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Low-wage employment versus unemployment: Which one provides better prospects for women?

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Abstract

Using German SOEP data, 1999 – 2009, this study analyzes state dependence in low-wage employment of western German women, where we distinguish between full-time and part-time working. We estimate a dynamic multinomial logit model with random effects and find that having a low-wage job – compared to having a high-wage job – *ceteris paribus* decreases the probability of being high-paid in the future. This negative effect is significantly larger for part-time jobs than for full-time jobs. We find mixed evidence for a *low-pay-no-pay cycle*: compared to being high-paid, having a low-paid job increases the risk of being unemployed in the next period only for part-time workers. However, concerning future wage prospects low-paid women are clearly better off than unemployed or inactive women. We argue that for women low-wage jobs can serve as stepping stones out of unemployment and are to be preferred to staying unemployed and waiting for a better job.

New JEL-Classification: J30; J60; C35

Keywords: Low-pay dynamics; State dependence; Dynamic multinomial logit model

While unemployment is a bad signal, being in a low-quality job may well be a worse one. (Layard et al. 1991, p. 249).

1 Introduction

In many European countries, low-wage employment has become a more and more important characteristic of the labor market and a controversial topic for debate, in particular since a disproportionate share of low-wage earners are women (European Commission 2004). It is an open and highly disputed question how the prominence of low-wage work is to be interpreted and whether low-paid work is beneficial to individuals or society. The answer to this question crucially depends on whether low-wage jobs are mainly transitory and serve as stepping stones to higher paid jobs or whether they tend to become persistent or even result in (repeated) unemployment. More specifically, is it better to take up a low-wage job or remain unemployed and wait for a better job offer?

On the one hand, accepting low-quality jobs avoids scarring effects of unemployment, and these jobs may serve as stepping stones into high-quality jobs. In other words: taking up an interim job may be better than having no job at all (McCormick 1990).

On the other hand, individuals could be trapped in low-quality jobs or driven into repeated unemployment for various reasons. For instance, employers may interpret bad jobs in an individual's employment history as indicators of low future productivity (McCormick 1990). Similarly, accumulation of human capital in low-quality jobs is limited (Dickens and Lang 1985) and probably not much higher than during unemployment - in particular when unemployed persons receive training measures. Furthermore, transaction costs complicate job mobility. If costs of search differ between employment states (Burdett 1978), on-the-job-search is likely to be less effective than search during unemployment.

Knowing the consequences and future employment prospects of taking up a low-wage job is not only important for (unemployed) individuals but also for government when designing labor market institutions and policies. There are a number of labor market policies that may hinder or force unemployed individuals to accept sub-optimal job offers and low-paid work. While unemployment benefits provide a search subsidy for finding a good job match (Acemoglu 2001; Burdett 1979; Marimon and Zilibotti 1999), sanctions on rejections of job offers may drive unemployed persons into low-quality jobs (Van den Berg and Vikström 2014). Moreover, unemployed individuals are often subsidized by government when taking up a low-wage job, and many individuals in subsidized jobs earn low wages (Stephan 2010). Whether these policies are helpful depends very much on the prospects of low-wage earners (compared to unemployed persons) and on their transitions out of the low-wage sector.

In order to answer these questions, the labor market dynamics of low-paid and unemployed individuals must be investigated. Here, it should be taken into account that current labor market outcomes may affect future employment prospects, a phenomenon called (true) state dependence (Heckman 1981a). The experience of a low-wage job may alter prices, preferences or constraints and therefore have a genuine effect on the probability of being high-paid or unemployed in future periods. As explained earlier, this could be due to low human capital accumulation, signalling effects or transaction costs. Furthermore, individual characteristics (as well as labor market conditions) determine the probability of the experience of labor market states. If this individual-specific heterogeneity is correlated over time it may lead to persistence in low-pay (and spurious state dependence). If this is not controlled for in the econometric analysis, the estimated effect of a low-wage job on future labor market prospects will be biased.

In recent years, state dependence regarding labor market transitions between low-wage employment, high-wage employment and unemployment has been analyzed by Stewart (2007) for the UK and by Buddelmeyer et al. (2010) for Australia, using panel data models with lagged dependent variables. While Stewart (2007) finds that low-wage earners incur the same unemployment risk as unemployed persons, Buddelmeyer et al. (2010) show that low-wage employment is associated for men with weak, but for women with considerable scarring effects. Clark and Kanellopoulos (2013) find positive, statistically significant state dependence in low pay for male workers in each of the twelve European countries under inverstigation. Uhlendorff (2006) analyzes German SOEP-data and shows that for men low-wage jobs are stepping stones to high-paid jobs. Also using SOEP-data, Knabe and Plum (2013) analyze labor market transitions of women and men and find that taking up a low-paid job is especially appropriate for less-skilled persons and those with longer unemployment durations. The former result has also been found by Mosthaf (2014) with German administrative data for men working full-time.

A second strand of the literature has investigated the determinants of labor market transitions using multivariate probit models (without lagged dependent variables). For men in Britain, Capellari and Jenkins (2008) find that the entry into low-wage employment is more probable for singles, young individuals and those with low qualification, whereas the probability of becoming unemployed is higher for singles and individuals with bad health. Capellari (2007) studies transitions of low-wage earners in Italy and concludes that becoming low-paid strongly increases the probability of being in the low-wage sector in the future. The transition into high-wage employment is affected by region, industry and firm size. Schank et al. (2009) find that in Germany upward mobility is lower for women, for older workers and in small establishments. According to the results of Aretz and Gürtzgen (2012), genuine state dependence in low-pay has increased in Germany since the beginning of the nineties.

