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

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Abstract

This study analyzes state dependence in low-wage employment of western German women using GSOEP data, 2000-2006. We estimate dynamic multinomial logit models with random effects and find that having a low-wage job increases the probability of being low-paid and decreases the chances of being high-paid in the future, in particular for low-paid women working part-time. 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.

Zusammenfassung

Mit Daten des Sozio-ökonomischen Panels für 2000-2006 untersucht diese Studie die Wahrscheinlichkeit westdeutscher Frauen, in Niedriglohnbeschäftigungen zu verbleiben („state dependence“). Wir schätzen dynamische multinomiale Logit-Modelle mit zufälligen Effekten und finden, dass ein Niedriglohnjob die Wahrscheinlichkeit einer Niedriglohntätigkeit in der Zukunft erhöht und die Chancen auf einen Hochlohnjob verringert. Dies gilt insbesondere für geringverdienende Frauen, die Teilzeit arbeiten. Allerdings sind die Aussichten bezüglich künftiger Löhne für Frauen in Niedriglohntätigkeiten deutlich besser als für solche, die arbeitslos oder inaktiv sind. Wir folgern daraus, dass für Frauen Niedriglohnjobs als Sprungbrett aus der Arbeitslosigkeit dienen können und dass sie eine bessere Alternative darstellen als arbeitslos zu bleiben und auf bessere Arbeitsplatzangebote zu warten.

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 labor markets 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 (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, 2009). 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, 2009). 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, 1981*b*). 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 this 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 Uhlendorff (2006) for Germany. Both apply dynamic discrete choice models. While Stewart (2007) finds that low-wage earners incur the same unemployment risk as unemployed persons, Uhlendorff (2006) shows that for men low-wage employment is associated with weaker scarring effects than unemployment. A second strand of the literature has investigated the determinants of labor market transitions using multivariate probit models. For men in Britain, Cappellari 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. Cappellari (2007) studies transitions of low-wage earners in Italy and concludes that getting 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.

In this paper, we apply dynamic multinomial logit models to investigate state dependence of low-wage employment. We test how state dependence differs with respect to firm and individual characteristics. We analyze the unemployment risk and the upward mobility of low-wage earners and are able to show in which circumstances low-wage jobs can serve as stepping stones. In contrast to previous studies, we distinguish between five states, namely high-wage employment, low-wage employment (part-time and full-time), unemployment and inactivity.

Whereas Uhlendorff (2006) analyzes western German men in the period 1998 to 2003, our focus is on the labor market dynamics of women in western Germany between 2000 and 2006. The vast majority of low-wage earners in Germany are women, and their chance of obtaining higher wages is significantly lower than that of men (Schank et al., 2009). In contrast to men, women are more involved in household production and thus more often inactive on the labor market or working part-time. Hence it is important to distinguish between low-wage earners working full-time or part-time (which may be associated with occupational downgrading, see Prowse (2008)), and to account for inactivity as an additional state. Since labor market dynamics of women could differ considerably from those of men, it will be interesting to see whether the extant results for low-paid men also hold for women.

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 2000–2006 of the German Socio-Economic Panel Study (GSOEP). The GSOEP is a representative longitudinal study of private households in Germany. Interviews have been carried out yearly since 1984. The GSOEP 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. In 2006 22,639 adult persons from 12,499 households were sampled (Wagner et al., 2007).

For our analysis, we first define four mutually exclusive labor market states: high-wage employment, low-wage employment (where we subsequently also distinguish between full- and part-time work), unemployment, and inactivity. 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 which are neither employed nor unemployed are defined as inactive.

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. The share of low-paid workers employed in this sector is so small that it would be difficult to draw conclusions about their branch-specific labor market opportunities. 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 2000 and older than 55 in 2006.

In order to take account of the business cycle, we add data from the Federal Employment Agency about monthly unemployment rates at the month of the GSOEP-interview. We form an unbalanced dataset including all individuals who are observed in the years 2000 and 2001. 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 8.06 Euro in 2000 and 8.47 Euro in 2003 and decline to 7.99 Euro in 2006 (in prices of 2000).

- Table 1 about here -

Table 1 reports sample statistics broken down by labor market states. 51 percent of women in the pooled unweighted regression sample work in high-wage jobs, 14 percent are low-paid, 4 percent are unemployed while 31 percent are inactive. High-paid women are on average older than low-paid, unemployed and inactive women. Unsurprisingly, high-paid women tend to be better educated. Individuals with a migration background are overrepresented in unemployment and inactivity, while the share of migrants is lower in low-wage and high-wage employment. The share of women with children is always smallest in high-wage employment and (in most age groups) largest in inactivity, where the differences are most pronounced with respect to children younger than 4 years. In comparison with high-paid women, low-paid women more often have children, work in jobs with less than 30 working hours, in small firms and in the construction sector, while high-paid women work more frequently in the service sector.

