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# Earnings prospects for low-paid workers higher than for the unemployed but only in high-pay areas with high unemployment

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**Abstract** There is considerable debate on whether the prospects of entering a high-paid job are better for those in low-paid jobs compared to the unemployed. Whilst some scholars argue that there is a scarring effect of unemployment others highlight that low pay might signal a low productivity and furthermore reduce the time searching for a better paid job. Using longitudinal data for working age men in England matched with local labor market indicators, we estimate several random-effects probit models and find no difference in the probability of becoming high-paid employed between low-paid workers and the unemployed in areas with low unemployment. However, in areas with high unemployment and high pay, low-paid workers have a higher probability of entering high-paid employment than the unemployed. Moreover, there is a penalty for low-wage workers compared to the unemployed in low-pay areas in their probability of entering high-paid employment.

**Keywords:** neighborhood data, employment dynamics, state dependence, initial conditions problem

**JEL Classification Numbers:** J64, J62, J31

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# 1 Introduction

Economic and sociological labor market theories suggest a number of different mechanisms through which unemployment affects employment and earnings prospects negatively (see, e.g., Gangl 2004). Unemployment, so the theories go, signals human capital depreciation (Blanchard and Diamond 1994), places constraints on worker search behavior via access to both information networks and economic resources (Calvo-Armengol and Jackson 2004), and is associated with loss of workers' firm-specific human capital (Acemoglu 1995). Against the backlight of rising unemployment and increases in the low pay sector in many countries (OECD 2013), the question arises whether the earnings prospects of low-paid workers compared to the unemployed are improved. Low-paid workers build-up firm specific human capital which may enable them to move up the pay scale, they have access to information networks with other people in employment and higher economic resources, and, all else being equal, their being employed signals a lesser human capital depreciation and the willingness for working.

The emerging empirical research has produced evidence both in support and in contradiction with the hypothesis that low-pay employment may be a springboard into high-pay employment and is, therefore, preferable to unemployment. For example, using data for Britain, Stewart (2007) found no statistically significant differences in the employment prospects of low-wage workers and the unemployed: low-wage workers were as likely to become unemployed as the unemployed were likely to remain unemployed. Plum (2014), on the other hand, found that low-paid workers in the UK have a higher probability of becoming high-paid employed compared to the unemployed. The 'springboard effect' - that is, the greater naught difference in the probability of entering high pay at the current period  $t$  for someone who was in low pay  $t - 1$  compared to someone who was unemployed in  $t - 1$  - was most marked for men without post-secondary education.

A common feature of these studies is that for modeling labor market dynamics they take differences in observable and unobservable characteristics and the previous labor market position into account. However, there are several theoretical and empirical examinations showing that neighbors have an effect on the individual labor market outcome. The transmission channel of the neighbors' influence on the labor market outcome could be, among other<sup>1</sup>, via peer effects in the accumulation of human capital (Arnott and Rowse 1987), the harmonizing of work attitudes (Wilson 1987), using social networks as an informal job market, which is especially relevant for low-skilled workers, (Selod and Zenou 2006, Bayer et al. 2008) or spatial discrimination by the employer (Zenou and Boccoard 2000). In this study existing research on the springboard effect of low-wages is extended by taking the following neighborhood characteristics into account: local labor market tightness and the importance of the local low-wage sector. In empirical examinations indications are found that the local unemployment rate has a negative impact on the probability exiting unemployment (Hoynes 2000, Van der Klaauw and Van Ours 2003, Hedström et al. 2003).

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<sup>1</sup>Galster (2012) lists 15 potential causal pathways for the neighborhood influencing the individual decision.

Moreover, evidence exist that the local income structure has an impact on the earnings of its residents (Galster et al. 2008, Galster et al. 2014). To the best of our knowledge, in the context of low-wage dynamics this is the first study that takes the heterogeneity of the local labor market into account.

When taking neighborhood information into account, it must be noted that the unobserved heterogeneity that might have an influence on the labor market outcome is likely to be correlated with the choice of residence, hence there might be selection into the are of living (Manski 1993). In this study, we apply a two folded strategy to take care of unobserved heterogeneity and the non-random selection into the residence: we include random-effects error terms to capture the effect of unobserved heterogeneity (Heckman 1981a) and we follow the suggestion of Galster et al. (2008) by only considering non-movers. Additionally, several robustness estimations are conducted to derive the stability of the results. For the study, we draw on data from a very large national representative panel survey matched with labor market indicators at a very immediate level. Advantage of taking labor market indicators at a very immediate level is that it captures better the heterogeneity on the labor market and in the residential income structure. Moreover, as the number of individuals in the sample who live in the same area (here the LSOA) is very low and with a few exceptions equal to one, issues of clustered standard errors do not arise.

The results suggest that there is no springboard effect in areas that are characterized by high pay and low unemployment. However, low-paid workers in areas that are characterized by high pay and high unemployment, experience a sizable springboard effect, mainly caused by a strong deterioration of the employment chances of the unemployed. This goes along with the hypothesis of the deterioration of human capital during an unemployment spell and the negative duration dependence within unemployment. We also find some empirical evidence that low-paid workers living in low-pay, low unemployment areas have worse earnings prospects, as operationalised here, than the unemployed. This is consistent with the hypothesis that time spent working in a low-paid job cannot be invested searching for a better paid job, in particular when these better paid jobs are difficult to come by (Pissarides 1990). Another reason could be, that in low pay areas the social network for finding better jobs could be less well working for low-paid workers (Calvo-Armengol and Jackson 2004). Last but not least, low-paid workers living in low-pay areas that are also characterized by high unemployment experience a small springboard effect. The results could be pointing at the hypothesis that when good jobs are scarce, being low-paid employed signals the attempt to prevent human capital atrophy (Acemoglu 1995).

The remainder is structured as following: in Section 2, we review the key economic literature on employment prospects of the unemployed and low-paid workers as this helps us draw out the hypotheses. Section 3 introduces the data and provides descriptive statistics and Section 4 describes the empirical strategy. Results are presented in Section 5 and discussed in Section 6.

## 2 Literature review

### 2.1 Employment and earning prospects for the unemployed

There exist several theoretical contributions which analyze the effect of unemployment on the employment prospects. Vishwanath (1989) shows that unemployment might cause a negative signal as firms might view the unemployment duration as an indicator for the productivity level. Considering this stigma in a job search model, the author concludes that the unemployment spell increases with the unemployment duration, also referred to in the economic literature as the negative duration dependence in unemployment. Blanchard and Diamond (1994) analyze in a labor market model with job creation/destruction and matching the effect of the hiring rule on the exit rates out of unemployment. The authors show that if the firm chooses for hiring the unemployment duration of the applicant as a ranking device, the exit probability of an employed worker, were they to become unemployed, is better than the one of an unemployed worker. Another theoretical explanation for unemployment persistence is presented by Acemoglu (1995). When assuming that during an unemployment spell the unemployed faces the deterioration of his skills and that maintaining the skill level is costly and not observable, then firms will discriminate against these individuals. In response to this discrimination, no measures are undertaken by those unemployed to improve their skill level. In the equilibrium, there is some negative duration dependence in unemployment as the exit probability drops with the length of the unemployment spell. However, Pissarides (1990) notes that high-skilled unemployed might be willed to wait for an appropriate job offer (e.g. high quality jobs) and this might increase the unemployment duration, which is incorporated into the hiring decision of the employer. In this case, the unemployed does not suffer necessarily from a scarring effect.

Based on survey data, there exist several studies that investigate empirically the impact of past unemployment on the employment prospects. For the US, little evidence for the scarring effects is found (see, e.g., Heckman and Borjas 1980), whereas for UK (Arulampalam et al. 2000), Germany (Mühleisen and Zimmermann 1994), Australia (Doiron and Gørgens 2008), Spain (Ayllón 2013) and Norway (Raaum and Røed 2006) strong evidence is found. Based on experimental data, for the US (Kroft et al. 2013) and for Switzerland (Oberholzer-Gee 2008) strong evidence for duration dependence in unemployment is found. However, Eriksson and Rooth (2014), also using data from a field experiment, only find little evidence for stigma effects of unemployment for Sweden; the authors note that the scarring effect of unemployment is mainly limited to contemporary unemployment spells which are lasting at least nine months.

### 2.2 Employment and earning prospects for low-paid workers

While there are some theoretical explanations for negative duration dependence in unemployment, the effect of low-wages on the occupational advancement probabilities is more mixed. On the one hand, it can be assumed that picking up an employment at least stops the deterioration of the human capital. Furthermore, the worker signals his willingness

to work when he picks up an employment instead of staying unemployed. However, the type of job might reveal some below average productivity. McCormick (1990) shows that skilled workers might tend to avoid unskilled jobs as skilled jobs are more satisfying to them. When becoming unemployed, high-skilled unemployed will specialize in job search and firms will use the search-strategy of the unemployed as a screening device for productivity. This leads to the famous note of Layard et al. (1991)[p. 249]: “While unemployment is a bad signal, being in a low-quality job may well be a worse one.”

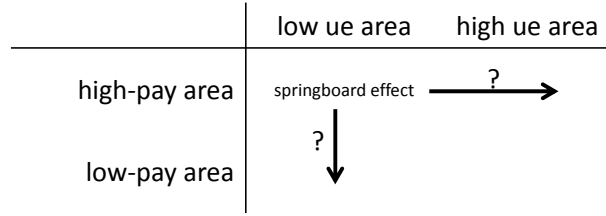
In the case of empirical examinations of the employment prospects of low-wage worker, the results are more heterogeneous: using data from the British Household Panel Survey (BHPS) and applying a range of random-effects and fixed-effects estimator, Stewart (2007) does not find any significant difference between low-paid employed and unemployed in their employment prospects. Also using data from the BHPS and restricting the sample to initially employed men who become unemployed, Plum (2014) finds some indications that low-paid men without post-secondary have a significantly higher probability of becoming high-paid employed in the subsequent period than their unemployed colleagues. Referring to Germany, empirical examinations also indicate that low-paid employed have better chances climbing up the salary ladder than the unemployed (Uhlendorff 2006, Knabe and Plum 2013, Mosthaf 2014, Mosthaf et al. 2014). Also for Australia, a springboard effect of low-wages is detected (Buddelmeyer et al. 2010). However, for Italy Cappellari (2007) finds a high persistence in low-pay and that the accumulation of human capital only has a little impact of exiting the low-wage sector. These findings are verified for Europe by Clark and Kanellopoulos (2013).

### **2.3 The impact of local labor market conditions**

In a bulk of studies it is shown that neighborhood characteristics have an impact on the individual labor market outcome. As already mentioned, there exist several transmission channels by which the characteristics of the neighborhood might effect the earning probabilities. Numerous studies have shown that the local unemployment level is one indicator to capture the influence of the neighborhood. Hoynes (2000) finds for California indications that the local unemployment rate has a positive impact on the welfare spell. Using administrative data, Van der Klaauw and Van Ours (2003) find for for young Dutch welfare recipients in Rotterdam a negative relationship between the local unemployment rate and the transition probability from welfare to work. Moreover, Hedström et al. (2003) results indicate that in Stockholm the exiting probability from unemployment is strongly influenced by the local unemployment level.

