Does Neighbourhood Unemployment Affect the Springboard Effect of Low Pay?

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Non-Technical Summary

One in five workers in the United Kingdom is employed on a low wage. Whilst some view an expansion of the low wage sector as a necessary measure to increase economic productivity, from the perspective of the individual and their families a paramount question is whether low pay offers a promising way out of unemployment as well as better prospects of climbing to higher pay, or whether accepting low pay means entering a low-pay–no-pay cycle which it will be difficult to escape from in the future.

Recent research on low-pay dynamics has produced evidence both for and against the hypothesis that low-pay employment is a stepping-stone to higher-pay employment and that it is therefore preferable to unemployment. This study contributes to this literature by tracking the lives of more than 1,500 men living in England over the course of 2009-2013. In addition to observing their personal characteristics and family living contexts we consider the immediate local contexts in which workers live. Opportunities to access jobs and higher salaries are not available to the same extent to people in all different parts of the country, regions and neighbourhoods. There are some economically vibrant areas which offer good employment and earning prospects on the one hand and depressed areas which suffer from a scarcity of (well-paid) jobs on the other. Lack of (affordable) access to private and public modes of transportation furthermore mean that jobs may be out of reach.

In the context of low-pay dynamics, this is the first study that takes the effect of accessibility to employment and competition for local jobs into account. We use longitudinal data from Understanding Society matched with information provided by the Department of Transport on accessibility of employment in the study participants' neighbourhoods. Our results suggest that those who work on low pay are less likely to become unemployed than the unemployed are likely to remain unemployed. Furthermore, the probability of entering employment with more than low pay is higher for the low-paid than for the unemployed. These findings are most marked in neighbourhoods with high unemployment mainly because of the much poorer prospects of the unemployed in these neighbourhoods. There are a number of possible reasons for this. For example, areas may have experienced major economic change or people may have moved away to more promising neighbourhoods. We conducted a range of robustness estimations to explore these notions and find that in economically vibrant areas no great distinction is made between unemployment and low-pay.

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Abstract

There is considerable debate on whether the employment and earnings prospects are better for those on low pay or for the unemployed. We use Understanding Society data for England and estimate dynamic random effects panel models which show robust evidence that the future unemployment risk is lower for those who are currently on low pay compared to those who are currently unemployed and the low-paid also have a higher chance than the unemployed of becoming higher-paid. These findings are most marked in neighbourhoods with high unemployment which is attributable to the much poorer prospects of the unemployed in these neighbourhoods.

Keywords: neighbourhood effect; unemployment dynamics; low pay dynamics; state dependence; initial conditions problem; household panel study
JEL classification: J64, J62, J31

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1. Introduction

Whilst unemployment is an undesirable position for an individual to be in, the jury is still out on whether any kind of employment is preferable to unemployment (see, e.g., Layard et al. 1991). Many countries, the UK in particular, have seen the establishment of a low wage sector which, so the common assertion, offers 'bad' jobs that involve part time, non-permanent and short-term employment contracts, and that do not provide access to training or transferable skills. In this view, low-pay employment has little positive impact on the worker's human capital stock and may not provide the worker with access to more promising employment networks. On the other hand, being low-pay employed may nevertheless signal a lesser human capital depreciation than being unemployed and it may signal the willingness to work, both of which should translate into positive labour market outcomes such as a lower risk of becoming unemployed and entering higher-pay employment more easily compared to unemployment. Such positive returns to signalling have been shown, for instance, in the literature on unpaid overtime and may be higher in areas with high local unemployment (see, e.g., Anger 2005).

There is in fact a long and rich tradition in the predominantly sociological theoretical literature devoted to linking individuals' labour market outcomes and opportunities to the local context[3]. The economic literature, too, has demonstrated that differences in the local unemployment rate are sizeable and persistent (see, e.g., Patacchini and Zenou 2007), and empirical studies have shown that the local unemployment rate has a negative impact on the probability of exiting unemployment (Hoynes 2000, Van der Klaauw and Van Ours 2003, Hedström et al. 2003).