- Table 2 about here -

Table 2 shows the yearly transitions between the four labor market states.

State dependence seems to be strong for high-wage employment and inactivity, with over 80 percent of individuals staying in these segments. About 33 percent of the unemployed are observed to be in the same state in the consecutive year. 61 percent of low-paid workers stay in low-wage employment. 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.

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.

3 Empirical Specification

The multinomial model for the latent propensity Y^* of individual i to be in employment status j (high-wage, low-wage, unemployed, inactive) at time t is specified as follows:

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

where $i = 1, \ldots, N$; $j = 1, \ldots, 4$; $t = 1, \ldots, T$.[1] $\mathbf{x}$ is a vector of strictly exogenous observable characteristics, which may be associated with the employment status. To capture state dependence, $\mathbf{y}$ is a vector of three mutually exclusive dummy variables (low-wage, unemployed, inactive) indicating the observed employment state in period $t-1$. ϵ_{ijt} denotes a strictly exogenous disturbance and α_{ij} measures individual-specific and time-invariant unobserved heterogeneity. Its inclusion allows

[1]In subsequent analysis we stratify the low-wage status into part-time and full-time work, such that there will be five states.

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 $\mathbf{x}$. However, if this assumption is violated, then the estimate of $\boldsymbol{\beta}$ 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. Alternatively, following Mundlak (1978) and Chamberlain (1984), the α_{ij} and the observed characteristics are allowed to be correlated by modelling α_{ij} to be linear in the means of all time-varying covariates

$$\alpha_{ij} = \bar{\mathbf{x}}_i \boldsymbol{\lambda}_j + \eta_{ij} \tag{2}$$

where η_{ij} is independent of $\mathbf{x}_{it}$ and ϵ_{ijt} for all i, t, j. Inserting into equation (1) yields:

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

Correlation of the unobservables η_{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.[2] 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, which requires the specification of a conditional distribution for $\mathbf{y}_{i1}$. However, it is typically not possible to find a solution for the conditional

[2]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.

distribution which is consistent with the rest of the model.

Heckman (1981a) suggests an approximate solution to the conditional distribution of the initial values using a reduced-form equation of the following form:

$$y^*_{ij1} = \mathbf{z}_i \boldsymbol{\pi}_j + \theta_{ij} + \epsilon_{ij1}, \tag{4}$$

where $\mathbf{z}$ includes observed variables in the first period and available pre-sample information.

An alternative estimator has been proposed by Wooldridge (2005) which has the virtue of being computationally more tractable.[3] The distribution of unobserved individual heterogeneity is specified conditional on initial values and exogenous variables, similar to the strategy of Chamberlain (1984) discussed above.

$$\alpha_{ij} = \bar{\mathbf{x}}_i \boldsymbol{\lambda}_j + \mathbf{y}_{i1} \boldsymbol{\nu}_j + \eta_{ij} \tag{5}$$

Substitution into into equation (1) yields:

$$y^*_{ijt} = \mathbf{x}_{it} \boldsymbol{\beta}_j + \mathbf{y}_{it-1} \boldsymbol{\gamma}_{jt} + \mathbf{y}_{i1} \boldsymbol{\nu}_j + \bar{\mathbf{x}}_i \boldsymbol{\lambda}_j + \eta_{ij} + \epsilon_{ijt} \tag{6}$$

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:

$$P(y_{ijt} | \mathbf{x}_{it}, \mathbf{y}_{it-1}, \alpha_{ij}) = \frac{exp(\mathbf{x}_{it} \boldsymbol{\beta}_j + \mathbf{y}_{it-1} \boldsymbol{\gamma}_j + \mathbf{y}_{i1} \boldsymbol{\nu}_j + \bar{\mathbf{x}}_i \boldsymbol{\lambda}_j + \eta_{ij})}{\sum_{k=1}^{4} exp(\mathbf{x}_{it} \boldsymbol{\beta}_k + \mathbf{y}_{it-1} \boldsymbol{\gamma}_k + \mathbf{y}_{i1} \boldsymbol{\nu}_k + \bar{\mathbf{x}}_i \boldsymbol{\lambda}_k + \eta_{ik})} \tag{7}$$

Being high-paid is the base category and the coefficient vectors $\boldsymbol{\beta}_1$, $\boldsymbol{\gamma}_1$, $\boldsymbol{\nu}_1$, $\boldsymbol{\lambda}_1$ and the unobserved heterogeneity η_{i1} are set to zero. If the random effects η_{ij} were