Another indicator variable for the transmission of neighborhood effects on the individuals’ earnings prospects is the local income distribution. Galster et al. (2008) find some evidence for Sweden that there is a non-linear relationship between the neighborhood income mix and the individuals’ earning prospects. The results indicate that for not fully-employed men (0-152 employment days per year) low-income neighbors have a negative marginal impact on the earnings prospects compared to middle-income neighbors. The authors conclude that “low-income neighbors provide negative role models and middle-income (but not high-income) neighbors provide access to networks with valuable employment-related

Figure 1: Transition to High-Paid Employment



information”(Galster et al. 2008, p. 868). These findings were verified by Galster et al. (2014). Referring to Britain, there exist some indications on job and income polarization starting in the 90’s, indicating an increased share of low-quality and high-quality jobs and a reduced share of medium-skilled jobs which is accompanied by incomes drifting apart (Kaplanis 2007).

One common feature of the studies analyzing the impact of low-wages on the employment prospects is that the regional disparity is only respected for in a limited way, for example by including information on the regional unemployment rate (see, e.g., Knabe and Plum 2013). An exception is the study of Stewart (2007), in which the unemployment-vacancy ratio in individual’s travel-to-work-area (TTWA) is included. However, the TTWA are defined on a much higher regional level than the LSOA’s which are used in this study. Moreover, no employment specific effects are assumed in the study.

Focus of this study is to analyze the springboard effect of low-wages and account for regional disparity, here the local unemployment rate and the importance of the local low-pay sector (see Figure 1). In general it can be assumed that the occupational advancement probabilities decline when the local unemployment rate or the number of low-paid jobs increase, simply as the number of available high-paid jobs is lowered. Going along with suggestion of Galster et al. (2008), it is assumed that the neighborhood effects are non-linear and vary across the labor market position (here high-pay, low-pay and unemployed). Or differently expressed: do unemployed and low-paid employed suffer equally from a high local unemployment rate or a low-pay area or does there exist labor market position specific effects?

It can be assumed that the springboard effect of low-paid jobs is strengthened in areas with a higher unemployment rate as the low-paid worker is signaling his willingness to work and showing that the deterioration of human capital is lingered. In the case of working in a low-pay area, the expected labor market specific results are less clear. Working in the low-wage sector might consist of a positive (willingness to work, stopping deterioration of human capital) and a negative (low-productivity) signal. Moreover, as pointed out by Galster et al. (2008), low-income neighbors might cause negative peer pressure, which might be especially relevant for low-wage worker.

## 3 Data and Descriptive Statistics

### 3.1 Understanding Society

We use data from the first four waves of annual data collected in *Understanding Society*, the new UK Household Longitudinal Study (University of Essex, 2014). The study started in 2009 with around 26,000 private households which were randomly selected to participate using a clustered and stratified sample design. Interviews are conducted annually with interviewers calling at the respondents' home and attempting to interview all adults (aged 16 years or older) living in the respondent's household. The study collects a wealth of questions relating to the respondent's economic and social circumstances, their values and attitudes and, as further data collections emerge, provides a detailed picture about how people move into and out of employment, how their pay and other life circumstances change. The study design and content closely follows the basic design of other longitudinal household panel studies which have been employed to investigate employment transitions, such as the British Household Panel Survey (BHPS), the American Panel Study of Income Dynamics (PSID) and the German Socio-economic Panel (SOEP). For more detailed information see Knies (2014).

*Understanding Society* is particularly well suited for the analysis. In addition to providing the relevant individual characteristics, the survey design assured that the sample is nationally representative for all Government Office Regions of the United Kingdom, and that there are enough respondents from metropolitan, urban and rural areas within them to provide enough statistical power for results on local area influences on individual outcomes. Moreover, it is possible to access look-up files between the respondent's home address and official geographical identifiers at very immediate scales, which allows us to augment the data from the study with published longitudinal data on labor market indicators for England at those geographical scales.

The focus of analysis necessitated our sample to be restricted to males, aged 20-60 years, who live in England and who were either employed (full-time or part-time) or unemployed in all survey waves. Employed respondents furthermore needed to report some positive number of hours worked in a current job and report a positive amount of gross pay to be in the analysis sample.<sup>2</sup> By the same token, unemployed respondents needed to have been looking for work in the last four weeks before the survey. Females, the self-employed, full-time students, retirees and those who are long term sick or disabled have been excluded as their labor market transitions are likely to follow different patterns. The final balanced sample consists of 7 704 respondents who were observed over the entire 4 year period and spent 96% of the time in employment and 4% of the time in unemployment.

Our key variable of interest is a marker of respondent's employment status (i.e., employed or unemployed) and a marker of their last gross pay (i.e., high-paid or low-paid). More specifically, the labor market position of employed respondents is differentiated into those

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<sup>2</sup>Both numbers are needed to categorize the employed into high-pay, resp. low-pay.



who are high-paid and those who are low-paid. We follow the standard definition by the Organization of Economic Cooperation and Development (OECD), whereby a worker is considered high-paid employed if his gross hourly wage exceeds two-thirds of the respective annual median gross hourly wage, and low-paid employed otherwise (OECD 1997). Table I reports the respective annual low-pay thresholds for England over the study period. It can be seen that the threshold increased somewhat over the observation period starting at £7.07 in 2009 and increasing up to £7.98 in 2012.

[Table I about here!]

Based on these definitions, we observe that out of 7 704 respondent-year observations 77% of time was spent high-paid employed, 19% low-paid employed and 4% in unemployment, and there was considerable movement into and out of these positions (see Table II).

## 3.2 Neighborhood Data

In order to consider differences in employment and earnings prospects for the low-paid and unemployed, we also needed measures of local labor market tightness and the importance of the local low-pay sector. Such measures are not supplied with the Understanding Society data. However, we obtained permission to access a look-up file between household identifiers and Lower Super Output Area (LSOA) codes allowing us to merge in relevant information from published tables using that area identifier (Rabe 2011). LSOA are intermediate-level Census output units that cover around 1 000 to 1 500 individuals. Overall, there were 3 2482 LSOA's in England in 2001. The geography is used to monitor regeneration in England which means there is a wealth of area data that is produced at this scale.

### 3.2.1 Local labor market tightness

We operationalize local labor market tightness on the basis of indicators sourced from the Department for Transport (DfT) Accessibility Statistics 2012. Accessibility Statistics provide information about access to eight domains of public services in the immediate areas in which study members live. The statistics offer more than 600 unique data items relating to how easy or difficult it is for different types of people in the local area to access employment centers, primary schools, secondary schools, institutions for further education, General Practitioners, hospitals, food stores, and town centers and have been linked with Understanding Society (Knies and Menon 2014).

Firstly, we derive a marker of the local unemployment rate. An area is considered to have a high unemployment rate if the ratio of recipients of job seekers allowance (i.e., “users at risk” in Accessibility Statistics terminology) to 16-74 year olds (i.e., “users of employment centers” in Accessibility Statistics terminology) who can reach the nearest 5-10 employment centers in the area within 20 minutes on bicycle is above 2%. Based

on this definition, 3 158 (55%) observations live in a high-unemployment area (see Table V).<sup>3</sup>

[Table V about here!]

To illustrate the regional variation in local unemployment rates, we report the rates separately for each region in England, see Table VI. It can be seen that the share of areas with a high local unemployment rate is especially high in London and in North East, whereas below average shares can be found in South East and South West. Moreover, areas with a relatively high local unemployment rate have below average number of high-paid employed and above average number of low-paid employed and unemployed (see Table VII).

[Table VI about here!]

Secondly, to consider heterogeneity in other structural factors that impact employment and earnings prospects and might be correlated with the local unemployment rate as operationalized here<sup>4</sup>, we use an LSOA-level indicator of urbanicity. The indicator is taken from the DfT National Travel Survey and classifies each address in 2001 into one of six metropolitan areas, one of xy urban areas with a population size ranging from x-x to x-x inhabitants, or rural areas. Note that in contrast to regions or local authority boundaries, the urbanicity marker considers the spatial (dis)connectedness of build-up areas to decide which area type is appropriate. This means, for instance, that not all LSOA in the region London are also classified as falling into the NTS area type Inner or outer London metropolitan area depending on whether it is connected to the bulk of the metropolitan area addresses or not.

### 3.2.2 Importance of the low-wage sector

Adopting the approach suggested by Kaplanis (2007), we use data on the number of (fuel) poor households in the LSOA as a marker for the size of the low-wage sector in the area. The data are provided on an annual basis for the period 2010-2012 by the Department for Environment and Climate Change (DECC)<sup>5</sup>. In these statistics, a household is considered as fuel-poor if *i*) the household members required fuel costs that were above the national median level of energy costs and *ii*) the difference between income and energy costs is below the national poverty threshold (DECC 2014). Note that a household is not considered fuel-poor if the residual of income and energy costs is below the national poverty

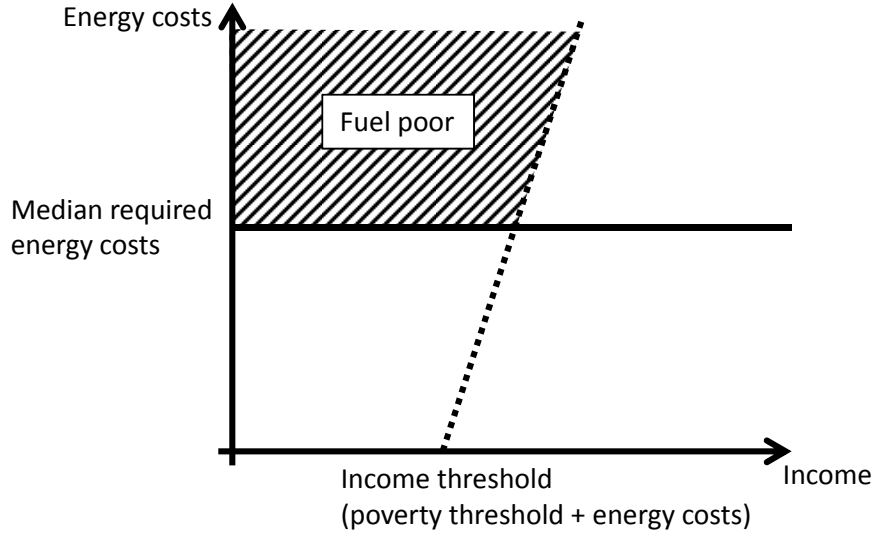
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<sup>3</sup>The mean local unemployment rate is 2.95% and the median local unemployment rate is 2.25%. For robustness we changed the unemployment threshold to 4%; we also increased the time radius for accessibility by cycling from 20 to 40 minutes. The robustness tests did not falsify our key results.

<sup>4</sup>It must be noted that this strategy implies the assumption that the distance within a LSOA to employment centers is randomly distributed. This is, however, likely not the case as distances in sparsely populated or rural areas are likely greater. This in turn would lead to an underestimation of the local unemployment rate in low density areas. To control for these aspects, two robustness estimations were run: in the first one individuals living in low density areas, were dropped. In a second estimation, men living in London or in South-East are dropped from the sample. However, the results were not not falsified

<sup>5</sup>Statistics can be downloaded from the following homepage: <https://www.gov.uk/government/collections/fuel-poverty-statistics>

Figure 2: Low Income



Source: adopted from DECC (2014)

threshold and the energy costs are also below the median required energy costs (see also Figure 2).

In this study an area is defined as a low income area if the huge of fuel-poor households in the area falls into the 75th poorest percentile in the distribution, and a high income area otherwise. As can be seen in Table V, low income areas are particularly prevalent in the West Midlands whereas high income areas are most prevalent in the South East. Low income areas are also characterized by a disproportionately high share of men in low-paid employment (Table VII).

[Table VII about here!]