In this paper, we apply a dynamic multinomial logit model to investigate state dependence of low-wage employment, thereby analyzing the unemployment risk and the upward mobility of low-wage earners. We focus on the labor market dynamics of women in western Germany between 1999 and 2009. The probability to get a low-paid job is much higher for women (32.4%) than for men (16.7%) (Rhein 2013). In addition, their chance of moving from a low-paid to a high paid job is significantly lower (Schank et al. 2009). In contrast to men, women are more involved in household production and thus more often inactive on the labor market such that we need to take unemployment and inactivity separately into account. In addition, women are much more likely to work part-time than men. In 2008, almost every second woman in Germany worked part-time, but only one out of ten men (Brenke 2011)[1]. If working part-time is associated with occupational downgrading (see Connolly and Gregory 2008; Manning and Petrongolo 2008; Prowse 2006), it is entirely possible that state dependence differs between low-wage earners working full-time and those working part-time. For Germany, evidence for segregation of part-timers in occupations with lower human capital accumulation is found by Nelen (2012). Therefore, it seems important to take the heterogenous labor supply of women into account. In contrast to previous studies on wage mobility, we thus distinguish between part-time employment and full-time employment as well as between unemployment and inactivity. In total, we consider six states, namely high-wage employment (part-time and full-time), low-wage employment (part-time and full-time), unemployment and inactivity[2].

Furthermore, the distinction between both working-time regimes also allows us to contribute to another strand of the literature which investigates whether part-time jobs can be seen as stepping stones out of inactivity into full-time employment. Evidence in favor of this hypothesis is found by Fok et al. (2013) for Australia and Prowse (2012) for the UK[3]. Haan (2010) estimates state dependence in labor supply using German SOEP data and also finds that state dependence with respect to full-time employment is smaller in part-time employment than in inactivity. None of these studies has distinguished between high-wage and low-wage employment.

The paper proceeds as follows: Section 2 describes the dataset and descriptive statistics. Section 3 discusses the empirical specification. Section 4 presents the results and section 5 concludes.

2 Data

We use the waves 1999–2009 of the German Socio-Economic Panel Study (SOEP). The SOEP is a representative longitudinal study of private households in Germany. Interviews have been carried out yearly since 1984. The SOEP includes detailed information on the working life of the interviewed persons, but also a wide range of socio-economic variables related to other research fields (Wagner et al. 2007).

For our analysis, we define six mutually exclusive labor market states: high-wage employment with 30 working hours or more, high-wage employment with less than 30 working hours, low-wage employment with 30 working hours or more, low-wage employment with less than 30 working hours, unemployment, and inactivity[4]. To distinguish between unemployed and inactive women, we rely on the ILO definition of unemployment. An individual is considered as unemployed if she does not work, has actively searched for a job within the last four weeks and is ready to take up a job within the next two weeks. Individuals who are neither employed nor unemployed are defined as inactive[5].

We restrict our analysis to western Germany since labor market conditions and particularly the wage level still differ remarkably between western and eastern Germany. Furthermore, we exclude self-employed, trainees, students, women who are in disabled employment, and women working in agriculture. Since we are not interested in transitions from education to work and transitions from work to retirement, we do not investigate labor market transitions of women who are younger than 20 in 1999 and older than 58 in 2009.

In order to take account of the business cycle, we add data from the Federal Employment Agency about yearly local unemployment rates. We form an unbalanced dataset including all individuals who are observed at least in two consecutive waves during the period of observation. An individual stays in the sample until the first wave in which she is not observed or has a missing value in one of the considered variables.

Following a large part of the literature, we define an individual as low-paid if she earns less than two thirds of the median hourly gross wage and as high-paid if her wage is above this threshold. The low-wage thresholds are calculated for each year among the whole western German population using a weighted sample. They lie between 8.12 Euro in 2000 and 8.41 Euro in 2003 and decline to 7.88 Euro in the Great Recession in 2009 (in prices of 2000).

Table 1 reports sample statistics stratified by labor market states. 34 percent of observations from the pooled unweighted regression sample are from high-paid full-time jobs (with more than 30 working hours), 26 percent are from high-paid part-time jobs, 5 percent from low-paid full-time jobs while 11 percent are from low-paid part-time jobs. Hence, part-time working is more prominent within low-wage jobs than within high-wage jobs. 3 percent are from women being unemployed and 21 percent from inactive women. Unsurprisingly, high-paid women tend to be better educated. 23 percent of the women working in a high-paid full-time job hold an university degree. Within high-paid part-time workers the share is only slightly lower (16 percent), while the share within low-paid, unemployed, and inactive women ranges from 5 to 11 percent. Individuals with a migration background are underrepresented in high-wage employment. The reported average gross wage of the partner is higher for part-time employed and inactive women than for women working full-time which is due to the higher share of women without partner in the household under full-time employed women[6]. The average number of children

Table 1 Variable means by labor market state

	High-pay, ≥ 30 hours	High-pay, ≤ 30 hours	Low-pay, ≥ 30 hours	Low-pay, ≤ 30 hours	Unemployment	Inactivity
Number of individuals	1,305	1,149	379	627	284	970
Number of observations	5,157	3,931	748	1,661	472	3,088
Share of observations	34.25	26.11	4.97	11.03	3.13	20.51
No apprenticeship (dummy)	0.10	0.10	0.32	0.23	0.26	0.23
Apprenticeship (dummy)	0.68	0.75	0.63	0.70	0.68	0.66
University or technical college degree (dum.)	0.23	0.16	0.05	0.06	0.06	0.11
Age	42.02	43.62	40.42	42.00	41.96	39.90
Immigrant (dummy)	0.15	0.09	0.30	0.20	0.25	0.20
Handicap (dummy)	0.05	0.03	0.08	0.03	0.08	0.10
No partner in the household (dummy)	0.29	0.09	0.27	0.08	0.32	0.08
Monthly gross wage of the partner (in €)	1763.97	2781.51	1536.32	2348.23	1510.22	2570.46
Number of children (age: 0 - 3)	0.04	0.09	0.03	0.08	0.08	0.44
Number of children (age: 4 - 6)	0.03	0.14	0.03	0.14	0.19	0.26
Number of children (age: 7 - 10)	0.06	0.23	0.11	0.28	0.22	0.32
Number of children (age: 11 - 17)	0.20	0.55	0.39	0.60	0.48	0.41
Local unemployment rate (in percent)	8.24	8.27	8.12	8.33	8.49	8.32

Data source: SOEP 2000–2009; unbalanced panel; unweighted. 15,057 observations from 2,893 individuals (number is lower than sum of the second row (*Number of individuals*) because some individuals enter more than one state).

is always smallest in full-time employment (high-paid and low-paid) while it is largest in inactivity (except for children which are eleven years or older). The difference in the average number of children between inactivity and the other labor market states is most pronounced for children younger than 4 years.

