 2006, Plum 2014), a correlated simulated multivariate random effects (CSM RE) probit model is applied. In the standard random effects probit model the individual likelihood is estimated for each point in time and the product of each is taken for the total length of time under observation. In contrast, the correlation of the labor market positions between the different time points is estimated at once in the CSM RE probit model. The advantage of this technique is that a high degree of accuracy is already achieved when using a small number of pseudo-random numbers (here, Halton draws) for simulation (Plum 2014).

The main findings of the paper are that for men with no post-secondary education, low wages significantly increase the likelihood of obtaining a high-paying job compared to remaining unemployed. Furthermore, the risk of becoming unemployed in the future is noticeably reduced. The effects are far fewer when there are no allowances made for correlated random effects. The probability of transitioning into a better-paying job is marginally lowered when the job is associated with a low social class, but the risk of future unemployment is still strongly reduced. Indications for persistence in low-pay employment are only found when not allowing for correlated random effects. The results are compared to an estimation based on the total sample, and there are indications that, especially for someone who was low-paid, the average partial effect of becoming unemployed is lower when compared to the findings in the reduced sample. Several further estimations are applied that refer to the effect of negligible wage changes and the definition of the low-wage threshold. In both estimations, evidence is found that low wages substantially reduce the risk of future unemployment. However, the probability of climbing up the salary ladder is very sensitive to changes in the definition of the low-pay threshold: wage mobility seems to be higher for lower wages, indicating an increased probability of staying in a low-paying job when the respective threshold is lifted.

The remainder of the paper is structured as follows: the second section gives an overview of the data used and some descriptive statistics. The third section describes the applied econometric model, and in section 4, the results are presented together with some robustness checks. The last section concludes the paper.

2 Data and Descriptive Statistics

To derive the impact of low-paying work on the probability obtaining a high-paying job in Great Britain, data from the BHPS from the years 1996-2008 are used. The BHPS is a nationally representative survey of households and individuals, which includes information on employment (Taylor 2006). Starting in 1991, the households were re-interviewed each year, and the panel covers 18 years, with the final wave occuring in 2008.

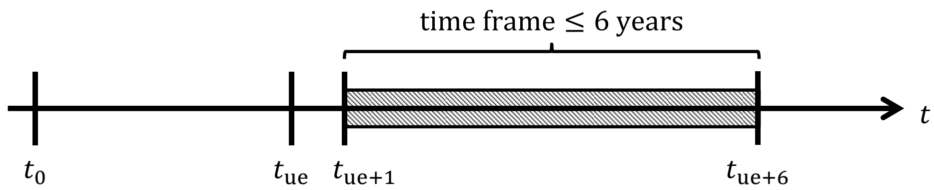
Because earning dynamics between men and women differ substantially (see for instance Blackaby et al. 2005, Arulampalam et al. 2007), it is assumed that to capture the effect of gender, it would not be sufficient to integrate a gender-related indicator variable into the estimation (for discussion, see Machin and Puhani 2003, Cappellari and Jenkins 2008). Therefore, the sample is split according to sex, and only the employment dynamics of men are considered. It is also assumed that the employment schemes of self-employed or disabled men and men attending school or who served in the army differ substantially compared to the employment dynamics of employees and are therefore dropped from the sample. Due to the schooling and retirement schemes, observations for individuals younger than 20 years and older than 60 years are also dropped.

Those individuals without employment are separated into unemployed and inactive. Applying the ILO definition, individuals are defined as unemployed when they are actively searching for a job and are defined as inactive otherwise.[5] It is unclear to what degree those who are inactive seek to participate in the labor market and are therefore excluded from the sample.

The goal of the study is to analyze the medium-term effect of low-paying jobs on the future labor market outcomes of initially unemployed men. Therefore, the sample is restricted

[5] According to the ILO definition, the second restriction for the differentiation between being unemployed and inactive is whether the person is ready to begin a work within the next two weeks. The BHPS does not have any information concerning this issue; therefore, the differentiation is solely based on the searching scheme.

Figure 1: Identification of labor market dynamics



t_0 = first time observed in the sample; t_{ue} = being observed for the first time unemployed after being employed; $t_{\text{ue+6}}$ = up to six years after t_{ue}. The shadowed box indicates the analyzed time frame.

to the first six years after becoming unemployed for the first time. Caused by factors such as a lack of employment experience, one can expect that the labor market outcome of someone who had never been employed before would differ substantially compared to someone who had been employed in the past. Therefore, the individual has to be employed in the period before becoming unemployed for the first time (see also Figure 1). Moreover, individuals who are in the sample for fewer than two consecutive waves are dropped, without allowing for reentry into the sample. The final sample contains 210 individuals and 796 observations.

Table I: Transition into High-Paying Job

years after becoming unemployed[1]	First time being high-paid[†] Total	Without post-secondary education	With post-secondary education
1	95 (−)	59 (−)	36 (−)
2	34 (17)	21 (12)	13 (5)
3	14 (12)	12 (11)	2 (1)
4	12 (11)	8 (7)	4 (4)
5	2 (2)	− (−)	2 (2)
6	1 (1)	1 (1)	− (−)
$\sum$	158 (43)	101 (31)	57 (12)
Total	210	143	67
Share	75.23% (20.47%)	78.32% (21.67%)	85.07% (17.91%)

Source: BHPS waves 8-18, $N = 796$.

† Number in parentheses refers to being low-paid in at least one period before.

1 *years after becoming unemployed* refers to years when the initially unemployed man obtains a high-paying job for the first time. Note that the labor market position is observed at one time point in the respective year.

To separate between high-paying and low-paying employment, the definition used by the OECD (1997) is applied: a job with a labor market income that exceeds at least two-thirds of the median gross hourly wage of both sexes (including paid overtime) is defined as a high-paid job, and otherwise as a low-paid job. The low-wage threshold is annually adjusted according to the weighted labor market income. The low-wage threshold stood at £4.73 in 1998 and increased annually up to £7.70 in 2008.

Table I lists the length, measured in years, when an initially unemployed man obtains a high-paying job for the first time. Approximately half of the initially unemployed men (95 out of 210) switched directly from unemployment to high-paid employment (first number of column II). This number drops for the preceding periods, e.g., 34 men were able to obtain a high-paid job two years after entering unemployment, 14 three years after unemployment, and so on. Altogether, three-quarters of initially unemployed men were able to become high-paid employees within the first six years. The number inside the brackets lists the number of men who worked in the low-wage sector before beginning high-paid employment. Altogether, 43 out of the 210 (21%) initially unemployed men were working in the low-wage sector before being able to obtain high-paid employment. If only those men who did not manage to transition directly into high-paid employment in the first period are considered, approximately 63% worked in the low-wage sector before obtaining a high-paid job. Following the suggestions in Table I, the low-wage sector plays a role for those men who did not obtain high-paid employment immediately after unemployment.

Table II: Transition Matrix

	High-Paid$_t$	Low-Paid$_t$	Unemployed$_t$	Total$_{t-1}$
High-Paid$_{t-1}$	81.88	14.06	4.06	40.20
Low-Paid$_{t-1}$	30.93	62.37	6.70	24.37
Unemployed$_{t-1}$	42.55	31.21	26.24	35.43
Total$_t$	55.53	31.91	12.56	100.00

Source: BHPS waves 8-18, $N = 796$.

A first impression as to whether low-paying employment helps to improve occupational advancement probability might be derived by looking at a transition matrix. The transition matrix gives the probability of being high-paid, low-paid, or unemployed in the current period t conditional on one of those three labor market positions in the previous period $t-1$. Table II suggests that the best chance of becoming high-paid is when that person was already highly paid in the previous year. Furthermore, the transition matrix indicates that the chances of becoming high-paid after having been low-paid in the previous year are much lower (31%) compared to the conditional probability of someone who was unemployed (43%).