## 4 Econometric Model

The aim of this study is to analyze the effect of the previous labor market position on the probability of staying or becoming high-paid employed in the subsequent period. For this reason, several dynamic random-effects probit models are used. As Arulampalam and Stewart (2009) have noted in their study, dynamic random-effects probit models which account for the initial conditions problem will derive consistent estimators at sample sizes of at least  $N = 1000$  observations if the number of waves is four or higher.

### 4.1 Heckman's Estimator

The observed binary variable outcome variable is defined as:

$$y_{it} = \begin{cases} 1 & \text{if the person is high-paid,} \\ 0 & \text{otherwise.} \end{cases} \quad (1)$$

The model is defined as:

$$y_{it} = \mathbf{1} \left\{ x'_{it}\beta + z'_i\kappa + y_{i(t-1)}\gamma + \epsilon_i + u_{it} > 0 \right\}. \quad (2)$$

The variable  $y_{it}$  refers to the labor market position of individual  $i = 1, \dots, N$  at time point  $t = 1, \dots, T$ . Note that  $N$  is large but  $T$  is small and therefor asymptotic is on  $N$  alone. The probability of being or staying high-paid is influenced by the time-varying explanatory variables  $x_{it}$ , the time-constant explanatory variables  $z_i$  and the labor market position in the previous period  $y_{i(t-1)}$ . As noted by Heckman (1981a), individuals might not only differ in observable but also in unobservable characteristics and therefore the individual-specific time-constant error term  $\epsilon_i$  is included. The  $u_{it}$  is referring to the time-specific idiosyncratic error term. So far, the individual-specific time-invariant  $\epsilon_i$  is assumed to be uncorrelated with the time-varying explanatory variables  $x_{it}$ . To relax this assumption, we follow the suggestion of Mundlak (1978) and Chamberlain (1984) by including the time-means of the time-varying explanatory variables:  $\epsilon_i = \bar{x}_i\delta + \alpha_i$ . Implementing this into equation 3 leads to:

$$y_{it} = \mathbf{1} \left\{ x'_{it}\beta + z'_i\kappa + y_{i(t-1)}\gamma + \bar{x}_i\delta + \alpha_i + u_{it} > 0 \right\}. \quad (3)$$

However, these unobservable characteristics might be correlated with the labor market outcome in the initial period (Heckman 1981b). There exist several strategies to take care of the initial conditions problem (for an overview see Arulampalam and Stewart 2009). Heckman (1981b) suggests to estimate a static equation for the initial period. Based on that approach, Orme (1996) suggests to apply a two-step estimation method. Another strategy is presented by Wooldridge (2005), who suggests to condition the dynamic sequence of the estimation on the outcome in the initial period. Arulampalam and Stewart (2009) show in a set of simulations that all three methods produce comparable results for panels of at least three time periods and a high number of observations ( $N = 1000$ ). In this study, the suggestion of Heckman (1981b) is followed, which was applied in other labor market studies (*e.g.* Stewart 2007). However, in a robustness estimation also the approach of Wooldridge (2005) is applied and the econometric model is presented further below. For the initial period  $t = 0$ , Heckman (1981b) suggests the following static equation:

$$y_{i0} = \mathbf{1} \left\{ x'_{i0}\eta + z'_i\pi + \text{ins}'_i\omega + \epsilon_i > 0 \right\}. \quad (4)$$

with  $\text{ins}_i$  being a matrix of instruments which only have an influence on the labor market outcome of the initial period but not of on the subsequent periods. It is assumed that the error term  $\epsilon_i$  is not correlated with  $u_{it}$  for  $t \in \{2, \dots, T\}$  but with  $\alpha_i$  in the following way:  $\epsilon_i = \theta\alpha_i + u_{i1}$ . Note that the parameter  $\theta$  indicates whether the individual-specific time-invariant error term  $\alpha_i$  has an effect on the labor market outcome in the initial period ( $\theta \neq 0$ ) and how the effect differs compared to the dynamic sequence ( $\theta \neq 1$ ). Incorporating this into equation 4 leads to:

$$y_{i0} = \mathbf{1} \left\{ x'_{i0}\eta + z'_i\pi + \text{ins}'_i\omega + \theta\alpha_i + u_{i0} > 0 \right\}. \quad (5)$$

For identification, it is assumed that  $\alpha_i \sim N(0, \sigma_\alpha^2)$  and  $u_{it} \sim N(0, \sigma_u^2)$ . Note that the composite error term  $\nu_{it} = \alpha_i + u_{it}$  is correlated over time with a constant correlation

structure  $\lambda = corr(\nu_{it}, \nu_{is}) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_u^2}$  for each  $t \neq s$ .<sup>6</sup> For normalization, it is assumed that the idiosyncratic error term is standard normal distributed, hence  $u_{it} \sim N(0, 1)$ . The individual outcome probabilities are:

$$P_{it}(\alpha^*) = \begin{cases} \Phi \left[ \left( x'_{it}\beta + z'_i\kappa + y_{i(t-1)}\gamma + \bar{x}_i\delta + \sigma_\alpha\alpha^* \right) (2y_{it} - 1) \right] & \text{if } t \geq 1 \\ \Phi \left[ \left( x'_{i0}\eta + z'_i\pi + ins'_i\omega + \theta\sigma_\alpha\alpha^* \right) (2y_{i0} - 1) \right] & \text{if } t = 0 \end{cases} \quad (6)$$

with  $\Phi$  referring to the standard normal cumulative distribution function and  $\alpha^* = \alpha/\sigma_\alpha$ . The individual likelihood contribution is:

$$L_i = \int_{\alpha^*} \left\{ P_{i0}(\alpha^*) \prod_{t=1}^T P_{it}(\alpha^*) \right\} g(\alpha^*) d\alpha^* \quad (7)$$

and  $g(\alpha^*)$  is the probability density function, which needs to be integrated out. If assuming a normal density of the random effects, there exist different techniques to estimate the size of the individual-specific time-constant error term, like Gaussian-Hermite quadrature or simulation. In this study, the maximum simulated likelihood (MSL) approach based on Halton draws is applied. Using primes numbers,  $R$  standard uniform distributed draws  $\tilde{\alpha}^r \in \{0, \dots, 1\}$  are derived and transformed by the inverse cumulative standard normal distribution  $\Phi^{-1}(\tilde{\alpha}^r)$ . Afterward, for deriving the lower triangular matrix of the variance-covariance matrix of the individual-specific time-constant error term  $V_\alpha$  the Cholesky decomposition is applied, which is  $V_\alpha = CC'$ . Hence, in this case the Cholesky decomposition is simply  $\sqrt{\sigma_\alpha^2}$ . In the simulation,  $\alpha^r = \sigma_\alpha\tilde{\alpha}^r$  and for each draw the likelihood is derived for each observation, multiplied over all individuals and time-points and averaged over all draws:

$$MSL = \prod_{i=1}^N \frac{1}{R} \sum_{r=1}^R \left\{ P_{i1}(\alpha^r) \prod_{t=1}^T P_{it}(\alpha^r) \right\} \quad (8)$$

In this application, 70 Halton draws are applied.

## 4.2 Heckman's Estimator with correlated random effects

In the previous model it is assumed that the individual's probability of becoming high-paid employed is uncorrelated with the individual's probability of becoming unemployed. There exist some studies (see among others Knabe and Plum 2013, Plum 2014) indicating that not respecting for correlation in the unobservables between the labor market positions might over/underestimate the effect of the lagged dependent variable. Extending the previ-

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<sup>6</sup>Note that in the original suggestion of Heckman (1981b), it is allowed for freely correlated composite error term between the time points (also see Arulampalam and Stewart 2009).

ous approach, the following depending variables are considered:

$$y_{1it} = \begin{cases} 1 & \text{if the person is high-paid,} \\ 0 & \text{otherwise.} \end{cases} \quad (9)$$

$$\text{and if } y_{1it} = 0, y_{2it} = \begin{cases} 1 & \text{if the person is unemployed,} \\ 0 & \text{otherwise.} \end{cases} \quad (10)$$

Note that the second dependent variable  $y_{2it}$  will be considered only if the first depending variable  $y_{1it} = 0$ . The respective latent response formulations for the dynamic sequence  $t \geq 1$  are:

$$y_{1it} = \mathbf{1} \left\{ x'_{1it}\beta_1 + z'_{1i}\kappa_1 + y_{1i(t-1)}\gamma_{11} + y_{3i(t-1)}\gamma_{12} + \bar{x}_{1i}\delta_1 + \alpha_{1i} + u_{1it} > 0 \right\}, \quad (11)$$

$$y_{2it} = \mathbf{1} \left\{ x'_{2it}\beta_2 + z'_{2i}\kappa_2 + y_{1i(t-1)}\gamma_{21} + y_{3i(t-1)}\gamma_{22} + \bar{x}_{2i}\delta_2 + \alpha_{2i} + u_{2it} > 0 \right\} \text{ if } y_{1it} = 0. \quad (12)$$

Referring to the initial conditions problem, the suggestion of Heckman (1981b) is applied and equation 5 is extended to the bivariate case:

$$y_{1i0} = \mathbf{1} \left\{ x'_{1i0}\eta + z'_{1i}\pi_1 + \text{ins}'_{1i}\omega_1 + \theta_1\alpha_{1i} + u_{1i0} > 0 \right\}, \quad (13)$$

$$y_{2i0} = \mathbf{1} \left\{ x'_{2i0}\eta + z'_{2i}\pi_2 + \text{ins}'_{2i}\omega_2 + \theta_2\alpha_{2i} + u_{2i0} > 0 \right\} \text{ if } y_{1i0} = 0. \quad (14)$$

As normalizations, it is assumed that  $u_{jit} \sim N(0, \sigma_{u_j}^2)$  and  $\alpha_{ji} \sim N(0, \sigma_{\alpha_j}^2)$  with  $j \in \{1, 2\}$ . Furthermore, it is assumed that bot random-effects are correlated with  $\rho_\alpha$ . For identification it is assumed that the idiosyncratic error terms are standard-normal distributed, hence  $u_{jit} \sim N(0, 1)$ . Note that the composite error term is  $\nu_{jit} = u_{jit} + \alpha_{ji}$  and is correlated over time in the following way  $\lambda_j = \text{corr}(\nu_{jit}, \nu_{jis}) = \frac{\sigma_{\alpha_j}^2}{\sigma_{\alpha_j}^2 + \sigma_{u_j}^2}$  for each  $t \neq s$  with  $j \in \{1, 2\}$ . The variance-covariance matrix of the random-effects error terms take now the following form:

$$V_\alpha = \begin{pmatrix} \sigma_{\alpha_1}^2 & \cdot \\ \rho_\alpha \sigma_{\alpha_1} \sigma_{\alpha_2} & \sigma_{\alpha_2}^2 \end{pmatrix} \quad (15)$$

The individual outcome probabilities are:

$$P_{it}(\alpha_1^*, \alpha_2^*) = \begin{cases} \left\{ \Phi \left[ \mu_1^{\text{dyn}} \right] \right\}^{y_{1it}} \left\{ \Phi \left[ -\mu_1^{\text{dyn}} \right] \Phi \left[ \left( \mu_2^{\text{dyn}} \right) (2y_{2it} - 1) \right] \right\}^{(1-y_{1it})} & \text{if } t \geq 1 \\ \left\{ \Phi \left[ \mu_1^{\text{init}} \right] \right\}^{y_{1i0}} \left\{ \Phi \left[ -\mu_1^{\text{init}} \right] \Phi \left[ \left( \mu_2^{\text{init}} \right) (2y_{2i0} - 1) \right] \right\}^{(1-y_{1i0})} & \text{if } t = 0 \end{cases} \quad (16)$$

with

$$\mu_j^{\text{dyn}} = x'_{jit}\beta_j + z'_{ji}\kappa_j + y_{1i(t-1)}\gamma_{j1} + y_{3i(t-1)}\gamma_{j2} + \bar{x}_{ji}\delta_1 + \sigma_{\alpha_j}\alpha_j^*$$

and

$$\mu_j^{\text{init}} = x'_{ji0}\eta + z'_{ji}\pi_j + \text{ins}'_{ji}\omega_j + \theta_j\sigma_{\alpha_j}\alpha_j^*$$

for  $j \in \{1, 2\}$ .  $\Phi$  is referring to the standard normal cumulative distribution function and