[3]Studies also relying on the Wooldrige approach include Contyannis et al. (2004), Haan (2005), Stewart (2007) and Arulampalam and Stewart (2007). Akay (2009) shows with Monte Carlo experiments based on dynamic random-effects probit and tobit models that the Heckman reduced form approximation is preferred in panels shorter than 5 periods.

observed, the likelihood contribution of individual i would be given by:

$$L_i = \prod_{t=2}^{T} \prod_{j=2}^{4} P(y_{ijt}|\mathbf{x}_{it}, \mathbf{y}_{it-1}, \alpha_{ij})^{d_{ijt}} \tag{8}$$

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 (8), that is the η_{ij} are integrated out:

$$L_i = \int_{-\infty}^{\infty} \prod_{t=2}^{T} \prod_{j=2}^{4} \left\{ \frac{exp(\mathbf{x}_{it}\boldsymbol{\beta}_j + \mathbf{y}_{it-1}\boldsymbol{\gamma}_j + \mathbf{y}_{i1}\boldsymbol{\nu}_j + \bar{\mathbf{x}}_i\boldsymbol{\lambda}_j + \eta_{ij})}{1 + \sum_{k=2}^{4} exp(\mathbf{x}_{it}\boldsymbol{\beta}_k + \mathbf{y}_{it-1}\boldsymbol{\gamma}_k + \mathbf{y}_{i1}\boldsymbol{\nu}_k + \bar{\mathbf{x}}_i\boldsymbol{\lambda}_k + \eta_{ik})} \right\}^{d_{ijt}} f(\boldsymbol{\eta})d(\boldsymbol{\eta}) \tag{9}$$

Unobserved heterogeneity $\boldsymbol{\eta}_i \equiv (\eta_{i2}, \eta_{i3}, \eta_{i4})'$ is assumed to follow a multivariate normal distribution with an unrestricted variance-covariance structure. There exists no analytical solution for the integral in (9), such that approximative methods must be used. Since numerical procedures like the Gauss-Hermite quadrature or adaptive quadrature are computationally intensive, we estimate the model with maximum simulated likelihood (MSL).[4] MSL draws values from the distribution of the unobserved heterogeneity. For each of these draws, the likelihood is calculated and then the sum is averaged over the R draws, which implies that instead of the exact likelihood, a simulated sample likelihood is maximized:

$$SL_i = \frac{1}{R} \sum_{d=1}^{R} \prod_{t=2}^{T} \prod_{j=2}^{4} \left\{ \frac{exp(\mathbf{x}_{it}\boldsymbol{\beta}_j + \mathbf{y}_{it-1}\boldsymbol{\gamma}_j + \mathbf{y}_{i1}\boldsymbol{\nu}_j + \bar{\mathbf{x}}_i\boldsymbol{\lambda}_j + \eta_{ij}^r)}{1 + \sum_{k=2}^{4} exp(\mathbf{x}_{it}\boldsymbol{\beta}_k + \mathbf{y}_{it-1}\boldsymbol{\gamma}_k + \mathbf{y}_{i1}\boldsymbol{\nu}_k + \bar{\mathbf{x}}_i\boldsymbol{\lambda}_k + \eta_{ik}^r)} \right\}^{d_{ijt}} \tag{10}$$

Following Haan and Uhlendorff (2006) and Uhlendorff (2006), (quasi-random) Halton sequences are applied instead of random draws to obtain $\boldsymbol{\eta}_i^r$.[5] In this paper,

[4] We use a Stata routine from Haan and Uhlendorff (2006), which we adjusted from two to three (and later on four) random intercepts.

[5] For details, see Train (2003) or Cameron and Trivedi (2005, chapter 12). Computer time can be reduced when using Halton draws because they provide a better coverage of the sample space and a lower variance of the simulated likelihoods.

we use 200 Halton draws per individual.

4 Results

Table 3 presents the marginal effects (evaluated at sample means) of the dynamic multinomial logit model for different labor market states of western German women.[6] 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. Significant estimates of σ_j^2 and $\rho_{k,j}$ imply the existence of unobserved heterogeneity. Furthermore, since all correlation coefficients are significant, it would be statistically inappropriate to omit one category.[7] The positive correlation coefficients indicate that unobserved characteristics of low-paid, unemployed and inactive persons are similar, but different from unobserved characteristics of high-paid workers.

- Table 3 about here -

The $\mathbf{x}$-vector contains all the control variables listed in Table 3 plus year dummies. In comparison with no education, an apprenticeship and (even more) a university degree increase the probability of high-pay.[8] Inactivity is more likely to occur if a person is handicapped. As expected, children at age three or below are associated with a higher probability of being inactive, while there is a negative

[6]The results reported in this section are based on an unbalanced panel, but Akay (2009) shows with Monte Carlo experiments that the Wooldridge method is only very slightly biased when using unbalanced datasets. Moreover, estimates with a balanced panel are very similar to those shown in Table 3. However, we do not present results for the balanced panel because in the subsequent analysis below, where we distinguish between low-wage full-time and low-wage part-time workers (Table 5), the likelihood did not converge for the balanced sample.