Against the background of rising unemployment and a persistent high share of low-pay employment in many countries (OECD 2013), the aim of this study is to advance the empirical research on low-pay dynamics by using longitudinal data for England linked with local labour market information at the level of very immediate neighbourhoods. Whilst we may expect that the prospects of advancing ones career declines as competition for jobs in the local labour market gets fiercer -simply as the number of available higher-pay jobs is lower- given the expansion of

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[3] Galster (2012) lists 15 potential causal pathways through which the neighbourhood context may impact decision-making. Pathways include peer effects in the accumulation of human capital (see, e.g., Arnott and Rowse 1987), harmonization of work attitudes (see, e.g., Wilson 1987), use of social networks as an informal job market - which has been suggested to be particularly relevant for low-skilled workers (Selod and Zenou 2006, Bayer et al. 2008) - and spatial discrimination by the employer (see, e.g., Zenou and Boccard 2000).

low-pay and 'bad' jobs in many areas, we ask whether the unemployed and low-pay employed suffer equally from living in an area that has a high level of unemployment, or whether the effects are related to the labour market position. We hypothesize that low-pay employment will be more advantageous in areas with high unemployment as low-pay workers signal to employers their willingness to work and they actively counteract the deterioration of their human capital.

Whilst the emerging empirical research on low-pay dynamics has produced evidence both in support and in contradiction to the hypothesis that low-pay employment is a steppingstone to higher-pay employment and that it is, therefore, preferable to unemployment (see, e.g., Stewart (2007) and Plum (2014)) our study is the first in the field of low-pay dynamics to take into account that employment trajectories may also depend on where one lives (and that unemployment may prompt people to move (van Ham et al. 2013). More specifically, this research contributes to the empirical research on the steppingstone effect of low pay by taking into account heterogeneity in local labour market conditions and examining whether local competition for jobs alters the prospects of higher-pay employment and risk of experiencing unemployment.

There are a number of empirical challenges not only to estimating dynamic panel models but also to identifying neighbourhood effects (see, e.g., Manski 1993, Galster 2008) and we will address these inasmuch as is possible. In particular, to address common specification issues in dynamic modelling, we will include a random effects error term to address the problem that people may differ in their unobservable characteristics (Heckman 1981a), which may be correlated between the mutually exclusive labour market positions (see, e.g., Plum 2014), and we consider that the individuals' initial labour market position may not be randomly assigned (Heckman 1981b). With respect to issues related to identifying neighbourhood effects, we test labour market characteristics at three geographical scales, ranging from the very immediate neighbourhood to the local authority level; this deals not only with the problem that there is no theoretical guidance at which scale the neighbourhood effect is supposed to operate, but also provides indirect assurance as to whether results are driven by selection into specific neighbourhoods (or, put another way, that the labour market outcomes and the neighbourhood profiles are endogenous). Among our robustness tests we restrict the sample to non-movers which allows us to isolate the effects of unobserved neighbourhood characteristics (as suggested by Knies et al. 2008 and Galster 2012).

We draw on data for England from Understanding Society, a very large nationally representative panel survey for the UK, matched with local labour market indicators. These indicators of labour market characteristics at the level of neighbourhoods have the advantage of capturing more appropriately any heterogeneity in the labour market than has been possible in previous analyses, e.g., when using regional indicators (see, e.g., Stewart 2007).

The results indicate that those who are in low pay have a lower risk of becoming unemployed in the subsequent period than the unemployed, in particular when they live in a neighbourhood with a high share of jobseekers to working age-population (dubbed here: local unemployment). But it is the prospects of becoming higher-pay employed in particular which are better for workers on low pay in these neighbourhoods. This is predominantly attributable to the much lower employment prospects of the unemployed in this type of area. This finding is in line with the hypothesis that human capital deteriorates during an unemployment spell, and that the likelihood of entering employment is lower the longer unemployment has commenced. It also emphasizes the urgency to signal the willingness to work when competition for jobs in the local area is high. By contrast, in areas with low unemployment no indication is found that low-pay employment helps climbing up the salary ladder. Low pay nevertheless still lowers the risk of future unemployment. Overall, the results suggest that entering low-pay employment is preferable - in terms of lowering the risk of future unemployment and increasing the chances to enter higher-pay employment - to unemployment, especially when local unemployment is high. These results are robust to a range of sensitivity tests.