Table 2 shows yearly transitions between the six labor market states. State dependence seems to be strong for high-wage employment and inactivity. About 86 percent of women working in a high-paid full-time job in period $t-1$ stay in this employment state in period t. 76 percent stay in high-paid part-time jobs and about 80 percent in inactivity. About 37 percent of the unemployed are observed to be in the same state in the consecutive year. 46 percent of low-paid workers who work 30 hours or more stay in this employment state while the degree of persistence is considerably higher in low-wage employment with less than 30 working hours (61 percent). Low-paid women clearly have worse labor market opportunities than high-paid, i.e. they have lower probabilities to be high-paid and higher probabilities to be unemployed or inactive in the future. However, concerning these unconditional measures, low-paid women still have considerably better prospects than unemployed women[7].

Thus, regarding transition probabilities, it seems plausible that low-wage jobs can serve as stepping stones out of unemployment. Nevertheless, in order to draw conclusions for labor market policy, one has to assess whether the unequal labor market opportunities stem from differences in individual characteristics of low-paid and unemployed individuals or from a genuine effect of experiencing these labor market states.

Table 2 Transitions between labor market states

	Year t						
	High-pay, $\geq$ 30 hours	**High-pay, < 30 hours**	**Low-pay, $\geq$ 30 hours**	**Low-pay, < 30 hours**	**Unemployment**	**Inactivity**	**Total**
Year $t-1$							
High-pay, $\geq$ 30 hours	86.29	5.19	4.12	0.19	0.79	3.43	100.0
High-pay, < 30 hours	8.36	76.40	1.74	8.54	1.15	3.80	100.0
Low-pay, $\geq$ 30 hours	31.44	7.32	45.58	6.69	2.90	6.06	100.0
Low-pay, < 30 hours	1.59	21.65	3.90	61.04	2.74	9.09	100.0
Unemployment	5.47	11.85	5.47	15.95	37.36	23.92	100.0
Inactivity	0.88	7.05	0.52	6.33	5.02	80.20	100.0
Total	34.25	26.11	4.97	11.03	3.13	20.51	100.0

Data source: SOEP 1999–2009; unbalanced panel; unweighted; 15,057 observations from 2,893 individuals; figures indicate row percentages.

3 Empirical specification

The multinomial model for the latent propensity $\mathbf{y}^*$ of individual i to be in one of the six employment states j at time t is specified as follows:

$$\mathbf{y}^*_{ijt} = \mathbf{x}_{it}\boldsymbol{\beta}_j + \mathbf{y}_{it-1}\boldsymbol{\gamma}_j + \alpha_{ij} + \epsilon_{ijt} \tag{1}$$

where $i = 1, \ldots, N$; $j = 1, \ldots, 6$; $t = 2, \ldots, T$. $\mathbf{x}$ is a vector of a constant and strictly exogenous observable characteristics, which may be associated with the employment status. To capture state dependence, $\mathbf{y}$ is a vector of five mutually exclusive dummy variables indicating the observed employment state in period $t-1$ (one of the six labor market states is excluded as the reference category). ϵ_{ijt} denotes a strictly exogenous disturbance and α_{ij} measures individual state-specific and time-invariant unobserved heterogeneity. Its inclusion allows us to disentangle true state dependence (through $\boldsymbol{\gamma}_j$) and spurious state dependence (through α_{ij}).

The standard uncorrelated random-effects model assumes $\boldsymbol{\alpha}$ to be uncorrelated with $\mathbf{x}_{it}$ and $\mathbf{y}_{it-1}$. However, if this assumption is violated, then the estimates of $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ will pick up some of the unobservables $\boldsymbol{\alpha}$. As an example, $\boldsymbol{\alpha}$ may include an individual's attitude towards classical roles of men and women, which is likely to be correlated both with the employment status of a woman as well as with the number of a woman's children. If the latter is included in the $\mathbf{x}$-vector, its impact on, say, the probability of not being in the labor force is likely to be overestimated. Moreover, correlation of the unobservables α_{ij} and the initial observation $\mathbf{y}_{i1}$ leads to the so-called initial conditions problem. This problem does not arise if the $\mathbf{y}_{i1}$ are known constants (that is non-stochastic). However, this is certainly not the case if (as in the context of our study) the first year of the observed panel data does not coincide with the start of the stochastic process generating individuals' employment status[8]. For example, an individual who is a low-wage employee in $t = 1$ may be there because of a previous low-wage employment (state dependence) or because of some observed or unobserved characteristics affecting this propensity. Thus, the initial values are endogenous (Heckman 1981b). An estimator to deal with the initial conditions problem has been proposed by Wooldridge (2005)[9]. The distribution of unobserved individual heterogeneity is specified conditional on initial values and exogenous variables, similar to the strategies proposed by Mundlak (1978) and (1984)[10].

$$\alpha_{ij} = \varphi_j + \bar{\mathbf{x}}_i \boldsymbol{\lambda}_j + \mathbf{y}_{i1} \boldsymbol{\nu}_j + \eta_{ij} \tag{2}$$

Substitution into Equation (1) yields:

$$y^*_{ijt} = \mathbf{x}_{it} \boldsymbol{\beta}_j + \mathbf{y}_{it-1} \boldsymbol{\gamma}_{jt} + \mathbf{y}_{i1} \boldsymbol{\nu}_j + \bar{\mathbf{x}}_i \boldsymbol{\lambda}_j + \eta_{ij} + \epsilon_{ijt} \tag{3}$$