[7]This is often the case in previous empirical investigations which neglect the group of inactive persons (mainly due to lack of data).

[8]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.

relationship with high-wage employment.[9] Although quantitatively smaller, the same effects are found for children between four and ten, while the estimates for children above ten are all insignificant. As expected, the local unemployment rate is negatively correlated with being high-paid, but it is statistically not significant.

We turn now to the main variables of interest which are the lagged labor market states. Being high-paid in $t-1$ serves as the reference category, such that the reported marginal effects must be interpreted relative to this group. We observe true state dependence for low-paid western German women: being low-paid in year $t-1$ increases the probability of being low-paid in year t and reduces the probability of being high-paid in t. Both effects are equal in absolute size. The marginal effects of low-pay in year $t-1$ on the other two labor market states (unemployed and inactive) are zero. Taken together, these estimates imply that being low-paid in year $t-1$ increases the probability of being unemployed or inactive in year t (where the marginal effects are zero) compared to the probability of being high paid in year t (where the marginal effects are negative). This is consistent with the results of Uhlendorff (2006) for men.

While a low-pay state in year $t-1$ reduces the likelihood of being in high-pay employment in t, unemployment or inactivity in $t-1$ is even worse. The marginal effects (-0.159 for low-pay versus -0.372 and -0.462 for unemployment respectively inactivity) differ substantially, and their confidence intervals do not overlap. Moreover, the probability of being unemployed in year t or being inactive in year t rises with unemployment in $t-1$, but is unaffected by low-pay employment in $t-1$ (compared to high-wage jobs in $t-1$). Therefore, we can conclude that for our sample of western German women working in a low-paid job is indeed better for future employment prospects than not working. Uhlendorff (2006) obtained the same pattern for men in western Germany, while for Britain Stewart (2007) found only insignificant differences between low-wage employment and unemployment on future prospects.

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

- Table 4 about here -

Next, we investigate whether the effects of being low-paid in $t-1$ differ by subgroups. For this reason, we have interacted the labor market state low-pay in $t-1$ with broad categories of sector, firm size and children in the household, the results of which are reported in Table 4.[10] First of all, we should note that the marginal effects of unemployment or inactivity in $t-1$ are almost identical to those in Table 3. We observe that there is no significant variation in the impact of low-wage employment in $t-1$ across sectors. By contrast, working for a large firm increases the likelihood of upward mobility and reduces the probability of becoming unemployed or inactive (which may reflect the existence of internal labor markets or other opportunities to accumulate human capital). As expected, if there are young children in the household a women is more likely to move from low-pay employment to inactivity whereas upward mobility is less likely (compared to no children in the household).[11] Transition probabilities are not affected, however, by the existence of children aged four years or older.

Finally, in the low-paid state we now distinguish between two groups of full- and part-time workers, that is those with 30 working hours and more and those with less than 30 working hours.[12] The results of the multinomial logit model with random effects for these five labor market states are reported in Table 5. The impacts of the control variables on high-pay, unemployment or inactivity in year t are similar to those displayed for the base model in Table 3. Concerning the the control variables on the two low-wage categories in Table 5, different effects are mainly observed for 'no partner in the household' (which has a negative marginal effect on the likelihood

[10]By construction, it was not possible to interact firm size or sector with unemployment or inactivity in $t-1$.

[11]This is consistent with recent studies finding that women's labor supply at the firm level is less wage-elastic than men's which may reflect that women place greater importance on non-pecuniary job characteristics and have higher opportunity costs of moving due to greater household responsibilities (Hirsch et al., 2008).

[12]For a similar classification see Prowse (2008). Table 1 shows that that 67% of the observations in low-pay work fall into the second category.

of working low-pay and part-time) and for the number of children (which increases the probability of working low-pay and part-time).

- Table 5 about here -

Transition probabilities from unemployment or inactivity into high-pay, unemployment or inactivity are very similar to those reported in Table 3. We also see that true state dependence still exists for low-paid women but is much more pronounced for those working part-time. Concerning the prospect of reaching high-pay employment in t, working low-paid in $t-1$ is still better than being unemployed or inactive. This applies in particular to low-paid women working full-time, whose chance of reaching a high-pay status are hardly lower than those of high-paid women. As before, the probability of being unemployed or inactive in t rises with unemployment in $t-1$ but is unaffected by low-paid work in $t-1$ (irrespective of working time). This again underscores our finding that working in low-paid jobs provides better prospects than not working at all. Given that episodes of inactivity and low-paid part-time work are much more common for women than for men, our results also suggest that the lower incidence of females in the high-wage sector is not only due to individual characteristics, preferences or discrimination but also reflects substantial state dependence.