However, it must be doubted whether safe conclusions about the effect of low wages can be drawn when only considering the transition matrix. The implicit assumption is that the differences in the conditional probabilities in the transition matrix are exclusively caused by the different labor market positions and not by differences in the (un)observable characteristics. However, for example, it is expected that a high educational level has a positive impact on the probability of becoming high-paid and that men with no post-secondary education are more often affected by low-paid jobs. However, unobservable aspects, such as an individual's level of motivation could also cause differences in his probability of achieving labor market transition, e.g., someone who is highly motivated might have a better chance of climbing up the salary ladder. Hence, the source of heterogeneity in labor market transitions among men might be explained by differences in their observable and unobservable characteristics. Table III lists the control variables that are assumed to have an influence on the probability of occupational advancement.

Table III: Control variables

Variables	Description
Young	Dummy: 1 if observation is 30 years or younger, 0 otherwise
Old	Dummy: 1 if observation is older than 54 years, 0 otherwise
Married	Dummy: 1 if observation is married, 0 otherwise
Health	Dummy: 1 if self reported health status is excellent or good, 0 else
Unemployment rate	State-level unemployment rate; annual averages; in percent
Interaction with labor market position	
Post-sec. educ.	Dummy: 1 if individual has post-secondary education (ISCED 5 or 6), 0 otherwise[1]
Low job status	Dummy: 1 if presents' job RGSC-value is 5 or 6, 0 otherwise[2]

[1] *ISCED*: International Standard Classification of Education
[2] *RGSC*: Registrar General's Social Classes is 1=Professional occ., 2=Managerial & technical occ., 3=Skilled non-manual, 4=Skilled manual, 5=Partly skilled occ., 6=Unskilled occ.

In Table IV, the distribution of the control variables according to the individual's labor market position is presented. It can be easily noted that the observable characteristics differ according to labor market position. For example, approximately 20% of high-paid individuals are 30 years old or less, and this figure is approximately twice as high for the low-paid (38%) and still 14 percentage points higher for the unemployed (34%). Noticeable labor market-related variations in the distribution of the control variables are also observable for the variables referring to an individual's marital status and state of health.

In reference to educational background, the highest share of men with post-secondary education can be found among the high-paid (37%), followed by the unemployed (31%) and the low-paid (24%). Indications are also found in the descriptive statistics that educational background has an impact on the lenght of time from entering unemployment until switching to high-paid employment. In columns III and IV of Table I, the length of time until an individual obtains a high-paid job for the first time, measured in years, is also differentiated according to the level of education. It can be noted that approximately 40% of men with no post-secondary education are able to switch directly from initial unemployment to high-paid employment (59 out of 143), while this share is approximately 14 percentage points higher for men with post-secondary education (36 out of 67). Moreover, approximately one-third of men without a post-secondary education and who were able to obtain a high-paying job within the six year interval previously worked in the low-wage sector (31 out of 101). Referring to men with a post-secondary education, the share is approximately 10 percentage points lower (12 out of 57).

Table IV: Descriptive Statistics[1]

	Full Sample$_t$	high-paid$_t$	low-paid$_t$	unemployed$_t$
Young	0.274	0.199	0.378	0.340
Old	0.104	0.109	0.098	0.100
Married	0.665	0.744	0.594	0.490
Health	0.687	0.708	0.665	0.650
Unemployment-rate	5.198	5.190	5.247	5.111
Post-sec. educ.	0.323	0.373	0.240	0.310
Low job status	0.257[2]	0.183	0.386	–
Observations	796	442	254	100

Source: BHPS waves 8-18, $N = 796$.
[1] Share of observations in the respective group.
[2] Only including high-paid employed and low-paid employed in the full sample.

Job-related differences can also be observed on the social class level: approximately one-quarter of the low-paid workers have employment that is associated with a low social class – but referring to high wages, only 18% have employment associated with a low social class. Hence, to evaluate low wages and their labor market impact, it is necessary to take the differences in the observable characteristics into account.

3 Econometric Specification

The general assumption in this study is that one's previous labor market position has a genuine effect on one's present labor market position. Furthermore, it is assumed that the probability of remaining in a labor market position is influenced by its respective duration. Thus, to evaluate low wages and their labor market impact, the sample is restricted to the first six years after becoming unemployed (see also Figure 1). It is also assumed that labor market transitions follow a first-order Markov process. In other words, it is assumed that a person's labor market position in the previous year $(t-1)$ has a genuine effect on his current (t) labor market position. In general, when dynamic models are applied, it must address several aspects such as unobserved heterogeneity (Heckman 1981a) and their correlation with the initial conditions (Heckman 1981b). As Stewart and Swaffield (1999) and Arulampalam and Stewart (2009) have noted, not addressing these aspects might cause spurious state dependence.

Referring to the labor market process, the two binary outcome variables are defined as:

$$y_{1it} = \begin{cases} 1 & \text{if the person is employed in a high-paid job,} \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

$$\text{and if } y_{1it} = 0, y_{2it} = \begin{cases} 1 & \text{if the person is unemployed,} \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

where the subscripts $i \in \{1, \ldots, N\}$ indicate the individuals and $t \in \{t_{\text{ue+1}}, \ldots, t_{\text{T}}\}$ indicates the time point. Note that the time point t is in the interval between one year after being unemployed for the first time (t_{ue}) and up to six years later $(t_{\text{ue+6}})$ (see Figure 1). Furthermore, the labor market states are mutually exclusive, e.g., someone who is high-paid $(y_{1it} = 1)$ cannot be unemployed $(y_{2it} = 0)$. For the time period $t \geq 1$, the latent variables $\tilde{y}_{jit}$ with $j \in \{1, 2\}$ are specified by:

$$\tilde{y}_{1it} = x'_{1it}\beta_1 + \gamma_{11}y_{1i(t-1)} + \gamma_{13}y_{3i(t-1)} + \sum_{s=1}^{3} z'_{1i(t-1)}\eta_{1j}y_{si(t-1)} + \alpha_{1i} + \epsilon_{1it}, \tag{3}$$

$$\tilde{y}_{2it} = x'_{2it}\beta_2 + \gamma_{21}y_{1i(t-1)} + \gamma_{23}y_{3i(t-1)} + \sum_{s=1}^{3} z'_{2i(t-1)}\eta_{2j}y_{si(t-1)} + \alpha_{2i} + \epsilon_{2it}. \tag{4}$$

Explanatory variables are the exogenous regressors x'_{1it} and x'_{2it} and the lagged dependent variables y_{2it-1} and y_{3it-1}, with y_{3it-1} referring to being low-paid in the previous period. On the right side of the equation system, being unemployed in $t-1$ is chosen as the reference category. The vectors $z'_{1i(t-1)}$ and $z'_{2i(t-1)}$ refer to those variables that are interacted with the lagged labor market position. The time-invariant error term α_{ji} captures individual-specific effects such as motivation or ability, and ϵ_{jit} is a time-specific idiosyncratic shock. The assumption by now is that the random-effects error terms and the explanatory variables are uncorrelated. However, this assumption seems unrealistic. For example, a high level of motivation might positively influence the educational level. To relax this assumption, the approach of Mundlak (1978) and Chamberlain (1984) is applied by including the time-means of the explanatory variables:

$$\alpha_{1i} = \overline{x}'_{1i}\delta_1 + \kappa_{1i}, \tag{5}$$
$$\alpha_{2i} = \overline{x}'_{2i}\delta_2 + \kappa_{2i}. \tag{6}$$