The remainder of this paper is structured as follows. In Section 2, we review the key economic literature on employment prospects of the unemployed and low-pay 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 Section 6 concludes.

2. Literature review

2.1 Unemployment persistency

There are a number of theoretical contributions that incorporate the experience of unemployment in labour market models. An early example is provided by Vishwanath (1989) who posited that unemployment sends a negative signal as firms view the unemployment duration as an indicator for the productivity level. This stigma, when considered in a job search model, means 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) examined in a labour market model with job creation/destruction and matching the effect of incorporating the length of unemployment in a firm's hiring decision on the exit rates out of unemployment. The authors demonstrated that if the applicants' unemployment duration is chosen by the firm as a ranking device in the hiring process, the exit probability of employed workers, were they to become unemployed, is higher than that of an already unemployed worker. A further theoretical explanation for unemployment persistence has been presented by Acemoglu (1995). Under the assumption that the unemployed face a deterioration of their skills during an unemployment spell and that maintaining the skill level is both costly and not observable, firms will discriminate against the unemployed. In response to this discrimination, no measures will be undertaken by the unemployed to improve their skill level. In the equilibrium, this will result in some negative duration dependence in unemployment seeing as the exit probability declines with the length of the unemployment spell. Note, however, that the high-skilled unemployed may be willing to wait for an appropriate job offer (i.e., high quality jobs), hence, increase the duration of their unemployment voluntarily. Pissarides (1990) has suggested that this preference to wait for higher quality jobs is being considered in the employers' hiring decisions. In other words, the high-skilled will not necessarily suffer from a scarring effect in unemployed.

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

2.2 Employment and earnings prospects for low-pay workers

While there is broad consensus in the theoretical literature that there exists negative duration dependence in unemployment, theoretical predictions about the direction of the effect of low-pay work on employment and earnings prospects are less clear. On the one hand, taking up employment will attenuate, if not stop, the deterioration of human capital. In addition, workers signal their willingness to work even if the pay is low. On the other hand, the type of job might reveal some below average productivity. McCormick (1990) has shown that skilled workers tend to avoid unskilled jobs, as skilled jobs are more satisfying to them. When becoming unemployed, the high-skilled will spent their time searching for an adequate job and will not take up poorly paid employment in the interim, and firms use the respective search-strategy of the unemployed as a screening device for productivity. This mechanism led to Layard et al. (1991)'s famous remark that "while unemployment is a bad signal, being in a low-quality job may well be a worse one." [p. 249].

Given these counteracting forces it is perhaps little surprising that empirical results on the employment prospects of low-pay workers are heterogeneous. Using data from the British Household Panel Survey (BHPS) and applying a range of random-effects and fixed-effects estimators, Stewart (2007) found no statistically significant differences between low-pay workers and the unemployed in their employment prospects (expressed as the likelihood of entering unemployment). Also using data from the BHPS and restricting the sample to initially employed men who become unemployed, Plum (2014) shows that men without post-secondary education who do low-pay work have a significantly higher probability to become high-pay employed in the subsequent period than the unemployed. Low-pay workers have also been shown to have better chances than the unemployed to climb up the salary ladder in Germany (Uhlendorff 2006, Knabe and Plum 2013, Mosthaf 2014, Mosthaf et al. 2014) and Australia (Buddelmeyer et al. 2010). However, for Italy, Cappellari (2007) found a high persistence in low pay and the author concludes that the accumulation of human capital only has a little impact on exiting the low-wage sector. These findings have been confirmed widely for Europe by Clark and Kanellopoulos (2013).