5 Conclusions

This study analyzes true state dependence in low-wage employment of 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 GSOEP 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 that there is true state dependence in low-wage employment, i. e. being in a low-wage job reduces future employment prospects of German women by increasing the probability of being low-paid and decreasing the chances of being high-paid in the future. This effect is most pronounced for low-paid women working part-time. However, concerning future wage prospects, low-paid women are clearly better off than unemployed or inactive women. Being unemployed or inactive leads to a stronger decline in the probability of getting a high-paid job than being low-paid and to a higher probability of becoming unemployed or inactive again. 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.

Further analysis suggests that the effect of low-paid jobs on future employment prospects differs with respect to individual and firm characteristics. Low-paid women working in large firms face a lower probability of getting unemployed or inactive and better chances to move into a higher-paid job, indicating that some sources of true state dependence in low-wage employment (such as insufficient accumulation of human capital) play a minor role in large firms. Besides, upward mobility of low-paid women is lower when there are young children in the household.

While the existence of state dependence has been found before (see e.g. Uhlendorff (2006) for German men), we have been able to demonstrate that the effect of low-wage jobs on future employment prospects differs with respect to firm size, household context and working hours. This suggests that it may be worthwhile to investigate the heterogeneity of this effect more deeply. For instance, taking up a low-wage job could be 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. This could be tested in future research by using administrative data with daily information and applying multivariate duration models (as employed, for instance, by Cockx and Picchio (2009)).

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Table 1: Variable means by labor market state

	High-pay	Low-pay	Unemployment	Inactivity
Share of individuals	51.13	14.42	3.51	30.94
Number of individuals	1,690	730	276	1,132
Number of observations	6,044	1,705	415	3,657
No apprenticeship (dummy)	0.13	0.27	0.28	0.29
Apprenticeship (dummy)	0.71	0.68	0.63	0.63
University or technical college degree (dum.)	0.16	0.05	0.09	0.07
Age	40.10	38.70	38.82	37.67
Immigrant (dummy)	0.15	0.23	0.30	0.27
Handicap (dummy)	0.03	0.04	0.04	0.08
No partner in the household (dummy)	0.25	0.15	0.29	0.07
Monthly gross wage of the partner (in €)	2,137.32	2,213.25	1,622.70	2,774.86
Children (age: 0 - 3) (dummy)	0.06	0.08	0.12	0.37
Children (age: 4 - 6) (dummy)	0.10	0.15	0.25	0.31
Children (age: 7 - 10) (dummy)	0.16	0.26	0.25	0.35
Children (age: 11 - 17) (dummy)	0.30	0.44	0.36	0.35
Local unemployment rate (in percent)	8.65	8.91	9.08	8.77
Working hours: less than 30 (dummy)	0.40	0.67	0.00	0.00
Working hours: 30 and more (dummy)	0.60	0.33	0.00	0.00
Energy, mining, manufacturing (dummy)	0.18	0.17	0.00	0.00
Construction sector (dummy)	0.17	0.31	0.00	0.00
Services (dummy)	0.65	0.52	0.00	0.00
Firm size: less than 20 employees (dum.)	0.23	0.52	0.00	0.00
Firm size: 20–200 employees (dummy)	0.27	0.30	0.00	0.00
Firm size: more than 200 employees (dum.)	0.49	0.18	0.00	0.00

Data source: GSOEP 2000–2006; unbalanced panel; unweighted. 2,661 individuals (number is lower than sum of the second row (*Number of individuals*) because some individuals enter more than one state).

Table 2: Transitions between labor market states

	Period t				
	High-pay	Low-pay	Unemployment	Inactivity	Total
Period $t-1$					
High-pay	87.4	6.8	1.3	4.6	100.0
Low-pay	27.3	61.8	3.0	8.0	100.0
Unemployment	16.4	20.1	33.4	30.0	100.0
Inactivity	5.9	4.9	4.6	84.7	100.0
Total	51.13	14.42	3.51	30.94	100.0

Data source: GSOEP 2000-2006; unbalanced panel; unweighted; 11,821 observations from 2,661 individuals; figures indicate row percentages.