$\alpha_j^* = \alpha_j / \sigma_{\alpha_j}$ . The individual likelihood contribution is:

$$L_i = \int_{\alpha_1^*} \int_{\alpha_2^*} \left\{ P_{i0}(\alpha_1^*, \alpha_2^*) \prod_{t=1}^T P_{it}(\alpha_1^*, \alpha_2^*) \right\} g(\alpha_1^*) g(\alpha_2^*) d\alpha_1^* d\alpha_2^* \quad (17)$$

and  $g(\alpha_j^*)$  are the probability density functions which need to be integrated out. As in the uncorrelated model, maximum simulated likelihood is used. The Cholesky decomposition  $C_\alpha$  of the variance-covariance matrix of the random-effects  $V_\alpha$  is:

$$C_\alpha = \begin{pmatrix} \sigma_{\alpha_1} & 0 \\ (\rho_\alpha \sigma_{\alpha_1} \sigma_{\alpha_2}) / \sigma_{\alpha_1} & \sqrt{\sigma_{\alpha_2}^2 - (\rho_\alpha^2 \sigma_{\alpha_1}^2 \sigma_{\alpha_2}^2) / \sigma_{\alpha_1}^2} \end{pmatrix}$$

Using primes numbers, two times  $R$  standard uniform distributed draws  $\tilde{\alpha}_j^r \in \{0, \dots, 1\}$  with  $j \in \{1, 2\}$  are derived and transformed by the inverse cumulative standard normal distribution  $\Phi^{-1}(\tilde{\alpha}_j^r)$ . In the simulation,  $\alpha_1^r = \sigma_{\alpha_1} \tilde{\alpha}_1^r$  and  $\alpha_2^r = ((\rho_\alpha \sigma_{\alpha_1} \sigma_{\alpha_2}) / \sigma_{\alpha_1}) \tilde{\alpha}_1^r + \sqrt{\sigma_{\alpha_2}^2 - (\rho_\alpha^2 \sigma_{\alpha_1}^2 \sigma_{\alpha_2}^2) / \sigma_{\alpha_1}^2} \tilde{\alpha}_2^r$ . For each draw the likelihood is derived for each observation, multiplied over all individuals and time-points and averaged over all draws:

$$MSL = \prod_{i=1}^N \frac{1}{R} \sum_{r=1}^R \left\{ P_{i0}(\alpha_1^r, \alpha_2^r) \prod_{t=1}^T P_{it}(\alpha_1^r, \alpha_2^r) \right\} \quad (18)$$

In this application, 70 Halton draws are applied.

### 4.3 The Wooldridge approach

Another approach to handle the initial conditions problem is suggested by Wooldridge (2005). Instead of estimating a static equation for the first period as suggested by Heckman (1981b), Wooldridge (2005) suggests to condition the dynamic sequence of the panel ( $t \geq 1$ ) on the initial labor market position. Referring to the individual-specific time-invariant error term of equation 2, the  $\epsilon_i$  takes the following form (Wooldridge 2005):

$$\epsilon_i = a_0 + y_{i0} \delta + \bar{x}_i \eta + \kappa_i \quad (19)$$

Plugging equation 19 into equation 2 leads to:

$$y_{it} = \mathbf{1} \left\{ x'_{it} \beta + z'_i \kappa + y_{i(t-1)} \gamma + a_0 + y_{i0} \delta + \bar{x}_i \eta + \kappa_i + u_{it} > 0 \right\}. \quad (20)$$

Note that the correlation of the composite error term  $v_{it} = \kappa_i + u_{it}$  over time is  $\lambda_v = \text{corr}(v_{it}, v_{is}) = \frac{\sigma_\kappa^2}{\sigma_\kappa^2 + \sigma_u^2}$  for each  $t \neq s$ . One advantage of the suggestion of Wooldridge (2005) is that the random-effects can be easily integrated out by using standard software packages. In this study, Gauss-Hermite quadratures are used (Butler and Moffitt 1982).

## 5 Results

A first impression about the impact of the previous labor market position on the current one can be obtained by looking at the transition matrix in Table II. In the rows the three labor market positions high-paid employed, low-paid employed and unemployed at the previous period  $t - 1$  can be found and in the columns the labor market position at the current time point  $t$ . The numbers in the matrix refer to the conditional probability of being in a certain labor market at  $t$  conditional on being in a certain labor market position at  $t - 1$ . Unsurprisingly, with 94.15% refers the highest conditional probability of becoming high-paid employed to those who were already high-paid employed in the previous period. Furthermore, it can be noted that the conditional probability of becoming high-paid employed is at a comparable between those who were low-paid employed (23.21%) or unemployed (20.72%) at  $t - 1$ . However, it must be noted that beside the previous labor market position there exist several determinants that have a potential influence on the labor market outcome, like differences in observable and unobservable characteristics and neighborhood effects.

[Table II about here!]

To control for the influence of differences in observable characteristics, the following control variables as enlisted in Table III are used in the econometric model. Note that the variables are differentiated according to time-varying explanatory variables and time-constant explanatory variables. Furthermore, some variables will be interacted with the labor market position in the previous period, such as whether someone has attained some post-secondary education or the characteristics of the local labor market or low-pay area index.

[Table III about here! and Table IV]

As can be seen from Table IV, some variation in the observable characteristics between the different labor market positions can be found. For example, the number of individuals with post-secondary education is more than two-and-a-half times higher among the high-paid employed (56.2%) than among the low-paid employed (18.4%) and about two times higher compared to the unemployed (24.3%). Furthermore, indications are found that the share of young men is higher among the unemployed (23.0%) and the low-paid employed (20.2%) than among the high-paid employed (13.7%). Furthermore, while about half of the low-paid employed and roughly about 60% of the high-paid employed are married, this is only the case for every fifth unemployed.

Aim of this study is derive the springboard effect of low-wages in dependence of the local unemployment rate and the local size of the low-wage sector. For this reason, neighborhood data on the LSOA level provided from the Department for Transport and the Department of Environment and Climate Change were matched with data from the panel survey Understanding Society. The local unemployment rate is defined as the ratio of at risk users



of employment centers to the number of users of employment centers. As a proxy for the importance of the local low-pay sector statistics about the number of fuel-poor households within a LSOA were used: a household is defined as fuel-poor if the household faces above median required energy costs and a residual between income and energy costs which is below the poverty threshold.

To estimate the springboard effect of low-wages on the probability of becoming high-paid employed, dynamic models are applied. As individuals are much likely to differ in their unobservable (Heckman 1981a), a random-effects error term is included. This individual-specific time-constant error term is likely to be correlated with the labor market position in the initial period, in the economic literature also referred to as the initial conditions problem (Heckman 1981b). To control for the initial conditions problem, the suggestion of Heckman (1981a) is followed by estimating a static equation for the initial period. The results are controlled by also applying the suggestion of Wooldridge (2005) by conditioning the estimation on the labor market outcome in the initial period. Furthermore, there exist several studies indicating that the random-effects might be correlated between the mutual exclusive labor market positions and that the correlation might have some severe impact (see *inter alia* Plum 2014). For this reason, the Heckman model is replicated and this time accounting for correlated random-effects.

**[Table VIII about here!]**

The estimation results of the Heckman estimator without correlated random-effects can be found in Table VIII. In the tables referring to the estimation results, only the lagged dependent variables are presented as these one's are needed to derive the springboard-effect of low-wages. Interaction terms with the lagged labor market position are used to derive the impact of a high local unemployment rate, a low-pay area and post-secondary education on the probability of becoming/staying high-paid employed at  $t$ . As reference category, being unemployed and having no post-secondary education is chosen. In the first model (column one of Table VIII), a basic model without any further information on the neighborhood level is estimated. Referring to someone without post-secondary education, being high-paid employed in the previous period increases the probability of staying high-paid employed compared to someone unemployed. This effect is significantly different from zero at the 1% level. Furthermore, being low-paid employed also has a positive impact on the chances of becoming high-paid employed compared to someone who was unemployed, though this effect is not significantly different from zero at the 10% level ( $p$ -value = 0.104). Hence, indications for a weak springboard-effect of low-wages for men without post-secondary employment can be detected. There also exist indications that it is necessary to take individual-specific time-constant error-terms into account: the variance of the random-effects error term  $\sigma_\alpha^2$  is significantly different from zero at the 1% level. Furthermore, the parameter  $\theta = 0.942$  indicates that the random-effects has a comparable impact on the initial period as on the subsequent periods.

**[Table IX about here!]**

When allowing for correlated random-effects (first column of Table IX), indications are found that the two individual-specific time-invariant error terms  $\sigma_{\alpha_1}^2$  and  $\sigma_{\alpha_2}^2$  are positively correlated ( $\rho_\alpha = 0.272$ ). Furthermore, the correlation parameter is significantly different from zero at the 10% level. The findings of the uncorrelated model are confirmed, though the coefficient referring to being low-paid employed in the previous period is now significantly different from zero at the 5% level ( $p$  – value = 0.020). When applying the suggestion of Wooldridge (2005) to control for the initial conditions problem, the previous findings are confirmed (first column of Table X): the results also point at a positive impact of low-wages on the probability of becoming high-paid employed compared to unemployment for men without post-secondary education.

**[Table X about here!]**

In the second model, the indicator variable that refers to the local unemployment rate is added to the estimation (column two of Table VIII). Reference category is now an unemployed men without post-secondary education living in a LSOA with a low local unemployment rate. Being high-paid employed in a LSOA with a low unemployment rate still has a positive impact on the probability of staying high-paid, though the parameter is only significant at the 10% level. Referring to the springboard effect of low-wages, the preliminary findings of the initial model without any neighborhood information are now turned, indicating that picking up a low-paid job in a LSOA with a low unemployment rate might weaken the prospects of becoming high-paid employed compared to someone unemployed. However, this parameter is highly insignificant ( $p$  – value = 0.509). When taking correlated random effects into account (second column of Table IX), a negative sign of the low-pay coefficient is still detectable, though still highly insignificant ( $p$  – value = 0.969). Also the Wooldridge estimator derives comparable results (second column of Table X), indicating that in a LSOA with a low unemployment rate, no springboard effect of low-wages can be found. Instead some weak indications can be found that low-wages might even lead to a deterioration of the employment prospects.

**[Table XI about here!]**

When considering the impact of a high local unemployment rate, it can be noted that in general the employment prospects deteriorate: independent of the lagged labor market position, living in a LSOA with a high unemployment rate reduces the chances of becoming/staying high-paid employed in the subsequent period within the same labor market category. This deterioration can be detected in all three estimators and is significantly different from zero at least at the 10% level in each specification. However, it must be noted that the deterioration in the labor market prospects is much stronger for the unemployed. When testing  $\hat{\beta}_{LP,t-1} + \hat{\beta}_{LP \times \text{high local } ue_{t-1}} = \hat{\beta}_{Ue \times \text{high local } ue_{t-1}}$  then  $\chi^2(1) = 4.225$  ( $p$  – value = 0.040) (see Table XI). This indicates that in LSOA's with a high unemployment rate, a springboard effect of low-wages can be detected. These findings are confirmed by the two other estimations.