Furthermore, the labor market position in the initial period might not be randomly distributed due to a correlation between the time-invariant error term and the initial conditions. To address the "initial conditions problem", we follow the suggestion of Wooldridge (2005) by conditioning the estimation on the labor market in the initial period t_0 with being unemployed in t_0 as a reference category:

$$\begin{aligned}\tilde{y}_{1it} = \; & x'_{1it}\beta_1 + \gamma_{11}y_{1i(t-1)} + \gamma_{13}y_{3i(t-1)} + \sum_{s=1}^{3} z'_{1i(t-1)}\eta_{1s}y_{si(t-1)} \\ & +\pi_{11}y_{1i0} + \pi_{13}y_{3i0} + \overline{x}'_{1i}\delta_1 + \kappa_{1i} + \epsilon_{1it},\end{aligned} \tag{7}$$

$$\begin{aligned}\tilde{y}_{2it} = \; & x'_{2it}\beta_2 + \gamma_{21}y_{1i(t-1)} + \gamma_{23}y_{3i(t-1)} + \sum_{s=1}^{3} z'_{2i(t-1)}\eta_{2s}y_{si(t-1)} \\ & +\pi_{21}y_{1i0} + \pi_{23}y_{3i0} + \overline{x}'_{2i}\delta_2 + \kappa_{2i} + \epsilon_{2it}.\end{aligned} \tag{8}$$

The observed binary outcome variable is defined as:

$$\begin{aligned}y_{1it} = \; & \mathbf{1}(x'_{1it}\beta_1 + \gamma_{11}y_{1i(t-1)} + \gamma_{13}y_{3i(t-1)} + \sum_{s=1}^{3} z'_{1i(t-1)}\eta_{1s}y_{si(t-1)} \\ & +\pi_{11}y_{1i0} + \pi_{13}y_{3i0} + \overline{x}'_{1i}\delta_1 + \kappa_{1i} + \epsilon_{1it} > 0),\end{aligned} \tag{9}$$

$$\begin{aligned}\text{and if } y_{1it} = 0, y_{2it} = \; & \mathbf{1}(x'_{2it}\beta_2 + \gamma_{21}y_{1i(t-1)} + \gamma_{23}y_{3i(t-1)} + \sum_{s=1}^{3} z'_{2i(t-1)}\eta_{2s}y_{si(t-1)} \\ & +\pi_{21}y_{1i0} + \pi_{23}y_{3i0} + \overline{x}'_{2i}\delta_2 + \kappa_{2i} + \epsilon_{2it} > 0).\end{aligned} \tag{10}$$

For idiosyncratic shock, the normalization $\epsilon_{jit} \sim N(0,1)$ is chosen and for random effects $\kappa_{ji} \sim N(0, \sigma^2_{\kappa_j})$ is chosen. The composite error term is $\nu_{jit} = \kappa_{ji} + \epsilon_{jit}$[6], and due to the

[6] Note that because the idiosyncratic shock is standard normal distributed and the time-invariant error

time-invariant error term correlated over time, assuming an equi-correlation structure:

$$corr(\nu_{jit}, \nu_{jis}) = \begin{cases} \sigma^2_{\kappa_j} & \text{if } t \neq s, \\ \sigma^2_{\kappa_j} + 1 & \text{if } t = s, \end{cases} \tag{11}$$

and $t, s \in \{t_{\text{ue}+1}, \ldots, t_{\text{T}}\}$. Furthermore, it is assumed that the composite error terms ν_{1it} and ν_{2it} are correlated in the following way:

$$corr(\nu_{1it}, \nu_{2is}) = \rho_\kappa \sigma_{\kappa_1} \sigma_{\kappa_2} \tag{12}$$

and $t, s \in \{t_{\text{ue}+1}, \ldots, t_{\text{T}}\}$.[7] Note that equation (9) can be estimated on its own (e.g. by applying a standard random effects probit model) if $\gamma_{13} = 0$; hence, the probability of becoming high-paid is independent of being low-paid or unemployed in the previous period, and both random effects are uncorrelated ($\rho_\kappa = 0$). However, if being low paid in $t-1$ has a significant impact ($\gamma_{13} \neq 0$), then equation (9) can still be estimated on its own when the random effects σ_{κ_1} and σ_{κ_2} are uncorrelated, such as when $\rho_\kappa = 0$ (Stewart 2007).

To estimate equations (9) and (10), the standard approach is to apply a bivariate random effects probit model.[8] The main feature of this approach is that the individual likelihood for each time point is successively estimated and multiplied over the observed time-sequence, and finally, the logarithm of the product is summed over all individuals.[9] In an extension to this approach, a correlated simulated multivariate random effects (CSM RE) probit model is applied in this study. In the multivariate model, the complete variance-covariance matrix $\mathbf{\Omega_i}$ is estimated at once and not stepwise, as in the other approach.

The dependency between the different time points and labor market positions is caused by the correlation of random effects. Note that y_{2it} is only considered when $y_{1it} = 0$; hence, there exist various variance-covariance matrices with different sizes. The main challenge of this estimation technique is the identification of the order Ψ of the cumulative multivariate normal distribution function $\mathbf{\Phi_\Psi}$. The size of the variance-covariance matrix and with it the

term is normal distributed, the normalization of the composite error term is $\nu_{jit} \neq 1$. Hence, the estimated coefficients must be adjusted by multiplying them by $\left(\sigma^2_{\epsilon_{jit}} / (\sigma^2_{\epsilon_{jit}} + \sigma^2_{\kappa_{ji}})\right)^{1/2}$ (Arulampalam 1990).

[7] It is assumed that the idiosyncratic shocks are uncorrelated, hence $\rho_\epsilon = 0$. The results obtained by Knabe and Plum (2013) report a highly insignificant correlation parameter for the idiosyncratic shocks, and therefore, it is assumed that not controlling for this aspect only has negligible effects.

[8] For the application of this method, see inter alia Alessie et al. (2004), Stewart (2007), Miranda (2011) and Knabe and Plum (2013).

[9] Uhlendorff (2006) estimates dynamic multinomial logit panel data models with random effects, but the estimation strategy is the same.

order Ψ depends on the number of observed time periods $T \in \{2, \ldots, 6\}$ and the number of high-paid periods $t_{\text{hp}} \in \{0, \ldots, 6\}$ with $t_{\text{hp}} \leq T$:

$$\Psi = 2T - \sum_{t=1}^{T} y_{1it} \tag{13}$$

Hence, $\Psi \in \{2, \ldots, 12\}$, with $\Psi = 2$ referring to a person with $T = 2$ and who always been high-paid in the observed time interval and $\Psi = 12$ referring to a person with $T = 6$ and who has never been high-paid in the six years after first becoming unemployed. The likelihood contribution of each individual is:[10]

$$\begin{aligned}\mathbf{\Phi_\Psi} = (&k_{1i2}x'_{1i2}\beta_1, \ldots, k_{1iT}x'_{1iT}\beta_1, (1-y_{1i2})k_{2i2}x'_{2i2}\beta_2, \ldots, (1-y_{1iT})k_{2iT}x'_{2iT}\beta_2; \\ &k_{1i2}k_{1i3}\Omega_{2,1}, \ldots, k_{1i(T-2)}k_{1i(T-1)}\Omega_{T,T-1}, (1-y_{1i2})k_{1i2}k_{2i2}\Omega_{T+1,2}, \ldots, \\ &(1-y_{1i(T-1)})k_{1i2}k_{2i2}\Omega_{T,\Psi}, (1-y_{1i2})k_{2i2}k_{2i3}\Omega_{T+1,T+1}, \ldots, \\ &(1-y_{1i(T-1)})k_{2i(\Psi-1)}k_{2i(\Psi-1)}\Omega_{\Psi-1,\Psi}).\end{aligned} \tag{14}$$

$\mathbf{\Phi_\Psi}$ is the cumulative multivariate normal distribution function of order Ψ, and Ω is the variance-covariance matrix. $\Omega_{p,q}$ refers to row p and column q of the variance-covariance matrix $\mathbf{\Omega}$. In general the variance-covariance matrix Ω of size $\Psi \times \Psi$ is defined as:

$$\mathbf{\Omega_{\Psi\times\Psi}} = \begin{pmatrix} \nu_{1i2},\nu_{1i2} & & & & & \\ \vdots & \ddots & & & & \\ \nu_{1i2},\nu_{1iT} & \cdots & \nu_{1iT},\nu_{1iT} & & & \\ (1-y_{1i2})\nu_{1i2},\nu_{2i2} & \cdots & (1-y_{1i2})\nu_{1i2},\nu_{2iT} & (1-y_{1i2})\nu_{2i2},\nu_{2i2} & & \\ \vdots & \ddots & \vdots & \vdots & \ddots & \\ (1-y_{1iT})\nu_{1i2},\nu_{2iT} & \cdots & (1-y_{1iT})\nu_{1iT},\nu_{2iT} & (1-y_{1i2})\nu_{2i2},\nu_{2iT} & \cdots & (1-y_{1iT})\nu_{2iT},\nu_{2iT} \end{pmatrix} \tag{15}$$