Table 3: Dynamic Multinomial logit model with random effects for different labor market states; marginal effects; model I: four labor market states, no interactions with low-pay in $t-1$

	High-pay		Low-pay		Unemployment		Inactivity	
High-pay, $t-1$ (reference)	—		—		—		—	
Low-pay, $t-1$ (dummy)	–0.159	(0.028)***	0.160	(0.026)***	0.003	(0.005)	–0.004	(0.013)
Unemployment, $t-1$ (dummy)	–0.372	(0.057)***	0.128	(0.040)**	0.075	(0.027)**	0.169	(0.043)***
Inactivity, $t-1$ (dummy)	–0.462	(0.033)***	–0.008	(0.015)	0.051	(0.013)***	0.419	(0.035)***
No apprenticeship (reference)	—		—		—		—	
Apprenticeship (dummy)	0.205	(0.041)***	–0.056	(0.022)**	–0.011	(0.007)	–0.138	(0.033)***
University or technical college degree (dum.)	0.351	(0.048)***	–0.142	(0.024)***	–0.015	(0.010)	–0.194	(0.038)***
Age	0.053	(0.034)	–0.038	(0.018)*	0.015	(0.009)	–0.029	(0.026)
Age squared (divided by 100)	–0.040	(0.039)	0.055	(0.021)**	–0.012	(0.010)	–0.003	(0.030)
Immigrant (dummy)	–0.067	(0.038)	0.010	(0.018)	0.011	(0.007)	0.045	(0.028)
Handicap (dummy)	–0.219	(0.119)	–0.071	(0.032)*	–0.013	(0.013)	0.304	(0.121)*
No partner in the household (dummy)	0.079	(0.060)	–0.045	(0.029)	0.036	(0.026)	–0.070	(0.039)
Partner income (divided by 1,000)	0.002	(0.011)	0.001	(0.006)	–0.003	(0.003)	0.000	(0.008)
Number of children (age: 0–3)	–0.404	(0.045)***	0.027	(0.028)	0.020	(0.012)	0.356	(0.034)***
Number of children (age: 4–6)	–0.134	(0.040)***	0.033	(0.024)	0.014	(0.010)	0.087	(0.027)**
Number of children (age: 7–10)	–0.112	(0.037)**	0.040	(0.021)	–0.000	(0.009)	0.072	(0.026)**
Number of children (age: 11–17)	–0.051	(0.031)	0.030	(0.016)	0.007	(0.007)	0.014	(0.023)
Local unemployment rate	–0.024	(0.015)	0.003	(0.008)	0.003	(0.004)	0.018	(0.011)
High-pay, $t=1$ (reference)	—		—		—		—	
Low-pay, $t=1$ (dummy)	–0.502	(0.039)***	0.392	(0.034)***	0.030	(0.009)**	0.080	(0.021)***
Unemployment, $t=1$ (dummy)	–0.629	(0.083)***	0.136	(0.051)**	0.214	(0.052)***	0.280	(0.075)***
Inactivity, $t=1$ (dummy)	–0.774	(0.028)***	0.053	(0.018)**	0.034	(0.009)***	0.687	(0.033)***

Individual averages ($\overline{\mathbf{x}_i}$):								
Age	0.017	(0.039)	0.013	(0.021)	–0.017	(0.009)	–0.013	(0.029)
Age squared (divided by 100)	–0.046	(0.047)	–0.027	(0.025)	0.016	(0.011)	0.057	(0.035)
Handicap	–0.234	(0.119)*	0.091	(0.068)	0.023	(0.025)	0.120	(0.083)
No partner in the household	0.105	(0.081)	–0.018	(0.043)	–0.023	(0.018)	–0.064	(0.062)
Partner income (divided by 1,000)	–0.011	(0.015)	–0.004	(0.008)	–0.002	(0.004)	0.017	(0.010)
Number of children (age: 0–3)	–0.063	(0.062)	–0.075	(0.036)*	0.011	(0.013)	0.127	(0.041)**
Number of children (age: 4–6)	0.164	(0.070)*	0.021	(0.039)	–0.015	(0.014)	–0.170	(0.047)***
Number of children (age: 7–10)	0.030	(0.054)	–0.038	(0.029)	0.005	(0.011)	0.003	(0.037)
Number of children (age: 11–17)	–0.072	(0.039)	0.029	(0.020)	–0.001	(0.008)	0.043	(0.028)
Local unemployment rate	0.014	(0.016)	0.004	(0.009)	–0.002	(0.004)	–0.016	(0.012)
Variance η_2	3.695	(0.422)***						
Variance η_3	4.508	(0.798)***						
Variance η_4	6.064	(0.769)***						
Correlation coefficient: η_2, η_3	0.646	(0.074)***						
Correlation coefficient: η_2, η_4	0.644	(0.063)***						
Correlation coefficient: η_3, η_4	0.846	(0.049)***						
Log Likelihood	–6456.50							
χ^2-Test	870.93	***						

Data source: GSOEP 2000-2006. 11,821 observations from 2,661 individuals. Model estimated by Maximum Simulated Likelihood with 200 Halton Draws. Year dummies are additionally included. Marginal effects calculated at sample means. Standard errors in parenthesis. *, **, *** denotes significance at the 5%, 1% and 0.1 % level, respectively.