In the third model, the indicator variable referring to importance of the local low-pay sector is added to the basic model (third column of Table VIII, Table IX and Table X).

Being unemployed without post-secondary education and living in a high-pay LSOA is now the reference category. Independent of the chosen estimator, someone who was low-paid employed in the previous period and lives in a high-pay LSOA has a higher chance to become high-paid employed than someone who was living in a low-pay area. And for each estimator, the coefficient is significantly different from zero at the 10% level. However, the probability of becoming/staying high-paid employed deteriorates within the same labor market position if moving from a high-pay LSOA to a low-pay LSOA. Independent of the estimator, the coefficient is only significantly different from zero at the 10% level if the men was high-paid or low-paid employed. Referring to the springboard effect of low-wages, the test  $\hat{\beta}_{LP_{t-1}} + \hat{\beta}_{LP \times \text{low-pay area}_t} = \hat{\beta}_{Ue \times \text{low-pay area}_t}$  indicates with  $\chi^2(1) = 0.192$  ( $p$ -value = 0.661) that there is no springboard effect of low-wages within a low-pay area. This can be concluded independent of the applied estimator.

In the fourth model, both indicator variables that refer to the characteristic of the LSOA are added to the basic model (fourth column of Table VIII, Table IX and Table X). Referring to the coefficients of the lagged labor market position, being unemployed with no post-secondary education in a high-pay LSOA with a low local unemployment rate is the reference category. Being low-paid employed has a slightly negative effect in the Heckman estimator without correlated random effects and in the Wooldridge estimator, whereas the Heckman estimator with correlated random-effects derives a slightly positive impact. However, in none of the estimator the coefficient is significantly different from zero: Heckman (uncorrelated)  $p$ -value = 0.612, Heckman (correlated)  $p$ -value = 0.904 and Wooldridge  $p$ -value = 0.910. Hence, no springboard-effect of low-paid jobs can be detected in high-pay LSOA's with a low unemployment rate. Going along with the findings of the second model, indications are found that the general probability of becoming/staying high-paid deteriorates when moving from a LSOA with a low to a LSOA with a high unemployment rate. Independent of the estimator, the coefficient is significantly different from zero at least at the 10% level when the person was unemployed or high-paid employed at  $t - 1$ . A reduction of the employment prospects for low-paid worker which is significantly different from zero at the 10% level can only be detected in the Heckman estimator without correlated random effects. When testing  $\hat{\beta}_{LP_{t-1}} + \hat{\beta}_{LP \times \text{high local ue}_{t-1}} = \hat{\beta}_{Ue \times \text{high local ue}_{t-1}}$  then indications are found that low-ages might offer a stepping stone to high-paid employment (see Table XI). In the case of moving from a high-pay to a low-pay LSOA, like in the third model indications are found that the general prospects to become/stay high-paid are deteriorated. And this can be found for each estimator. However, the reduction is only significantly different from zero at the 10% level for men who were low-paid employed in the previous period. Going along with the findings of the third model, testing  $\hat{\beta}_{LP_{t-1}} + \hat{\beta}_{LP \times \text{low-pay area}_t} = \hat{\beta}_{Ue \times \text{low-pay area}_t}$  reveals that picking up a low-paid job in a low-pay LSOA deteriorates the employment prospects compared to someone unemployed, though not significantly different from zero. In the case of moving from a high-pay LSOA with a low unemployment rate to a low-pay LSOA with a high unemployment rate, the test  $\hat{\beta}_{LP_{t-1}} + \hat{\beta}_{LP \times \text{high local ue}_{t-1}} + \hat{\beta}_{LP \times \text{low-pay area}_t} = \hat{\beta}_{Ue \times \text{high local ue}_{t-1}} + \hat{\beta}_{Ue \times \text{low-pay area}_t}$  also indicates that there is no significant difference between unemployment and low-wage employment in the probability of becoming high-paid employed.

To sum up the findings, indications are found that:

- In a high-pay LSOA with a low unemployment rate, no significant difference in the employment prospects between low-paid worker and unemployed can be found.
- Strong evidence for a springboard effect of low-wages can be found in the case of high-pay areas with a high local unemployment rate. However, it must be noted that the general employment prospects deteriorate.
- In the case of low-pay areas with a low local unemployment rate, the employment prospects of the low-paid worker deteriorate very strong. Furthermore, independent of the estimator indications for a negative effect of low-paid jobs compared to unemployment are found, however these are not statistically significant different from zero at the 10% level.
- In the case of high-pay areas with a high local unemployment rate, a slightly positive effects of low-wages in comparison to unemployment can be found, though not significantly different from zero at the 10% in any estimator.

It is likely that the impact of the local labor market characteristics differ in dependence of the educational background of the person: it can be assumed that individuals with a higher level of human capital search on a higher regional level for finding adequate job offers. Therefore, in a further specification (Model 5) those men with post-secondary education are dropped from the sample (fifth column of Table VIII, Table IX and Table X). Like in the Model 4, unemployed men living in a high-pay area with a low unemployment rate is the reference category. In this case, small negative (Heckman estimator, uncorrelated) resp. positive (correlated Heckman estimator and Wooldridge estimator) impact of low-wages can be found, though not significantly different from zero in any of the estimations. Furthermore, indications are found that with a higher level of local unemployment the employment prospects deteriorate, especially strong for those unemployed. In these areas, again a springboard effect of low-wages can be found (see Table XI). However, the size of the low-wage sector has especially an impact on the prospects of the low-paid employed, though no indications for significant difference can be found.

## 5.1 Partial effects

Based on the derived coefficients, the springboard effect of low-wages compared is calculated. For this reason, the difference in the probability of becoming high-paid employed between someone who was low-paid employed in the previous period and someone unemployed is calculated. Instead of using the sample mean, the probability is calculated for the following reference person: a mature married men with children living in his household, living in a ntsarea 1 (but not London or South-East of England), with no health limits at work.<sup>7</sup> The partial effects are differentiated according to the labor market characteristics within the LSOA. In Table XII (Table XIII) the partial effects for a men without (with) post-secondary education are presented, differentiated according to the three different estimators.

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<sup>7</sup>It is assumed that the individual has no change in his characteristics over the observed time period.

[Table XII about here!]

In the first cell of Table XII, the partial effect for a high-pay LSOA with a low unemployment rate is presented. In the case of the Heckman (uncorrelated) and Wooldridge estimator, a slight reduction of the employment prospects can be found when instead of being unemployed a low-paid job is chosen. In the case of the correlated Heckman estimator, a small positive effect is found. However, in none of these models the effect is significantly different from zero. In the case of a high-pay LSOA with a high unemployment rate, a strong increase in the probability of climbing up the salary ladder can be found: between 10.9%-points in the uncorrelated Heckman estimator and 14.6%-points in the correlated Heckman estimator. Furthermore, each partial effect is significantly different from zero at the 5% level. If the number of the unemployed within the low-pay LSOA is low, then a noticeable decline of the springboard effect can be detected: the chances of becoming high-paid employed decrease between 5.7%-points (correlated Heckman estimator) and 9.2%-points (uncorrelated Heckman estimator). However, none of the partial effects are significantly different from zero at the 10% level. In the case of a low-pay LSOA with a high number of unemployed, weak indications for a springboard effect of low-wages can be detected (between 4.5%-points in the Wooldridge estimator and 8.0%-points in the correlated Heckman estimator), though none of the partial effects are significantly different from zero at the 10% level. To sum up the findings for men without post-secondary education, weak indications of a negative impact of low wages can be found in areas with a low local unemployment rate, especially in low-pay LSOA's. A positive effect of low-wages can be found in areas with a high local unemployment, and significantly different at the 5% level if it is a high-pay area.

[Table XIII about here!]

In Table XIII, the partial effects of a low-wage employment compared to unemployment are presented. Indications are found that independent of being a high-pay or low-pay LSOA, if the local share of unemployed is low then low-wages deteriorate the prospects of becoming high-paid employed compared to unemployment. However, none of the partial effects are significantly different from zero at the 10% level.<sup>8</sup> If the local unemployment rate is high and the area high-pay, then a springboard effect can be detected. However, in none of the estimator the partial effects are different from zero at the 10% level. Furthermore, the partial effects are below of those men without post-secondary education, especially in the case of the Heckman estimators. In general it can be concluded that low-wages work less favorable for men with post-secondary education, which goes along with existing findings (Knabe and Plum 2013, Plum 2014).

## 5.2 Further Specifications

To evaluate the sensitivity of the findings, the following robustness estimations were derived:

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<sup>8</sup>In the case of the Wooldridge estimator when the local unemployment rate is low in a low-pay area, the  $p$  - value = 0.103.

- Specification 1: To improve the labor market outcome, one strategy is change the region living. However, the labor market outcome could be correlated with the propensity to change the place of residence. Therefore, in the initial sample those men were dropped from the sample who changed their ntsarea or moved to or away from London or South-East of England. However, the change of residence might occur on some lower regional level. In the first robustness estimation, those men who changed their LSOA living in are dropped from the sample.
- Specification 2: In the panel survey *Understanding Society*, those men with a non-British background are overrepresented. There exist several studies indicating that migrants perform better on the British labor market then their native colleagues. To investigate the impact of the ethnic background, those observations that belong to the *Ethnic Minority Boost Sample* are dropped from the sample.
- Specification 3: To derive the local unemployment rate, the ratio of number of users reaching the next employment center with the bike within 20 minutes to the number of at risk users reaching the next employment center with the bike within 20 minutes is calculated. However, it could be assumed that the distance between residence and employment center is not randomly distributed. In this specification, the distance to the next employment center is increased by considering those individuals who live 40 minutes by bike far away from the next employment center.
- Specification 4: The identification of the unemployed is relaxed by also including those who identify themselves as unemployed without having been searching for a job are included in the sample.
- Specification 5: London and South-East of England have some major impact on the British economy, going along with above-average wages. Major parts of the labor market transitions to high-paid employment could be happening in this area. In this specification, men living in London or in South-East of England are dropped from the sample.
- Specification 6: The local unemployment rate could be underestimated in especially rural areas, in which the distance to the next employment center is noticeably above 20 or 40 minutes by bike. In the last specification, those men are dropped from the sample who live in ntsarea 3, an area with a population below 100k.
- Specification 7: So far, it is assumed that local unemployment rate and the importance of the low-wage sector have an additive effect. In this specification, another variable is included which becomes one if the person is living in a low-pay area with a high local unemployment rate (see Table III).

For each estimation, the uncorrelated Heckman estimator is applied. The estimation results can be found in Table XIV and the test of the coefficients can be found in Table XV and the partial effects in Table XVI. It can be noted that no major differences compared to the initial estimation are found.

[Table XIV and Table XV about here!]

In another specifications (Specification 8 and Specification 9), the threshold for differentiating between low and high local unemployment rate is extended by adding another threshold which for a local unemployment rate of 4% and above (see Table XVII-Table XIX). As can be seen from the tables, indications are found that the stepping-stone effect of low-wages is mainly restricted to high-pay areas with a local unemployment rate of 4% and above. Though having a negative sign, no indications for a significantly reduced chance of becoming high-paid employed is found in low-pay areas with a low local unemployment rate.