Note that the lines and rows of the variance-covariance matrix that referr to y_{2it} are dropped when the person is high-paid in the respective time point; hence, $1 - y_{1it} = 0$. The model has Ψ levels of explanatory variables and $\Psi(\Psi - 1)\frac{1}{2}$ covariance parameters. There are Ψ sign variables k_{jit}, where:

$$k_{1it} \quad = \quad \begin{cases} 1 & \text{if } y_{1it} = 1, \\ -1 & \text{else.} \end{cases} \tag{16}$$

$$\text{and if } y_{1it} = 0, k_{2it} \quad = \quad \begin{cases} 1 & \text{if } y_{2it} = 1, \\ -1 & \text{else.} \end{cases} \tag{17}$$

[10]To simplify the notation, the lagged dependent variables, the variables that interact with the lagged dependent variables, the labor market position in the initial period and the time means of the explanatory variables are incorporated into x'_{jit}.

The log likelihood to be maximized is the sum of the individual log likelihood contributions:

$$\ln L = \sum_{i=1}^{N} \ln\Phi_{i\Psi}(\boldsymbol{\mu};\boldsymbol{\Omega}), \tag{18}$$

where $\boldsymbol{\mu} = (k_{1i2}x'_{1i2}\beta_1, \ldots, (1-y_{1iT})k_{2iT}x'_{2iT}\beta_2)$ and $\boldsymbol{\Omega} = \Big(k_{1i2}k_{1i3}\Omega_{2,1}, \ldots, (1-y_{1i(T-1)})k_{2i(\Psi-1)}k_{2i(\Psi-1)}\Omega_{\Psi-1,\Psi}\Big)$ refers to the variance-covariance matrix. To derive the likelihood, multivariate normal probability functions of order Ψ are required. Because multivariate normal probability functions of orders higher than two are difficult to specify, these are determined by simulation and by following the suggestions of Train (2003), Cappellari and Jenkins (2006) and Plum (2014).[11] The total number of generated Halton draws is R, and with each draw $r \in \{1, \ldots, R\}$, multivariate normal probabilities are simulated and the average of these simulations is derived. Hence, the logarithm of the simulated likelihood is:

$$\ln SL = \frac{1}{R}\sum_{r=1}^{R}\sum_{i=1}^{N} \ln\Phi^{r}_{i\Psi}(\boldsymbol{\mu};\boldsymbol{\Omega}). \tag{19}$$

One advantage of applying a simulated correlated multivariate random effects probit is the high accuracy that is achieved when using a small number of Halton draws (Plum 2014). For the simulation, 50 Halton draws are used.

4 Results

The aim of this study is to examine the medium-term labor market impact of low wages. In the econometric specification, correlated random effects were included to capture the effect of unobserved heterogeneity (Heckman 1981a). For this estimation, a CSM RE probit model with 50 Halton draws is applied.

Referring to the unobserved heterogeneity, in the studies by Stewart and Swaffield (1999), Stewart (2007) and Clark and Kanellopoulos (2013), the estimations are based on the strong assumption of independent random effects errors.[12] To evaluate the effect of the independence assumption, the estimations were re-run based on a standard

[11]Note that the simulation technique is also applied in the standard approach, but in this case, it is applied to specify the variance of the random effects error term.

[12]Although in the study by Stewart (2007), the estimation technique of the bivariate random effects probit model that takes correlated random effects into account is described, the estimation results are not presented.

random effects probit model.[13] In Table V, the coefficients and standard errors with reference to the labor market position in the previous period of the standard random effects probit model (columns II and III) and of the CSM RE probit model (column IV and V) are presented. The coefficients displayed in bold are significant at least at the 10% level. Labor market-related interaction dummies are included to differentiate between the impacts of job-related (social class of the job) and individual (educational background) characteristics on the labor market position. The upper part of the table presents the coefficients, resp. the standard errors, referring to the probability of obtaining a high-paying job. In the lower part of the table, the coefficients and standard errors refer to the probability of becoming unemployed conditional on not currently having a high-paid job.

When comparing the RE probit model and the CSM RE probit model, it can be observed that the variances of both random effects parameters are a bit greater in the second model, although only in the CSM RE probit model are both parameters significantly different from zero at the 10% level. Furthermore, it can be observed that in the CSM RE probit model, both variances are positively correlated ($\rho_\kappa = 0.749$), and the correlation parameter is significantly different from zero at the 1% level. A positive correlation indicates that those individuals who are more likely to become high-paid are also more likely to become unemployed instead of low-paid employed. Referring to the initial conditions problem, in both models, only the coefficient of high-paying employment in the initial period t_0 has a significant positive impact on the probability of remaining high-paid employed.[14] Moreover, it must be noted that the log likelihood in the CSM RE probit model (-576.451) is slightly higher compared to the log likelihood of the RE probit model (-579.850).

Referring to the probability of finding a high-paying job (upper part of Table V), both models indicate that having been high-paid in the previous period has a strong and significant impact compared to being unemployed (reference category). If the high-paid employee in $t-1$ has also attained a post-secondary education, the probability is significantly improved compared to a high-paid worker without a post-secondary education. However, a

[13]Note that in the RE probit model, due to the uncorrelated random effects, two estimations are run: the first estimation estimates the dependent variable y_{1it}, and the second estimation estimates y_{2it} when $y_{1it} = 0$.

[14]The RE probit model strongly rejects the F-test that both coefficients that refer to the labor market position in the initial period of the upper part of Table V have no significant effect together ($\chi^2(2) = 27.45, p-$value < 0.01). However, the hypothesis is not rejected for the coefficients of the lower part of Table V ($\chi^2(2) = 0.67, p-$value $= 0.7156$). The CSM RE probit model strongly rejects the F-test that all four coefficients referring to the initial conditions problem have no significant impact ($\chi^2(4) = 29.23, p-$value < 0.01.)

high-paying job with a low social class lowers the probability of obtaining a high-paying job in the subsequent period, though insignificant at the 10 percent level in both models.

The most prominent difference between both models in the upper part of Table V can be observed when comparing the coefficients that refer to the impact of low-paid employment in the previous period on the probability of obtaining a high-paying job in the subsequent period. Though being low-paid in the previous period has a positive effect on the probability of climbing the salary ladder compared to being unemployed in $t-1$, this effect is only significant in the CSM RE model. Furthermore, being low-paid and having a post-secondary education slightly increase the probability of obtaining a high-paying job in both models, though not significant in both estimations. Referring to the impact of a low-paid, low social class job, both models derive a positive but insignificant impact.