The φ_j are captured by the constant included in $\mathbf{x}$. We assume that the ϵ_{ijt} follow a Type I extreme value distribution, resulting in a dynamic multinomial logit model with random effects. The probability of individual i being in employment state j at time $t > 1$ is given by:

$$P(y_{ijt} | \mathbf{x}_{it}, \mathbf{y}_{it-1}, \alpha_{ij}) = \frac{exp(\mathbf{x}_{it} \boldsymbol{\beta}_j + \mathbf{y}_{it-1} \boldsymbol{\gamma}_j + \mathbf{y}_{i1} \boldsymbol{\nu}_j + \bar{\mathbf{x}}_i \boldsymbol{\lambda}_j + \eta_{ij})}{\sum_{k=1}^{6} exp(\mathbf{x}_{it} \boldsymbol{\beta}_k + \mathbf{y}_{it-1} \boldsymbol{\gamma}_k + \mathbf{y}_{i1} \boldsymbol{\nu}_k + \bar{\mathbf{x}}_i \boldsymbol{\lambda}_k + \eta_{ik})} \tag{4}$$

The coefficient vectors $\boldsymbol{\beta}_1$, $\boldsymbol{\gamma}_1$, $\boldsymbol{\nu}_1$, $\boldsymbol{\lambda}_1$ of the base category and its unobserved heterogeneity η_{i1} are set to zero. If the random effects η_{ij} were observed, the likelihood contribution of individual i would be given by:

$$L_i = \prod_{t=2}^{T} \prod_{j=2}^{6} P(y_{ijt} | \mathbf{x}_{it}, \mathbf{y}_{it-1}, \alpha_{ij})^{d_{ijt}} \tag{5}$$

where $d_{ijt} = 1$ if individual i is in labor market state j at time t. Since the η_{ij} are not observed, however, the likelihood contribution is given by the expected value of (5), that is the η_{ij} are integrated out:

$$L_i = \int_{-\infty}^{\infty} \prod_{t=2}^{T} \prod_{j=2}^{6} \left\{ \frac{exp(\mathbf{x}_{it} \boldsymbol{\beta}_j + \mathbf{y}_{it-1} \boldsymbol{\gamma}_j + \mathbf{y}_{i1} \boldsymbol{\nu}_j + \bar{\mathbf{x}}_i \boldsymbol{\lambda}_j + \eta_{ij})}{1 + \sum_{k=2}^{6} exp(\mathbf{x}_{it} \boldsymbol{\beta}_k + \mathbf{y}_{it-1} \boldsymbol{\gamma}_k + \mathbf{y}_{i1} \boldsymbol{\nu}_k + \bar{\mathbf{x}}_i \boldsymbol{\lambda}_k + \eta_{ik})} \right\}^{d_{ijt}} f(\boldsymbol{\eta}) d(\boldsymbol{\eta}) \tag{6}$$

Unobserved heterogeneity $\boldsymbol{\eta}_i \equiv (\eta_{i2}, \eta_{i3}, \eta_{i4})'$ is assumed to follow a discrete distribution with an *a-priori* unspecified number of M mass-points (Heckman and Singer 1984)[11]. Each of these mass-points takes on different values τ_{mj} in each labor market state j. This yields the following likelihood-function:

$$L_i = \sum_{m=1}^{M} p_m \prod_{t=2}^{T} \prod_{j=2}^{6} \left\{ \frac{exp(\mathbf{x}_{it} \boldsymbol{\beta}_j + \mathbf{y}_{it-1} \boldsymbol{\gamma}_j + \mathbf{y}_{i1} \boldsymbol{\nu}_j + \bar{\mathbf{x}}_i \boldsymbol{\lambda}_j + \tau_{mj})}{1 + \sum_{k=2}^{6} exp(\mathbf{x}_{it} \boldsymbol{\beta}_k + \mathbf{y}_{it-1} \boldsymbol{\gamma}_k + \mathbf{y}_{i1} \boldsymbol{\nu}_k + \bar{\mathbf{x}}_i \boldsymbol{\lambda}_k + \tau_{mk})} \right\}^{d_{ijt}} \tag{7}$$

where the probability of mass point points τ_{mj} is denote by p_m. Note the absence of the subscript j which indicates that the probability does not vary between different labor market states[12].

As is well-known, coefficients from multinomial logit models cannot be used directly to interpret the economic significance of the respective variables. Therefore, for each observation in the data-set and for all possible labor market states in period $t-1$ we simulate the individual probabilities of being in a particular labor market state j at time t

via parametric bootstrap methods (Cameron and Trivedi 2005, p. 358). To achieve this, we draw the parameters $(p_m, \boldsymbol{\beta}_j, \boldsymbol{\gamma}_j, \boldsymbol{\nu}_j, \boldsymbol{\lambda}_j, \tau_{mj})$ thousand times from the distribution of the estimated coefficients and calculate the predicted probabilities averaged over observations and draws. To calculate the accompanying confidence intervals we proceed as follows, separately for each of the 36 transition probabilities: The average predictions per draw are ranked according to their size. The lower bound of the confidence interval is obtained by using the 25th smallest average prediction and the upper bound by using the 976th largest average prediction.

4 Results

Table 3 presents the coefficient estimates of the dynamic multinomial logit model for six different labor market states of western German women (Equation 7). The results reported in this section are based on a random-effects distribution with two mass points. A model with three mass points delivered coefficients estimates from which we obtained very similar transition probabilities as those reported in Table 4, but with somewhat larger standard errors. This is due to the fact that the coefficient of the third mass point of one labor market state (namely low paid and working part-time) was estimated with a large standard error.

The highly significant effects of the labor market states in the first observed period ($t = 1$) indicate that the initial state is strongly correlated with unobserved characteristics and that it is indeed necessary to control for the initial conditions problem. The probability to be observed in a particular labor market state in period t is highest if a women was in the same labor market state in period 1. Only concerning being unemployed in t, the size of the coefficients of low pay full-time and unemployment in period 1 are equal. Both mass points are significant in all labor markets states indicating that these are affected by unobserved heterogeneity.