## 6 Conclusion

The main objective of this study is to derive the differences in the prospects of becoming high-paid employed between someone who was low-paid employed and someone unemployed in the previous period. In extension to existing studies, this study also takes the heterogeneity on the local residential level into account. For this reason, survey panel data from *Understanding Society* are matched with neighborhood data, indicating local labor market tightness and the importance of the local low-wage sector. Indications are found for men without post-secondary education that within high-pay areas with a low unemployment rate no springboard effect of low-wages can be detected. If the local unemployment rate is high, than strong indications for a springboard effect of low-wages can be detected. One explanation is that the value of the signal to be willing to work is positively correlated with the number of unemployed within an area and that therefore the prospects of becoming high-paid employed of the employed deteriorate much stronger than the prospects of the low-wage worker compared to an area with a low local unemployment rate. However, if the area has a low unemployment rate and is affected by a higher share of low-paid jobs, than the springboard effect of low-wages declines, indicating that the prospects of someone unemployed are better than of a low-wage worker. However, these results are not statistically significantly different from zero at the 10% level. If the low-pay area is also affected by a high local unemployment rate, than only weak indications for a stepping-stone effect are found.

Referring to men with post-secondary education, now significant positive springboard effect is detected. Instead, indications are found that the prospects of becoming high-paid employed deteriorate for an unemployed man with post-secondary education if he picks up a low-paid job. However, none of the effects are significantly different from zero at the 10% level. These findings go along with other empirical studies (Knabe and Plum 2013, Plum 2014) and might indicate, that men with post-secondary education do not pick up a low-paid job in order not to avoid some negative signal about their productivity (McCormick 1990) and wait until finding an appropriate match (Pissarides 1990).

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Table I: Low-pay threshold

	2009	2010	2011	2012
Threshold in £	7.07	7.69	7.90	7.98

*Source:* Understanding Society, waves 1-4. For calculation, the weighted gross hourly wages of both sexes in England are used.

Table II: Transition Matrix

	High-Paid <sub>t</sub>	Low-Paid <sub>t</sub>	Unemployed <sub>t</sub>
High-Paid <sub>t-1</sub>	94.15%	4.92%	0.93%
Low-Paid <sub>t-1</sub>	23.21%	73.66%	3.13%
Unemployed <sub>t-1</sub>	20.72%	26.69%	52.59%
Total <sub>t</sub>	77.21%	19.19%	3.60%

*Source:* Understanding Society, waves 2009-12.  $N=5\,778$

Table III: Control Variables

Variables	Description
<i>Time-varying explanatory variables</i>	
Young	Dummy: 1 if person is 30 or below, 0 otherwise.
Old	Dummy: 1 if person is 55 or above, 0 otherwise.
Health limits work	Categorical: between 1 (all of the time) and 5 (none of the time)
Child	Dummy: 1 if a child under age 17 is living in the household, 0 otherwise
Married	Dummy: 1 if married, 0 otherwise
<i>Time-constant explanatory variables<sup>†</sup></i>	
lonse	Dummy: 1 if living in London or South-East of England and 0 otherwise
ntsarea 1	Dummy: 1 if individual is living in (1) Inner London, (2) Outer London built-up areas, (3) West Midlands, (4) Greater Manchester, 0 otherwise
ntsarea 2	Dummy: 1 if individual is living in (5) West Yorkshire, (7) Liverpool, (8) Tyneside, (9) South Yorkshire, (10+11) urban area over 100k population, 0 otherwise
ntsarea 3	Dummy: 1 if individual is living in area below 100k population, 0 otherwise
<i>Interaction with the lagged labor market position</i>	
Post-sec. educ.	Dummy: 1 if individual has post-secondary education, 0 otherwise <sup>1</sup>
high-ue area	Dummy: 1 if unemployment rate at the LSOA level is 2% or more, 0 otherwise
low-pay area	Dummy: 1 if LSOA belongs to the 75th poorest percentile, 0 otherwise exceeds 1, 0 otherwise
cross*	Dummy: 1 if unemployment rate at the LSOA level is 2% or more and if LSOA LSOA belongs to the 75th poorest percentile, 0 otherwise
<i>Instruments for the initial period</i>	
ukborn	Dummy: 1 if individual was born in England, Scotland, Wales or Northern Ireland, 0 otherwise
parents ukborn	Dummy: 1 if father and mother were born in England, Scotland, Wales or Northern Ireland, 0 otherwise
english	Dummy: 1 if English is first language, 0 otherwise
father not working	Dummy: 1 if father was not working when resp. individual was aged 14, 0 otherwise
living with parents	Dummy: 1 if individual was living with his biological parents from the time he was born until you were 16

<sup>1</sup> ISCED: International Standard Classification of Education.

\* Only used in a robustness estimation.

Table IV: Descriptive Statistics

Variables	Total <sub>t</sub>	High-Paid <sub>t</sub>	Low-Paid <sub>t</sub>	Unemployed <sub>t</sub>
Young	0.153	0.137	0.202	0.230
Old	0.098	0.092	0.113	0.141
Health limits at work: all of the time	0.010	0.009	0.011	0.019
Health limits at work: most of the time	0.022	0.019	0.030	0.051
Health limits at work: some of the time	0.075	0.067	0.102	0.102
Health limits at work: a little of the time	0.152	0.151	0.167	0.112
Health limits at work: none of the time	0.741	0.755	0.691	0.716
Child	0.016	0.016	0.011	0.029
Married	0.614	0.658	0.525	0.214
lonse	0.298	0.324	0.198	0.291
ntsarea 1	0.228	0.228	0.210	0.323
ntsarea 2	0.311	0.297	0.346	0.415
ntsarea 3	0.461	0.475	0.444	0.262
Post-sec. educ.	0.476	0.562	0.184	0.243

<sup>1</sup> *ISCED*: International Standard Classification of Education.

Table V: Local unemployment and low-pay area

	low local ue	high local ue	Total
high-pay area	2230	2108	4338
low-pay area	390	1050	1440
Total	2620	3185	5778

*Source*: Understanding Society, waves 1-4 and own calculations.

Table VI: LSOA

Region	$H_{pt}$	$L_{pt}$	$U_{et}$	Mean local $ue_{t-1}$	High-local $ue_{t-1}$	Mean share of fuel poor $hh_t$	Low-pay areas $_t$	Share
North East	0.704	0.242	0.053	0.040	0.708	0.143	0.368	0.055
North West	0.772	0.190	0.037	0.031	0.570	0.137	0.348	0.129
Yorkshire and the Humber	0.703	0.262	0.035	0.033	0.616	0.133	0.284	0.088
East Midlands	0.743	0.217	0.040	0.027	0.541	0.140	0.374	0.094
West Midlands	0.675	0.276	0.049	0.036	0.601	0.155	0.485	0.109
East of England	0.792	0.182	0.026	0.026	0.517	0.113	0.172	0.120
London	0.828	0.134	0.038	0.037	0.770	0.105	0.182	0.139
South East	0.845	0.127	0.028	0.021	0.328	0.088	0.051	0.159
South West	0.786	0.187	0.028	0.021	0.391	0.110	0.155	0.106
England	0.772	0.192	0.036	0.030	0.547	0.121	0.249	

Source: Understanding Society, waves 1-4 and own calculations.

Table VII: Labor market positions

	Total	high-ue area <sub><math>t-1</math></sub>	low-pay areas <sub><math>t</math></sub>
High-paid <sub><math>t</math></sub>	77.21	69.03	65.76
Low-paid <sub><math>t</math></sub>	19.19	25.43	28.82
Unemployed <sub><math>t</math></sub>	3.60	5.54	5.41

*Source:* Understanding Society, waves 1-4 and own calculations.



Table VIII: Heckman estimator (uncorrelated)

	Model 1		Model 2		Model 3		Model 4		Model 5 <sup>†</sup>	
	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.
dependent variable:	<i>high-paid in t</i>									
Hp <sub>t-1</sub>	1.004	0.214	0.563	0.338	1.051	0.231	0.605	0.342	0.749	0.413
Hp <sub>t-1</sub> × high-ue area <sub>t-1</sub>			-0.385	0.113			-0.366	0.113	-0.410	0.144
Hp <sub>t-1</sub> × low-pay area <sub>t</sub>					-0.233	0.117	-0.181	0.115	-0.204	0.141
Hp <sub>t-1</sub> × post sec.-edu.	1.973	0.231	1.789	0.219	1.887	0.225	1.742	0.215		
Lp <sub>t-1</sub>	0.329	0.203	-0.221	0.334	0.403	0.226	-0.172	0.340	-0.052	0.411
Lp <sub>t-1</sub> × high-ue area <sub>t-1</sub>			-0.326	0.146			-0.244	0.147	-0.247	0.173
Lp <sub>t-1</sub> × low-pay area <sub>t</sub>					-0.448	0.137	-0.420	0.137	-0.365	0.156
Lp <sub>t-1</sub> × post sec.-edu.	1.954	0.256	1.773	0.243	1.863	0.250	1.725	0.238		
Ue <sub>t-1</sub>	<i>reference category</i>									
Ue <sub>t-1</sub> × high-ue area <sub>t-1</sub>			-0.991	0.337			-0.972	0.336	-0.871	0.432
Ue <sub>t-1</sub> × low-pay area <sub>t</sub>					-0.177	0.308	-0.102	0.307	0.006	0.372
Ue <sub>t-1</sub> × post sec.-edu.	2.448	0.374	2.190	0.364	2.354	0.368	2.136	0.360		
$\sigma_\alpha^2$	3.149	0.716	3.773	0.812	3.422	0.763	2.962	0.686	3.130	0.878
$\theta$	0.942	0.124	0.868	0.107	0.909	0.117	0.968	0.131	1.007	0.165
log likelihood		-2461.8122		-2451.7406		-2455.147		-2446.1554		-1676.5246
observations		7 704		7 704		7 704		7 704		4 036

Source: Understanding Society, waves 1-4 and own calculations. Estimations include additional covariates (and their mean values) as enlisted in Table III and year dummies.  
<sup>†</sup>From sample excluded are men with post-secondary education.

Table IX: Heckman estimator (correlated)

	Model 1		Model 2		Model 3		Model 4		Model 5 <sup>†</sup>	
	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.
dependent variable:	<i>high-paid in t</i>									
H <sub>p</sub> <sub>t-1</sub>	1.174	0.234	0.739	0.355	1.225	0.250	0.793	0.360	0.944	0.452
H <sub>p</sub> <sub>t-1</sub> × high-ue area <sub>t-1</sub>		-0.378	0.113				-0.360	0.113	-0.408	0.143
H <sub>p</sub> <sub>t-1</sub> × low-pay area <sub>t</sub>					-0.225	0.117	-0.173	0.115	-0.198	0.140
H <sub>p</sub> <sub>t-1</sub> × post sec.-edu.	1.952	0.229	1.764	0.219	1.857	0.223	1.710	0.214		
L <sub>p</sub> <sub>t-1</sub>	0.537	0.231	-0.014	0.358	0.612	0.254	0.044	0.365	0.143	0.440
L <sub>p</sub> <sub>t-1</sub> × high-ue area <sub>t-1</sub>			-0.319	0.146			-0.235	0.147	-0.233	0.172
L <sub>p</sub> <sub>t-1</sub> × low-pay area <sub>t</sub>					-0.454	0.137	-0.426	0.136	-0.362	0.155
L <sub>p</sub> <sub>t-1</sub> × post sec.-edu.	1.923	0.252	1.743	0.240	1.828	0.245	1.691	0.235		
U <sub>e</sub> <sub>t-1</sub>	<i>reference category</i>									
U <sub>e</sub> <sub>t-1</sub> × high-ue area <sub>t-1</sub>			-0.955	0.338			-0.934	0.338	-0.909	0.435
U <sub>e</sub> <sub>t-1</sub> × low-pay area <sub>t</sub>					-0.163	0.303	-0.081	0.303	-0.019	0.364
U <sub>e</sub> <sub>t-1</sub> × post sec.-edu.	2.434	0.363	2.138	0.358	2.326	0.358	2.074	0.355		
$\sigma_{\alpha_1}^2$	3.812	0.836	3.149	0.740	3.413	0.781	2.931	0.705	2.951	0.877
$\sigma_{\alpha_2}^2$	1.391	1.184	1.269	0.990	1.347	1.162	1.316	1.040	0.555	1.305
$\theta_1$	0.856	0.106	0.935	0.125	0.901	0.117	0.965	0.133	1.016	0.170
$\theta_2$	1.511	0.836	1.764	0.985	1.535	0.868	1.700	0.930	1.743	2.040
$\rho_\alpha$	0.272	0.160	0.266	0.162	0.277	0.159	0.272	0.162	0.415	0.311
log likelihood	-3020.7182		-3008.5527		-3013.3100		-3002.1258		-2092.3962	
observations	7704		7704		7704		7704		4036	

Source: Understanding Society, waves 1-4 and own calculations. Estimations include additional covariates (and their mean values) as enlisted in Table III and year dummies.  
<sup>†</sup>From sample excluded are men with post-secondary education.