Table V: Regression results

	RE Probit		CSM RE Probit	
	coeff.	std. err.	coeff.	std. err.
dependent variable:	*employed in a high-paying job in t*			
high wage$_{t-1}$	**0.859**	0.201	**0.930**	0.203
$\times$post-sec. educ.$_{t-1}$	**0.469**	0.251	**0.471**	0.254
$\times$low job status$_{t-1}$	-0.237	0.250	-0.224	0.252
low wage$_{t-1}$	0.252	0.211	**0.471**	0.231
$\times$post-sec. educ.$_{t-1}$	0.039	0.298	0.104	0.303
$\times$low job status$_{t-1}$	-0.198	0.248	-0.174	0.248
unemployed$_{t-1}$	*reference category*			
$\times$post-sec. educ.$_{t-1}$	**0.491**	0.224	**0.482**	0.229
high wage$_{t_0}$	**0.912**	0.269	**0.973**	0.278
low wage$_{t_0}$	-0.115	0.266	-0.110	0.276
dependent variable:	*unemployed in t, conditioned on not being high-paid employed in t*			
high wage$_{t-1}$	**-0.965**	0.422	**-1.278**	0.434
$\times$post-sec. educ.$_{t-1}$	0.820	0.600	**1.081**	0.598
$\times$low job status$_{t-1}$	-0.326	0.622	-0.384	0.608
low wage$_{t-1}$	**-0.704**	0.367	**-0.728**	0.348
$\times$post-sec. educ.$_{t-1}$	-0.236	0.543	-0.115	0.527
$\times$low job status$_{t-1}$	-0.325	0.445	-0.430	0.433
unemployed$_{t-1}$	*reference category*			
$\times$post-sec. educ.$_{t-1}$	0.061	0.367	0.117	0.358
high wage$_{t_0}$	-0.193	0.390	0.193	0.417
low wage$_{t_0}$	-0.319	0.395	-0.270	0.389
$\sigma^2_{\kappa_1}$	**0.466**	0.206	**0.546**	0.218
$\sigma^2_{\kappa_2}$	0.943	0.647	**0.967**	0.582
ρ_κ	–	–	**0.749**	0.253
log likelihood	-579.850		-576.451	
observations	796		796	

Source: BHPS waves 8-18, own calculations. Coefficients displayed in bold are significant at least at the 10% level. Estimations include additional covariates as enlisted in Table III and year dummies.

Table VI: Goodness-of-fit statistics

	RE Probit	CSM RE Probit
$R^2_{\text{Ben-Akiva and Lerman}}$	0.5278	0.5201
Share of correct predictions	0.6470	0.6407
Akaike information criterion (AIC)[1]	1283.700	1278.903
Bayesian information criterion (BIC)[1]	1596.646	1573.718
observations	796	796

Source: BHPS waves 8-18, own calculations.
[1] A lower value indicates a better model fit.

To compare both models, four goodness-of-fit statistics are calculated. The first two statistics, $R^2_{\text{Ben-Akiva and Lerman}}$ and the share of correct predictions, are based on predicted probabilities, whereas the last two, Akaike and Bayesian information criteria, are based on the likelihood function. The first statistic is normally adopted for binary choice models and adjusted in the following way:

$$\begin{aligned} R^2_{\text{Ben-Akiva and Lerman}} = \quad & (NT)^{-1} \sum_{1}^{N} \sum_{t=t_{ue+1}}^{t_T} y_{1it}\hat{\Phi}_{1it} + (1-y_{1it})y_{2it}(1-\hat{\Phi}_{1it})\hat{\Phi}_{2it} \\ & + (1-y_{1it})(1-y_{2it})(1-\hat{\Phi}_{1it})(1-\hat{\Phi}_{2it}) \end{aligned} \tag{20}$$

with

$$\begin{aligned} \hat{\Phi}_{jit} = \quad & \Phi\left\{\left(x'_{jit}\hat{\beta}_j + \hat{\gamma}_{j1}y_{1i(t-1)} + \hat{\gamma}_{j3}y_{3i(t-1)} + \sum_{s=1}^{3} z'_{1i(t-1)}\hat{\eta}_{1s}y_{si(t-1)} \right.\right. \\ & \left.\left. + \hat{\pi}_{j1}y_{1i0} + \hat{\pi}_{j3}y_{3i0} + \hat{\delta}_j\overline{x}'_{ji}\right)\left(\frac{1}{1+\hat{\sigma}^2_{\kappa_j}}\right)^{1/2}\right\} \end{aligned}$$

and $j \in \{1, 2\}$. As depicted in Table VI, the goodness-of-fit statistics propose different conclusions. Referring to the first two statistics, the standard RE probit model a slightly better $R^2_{\text{Ben-Akiva and Lerman}}$-value derives compared to the CSM RE probit model and a little higher share of correct predictions, though in both cases, the difference is hardly detectable. Referring to the last two goodness-of-fit statistics, both information criteria indicate a much better model fit for the CSM RE probit model.

4.1 Average partial effects

To derive the effect of an individual's previous labor market position on his occupational advancement probabilities, the average partial effect of high-paid and low-paid employment compared to the reference category of unemployment are calculated.[15] To capture the effect of different levels of education on labor market transitions, the sample is split according to the degree of education. Furthermore, the average partial effect is differentiated according to the social class of the job. To identify the impact of the independent correlation assumption, the average partial effects are calculated on the basis of the estimation results of the RE probit model and of the CSM RE probit model. The derived average partial effects can be found on the left side in Table VII for men without a post-secondary education (columns II to IV) and on the right side for men with post-secondary education (columns V to VIII). The upper part of Table VII presents the average partial effect of high-paid, resp. low-paid, employment in $t-1$ on the probability of obtaining a high-paid job in t compared to being unemployed in the previous period. The middle (lower) part of Table VII refers to the average partial effects of becoming low-paid (unemployed).

Referring to men without post-secondary education, it can be noted that being high-paid in the previous period strongly increases the probability of remaining high-paid compared to being unemployed. Furthermore, in both models, the calculated average partial effects are at a comparable size: in the CSM RE probit model (RE probit model), switching in the previous period from being unemployed to having a high-paying job increases the probability of remaining high-paid employed by approximately 26 (25) percentage points. Although to a smaller extent, the same can be found when an individual is employed in a high-paid job that is associated with a low social class instead of unemployed (19 percentage points in the RE probit model, resp. 20 percentage points in the CSM RE probit model). Differences between both models are prominent when comparing the average partial effects of low wages: the RE probit model indicates that instead of remaining unemployed, picking up low-paid employment increases the probability of obtaining a high-paying job in the subsequent period by approximately 7.5 percentage points; in addition, this effect is insignificant. When a low-paid job is associated with a low social class, the average partial effect decreases by two percentage points. In contrast, the CSM RE probit model indicates a much stronger effect on the mean of low-paid employment (13.5 percentage points), which is also significant at the 5% level. In the case of a low-paid job that is associated with a low social class, the partial effect is five times higher in the mean (eight percentage points), though still not significantly different from zero at the 10% level.

When considering the effect of low wages on the probability of remaining low-paid,

[15] The calculation of the average partial effect can be found in the Appendix.

Table VII: Average Partial Effects

	Men without post-secondary education				*Men with post-secondary education*			
	RE Probit		CSM RE Probit		RE Probit		CSM RE Probit	
	APE	p-value	APE	p-value	APE	p-value	APE	p-value
partial effect of obtaining high-paying employment in t (reference category: being unemployed in t-1)								
high-paid$_{t-1}$×high social class$_{t-1}$	**0.253**	0.000	**0.264**	0.000	**0.217**	0.005	**0.234**	0.003
high-paid$_{t-1}$×low job status$_{t-1}$	**0.185**	0.030	**0.203**	0.016	**0.163**	0.063	**0.185**	0.035
low-paid$_{t-1}$×high social class$_{t-1}$	0.075	0.230	**0.135**	0.040	-0.060	0.524	0.027	0.777
low-paid$_{t-1}$×low job status$_{t-1}$	0.016	0.830	0.084	0.278	-0.121	0.261	-0.024	0.827
partial effect of obtaining low-paying employment in t (reference category: being unemployed in t-1)								
high-paid$_{t-1}$×high social class$_{t-1}$	-0.077	0.181	-0.022	0.760	**-0.112**	0.022	-0.085	0.209
high-paid$_{t-1}$×low job status$_{t-1}$	0.001	0.833	0.054	0.672	-0.059	0.227	-0.035	0.637
low-paid$_{t-1}$×high social class$_{t-1}$	0.043	0.579	0.025	0.792	**0.144**	0.019	0.090	0.351
low-paid$_{t-1}$×low job status$_{t-1}$	**0.124**	0.082	0.110	0.275	**0.222**	0.001	0.167	0.158
partial effect of becoming unemployment in t (reference category: being unemployed in t-1)								
high-paid$_{t-1}$×high social class$_{t-1}$	**-0.177**	0.009	**-0.242**	0.004	**-0.104**	0.044	**-0.149**	0.035
high-paid$_{t-1}$×low job status$_{t-1}$	**-0.186**	0.010	**-0.256**	0.005	**-0.104**	0.070	**-0.150**	0.053
low-paid$_{t-1}$×high social class$_{t-1}$	**-0.118**	0.057	**-0.160**	0.021	-0.084	0.200	-0.117	0.133
low-paid$_{t-1}$×low job status$_{t-1}$	**-0.140**	0.046	**-0.194**	0.016	-0.102	0.162	-0.143	0.100
observations	143		143		67		67	