Table 4: Dynamic multinomial logit model with random effects for different labor market states; marginal effects; model II: four labor market states, interactions with low-pay in $t-1$

	High-pay		Low-pay		Unemployment		Inactivity	
High-pay, $t-1$ (reference)	—		—		—		—	
Unemployment, $t-1$	–0.376	(0.057)***	0.147	(0.043)**	0.065	(0.024)**	0.164	(0.041)***
Inactivity, $t-1$	–0.463	(0.032)***	–0.007	(0.017)	0.049	(0.012)***	0.422	(0.035)***
Low-pay, $t-1$	–0.141	(0.029)***	0.163	(0.026)***	-0.002	(0.004)	-0.021	(0.010)*
Low-pay, $t-1$ * mining, energy, manufacturing (reference)	—		—		—		—	
Low-pay, $t-1$ * construction sector	0.133	(0.070)	–0.110	(0.063)	–0.007	(0.009)	–0.017	(0.025)
Low-pay, $t-1$ * services	0.104	(0.065)	–0.106	(0.058)	0.006	(0.009)	–0.004	(0.024)
Low-pay, $t-1$ * firm size: less than 20 employees (reference)	—		—		—		—	
Low-pay, $t-1$ * firm size: 20-200 employees	0.181	(0.049)***	–0.130	(0.042)**	–0.023	(0.009)*	–0.028	(0.020)
Low-pay, $t-1$ * firm size: more than 200 employees	0.235	(0.051)***	–0.155	(0.046)***	–0.026	(0.009)**	–0.054	(0.018)**
Low-pay, $t-1$ * children (age: 0-3) in the household	–0.238	(0.080)**	0.048	(0.063)	0.026	(0.023)	0.165	(0.055)**
Low-pay, $t-1$ * children (age: 4-17) in the household	0.041	(0.047)	–0.036	(0.041)	–0.008	(0.008)	0.003	(0.018)

Data source: GSOEP 2000-2006. 11,821 observations from 2,661 individuals. Model estimated by Maximum Simulated Likelihood with 200 Halton Draws. All other variables listed in Table 3 are also included. In addition, low-pay, $t = 1$ has also been interacted with sector, size and children. Marginal effects calculated at sample means. Standard errors in parenthesis. *, **, *** denotes significance at the 5%, 1% and 0.1 % level, respectively.

Table 5: Dynamic multinomial logit model with random effects for different labor market states; marginal effects; model III: five labor market states

	High-pay		Low-pay, ≥ 30 hours		Low-pay, < 30 hours		Unemployment		Inactivity	
High-pay, $t-1$ (reference)	—		—		—		—		—	
Low-pay, ≥ 30 hours, $t-1$ (dummy)	–0.034	(0.036)	0.014	(0.007)*	–0.015	(0.009)	–0.002	(0.006)	0.036	(0.032)
Low-pay, < 30 hours, $t-1$ (dummy)	–0.164	(0.036)***	–0.002	(0.004)	0.160	(0.032)***	0.007	(0.006)	–0.000	(0.015)
Unemployment, $t-1$ (dummy)	–0.361	(0.059)***	0.007	(0.008)	0.090	(0.029)**	0.063	(0.022)**	0.201	(0.047)***
Inactivity, $t-1$ (dummy)	–0.489	(0.033)***	–0.012	(0.004)**	0.018	(0.010)	0.052	(0.013)***	0.431	(0.035)***
No apprenticeship (reference)	—		—		—		—		—	
Apprenticeship (dummy)	0.222	(0.042)***	0.000	(0.003)	–0.050	(0.016)*	–0.012	(0.007)*	–0.161	(0.036)***
University or technical college degree (dummy)	0.330	(0.048)***	–0.006	(0.003)	–0.093	(0.017)***	–0.015	(0.010)*	–0.216	(0.040)***
Age	0.017	(0.035)	–0.007	(0.003)*	–0.002	(0.013)	0.014	(0.008)	–0.023	(0.028)
Age squared (divided by 100)	–0.005	(0.039)	0.008	(0.003)*	0.015	(0.015)	–0.011	(0.009)	–0.007	(0.032)
Immigrant (dummy)	–0.038	(0.037)	0.010	(0.004)*	–0.011	(0.010)	0.009	(0.007)	0.030	(0.029)
Handicap (dummy)	–0.243	(0.126)	–0.005	(0.005)	–0.046	(0.017)**	–0.013	(0.012)	0.307	(0.125)*
No partner in the household (dummy)	0.093	(0.057)	0.001	(0.005)	–0.039	(0.018)*	0.031	(0.024)	–0.086	(0.040)*
Partner income (divided by 1,000)	0.009	(0.011)	0.001	(0.001)	–0.004	(0.004)	–0.004	(0.003)	–0.002	(0.008)
Number of children (age: 0–3)	–0.438	(0.045)***	–0.019	(0.006)**	0.060	(0.019)**	0.016	(0.011)	0.380	(0.036)***
Number of children (age: 4–6)	–0.140	(0.038)***	–0.005	(0.004)	0.039	(0.016)*	0.012	(0.009)	0.094	(0.029)***
Number of children (age: 7–10)	–0.112	(0.036)**	0.001	(0.003)	0.034	(0.013)*	–0.001	(0.009)	0.078	(0.028)**
Number of children (age: 11–17)	–0.046	(0.031)	0.002	(0.002)	0.022	(0.011)*	0.007	(0.007)	0.016	(0.024)
Local unemployment rate	–0.022	(0.005)	0.002	(0.002)	–0.001	(0.005)	0.003	(0.003)	0.019	(0.011)
High-pay, $t=1$ (reference)	—		—		—		—		—	
Low-pay, ≥ 30 hours, $t=1$ (dummy)	–0.246	(0.053)***	0.140	(0.034)***	0.056	(0.023)*	0.021	(0.011)*	0.029	(0.021)
Low-pay, < 30 hours, $t=1$ (dummy)	–0.561	(0.051)***	0.011	(0.005)*	0.354	(0.042)***	0.047	(0.015)**	0.149	(0.037)***
Unemployment, $t=1$ (dummy)	–0.631	(0.085)***	0.008	(0.007)	0.111	(0.041)**	0.231	(0.056)***	0.281	(0.076)***
Inactivity, $t=1$ (dummy)	–0.789	(0.029)***	–0.002	(0.002)	0.046	(0.011)***	0.028	(0.008)***	0.717	(0.032)***