2.3 The impact of local labour market conditions

There exist several theoretical contributions which suggest how the neighbourhood context influences individuals' labour market position, and how individual behaviour leads to

neighbourhood inequality in the aggregate. Galster and Killen (1995) provide a general perspective on how the local context influences young peoples' prospective socioeconomic status. In their model, decision-making depends upon actual and perceived opportunities. Opportunities and how they are perceived are influenced, on the one hand, by malleable and unmalleable personal characteristics (such as age, gender and family background and past decisions), and on the other hand by objective local circumstances (e.g., existence of institutions, labour market, housing), by the local social network (e.g., family, friends, neighbours), and by the characteristics of the neighbours (e.g., quality of schools). These shape individual values, aspirations and preferences but also define the local opportunity structure. More specific models for how the neighbourhood context affects decisions include Akerlof (1980) who shows that the local social code to not work for an unfair wage can result in voluntary unemployment, and Streufert (2000) who shows that the absence of high-income earners as positive role models from the neighbourhood can depress schooling because the distribution of returns to education that is observable to teenagers in the deprived neighbourhood is skewed and not representing the more favourable national distribution of returns to education.

A plethora of empirical research has shown that neighbourhood characteristics have an impact on individual labour market outcomes, for instance, the higher the local unemployment rate the longer people spent receiving income maintenance support (see, e.g., Hoynes 2000), the less likely they are to transition from welfare to work (see, e.g., Van der Klaauw and Van Ours 2003), or, more generally, from unemployment into work (see, e.g., Hedström et al. 2003). In the context of unemployment and low-pay dynamics, the focus often times has been on rather rough headline indicators such as the regional unemployment rate (see, e.g., Knabe and Plum 2013) which may not be the most appropriate scale at which some of the hypothesized neighbourhood effects may operate (for a discussion see Galster 2008).[4] We would expect that the availability and accessibility of (good) jobs in the local labour market influences labour market trajectories such as unemployment persistency or climbing up the pay distribution. To our knowledge, no study has reported whether the local level of unemployment (or indeed any other local labour market

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[4] Stewart (2007) includes information on the unemployment-vacancy ratio in individual's travel to work area (TTWA), which aggregates areas in which the ratio of workforce size and number of residents working in the specific area exceeds a certain threshold. According to the 2011 TTWA definition of the Office for National Statistics, the whole of UK is divided into 228 TTWAs. This geographical indicator is considered not to capture sufficiently spatial heterogeneity on labour markets and therefore not included in this study; for example, the whole of London and the surrounding area forms one TTWA.

indicator) affects the prospects of entering higher-pay employment, and whether there are advantages to taking on low-pay employment in the first instance.

The aim of this study, then, is to advance the empirical research on low-pay dynamics by using longitudinal data for England linked with local labour market information at the level of very immediate neighbourhoods. Whilst we may expect that the prospects of advancing ones career declines as competition for jobs in the local labour market gets fiercer -simply as the number of available higher-pay jobs is lower- given the expansion of low-pay and 'bad' jobs in many areas, we ask whether the unemployed and low-pay employed suffer equally from living in an area that has a high level of unemployment, or whether the effects are specific to the labour market position. We hypothesize that the steppingstone effect of low-pay employment will be more marked in areas with high unemployment as low-pay workers signal to employers their willingness to work and they actively counteract the deterioration of their human capital.

3. Data and Descriptive Statistics

3.1 Understanding Society

We use data from the first four waves of 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 responding households. The study collects a wealth of information relating to the respondents' economic and social circumstances, their values and attitudes and 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

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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 time series data on labour market indicators for England at those geographical scales.

The focus of analysis necessitated our sample to be restricted to respondents who, in all survey waves, were either employed (full-time or part-time) and reporting some positive number of hours worked in a current job and a positive amount of gross pay, or unemployed and looking for work in the last four weeks before the survey. For parsimony, we restricted the sample to males aged 25-55 years living in England.[5] The final balanced sample consists of 1,638 respondents who were observed over the entire four year period (yielding 6,552 person-year observations); the sample spent 96.7% of the time in employment and 3.3% of the time in unemployment.

Our key variable of interest is a marker of respondent's employment status which can assume three states: unemployed, low-pay employed, and higher-pay employed. Following the standard definition by the Organization of Economic Cooperation and Development (OECD), pay is considered low if the gross hourly wage is below two-thirds of the respective annual median gross hourly wage, and higher otherwise (OECD 1997). **Table 1** reports the respective annual low-pay thresholds for England over the study period. It can be seen that the threshold increased somewhat starting at £7.07 in 2009 and increasing up to £7.91 in 2012.