Source: BHPS waves 8-18, own calculations. APE=*Average Partial Effect*. Numbers displayed in bold are significant at least at the 10% level.

it can be noted that indications for low-pay persistence[16] can only be found in the RE probit model: a low-paid job with a low social class significantly increases the probability of remaining low-paid when not taking correlated random effects into account. Though just on a slightly lower level (RE probit model: 12 percentage points, CSM RE probit model: 11 percentage points), this effect turns highly insignificant in the mean in the second model. Finally, the lower part of Table VII indicates that, compared to someone who has been unemployed, entering the workforce in a low-wage sector reduces the probability of becoming unemployed: independent of the social class of the job, in the CSM RE probit model, this effect is significantly different from zero. When applying a RE probit model, the derived average partial effects are on a lower level but also significantly different from zero.

Referring to men with post-secondary education, in the case of low-paid employment, the derived average partial effects also differ substantially between the two models. For example, in the RE probit model, the chance of becoming high-paid is reduced by a low-paying low social class job in the mean by 12 percentage points, though not significantly different from zero. In the case of the CSM RE probit, this risk is reduced by two percentage points, and the average partial effect is still insignificantly different from zero. Furthermore, low-pay persistence is only detected when not allowing for correlated random effects. The RE probit model indicates that the risk of remaining low-paid after picking up a low-paying job is significantly increased (14 percentage points). In the CSM RE probit model, the average partial effect is on a lower level (nine percent points) and not significant in the mean. A comparable reduction can be found when the low-paid job is associated with a low social class (from 22 percentage points in the RE probit model to 17 percentage points in the CSM RE probit model), also including a change in the significance.

The main findings of Table VII are:

a) In spite of the individual's educational background and the social class of the job, someone who was working in a high-paid job in the previous period substantially increases the probability of remaining high-paid in the subsequent period compared to someone who is unemployed. Furthermore, the risk of falling back into unemployment is greatly reduced.

b) Men without post-secondary education can substantially benefit from low wages: com-

[16] In this study, low-pay persistence is defined as a significantly higher probability of staying low-paid when being low-paid compared to becoming low-paid when being unemployed. In contrast to this, Clark and Kanellopoulos (2013) define low-pay persistence as the significantly increased probability of staying low-paid when working in the low-wage sector compared to not being low-paid.

pared to unemployment, the probability of obtaining a high-paying job is significantly increased and the risk of future unemployment significantly reduced by having a low-paid job. When the low-paid job is associated with a low social class, the worker can still benefit from a strongly reduced risk of becoming unemployed, though at the expense of an increased probability of remaining low paid and a lower chance of becoming high-paid.

c) Men with post-secondary education can benefit much less from low wages as the employment prospects are only slightly increased, but the risk of future unemployment is also reduced, though both effects are not significantly different from zero. When a person's job is also associated with a low social class, his employment prospects deteriorate: the probability of obtaining a high-paying job is reduced by picking up a low-paid job and the probability of remaining in the low-wage sector increases. However, it must be taken into account that most of the average partial effects are insignificant, which goes along with the findings of Knabe and Plum (2013).

d) Indications for a significant low-pay persistence can be detected when not allowing for correlated random effects. All effects become insignificant when applying a CSM RE probit model.

4.2 Total Sample

To estimate the effect of low wages on the employment prospects of initially unemployed men, the sample was restricted to the first six years of those men after they became unemployed. The differences between the estimated results of the reduced sample compared to the total sample were examined. The total sample contains the first six years of each observation, resulting in 20 754 observations. The estimation results of the CSM RE probit model can be found in columns II and III of Table A.I.

A noticeable difference can be found between the estimation results of the reduced sample and the total sample with respect to the correlation coefficient between the two random effects parameters ρ_κ, which is on a substantially lower level and switches its sign (from $\rho_\kappa = 0.749$ to $\rho_\kappa = -0.204$) but is still significantly different from zero at the 10% level. One explanation for the switch in the sign can be found in the sample preparation: the total sample also consists of individuals who work in the low-wage sector for a longer time period by choice and transition between a low-paid and a high-paid job. Contrary to this, the reduced sample consists of individuals who pick up low-paid employment to exit from unemployment. Referring to the average partial effects (see Table A.II), it must be noted that for low-paid men without a post-secondary education, the increased probability of obtaining a high-paying job compared to someone who was unemployed is on a comparable level to that of the reduced sample (reduced sample: 0.135, total sample: 0.111) when a low-paying job is associated with a high social status. However, when a job is associated with a low social status, the average partial effect is much lower when the estimation is based on the total sample (reduced sample: 0.084, total sample: 0.028).[17] This finding is in support of the hypothesis that a certain share of workers is employed by choice in the low-wage sector, which is expressed in a lower upward mobility into high-paid employment.

Another difference can be found with respect to the probability of becoming unemployed: the unemployment risk is lowered by eight (seven) percentage points when instead of being unemployed, an individuals works in the low-wage sector in a job that is associated with a high (low) social status. In the reduced sample, the average partial effects are much greater, with 16 (19) percentage points. It must be noted that the reduced sample only consists of workers who were initially unemployed. Therefore, picking up employment (high-paid or low-paid) has a strong impact on the probability of remaining employed. Furthermore, it must be noted that the total sample also contains individuals who were unemployed for a longer time period without an intervening employment spell in the meanwhile. In sum, the effects of a low-wage job on a person's employment prospects are also detected when applying the total sample, though indications are found that the effects might be underestimated.

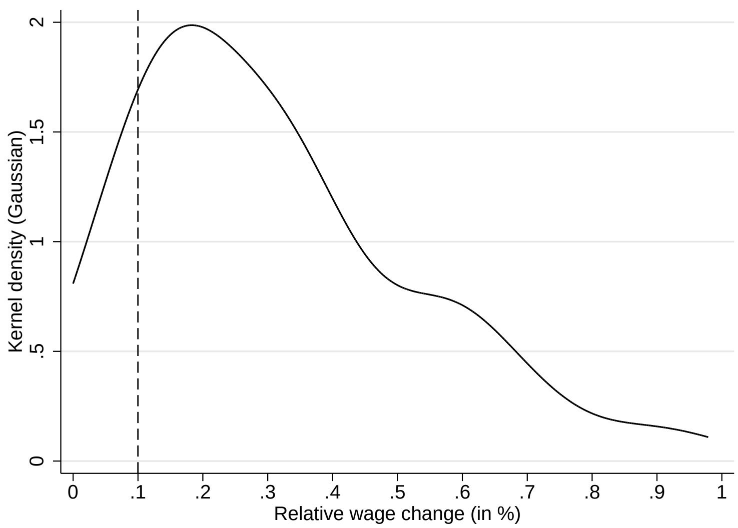
4.3 Transition probability

The OECD convention is applied to derive a relative threshold for differentiating between high-paid and low-paid employee. This threshold is calculated on the basis of the gross hourly wage distribution of the employed, including men and women. Some men receive a gross hourly wage that is slightly above or below the low-wage threshold. A small change in their salary or in working hours could lead to a change in their labor market position even though their gross hourly wage stays nearly unaffected. When a large percentage of men change their labor market position while employed, an overestimation of the transition probability between the two employment positions could result. In Figure 2, the relative wage change in absolute value for men who change their employment status (from high-paid$_{t-1}$ to low-paid$_t$ and vice versa) is depicted. As shown, the majority of those employed experience a substantial wage change in absolute terms of more than 10% (above

[17]However, in both cases, it is not significantly different from zero in the mean.

the vertical dashed line) when moving from one employment position to the other. In a robustness check, those workers who changed their labor market position and experienced a change of their wage of 10% (in absolute terms) or less are dropped. Altogether, the sample is reduced by 102 observations and therefore contains 694 observations.