Table X: Wooldridge estimator

	Model 1		Model 2		Model 3		Model 4		Model 5 <sup>†</sup>	
	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.
dependent variable:	<i>high-paid in t</i>									
Hp <sub>t-1</sub>	1.017	0.227	0.587	0.344	1.070	0.245	0.633	0.349	0.764	0.422
Hp <sub>t-1</sub> × high-ue area <sub>t-1</sub>			-0.345	0.112			-0.328	0.113	-0.384	0.145
Hp <sub>t-1</sub> × low-pay area <sub>t</sub>					-0.210	0.116	-0.165	0.115	-0.197	0.141
Hp <sub>t-1</sub> × post sec.-edu.	1.065	0.142	0.987	0.137	1.040	0.140	0.976	0.135		
Lp <sub>t-1</sub>	0.419	0.222	-0.100	0.345	0.507	0.247	-0.040	0.353	0.051	0.424
Lp <sub>t-1</sub> × high-ue area <sub>t-1</sub>			-0.289	0.149			-0.214	0.150	-0.237	0.177
Lp <sub>t-1</sub> × low-pay area <sub>t</sub>					-0.410	0.139	-0.389	0.139	-0.348	0.159
Lp <sub>t-1</sub> × post sec.-edu.	1.012	0.187	0.935	0.181	0.987	0.185	0.926	0.180		
Ue <sub>t-1</sub>	<i>reference category</i>									
Ue <sub>t-1</sub> × high-ue area <sub>t-1</sub>			-0.944	0.343			-0.937	0.344	-0.865	0.439
Ue <sub>t-1</sub> × low-pay area <sub>t</sub>					-0.096	0.313	-0.023	0.314	0.059	0.378
Ue <sub>t-1</sub> × post sec.-edu.	1.440	0.330	1.291	0.328	1.406	0.327	1.273	0.326		
λ <sub>v</sub>	0.629	0.046	0.598	0.049	0.614	0.048	0.590	0.050	0.589	0.060
log likelihood			-1500.3634	-1492.0624			-1494.941	-1487.455		
observations	5 778		5 778		5 778		5 778		5 778	3 027

*Source:* Understanding Society, waves 1-4 and own calculations. Estimations include additional covariates (and their mean values) as enlisted in Table III and year dummies.

<sup>†</sup>From sample excluded are men with post-secondary education.

Table XI: Test of coefficients<sup>◊</sup>

	Model 2	Model 3	Model 4	Model 5
<i>Heckman (uncorrelated)</i>				
Test 1 <sup>†</sup>	4.225 (0.040)		5.122 (0.024)	4.613 (0.032)
Test 2 <sup>‡</sup>		0.192 (0.661)	1.361 (0.243)	0.732 (0.392)
Test 3 <sup>*</sup>			0.619 (0.431)	0.350 (0.554)
<i>Heckman (correlated)</i>				
Test 1 <sup>†</sup>	6.682 (0.010)		7.656 (0.006)	6.191 (0.013)
Test 2 <sup>‡</sup>		1.033 (0.309)	1.479 (0.489)	0.146 (0.702)
Test 3 <sup>*</sup>			1.610 (0.205)	1.400 (0.237)
<i>Wooldridge</i>				
Test 1 <sup>†</sup>	5.353 (0.021)		6.400 (0.011)	5.260 (0.022)
Test 2 <sup>‡</sup>		0.372 (0.542)	0.885 (0.347)	0.495 (0.482)
Test 3 <sup>*</sup>			0.974 (0.324)	0.558 (0.455)

*Source:* Understanding Society, waves 1-4 and own calculations.

◊ First number in each cell refers to the  $\chi^2$ -statistic and the number in parenthesis to the respective  $p$ -value.

†  $\hat{\beta}_{LP,t-1} + \hat{\beta}_{LP \times \text{high-ue area}_{t-1}} = \hat{\beta}_{Ue \times \text{high-ue area}_{t-1}}$

‡  $\hat{\beta}_{LP,t-1} + \hat{\beta}_{LP \times \text{low-pay area}_t} = \hat{\beta}_{Ue \times \text{low-pay area}_t}$

\*  $\hat{\beta}_{LP,t-1} + \hat{\beta}_{LP \times \text{high-ue area}_{t-1}} + \hat{\beta}_{LP \times \text{low-pay area}_t} = \hat{\beta}_{Ue \times \text{high-ue area}_{t-1}} + \hat{\beta}_{Ue \times \text{low-pay area}_t}$

Table XII: Partial effects of becoming high-paid employed (without post-secondary education)<sup>†</sup>

		Local unemployment				
		low		high		Model
high-pay area		-0.030	(0.060)	0.109	(0.025)	Heckman (uncorrelated)
		0.008	(0.006)	0.146	(0.054)	Heckman (correlated)
		-0.008	(0.077)	0.112	(0.054)	Wooldridge
low-pay area		-0.092	(0.077)	0.047	(0.060)	Heckman (uncorrelated)
		-0.057	(0.081)	0.080	(0.063)	Heckman (correlated)
		-0.081	(0.092)	0.045	(0.047)	Wooldridge

*Source:* Understanding Society, waves 1-4 and own calculations. <sup>†</sup>Number refers to the difference in the probability of becoming high-paid employed for someone who was low-paid employed in the previous period compared to someone unemployed with the respective local labor market characteristics. Number in parenthesis refer to the standard errors. Partial effect of a mature married men with children living in his household, living in a ntsarea 1 (but not London or South-East of England), with no health limits at work and without any post-secondary education.

*Reading example:* The number of in the first row and cell (-0.030) tells us that the probability of becoming high-paid employed is 3%-points lower for someone who was low-paid employed in a high-pay area compared to the man with the same characteristics who was unemployed.

Table XIII: Partial effects of becoming high-paid employed (with post-secondary education)<sup>†</sup>

		Local unemployment				
		low		high		Model
high-pay area		-0.041	(0.029)	0.015	(0.033)	Heckman (uncorrelated)
		-0.025	(0.029)	0.038	(0.038)	Heckman (correlated)
		-0.098	(0.097)	0.083	(0.081)	Wooldridge
low-pay area		-0.076	(0.043)	-0.021	(0.043)	Heckman (uncorrelated)
		-0.059	(0.043)	—		Heckman (correlated)
		-0.191	(0.117)	-0.007	(0.093)	Wooldridge

*Source:* Understanding Society, waves 1-4 and own calculations. <sup>†</sup>Number refers to the difference in the probability of becoming high-paid employed for someone who was low-paid employed in the previous period compared to someone unemployed with the respective local labor market characteristics. Number in parenthesis refer to the standard errors. Partial effect of a mature married men with children living in his household, living in a ntsarea 1 (but not London or South-East of England), with no health limits at work and with any post-secondary education.

*Reading example:* The number of in the first row and cell (-0.041) tells us that the probability of becoming high-paid employed is 4%-points lower for someone who was low-paid employed in a high-pay area with a low unemployment rate compared to the man with the same characteristics who was unemployed.

# A Appendix

Table XIV: Heckman estimator - Robustness (uncorrelated)

	Specification 1		Specification 2		Specification 3		Specification 4		Specification 5		Specification 6		Specification 7	
	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.
dependent variable:														
	<i>high-paid in t</i>													
H <sub>pt-1</sub>	0.667	0.393	0.582	0.353	0.614	0.342	0.976	0.277	0.785	0.370	0.630	0.472	0.675	0.370
H <sub>pt-1</sub> × high-ue area <sub>t-1</sub>	-0.422	0.135	-0.275	0.119	-0.402	0.114	-0.344	0.105	-0.308	0.125	-0.544	0.175	-0.374	0.125
H <sub>pt-1</sub> × low-pay area <sub>t</sub>	-0.202	0.135	-0.254	0.124	-0.182	0.115	-0.205	0.108	-0.242	0.122	-0.063	0.157	-0.192	0.217
H <sub>pt-1</sub> × post sec.-edu.	1.950	0.261	1.928	0.238	1.744	0.215	1.575	0.191	1.585	0.235	1.684	0.303	1.745	0.216
H <sub>pt-1</sub> × cross <sub>t</sub>													0.019	0.255
L <sub>pt-1</sub>	-0.061	0.392	-0.162	0.353	-0.157	0.34	0.185	0.272	-0.146	0.366	-0.033	0.489	-0.049	0.369
L <sub>pt-1</sub> × high-ue area <sub>t-1</sub>	-0.222	0.172	-0.104	0.153	-0.279	0.146	-0.274	0.142	-0.111	0.160	-0.495	0.242	-0.345	0.162
L <sub>pt-1</sub> × low-pay area <sub>t</sub>	-0.468	0.159	-0.439	0.148	-0.419	0.136	-0.458	0.133	-0.440	0.143	-0.436	0.183	-0.851	0.320
L <sub>pt-1</sub> × post sec.-edu.	1.946	0.282	1.960	0.273	1.724	0.238	1.581	0.220	1.602	0.265	1.570	0.332	1.747	0.239
L <sub>pt-1</sub> × cross <sub>t</sub>													0.532	0.352
U <sub>et-1</sub>	<i>reference category</i>													
U <sub>et-1</sub> × high-ue area <sub>t-1</sub>	-0.899	0.390	-0.932	0.353	-0.986	0.336	-0.815	0.259	-1.059	0.368	-1.162	0.460	-0.891	0.380
U <sub>et-1</sub> × low-pay area <sub>t</sub>	-0.209	0.363	-0.108	0.337	-0.100	0.308	-0.082	0.242	0.115	0.342	-0.078	0.383	0.200	0.708
U <sub>et-1</sub> × post sec.-edu.	2.499	0.420	2.243	0.401	2.137	0.360	1.771	0.288	1.744	0.408	2.263	0.474	2.150	0.362
U <sub>et-1</sub> × cross <sub>t</sub>													-0.364	0.787
$\sigma^2_\alpha$	3.880	0.926	3.175	0.737	2.980	0.687	2.571	0.581	2.375	0.680	3.040	1.023	2.972	0.687
$\theta$	0.846	0.114	1.005	0.142	0.965	0.130	1.015	0.133	1.149	0.205	0.911	0.172	0.962	0.130
log likelihood	-2034.4564		-2161.1112		-2444.8937		-2696.9994		-1820.231		-1328.2938		-2444.8547	
observations	6 536		6 964		7 704		8 144		5 408		4 156		7 704	

Source: Understanding Society, waves 1-4 and own calculations. Estimations include additional covariates (and their mean values) as enlisted in Table XXX and year dummies. †From sample excluded are men with post-secondary education. Specification 1 is a subsample with individuals who did not change their LSOA, in Specification 2 the Ethnic Minority Boost Sample is dropped, in Specification 3 the identification of the local unemployed rate uses the range of 40 minutes per bike (initially 20 minutes), in Specification 4 the threshold for labeling high local unemployment rate is lifted to 4%, in Specification 5 those individuals living in London or South-East of England are dropped and in Specification 6 those individuals living in nsaeera 3 are dropped from the sample (see also Subsection 5.2 for a detailed description).