The $\mathbf{x}$-vector contains all the control variables listed in Table 1 plus year dummies. In comparison with no education, a university degree increases the probability of high-pay (in particular full-time) compared to all other groups[13]. Having an apprenticeship increases the probability of all labor market states in comparison with inactivity (although the coefficient is not statistically significant in one case).

Inactivity is more likely to occur if a person is handicapped. The probability of being unemployed compared to the probability of being inactive *ceteris paribus* increases if a women has no partner. As expected, children at age three or below are associated with a higher probability of being inactive compared to all other groups, while there is a negative relationship with high-wage full-time employment (which exhibits the most negative coefficient)[14]. Also for all other age groups, children reduce the likelihood of high-pay full-time relative to the other five labor market states.

We turn now to the main variables of interest which are the lagged labor market states. The predicted transition probabilites between past and current labor market states are reported in Table 4.

As is evident, there is true state dependence of low-wage employment, i.e. being in a low-wage job reduces future employment prospects of German women. Compared to being high-payed full-time in $t - 1$, being low-paid full-time in $t - 1$ reduces the chance of being high-paid full-time in t by 32.5 percentage points (0.356

Table 3 Multinomial logit model with random effects, coefficients

	High-pay, ≥ 30 hours, t	High-pay, < 30 hours, t	Low-pay, ≥ 30 hours, t	Low-pay, < 30 hours, t	Unemployment, t
High-pay, ≥ 30 hours, t-1 (dummy)	11.222***	6.123***	5.532***	0.750*	3.024***
	(0.792)	(0.666)	(0.561)	(0.413)	(0.622)
High-pay, < 30 hours, t-1 (dummy)	8.926***	8.072***	4.607***	3.825***	3.246***
	(0.729)	(0.662)	(0.558)	(0.248)	(0.605)
Low-pay, ≥ 30 hours, t-1 (dummy)	9.353***	5.512***	6.393***	3.045***	3.118***
	(0.781)	(0.685)	(0.570)	(0.334)	(0.632)
Low-pay, < 30 hours, t-1 (dummy)	5.397***	5.421***	4.366***	4.476***	2.768***
	(0.609)	(0.558)	(0.523)	(0.235)	(0.473)
Unemployment, t-1 (dummy)	4.900***	3.714***	3.090***	2.171***	3.561***
	(0.595)	(0.528)	(0.556)	(0.256)	(0.541)
Inactivity, t-1 (reference)	—	—	—	—	—
No Apprenticeship (reference)	—	—	—	—	—
Apprenticeship (dummy)	0.911***	0.873***	0.186	0.450***	0.521***
	(0.175)	(0.157)	(0.172)	(0.138)	(0.187)
University (dummy)	1.508***	0.858***	-0.393	-0.215	-0.068
	(0.232)	(0.216)	(0.276)	(0.216)	(0.303)
Age	0.132	0.304*	-0.036	0.042	0.497**
	(0.162)	(0.155)	(0.172)	(0.151)	(0.214)
Age squared	-0.296	-0.395**	-0.077	-0.128	-0.578**
	(0.186)	(0.177)	(0.198)	(0.173)	(0.243)
Immigrant (dummy)	0.044	-0.357**	0.267	0.050	0.051
	(0.171)	(0.163)	(0.176)	(0.146)	(0.194)
Handicap (dummy)	-2.318***	-1.892***	-2.409***	-1.579***	-0.808
	(0.498)	(0.441)	(0.523)	(0.430)	(0.545)
No Partner (dummy)	0.495	0.103	0.301	-0.388	0.874*
	(0.401)	(0.389)	(0.433)	(0.381)	(0.470)
Wage of the partner	-0.003	0.051	-0.050	0.041	0.011
	(0.047)	(0.044)	(0.063)	(0.046)	(0.076)
Number of children (age: 0-3)	-4.667***	-3.153***	-3.660***	-2.901***	-3.788***
	(0.304)	(0.271)	(0.385)	(0.286)	(0.429)
Number of children (age: 4-6)	-0.558*	0.189	-0.238	-0.077	0.190
	(0.296)	(0.244)	(0.363)	(0.224)	(0.325)
Number of children (age: 7-10)	-0.877***	-0.270	-0.274	-0.310	-0.356
	(0.259)	(0.219)	(0.291)	(0.202)	(0.295)
Number of children (age: 11-17)	-0.119	0.252	0.372*	0.174	0.206
	(0.205)	(0.183)	(0.223)	(0.169)	(0.239)
Local unemployment rate	0.055	0.112	0.105	0.110	0.043
	(0.103)	(0.096)	(0.118)	(0.095)	(0.124)
Initial state: high-pay, ≥ 30 hours (dummy)	3.022***	1.693***	1.900***	0.199	1.382***
	(0.293)	(0.233)	(0.318)	(0.216)	(0.279)
Initial state: high-pay,	2.120***	2.290***	2.158***	1.100***	1.295***
< 30 hours (dummy)	(0.281)	(0.216)	(0.309)	(0.183)	(0.268)
Initial state: low-pay, ≥ 30 hours (dummy)	2.260***	1.722***	3.043***	0.944***	1.960***
	(0.342)	(0.296)	(0.346)	(0.264)	(0.335)
Initial state: low-pay, < 30 hours (dummy)	0.622*	1.325***	1.472***	1.336***	0.971***
	(0.326)	(0.230)	(0.314)	(0.175)	(0.269)
Initial state: unemployment (dummy)	1.410***	1.221***	1.554***	0.720**	1.886***
	(0.485)	(0.369)	(0.447)	(0.293)	(0.332)
Initial state: Inactivity (reference)	—	—	—	—	—

Table 3 Multinomial logit model with random effects, coefficients (*Continued*)