Figure 2: Distribution of the relative wage change



BHPS waves 8-18. $N = 93$, wage change in absolute terms, vertical dashed line refers to a wage change of $\leq |10\%|$.

The estimation results of the CSM RE probit model can be found in columns III and IV of Table A.I. In the case of the random effects parameters, it can be observed that the size of their variances and their correlation are comparable for both the initial sample and the reduced sample. Referring to the labor market impact of low wages, the coefficient of the variable of being low-paid in the previous period is slightly lower and the standard error is slightly greater in the robustness estimation compared to the initial estimation. This results in the coefficient no longer being significantly different from zero at the 10% level.

Moreover, the average partial effects are derived (see Table A.II). Although the average partial effect of low-paid employment is nearly unchanged for men without a post-secondary education who were working in a job with a high social status, it is now no longer significant at the 10% level. When the low-paying job is associated with a low social status, the average partial effect almost doubles but remains insignificant. Referring to the risk of becoming unemployed, the results indicate that independent of the social status of the job, the risk of becoming unemployed is strongly reduced when instead of staying unemployed, a low-paid job is found. To sum up the findings, when controlling for the influence of men who experience a transition in their employment status caused by a negligible change in their hourly wage, the degree of the average partial effects is only slightly affected.

4.4 Gender specific threshold

The threshold to distinguish between high-paid and low-paid employment is derived from the sample, containing all employees within a certain age frame and of both sexes. However, it has to be taken into account that women are paid 20% less than men in Great Britain (see *inter alia* Swaffield 2000, Chevalier 2007). In the second robustness estimation, the threshold is derived solely from males employed within the same age frame. It is expected that an increase in the threshold has a negative impact on the transition probability because the required change in the gross hourly wage to switch from low-paid to high-paid employment is much higher. Compared to the old threshold, the new threshold increases by between £0.32 (1998) and £0.80 (2008). The estimation results of the CSM RE probit model can be found in columns VI and VII of Table A.I. Referring to the probability of obtaining a high-paying job, two severe differences can be observed. Being high-paid in the previous period and working in a job with a low social class has a significantly reduced effect. Furthermore, having worked in the low-wage sector has a positive but highly insignificant effect on the probability of obtaining a high-paying job.

The average partial effects are depicted in Table A.II. Referring to men without post-secondary education, substantial changes can be detected: at the expense of a lower probability of obtaining a high-paying job the risk of remaining in a low-paid position is increased; for someone who is working in the low-wage sector, the average partial effect decreases from 13.5 to five percentage points in the mean, and this effect is no longer different from zero. In the meantime, the probability of remaining in a low-paid position rises but is still not significantly different from zero. Although there is a shift in the average partial effect from the probability of obtaining a high-paying job towards an increased probability of remaining in a low-paid position, the risk of future unemployment is nearly unaffected and remains significantly different from zero.

5 Conclusion

The main objective of this study is to analyze whether low wages could work as an instrument to improve the labor market prospects of the unemployed in Great Britain. Only a subsample containing men that dropped from employment into unemployment is used to examine the labor market prospects of unemployed workers. Following Knabe and Plum (2013), it is assumed that the effect of low-paid employment on future labor market outcomes is heterogeneous and therefore, the employment effect of low wages is differentiated according to job-related (the social class of the job) and individual-related (attaining post-secondary education) characteristics. Because the medium-term effect of low wages is the variable of interest, the sample is restricted to the first six years after a worker became unemployed. For the analysis, BHPS panel data for the years 1996-2008 are used. In extension to the existing literature, an alternative econometric approach was presented that explicitly allows for correlated random effects between the three labor market states (being high-paid employed, low-paid employed, and unemployed). To derive the effect of the correlated random parameters, a simulation based on quasi-random numbers (Halton draws) is applied.

The results indicate that for men without a post-secondary education, low wages significantly increase the probability of switching to a high-paid job compared to remaining unemployed if the job is associated with a high social status. Furthermore, the risk of falling into future unemployment is noticeably reduced. The probability of transition into a high-paying job is clearly reduced when the job is associated with a low social class, but the risk of future unemployment is still strongly reduced. Men with post-secondary education profit less from low-paying jobs, though the risk of future unemployment is still reduced (but not on a significant level).

To analyze the robustness of these results, several further estimations were run. One finding is that in all estimations, the risk of future unemployment is considerably lowered when a low-paying job is picked. However, on the other hand, there are indications that the probability of climbing up the salary ladder is influenced by the definition of the low-wage threshold: wage mobility seems to be lower for lower wages, indicating an increased risk of remaining in a low-paid position when the threshold is lifted. To sum up the findings: for men without a post-secondary education, low wages can be considered helpful in reducing the risk of future unemployment. Furthermore, the results give support to the conclusion of Knabe and Plum (2013) that low-paid jobs can act as a "springboard" to better-paid employment, especially for men with a lower educational background and when the job is associated with a high social status. The findings contradict those of Stewart (2007), who concluded that there is no difference between low-wage employment and unemployment at $t-1$ in terms of the risk of becoming unemployed, and instead indicate that low wages offer an instrument against future unemployment. Evidence of a significant low-pay persistence is only detected when not allowing for correlated random effects.

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A Appendix

The estimated average partial effects $\widehat{ape}$ of a high-paying job and of a low-paying job in relation to being unemployed to become high paid employed ($\widehat{ape}_{\text{hp}}$), low paid employed ($\widehat{ape}_{\text{lp}}$), resp. unemployed ($\widehat{ape}_{\text{ue}}$) are derived in the following manner:[18]

$$\widehat{ape}_{\text{hp}} = N^{-1} \sum_{i=1}^{N} \left[\Phi\left((\hat{\xi}_1 + \widehat{\gamma}_{1\text{pos}} + \tilde{z}_{1i(t-1)} \hat{\eta}_{1\text{pos}}) \hat{\varsigma}_1 \right) - \Phi\left((\hat{\xi}_1 + \tilde{z}_{1i(t-1)} \hat{\eta}_{12}) \hat{\varsigma}_2 \right) \right] \tag{A.I}$$

$$\begin{aligned} \widehat{ape}_{\text{lp}} = N^{-1} \sum_{i=1}^{N} [&\Phi(-(\hat{\xi}_1 + \widehat{\gamma}_{1\text{pos}} + \tilde{z}_{1i(t-1)} \hat{\eta}_{1\text{pos}}) \hat{\varsigma}_1)(-(\hat{\xi}_2 + \widehat{\gamma}_{2\text{pos}} + \tilde{z}_{2i(t-1)} \hat{\eta}_{2\text{pos}}) \hat{\varsigma}_2 - \\ &\Phi(-(\hat{\xi}_1 + \tilde{z}_{1i(t-1)} \hat{\eta}_{12}) \hat{\varsigma}_2) \Phi(-(\hat{\xi}_2 + \tilde{z}_{2i(t-1)} \hat{\eta}_{22}) \hat{\varsigma}_2)] \end{aligned} \tag{A.II}$$

$$\begin{aligned} \widehat{ape}_{\text{ue}} = N^{-1} \sum_{i=1}^{N} [&\Phi(-(\hat{\xi}_1 + \widehat{\gamma}_{1\text{pos}} + \tilde{z}_{1i(t-1)} \hat{\eta}_{1\text{pos}}) \hat{\varsigma}_1)((\hat{\xi}_2 + \widehat{\gamma}_{2\text{pos}} + \tilde{z}_{2i(t-1)} \hat{\eta}_{2\text{pos}}) \hat{\varsigma}_2) - \\ &\Phi(-(\hat{\xi}_1 + \tilde{z}_{1i(t-1)} \hat{\eta}_{12}) \hat{\varsigma}_2) \Phi((\hat{\xi}_2 + \tilde{z}_{2i(t-1)} \hat{\eta}_{22}) \hat{\varsigma}_2)] \end{aligned} \tag{A.III}$$

with $\hat{\xi}_j = \overline{x}'_j \widehat{\beta}_j + \overline{x}_{ji} \widehat{\delta}_j + \widehat{\pi}_{j1} y_{ji0} + \widehat{\pi}_{j3} y_{ji0}$, $\hat{\varsigma}_j = \left(\frac{1}{1+\widehat{\sigma}^2_{\kappa_j}} \right)^{1/2}$ and pos $\in \{1, 3\}$.