Table XV: Test of coefficients (Robustness)<sup>◇</sup>

	Specification 1	Specification 2	Specification 3	Specification 4	Specification 5	Specification 6	Specification 7
Test 1 <sup>†</sup>	4.684 (0.030)	6.246 (0.012)	5.014 (0.025)	13.238 (0.001)	6.855 (0.009)	4.126 (0.042)	3.96 (0.047)
Test 2 <sup>‡</sup>	0.416 (0.519)	1.241 (0.265)	1.286 (0.257)	0.313 (0.576)	2.489 (0.115)	0.436 (0.509)	2.47 (0.116)
Test 3 <sup>*</sup>	0.941 (0.332)	1.023 (0.312)	0.587 (0.444)	1.857 (0.173)	0.623 (0.430)	0.552 (0.458)	1.12 <sup>**</sup> (0.290)

Source: Understanding Society, waves 1-4 and own calculations. Specification 1 is a subsample with individuals who did not change their LSOA, in Specification 2 the Ethnic Minority Boost Sample is dropped, in Specification 3 the identification of the local unemployed rate uses the range of 40 minutes per bike (initially 20 minutes), in Specification 4 the threshold for labeling high local unemployment rate is lifted to 4%, in Specification 5 those individuals living in London or South-East of England are dropped and in Specification 6 those individuals living in ntsaera 3 are dropped from the sample (see also Subsection 5.2 for a detailed description).

<sup>◇</sup> First number in each cell refers to the  $\chi^2$ -statistic and the number in parenthesis to the respective  $p$ -value.

<sup>†</sup>  $\hat{\beta}_{Lp,t-1} + \hat{\beta}_{Lp \times high-ue, area_{t-1}} = \hat{\beta}_{Ue \times high-ue, area_{t-1}}$

<sup>‡</sup>  $\hat{\beta}_{Lp,t-1} + \hat{\beta}_{Lp \times low-pay, area_t} = \hat{\beta}_{Ue \times low-pay, area_t}$

<sup>\*</sup>  $\hat{\beta}_{Lp,t-1} + \hat{\beta}_{Lp \times high-ue, area_{t-1}} + \hat{\beta}_{Lp \times low-pay, area_t} = \hat{\beta}_{Ue \times high-ue, area_{t-1}} + \hat{\beta}_{Ue \times low-pay, area_t}$

<sup>\*\*</sup>  $\hat{\beta}_{Lp,t-1} + \hat{\beta}_{Lp \times high-ue, area_{t-1}} + \hat{\beta}_{Lp \times low-pay, area_t} + \hat{\beta}_{Ue \times cross_t} = \hat{\beta}_{Ue \times high-ue, area_{t-1}} + \hat{\beta}_{Ue \times low-pay, area_t} + \hat{\beta}_{Ue \times cross_t}$



Table XVI: Partial effects of becoming high-paid employed, robustness (without post-secondary education)<sup>†</sup>

		Local unemployment				
		low		high		Specification
high-pay area		-0.010	(0.067)	0.111	(0.051)	1
		-0.024	(0.051)	0.114	(0.051)	2
		-0.028	(0.060)	0.108	(0.049)	3
		0.035	(0.053)	0.150	(0.042)	4
		-0.029	(0.073)	0.172	(0.065)	5
		-0.006	(0.093)	0.124	(0.059)	6
		-0.009	(0.065)	0.098	(0.049)	7
low-pay area		-0.057	(0.087)	0.064	(0.066)	1
		-0.079	(0.069)	0.061	(0.062)	2
		-0.089	(0.077)	0.046	(0.060)	3
		-0.038	(0.068)	0.074	(0.054)	4
		-0.144	(0.088)	0.053	(0.068)	5
		-0.076	(0.115)	0.053	(0.071)	6
		-0.206	(0.123)	0.068	(0.065)	7

*Source:* Understanding Society, waves 1-4 and own calculations. <sup>†</sup>Number refers to the difference in the probability of becoming high-paid employed for someone who was low-paid employed in the previous period compared to someone unemployed with the respective local labor market characteristics. Number in parenthesis refer to the standard errors. Partial effect of a mature married men with children living in his household, living in a ntsarea 1 (but not London or South-East of England), with no health limits at work and without any post-secondary education. Specification 1 is a subsample with individuals who did not change their LSOA, in Specification 2 the Ethnic Minority Boost Sample is dropped, in Specification 3 the identification of the local unemployed rate uses the range of 40 minutes per bike (initially 20 minutes), in Specification 4 the threshold for labeling high local unemployment rate is lifted to 4%, in Specification 5 those individuals living in London or South-East of England are dropped and in Specification 6 those individuals living in ntsaera 3 are dropped from the sample (see also Subsection 5.2 for a detailed description)

*Reading example:* The number of in the first row and cell (-0.024) tells us that the probability of becoming high-paid employed is 2.4%-points lower for someone who was low-paid employed in a low-pay area with a low unemployment rate compared to the man with the same characteristics who was unemployed.

Table XVII: Heckman estimator - Two thresholds (uncorrelated)

	Specification 8		Specification 9	
	coeff.	std. err.	coeff.	std. err.
dependent variable:	<i>high-paid in t</i>			
$Hp_{t-1}$	0.534	0.338	0.588	0.343
$Hp_{t-1} \times \text{local ue above } 2\%_{t-1}$	-0.309	0.125	-0.298	0.125
$Hp_{t-1} \times \text{local ue above } 4\%_{t-1}$	-0.237	0.136	-0.219	0.136
$Hp_{t-1} \times \text{low-pay area}_t$			-0.153	0.117
$Hp_{t-1} \times \text{post sec.-edu.}$	1.752	0.216	1.720	0.213
$Lp_{t-1}$	-0.264	0.334	-0.192	0.341
$Lp_{t-1} \times \text{local ue above } 2\%_{t-1}$	-0.266	0.163	-0.205	0.164
$Lp_{t-1} \times \text{local ue above } 4\%_{t-1}$	-0.188	0.158	-0.141	0.157
$Lp_{t-1} \times \text{low-pay area}_t$			-0.415	0.138
$Lp_{t-1} \times \text{post sec.-edu.}$	1.742	0.239	1.709	0.236
$Ue_{t-1}$	<i>reference category</i>			
$Ue_{t-1} \times \text{local ue above } 2\%_{t-1}$	-0.570	0.369	-0.564	0.367
$Ue_{t-1} \times \text{local ue above } 4\%_{t-1}$	-0.952	0.350	-0.941	0.350
$Ue_{t-1} \times \text{low-pay area}_t$			0.004	0.319
$Ue_{t-1} \times \text{post sec.-edu.}$	2.063	0.367	2.031	0.365
$\sigma_\alpha^2$	3.082	0.697	2.946	0.128
$\theta$	0.938	0.123	0.956	0.142
log likelihood	-2446.4413		-2441.2942	
observations	7 704		7 704	

*Source:* Understanding Society, waves 1-4 and own calculations. Estimations include additional covariates (and their mean values) as enlisted in Table XXX and year dummies.  
†.

Table XVIII: Test of coefficients (Two thresholds)<sup>◊</sup>

	Specification 8	Specification 9
Test 1 <sup>†</sup>	0.020 (0.890)	0.30 (0.583)
Test 2 <sup>‡</sup>	7.79 (0.005)	9.08 (0.003)
Test 4 <sup>*</sup>		2.06 (0.151)
Test 5 <sup>▲</sup>		0.45 (0.504)
Test 6 <sup>◊</sup>		2.50 (0.1136)

Source: Understanding Society, waves 1-4 and own calculations.

◊ First number in each cell refers to the  $\chi^2$ -statistic and the number in parenthesis to the respective  $p$ -value.

$$\begin{aligned}
 \dagger \hat{\beta}_{LP_{t-1}} &+ \hat{\beta}_{LP \times local\ ue\ above\ 2\%_{t-1}} &= \\
 \hat{\beta}_{Ue \times local\ ue\ above\ 2\%_{t-1}} & & \\
 \ddagger \hat{\beta}_{LP_{t-1}} &+ \hat{\beta}_{LP \times local\ ue\ above\ 2\%_{t-1}} &+ \\
 \hat{\beta}_{LP \times local\ ue\ above\ 4\%_{t-1}} &= \hat{\beta}_{Ue \times local\ ue\ above\ 2\%_{t-1}} &+ \\
 \hat{\beta}_{Ue \times local\ ue\ above\ 4\%_{t-1}} & & \\
 * \hat{\beta}_{LP_{t-1}} &+ \hat{\beta}_{LP \times low-pay\ area_t} = \hat{\beta}_{Ue \times low-pay\ area_t} & \\
 \blacktriangle \hat{\beta}_{LP_{t-1}} &+ \hat{\beta}_{LP \times local\ ue\ above\ 2\%_{t-1}} + \hat{\beta}_{LP \times low-pay\ area_t} &= \\
 \hat{\beta}_{Ue \times local\ ue\ above\ 2\%_{t-1}} &+ \hat{\beta}_{Ue \times low-pay\ area_t} & \\
 \diamond \hat{\beta}_{LP_{t-1}} &+ \hat{\beta}_{LP \times local\ ue\ above\ 2\%_{t-1}} &+ \\
 \hat{\beta}_{Ue \times local\ ue\ above\ 4\%_{t-1}} &+ \hat{\beta}_{LP \times low-pay\ area_t} &= \\
 \hat{\beta}_{Ue \times local\ ue\ above\ 2\%_{t-1}} &+ \hat{\beta}_{Ue \times local\ ue\ above\ 4\%_{t-1}} &+ \\
 \hat{\beta}_{Ue \times low-pay\ area_t} & &
 \end{aligned}$$

Table XIX: Partial effects of becoming high-paid employed, two thresholds (without post-secondary education)<sup>†</sup>

	Local unemployment					
	below 2%		between 2-4%		above 4%	
high-pay area	-0.034	(0.060)	0.032	(0.059)	0.192	(0.062)
low-pay area	-0.113	(0.076)	-0.050	(0.073)	0.109	(0.068)

Source: Understanding Society, waves 1-4 and own calculations. <sup>†</sup>Number refers to the difference in the probability of becoming high-paid employed for someone who was low-paid employed in the previous period compared to someone unemployed with the respective local labor market characteristics. Number in parenthesis refer to the standard errors. Partial effect of a mature married men with children living in his household, living in a nsarea 1 (but not London or South-East of England), with no health limits at work and without any post-secondary education.

Reading example: The number of in the first row and cell (-0.034) tells us that the probability of becoming high-paid employed is 3.4%-points lower for someone who was low-paid employed in a high-pay area with a low unemployment rate compared to the man with the same characteristics who was unemployed.