Individual averages ($\bar{X}_i$):					
Age	0.157	0.089	0.275	0.209	0.050
	(0.181)	(0.173)	(0.195)	(0.168)	(0.231)
Age squared	-0.101	-0.086	-0.294	-0.216	-0.096
	(0.213)	(0.202)	(0.230)	(0.197)	(0.268)
Handicap (dummy)	0.950	0.505	1.827***	0.307	0.102
	(0.603)	(0.553)	(0.617)	(0.530)	(0.678)
No partner	0.572	0.248	0.417	0.263	0.139
	(0.455)	(0.445)	(0.490)	(0.436)	(0.540)
Income of the partner	-0.086	-0.034	-0.055	-0.055	-0.150*
	(0.054)	(0.051)	(0.072)	(0.055)	(0.089)
Number of children	-0.691*	-0.299	-1.354**	0.080	-0.510
(age: 0-3)	(0.402)	(0.363)	(0.536)	(0.350)	(0.537)
Number of children	1.268**	0.726*	-0.130	0.238	0.373
(age: 4-6)	(0.518)	(0.433)	(0.675)	(0.392)	(0.583)
Number of children	-0.185	-0.214	-0.353	0.051	0.052
(age: 7-10)	(0.398)	(0.333)	(0.441)	(0.296)	(0.428)
Number of children	0.074	-0.254	-0.427	-0.259	-0.338
(age: 11-17)	(0.240)	(0.216)	(0.264)	(0.200)	(0.278)
Local unemployment	-0.062	-0.110	-0.084	-0.111	-0.027
rate	(0.106)	(0.099)	(0.122)	(0.098)	(0.129)
Constant	2.021***	3.922***	1.520**	3.753***	3.967***
	(0.710)	(0.657)	(0.772)	(0.641)	(0.713)
Mass point 1 (reference)	—	—	—	—	—
Mass point 2	-12.993***	-11.169***	-8.296***	-7.177***	-9.680***
	(0.879)	(0.816)	(0.957)	(0.670)	(1.02)
Probability of mass point 1	0.422				
Observations	15057				
Log Likelihood	-1.1e+04				
Wald-Test-Chi^2	791.76				
Prob > Chi^2	0.00				

Data source: SOEP 1999–2009. Year dummies additionally included. Inactivity serves as reference for the dependent variable. Standard errors in parantheses.
*, **, ***denotes significance at the 10%, 5% and 1% level, respectively.

versus 0.681). Equivalently, for low-paid part-timers in $t-1$, the chance of working high-paid part-time is 37.9 percentage lower compared to high-paid part-timers in $t-1$ (0.248 versus 0.627). Hence, our results indicate that the lower incidence of females in the high-wage sector is not only due to individual characteristics, time-constant preferences or discrimination but also reflects substantial (true) state dependence[15].

However, with respect to obtaining a high-paid job in period t, it is still better to be low-paid in $t-1$ than being unemployed or inactive in $t-1$[16]. This is true for those who are low-paid full-time employed in $t-1$ regarding the probability of being high-paid full-time employed in t: the transition probability is 27.8 percentage points higher compared to being unemployed in $t-1$ (0.356 versus 0.078) and the confidence intervals do not overlap. It is also true for those who had a low-paid part-time job in $t-1$ regarding the probability of being high-paid and working part-time in t, although the effect is less pronounced: the

Table 4 Simulated transition matrix, separating between full-time and part-time in period *t*

	High-pay, ≥ 30 hours, t	High-pay, < 30 hours, t	Low-pay, ≥ 30 hours, t	Low-pay, < 30 hours, t	Unemployment, *t*	Inactivity, *t*
High-pay, , ≥ 30 hours, t-1	0.681	0.116	0.066	0.008	0.016	0.113
	(0.618) (0.742)	(0.084) (0.154)	(0.040) (0.098)	(0.004) (0.015)	(0.007) (0.027)	(0.085) (0.145)
High-pay, < 30 hours, t-1	0.148	0.627	0.027	0.096	0.019	0.082
	(0.114) (0.188)	(0.559) (0.693)	(0.016) (0.042)	(0.067) (0.133)	(0.010) (0.032)	(0.060) (0.108)
Low-pay, , ≥ 30 hours, t-1	0.356	0.127	0.249	0.101	0.031	0.136
	(0.292) (0.423)	(0.008) (0.172)	(0.176) (0.332)	(0.065) (0.146)	(0.015) (0.055)	(0.099) (0.179)
Low-pay, < 30 hours, t-1	0.049	0.248	0.069	0.452	0.044	0.138
	(0.032) (0.070)	(0.197) (0.306)	(0.041) (0.106)	(0.372) (0.532)	(0.023) (0.073)	(0.099) (0.183)
Unemployment, $t-1$	0.078	0.154	0.058	0.161	0.247	0.301
	(0.047) (0.122)	(0.107) (0.210)	(0.030) (0.095)	(0.109) (0.222)	(0.160) (0.349)	(0.228) (0.382)
Inactivity, $t-1$	0.025	0.082	0.019	0.084	0.082	0.708
	(0.016) (0.036)	(0.062) (0.105)	(0.008) (0.036)	(0.054) (0.123)	(0.049) (0.129)	(0.644) (0.758)

Data source : SOEP 1999–2009; simulations based on parametric bootstrap using coefficients reported in Table 3; five percent confidence intervals in parentheses.

transition probability is 9.4 percentage points higher (0.248 versus 0.154) compared to being unemployed in $t-1$ (the difference is significant at the 1% level). Being inactive in $t-1$ leads even to a stronger decline in the probability of getting a high-wage job in the following period and again, the advantage of working in a low-wage job is stronger if it is full-time[17].

Similarly, future employment prospects are much better if a woman is low-paid than if she is unemployed or inactive. There is a high state dependence in unemployment and inactivity, that is the probability of unemployment (inactivity) is largest if an individual was unemployed (inactive) in the previous year. For example, a low-paid woman has a chance to become unemployed in the next year which is about 20 percentage points (0.031 respectively 0.044 versus 0.247) lower than if she was already unemployed. By contrast, being low paid and working part-time in $t-1$ increases the risk of being unemployed in the next period by 2.5 percentage points compared to being high-paid and working part-time in $t-1$ (0.044 vs. 0.019) which is statistically significant at the 5% level[18]. Interestingly, this difference reduces to 1.5 percentage points (0.031 vs. 0.016) and is not significant any more if we compare low-pay and high-pay within the group of full-time workers. Hence, a low-pay no-pay cycle seems to exist only for low-paid women working part-time[19]. When we did not stratifiy between full-time and part-time employment in an earlier version of the paper, we did not find any evidence for a low-pay no-pay cycle for women, which clearly demonstrates that it is vital to take the working time categories into account.