[18] Note that the explanatory variables are evaluated at the sample mean. Interaction effects are subsumed in γ_j.

Table A.I: Regression results†

	Robustness I[1]		Robustness II[2]		Robustness III[3]	
	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.
dependent variable:	*employed in a high-paying job in t*					
high wage$_{t-1}$	**1.064**	0.104	**1.062**	0.218	**1.120**	0.218
×post-sec. educ.$_{t-1}$	**0.618**	0.304	**0.718**	0.303	**0.587**	0.283
×low job status$_{t-1}$	**-0.411**	0.052	-0.091	0.311	**-0.525**	0.278
low wage$_{t-1}$	**0.434**	0.105	0.435	0.275	0.166	0.239
×post-sec. educ.$_{t-1}$	**0.458**	0.080	-0.027	0.374	0.190	0.302
×low job status$_{t-1}$	**-0.330**	0.060	0.050	0.299	-0.113	0.246
unemployed$_{t-1}$			*reference category*			
×post-sec. educ.$_{t-1}$	**0.730**	0.145	**0.636**	0.249	**0.578**	0.232
high wage$_{t_0}$	**0.954**	0.311	**0.997**	0.318	**1.034**	0.296
low wage$_{t_0}$	**0.249**	0.089	-0.300	0.314	-0.029	0.282
dependent variable:	*unemployed in t, conditioned on not being employed in a high-paying job t*					
high wage$_{t-1}$	**-0.567**	0.162	**-1.075**	0.451	**-0.834**	0.421
×post-sec. educ.$_{t-1}$	**1.482**	0.690	**1.175**	0.587	**1.242**	0.606
×low job status$_{t-1}$	**-0.338**	0.145	-0.189	0.683	-0.812	0.607
low wage$_{t-1}$	**-1.092**	0.161	-0.588	0.434	**-0.858**	0.312
×post-sec. educ.$_{t-1}$	-0.220	0.184	-0.104	0.551	-0.257	0.458
×low job status$_{t-1}$	0.087	0.126	-0.434	0.454	-0.190	0.367
unemployed$_{t-1}$			*reference category*			
×post-sec. educ.$_{t-1}$	-0.247	0.203	0.176	0.379	0.142	0.312
high wage$_{t_0}$	**-1.106**	0.212	0.231	0.449	-0.029	0.353
low wage$_{t_0}$	**-1.434**	0.205	-0.356	0.423	-0.275	0.328
$\sigma^2_{\kappa_1}$	**0.700**	0.066	**0.568**	0.265	**0.537**	0.253
$\sigma^2_{\kappa_2}$	**0.886**	0.226	0.906	0.616	**0.522**	0.385
ρ_κ	**-0.204**	0.120	**0.790**	0.271	**0.301**	0.383
log likelihood	-7 604.715		-476.811		-566.239	
observations	20 754		694		796	

Source: BHPS waves 8-18, own calculations. Coefficients displayed in bold are significant at least at the 10% level. Estimations include additional covariates as enlisted in Table III and year dummies.

† Estimation based on a CSM RE probit model.

1 Regression I contains the fist six years of each observation in the total sample. Number of applied Halton draws is 20.

2 In Regression II those men are dropped that have changed their employment position (low-paid or high-paid) and experienced an absolute relative change in their gross hourly wages of $\leq |10\%|$.

3 In Regression III a gender specific low-wage threshold is applied.

Table A.II: Average Partial Effects (APE)†

	Robustness I[1]				Robustness II[2]				Robustness III[3]			
	Without post-sec. educ.		With post-sec. educ.		Without post-sec. educ.		With post-sec. educ.		Without post-sec. educ.		With post-sec. educ.	
	APE	*p*-value	APE	*p*-value	APE	*p*-value	APE	*p*-value	APE	*p*-value	APE	*p*-value
partial effect of obtaining high-paying employment in t (reference category: being unemployed in t-1)												
high-paid$_{t-1}$×high social class$_{t-1}$	**0.242**	0.000	**0.213**	0.000	**0.290**	0.000	**0.260**	0.002	**0.319**	0.000	**0.287**	0.001
high-paid$_{t-1}$×low job status$_{t-1}$	**0.161**	0.000	**0.082**	0.002	**0.266**	0.007	**0.244**	0.011	**0.169**	0.075	**0.168**	0.080
low-paid$_{t-1}$×high social class$_{t-1}$	**0.111**	0.000	0.028	0.272	0.120	0.109	-0.064	0.582	0.045	0.486	-0.065	0.521
low-paid$_{t-1}$×low job status$_{t-1}$	0.028	0.336	-0.032	0.248	0.134	0.141	-0.050	0.697	0.014	0.847	-0.098	0.380
partial effect of obtaining low-paying employment in t (reference category: being unemployed in t-1)												
high-paid$_{t-1}$×high social class$_{t-1}$	**-0.163**	0.000	**-0.097**	0.000	-0.043	0.595	-0.116	0.118	-0.118	0.236	**-0.172**	0.038
high-paid$_{t-1}$×low job status$_{t-1}$	**-0.081**	0.003	**-0.060**	0.006	-0.012	0.859	-0.101	0.187	0.064	0.662	-0.047	0.597
low-paid$_{t-1}$×high social class$_{t-1}$	-0.030	0.171	0.001	0.897	0.025	0.808	0.135	0.257	0.107	0.244	**0.198**	0.080
low-paid$_{t-1}$×low job status$_{t-1}$	0.042	0.208	**0.056**	0.040	0.068	0.557	0.173	0.202	0.155	0.131	**0.243**	0.053
partial effect of becoming unemployment in t (reference category: being unemployed in t-1)												
high-paid$_{t-1}$×high social class$_{t-1}$	**-0.080**	0.002	**-0.026**	0.045	**-0.247**	0.005	**-0.144**	0.054	**-0.201**	0.023	-0.115	0.131
high-paid$_{t-1}$×low job status$_{t-1}$	**-0.008**	0.002	**-0.022**	0.067	**-0.254**	0.008	**-0.143**	0.072	**-0.233**	0.021	-0.121	0.138
low-paid$_{t-1}$×high social class$_{t-1}$	**-0.081**	0.001	**-0.029**	0.025	**-0.145**	0.054	-0.071	0.472	**-0.152**	0.040	**-0.133**	0.093
low-paid$_{t-1}$×low job status$_{t-1}$	**-0.070**	0.003	**-0.023**	0.051	**-0.201**	0.021	-0.123	0.212	**-0.169**	0.040	**-0.145**	0.090
observations	2 873		1 780		129		61		143		67	

Source: BHPS waves 8-18, own calculations. Numbers displayed in bold are significant at least at the 10% level.

† Estimation based on a CSM RE probit model.

1 Regression I contains the fist six years of each observation in the total sample. Number of applied Halton draws is 20.

2 In Regression II those men are dropped that have changed their employment position (low-paid or high-paid) and experienced an absolute relative change in their gross hourly wages of $\leq |10\%|$.

3 In Regression III a gender specific low-wage threshold is applied.