Individual averages ($\overline{\mathbf{x}_i}$):										
Age	–0.051	(0.040)	0.005	(0.003)	–0.009	(0.015)	–0.017	(0.009)	–0.029	(0.032)
Age squared (divided by 100)	–0.082	(0.047)	–0.005	(0.003)	–0.001	(0.017)	0.015	(0.010)	0.073	(0.038)
Handicap	–0.202	(0.116)	0.008	(0.009)	0.047	(0.047)	0.022	(0.024)	0.125	(0.088)
No partner in the household	0.095	(0.082)	–0.004	(0.006)	–0.014	(0.031)	–0.020	(0.017)	–0.057	(0.066)
Partner income (divided by 1,000)	–0.016	(0.014)	–0.003	(0.001)*	0.005	(0.005)	–0.003	(0.004)	0.017	(0.011)
Number of children (age: 0–3)	–0.110	(0.059)	–0.004	(0.006)	–0.037	(0.024)	0.012	(0.013)	0.138	(0.044)**
Number of children (age: 4–6)	0.190	(0.067)**	0.000	(0.007)	0.002	(0.023)	–0.014	(0.014)	–0.179	(0.050)***
Number of children (age: 7–10)	0.006	(0.052)	–0.008	(0.005)	–0.020	(0.018)	0.006	(0.011)	0.015	(0.039)
Number of children (age: 11–17)	–0.066	(0.038)	0.002	(0.003)	0.017	(0.013)	–0.001	(0.008)	0.049	(0.030)
Local unemployment rate	0.016	(0.016)	0.000	(0.001)	0.004	(0.006)	–0.003	(0.004)	–0.017	(0.012)
Variance η_2	4.580	(0.708)***								
Variance η_3	4.256	(0.554)***								
Variance η_4	4.512	(0.749)***								
Variance η_5	5.751	(0.727)***								
Correlation coefficient: η_2, η_3	0.653	(0.077)***								
Correlation coefficient: η_2, η_4	0.424	(0.100)***								
Correlation coefficient: η_2, η_5	0.355	(0.142)*								
Correlation coefficient: η_3, η_4	0.703	(0.063)***								
Correlation coefficient: $\eta_3\eta_5$	0.664	(0.053)***								
Correlation coefficient: η_4, η_5	0.778	(0.053)***								
Log Likelihood	-6898.55									
χ^2-Test	379.29	***								

Data source: GSOEP 2000-2006. 11,821 observations from 2,661 individuals. Model estimated by Maximum Simulated Likelihood with 200 Halton Draws. Year dummies are additionally included. Marginal effects calculated at sample means. Standard errors in parenthesis. *, **, *** denotes significance at the 5%, 1% and 0.1 % level, respectively.