Surprisingly, we do not find evidence that working part-time in $t-1$ *ceteris paribus* increases the risk of becoming unemployed in t compared to working full-time in $t-1$. The respective differential is with both, high-pay (0.019 versus 0.016) as well as low-pay employees (0.044 versus 0.031) small and statistically insignificant.

Finally, we look at the question of whether taking on a part-time job can be a stepping stone into future full-time employment. It turns out that for low-paid women this depends on the comparison group of non-employment. Clearly, low-paid part-timers have better prospects than inactive women: having a part-time job in $t-1$ significantly increases the probability of being full-time employed in the following period, either as low-paid (0.069 versus 0.019) or as high-paid (0.049 versus 0.025). However, the chances for women working part-time in $t-1$ to obtain a full-time job in the following year are not better than those of women being unemployed in $t-1$. Therefore, comparing low-pay part-timers and unemployed women, the stepping stone hypothesis cannot be confirmed. This is different for high-pay part-time jobs in $t-1$, which significantly increases the probability of having a high-pay full time job in t compared to being either unemployed or inactive in period $t-1$.

The probability of being inactive in t is not increased by taking up a part-time job compared to having a full-time job in $t-1$. The probabilities are 0.082 versus 0.113 when being high-paid and 0.138 versus 0.136 when being low-paid. Furthermore, the probability of being inactive is significantly larger when being unemployed (0.301) or inactive (0.708) in $t-1$ instead of part-time employed in $t-1$. Hence, working part-time in the past significantly increases the probability of being in the labor force in present. The same figures reveal that a low-paid part-time job in $t-1$ goes along with a significantly higher probability of being inactive than a high-paid part-time job in $t-1$ (0.138 versus 0.082).

In Table 5, we show a modified transition matrix using the coefficients from the same model as above. In this transition matrix we only separate between part-time employment and full-time employment in period $t-1$, while we do not distinguish between both states in period t. This makes it easier to compare the wage mobility of women, irrespective of whether they move between full-time and part-time employment. While an individual should prefer a high-paid job over a low-paid job it is not clear whether an individual prefers a full-time job over a part-time job — particularly if she is involved in bringing up children[20].

Table 5 reveals that a low-paid full-time job in $t-1$ is associated with a significantly larger probability of being high-paid than a low-paid part-time job (0.485 vs. 0.299). A low-paid part time job in $t-1$, however, still goes along with a higher chance of being high-paid in t than unemployment in $t-1$ (0.299 vs. 0.233 — this difference is significant at the 10% level).

5 Conclusions

This study analyzes true state dependence in low-wage employment of western German women and investigates whether it is better to take up a low-wage job or remain unemployed and wait for a better job offer. Using panel data of the SOEP and taking account of the initial conditions problem, we estimate dynamic multinomial logit models with random effects in order to analyze the effect of the experience of low-wage employment on future employment prospects. We find true state dependence in low-wage employment, i.e. being in a low-wage job reduces – compared to being in a high-wage job – future employment prospects of German women by decreasing the chances of being high-paid in the future. This negative effect of low-paid jobs on future wage prospects is significantly larger for women working part-time than for women working full-time.

Moreover, we do find some evidence for a *low-pay-no-pay cycle*: compared to being high-paid and working part-time, having a low-paid part-time job does *ceteris paribus* increase the risk of being unemployed in the next period, while the effect is insignificant for full-time workers. However, concerning future wage and employment prospects, low-paid women are clearly better off than unemployed or inactive women. Compared

Table 5 Simulated transition matrix, not separating between full-time and part-time in period *t*

	High-pay, t		Low-pay, t		Unemployment, *t*		Inactivity, *t*	
High-pay, $\geq$ 30 hours, t-1	0.798		0.073		0.016		0.113	
	(0.747)	(0.845)	(0.046)	(0.106)	(0.007)	(0.027)	(0.085)	(0.145)
High-pay, < 30 hours, t-1	0.777		0.122		0.019		0.082	
	(0.747)	(0.845)	(0.725)	(0.826)	(0.010)	(0.032)	(0.060)	(0.108)
Low-pay, $\geq$ 30 hours, t-1	0.485		0.347		0.031		0.136	
	(0.413)	(0.558)	(0.272)	(0.428)	(0.015)	(0.055)	(0.099)	(0.179)
Low-pay, < 30 hours, t-1	0.299		0.519		0.044		0.138	
	(0.244)	(0.359)	(0.443)	(0.593)	(0.023)	(0.073)	(0.099)	(0.183)
Unemployment, $t-1$	0.233		0.217		0.247		0.301	
	(0.171)	(0.311)	(0.153)	(0.288)	(0.160)	(0.349)	(0.228)	(0.382)
Inactivity, $t-1$	0.108		0.102		0.082		0.708	
	(0.084)	(0.134)	(0.067)	(0.147)	(0.049)	(0.129)	(0.644)	(0.758)

Data source : SOEP 1999–2009; simulations based on parametric bootstrap using coefficients reported in Table 3; five percent confidence intervals in parentheses.

to being low-paid, being unemployed or inactive leads to a higher probability of becoming unemployed or inactive again and – compared in particular to full-time low-wage earners – to a stronger decline in the probability of getting a high-paid job. In consideration of this evidence, we argue that for women low-wage jobs can serve as stepping stones out of unemployment and are to be preferred to staying unemployed and waiting for a better job. To paraphrase Layard et al. (1991, p. 249) and to contradict them: While having a low-paid job may be a bad signal, being unemployed seems to be a worse one. This may justify policies which induce women to accept low-wage jobs.

We also find that being full-time employed in the future is more likely for low-wage part-timers than for inactive women. Hence, any policy which induces for example young mothers to enter the labor market by taking up a low-wage part-time job is also beneficial with respect to successive progression to full-time jobs.

While the existence of state dependence has been found before (see e.g. Uhlendorff (2006) for men or Knabe and Plum (2013) for men and women for Germany), we are the first to distinguish further between full-time and part-time employment by allowing that unobserved characteristics have different effects on the probabilities of working full-time and part-time. We find that the effects differ between the two working-time categories. This suggests that it may be worthwhile to investigate this heterogeneity more deeply. It might also be interesting to see whether taking up a low-wage job is more appropriate for long-term than for short-term unemployed individuals. In addition, the effect of a low-wage job might also depend on its duration. Knabe and Plum (2013) use dynamic panel data models and show that taking up a low-paid job is most appropiate for long-term unemployed individuals. A further step to take the duration of (un-)employment episodes into account will be to use administrative data with daily information and to apply multivariate duration models.

Endnotes

[1]The share of women working part-time is in Germany much higher than the EU-average which is about one third. Only the Netherlands has a higher share of women working part-time than Germany (Brenke 2011).

[2]Knabe and Plum (2013) also investigate differences between full-time and part-time work of low-wage earners. This is achieved by including a lagged labor market state whereas their dependent variable does not differ according to working-time regime.

[3]See Hyslop (1999) for a seminal paper on state dependence in dynamics between inactivity and employment.

[4]In the following, we refer to working 30 hours or more as working full-time and to working less than 30 hours as working part-time.

[5]As a consequence of this definition, the group of inactive women consists of women who are not willing to work and of women who are willing to work but have not looked for a job during the last four weeks. The latter group may be regarded as discouraged workers and amounts to 26 percent of all inactive women. The empirical model presented in section 3 intends to control for this heterogeneity in unobserved preferences for work by including random effects.

[6]We assign a value of zero to the variable "monthly gross wage of the partner" for women without a partner in the household.

[7]Also note that transitions from low-pay to high-pay do not reflect negligible wage-changes. Within all 688 transitions from low-pay to high-pay (irrespective of the working-time regime in $t-1$ or t), only six observations report a wage increase of less than 2.5 percent.

[8]In the context of our study, S periods have passed before the first observation is observed. Thus $t = 1$ actually means $S + 1$, without loosing any generality.

[9]Heckman (1981b) suggests an alternative estimator where correlation of $\mathbf{y}_{i1}$ and $\boldsymbol{\eta}_{ij}$ is modeled in a separate equation. This approach, however, is computationally more expensive. Studies also relying on the Wooldrige approach include Contoyannis et al. (2004), Stewart (2007), Arulampalam and Stewart (2009), Haan (2010) and Fok et al. (2013). Arulampalam and Stewart (2009) show with Monte Carlo experiments based on dynamic random-effects probit models that the Heckman reduced form approximation and the Wooldridge-method provide similar results.

[10]Wooldridge (2005, p. 48, equation (27)), uses in his specification the exogenous variables in all years except the initial period $(\mathbf{x}_{i2}, \ldots, \mathbf{x}_{iT})$. Because of the unbalanced nature of our data and to reduce the number of parameters to be estimated, we include the means of the time-varying exogenous variables $\bar{\mathbf{x}}_i = \frac{1}{T-1} \sum_{t=2}^{T} \mathbf{x}_{it}$. Rabe-Hesketh and Skrondal (2013) show that this produces results which are similar to results from the specification by Wooldridge (2005) for panels with more than 4 periods. In our sample, about 14 percent of the 2,893 individuals are observed in 4 periods or less.

[11]One mass point serves as a reference category and is set to zero.

[12]All models are estimated using Mata 11.1.

[13]As there is no within-variation, we have not been able to include the means of the education dummies in the $\bar{\mathbf{x}}$-vector. Therefore, the positive relationship between education and high-wage jobs may partly capture unobserved ability.

[14]Of course, these effects may reflect reverse causality, i.e. that high-wage jobs reduce fertility.

[15]When using a model controlling neither for unobserved heterogeneity nor for the initial conditions problem, state dependence in low-wage employment and in unemployment is considerably larger. This is consistent with the literature. See for instance Stewart (2007).

[16]The two findings that (i) a low-pay state in year $t - 1$ (compared to being in a high-pay state in $t - 1$) reduces the likelihood of being in high-pay employment in t, and (ii) that unemployment or inactivity in $t - 1$ is even worse were also obtained with a simpler model with four labor market states where we do not distinguish between the working time categories.

[17]There are several possible reasons for true state dependence in inactivity. The experience of inactivity may increase the preferences for non-market work or leisure. Furthermore, low human capital accumulation could lead to a lower job offer arrival rate and following search theory to a lower intensity of searching for a job (Cahuc and Zylberberg 2004).

[18]It could be argued that low-wage jobs are closer substitutes for unemployment than for high-wage jobs, but this does not rule out that transitions from low-wage jobs into both states are possible and are considered by low-wage employees.

[19]For men, a low-pay no-pay circle is observed, for example, by Stewart (2007) and Uhlendorff (2006). Their obtained probability differential amounts to 2 respectively 1.9 percentage points and is therefore close to ours, but both studies do not stratify between full-time and part-time employment and, in addition, Uhlendorff does not distinguish between unemployment and inactivity.

[20]Nevertheless, it is still necessary to separate in our econometric model between full-time and part-time employment in the dependent variable when we just want to distinguish between full-time employment and part-time employment in $t - 1$ since the dependence between the random effects and the lagged dependent variables has to be modelled explicitly. Not allowing for the fact that unobserved characteristics have different effects on the probabilities of working full-time and part-time might lead to measuring spurious state dependence.

Competing interests
The IZA Journal of European Labor Studies is committed to the IZA Guiding Principles of Research Integrity. The authors declare that they have observed these principles and that they have no competing interests.

Authors' contributions
AM participated in the design of the study, performed the statistical analysis and participated in drafting the manuscript. TS participated in the design and coordination of the study and participated in drafting the manuscript. CS participated in the design and coordination of the study and participated in drafting the manuscript. All authors read and approved the final manuscript.

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