Table 1: Low-pay thresholds

Year	2009	2010	2011	2012
Threshold in £	7.07	7.51	7.77	7.91

Source: Understanding Society (2014), Waves 1-4, 2009-2013. Based on the weighted gross hourly wages of both males and females in England.

Based on these definitions, we observe that out of 6,552 respondent-year observations 79% were higher-paid employed, 18% low-paid employed and 3% in unemployment, and there was considerable movement into and out of these positions (see **Table 2**).

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[5] Females, the self-employed, full-time students, retirees and those who are long term sick or disabled have been excluded as their labour market transitions are likely to follow different patterns. Comparable local labour market indicators are not available for other parts of the UK.

Table 2: Persistence and change in labour market positions. Transition matrix.

	Higher-Paid$_t$	Low-Paid$_t$	Unemployed$_t$
Higher-Paid$_t$	94.64	4.43	0.93
Low-Paid$_t$	22.92	74.75	2.51
Unemployed$_t$	24.86	26.55	48.59
Total$_t$	79.32	17.75	2.93

Source: Understanding Society (2014), Waves 1-4, 2009-2013. *N*=4,914

3.2 Neighbourhood Data

We obtained permission to access a look-up file between household identifiers and Lower Super Output Area (LSOA) codes to allow us to augment the panel data with relevant neighbourhood context information from published tables using that identifier (Rabe 2011). LSOA are intermediate-level Census output units which cover around 1,000 to 1,500 individuals. LSOA are used to monitor regeneration in England, which means a wealth of area data is produced at this scale; there were 32,482 LSOA in England in 2001. On the basis of look-up files between LSOA and greater geographical scales, it was also possible to construct labour market indicators at less immediate scales for robustness tests.

3.3 Local unemployment

We operationalize local unemployment 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 have been linked with Understanding Society and 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 centres, primary schools, secondary schools, institutions for further education, General Practitioners, hospitals, food stores, and town centres (Knies and Menon 2014).

Firstly, we derive a marker of the local unemployment rate. We operationalized this as the ratio of recipients of job seekers allowance (i.e., "users at risk (of being excluded from employment)" in Accessibility Statistics terminology) to 16-74[6] year olds (i.e., "users of employment centres" in

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[6] This matches the ILO definition of the economically active population.

Accessibility Statistics terminology) who can reach (i.e., "access" in Accessibility Statistics terminology) on foot, by public transport and/or by bicycle (i.e., "by composite travel mode" in Accessibility Statistics terminology) the nearest 5-10 employment locations (i.e., "employment centres" in Accessibility Statistics terminology) within reasonable time (i.e., the actual time that 80-90% of journeys to work take, as per the National Travel Survey, and "taking into account the sensitivity of users to the travel time (to work by different travel modes and combinations thereof)" in Accessibility Statistics terminology).[7] A neighbourhood, then, is considered to have high unemployment if it belongs to the 25th percentile of the distribution with the highest unemployment rates.

In **Table 3**, we report the labour market positions of our sample differentiated by local unemployment. As can be seen, the low-paid and the unemployed are overrepresented in high-unemployment areas, while the higher-paid are overrepresented in areas with low unemployment.

Table 3: Local unemployment rate and labour market position.

	Low local ue	High local ue
Higher-Paid$_t$	79.86	20.14
Low-Paid$_t$	57.30	42.70
Unemployed$_t$	48.62	51.38
Total$_t$	74.82	25.18

Source: Understanding Society (2014), Waves 1-4, 2009-2013. *N*=6,552. Pearson $\chi^2(2) = 338.809$ (*p*-value < .001).

Secondly, to consider heterogeneity in other structural factors that impact employment and earnings prospects and may be correlated with the local unemployment rate as operationalized here[8], we use an LSOA-level indicator of urbanity. The indicator is taken from the DfT National Travel Survey and classifies each address in 2001 into one of four metropolitan areas, one of 6 urban areas with a population of at least 100,000 inhabitants, or rural areas. Note that in contrast to regions or local authority boundaries, the urbanity marker considers the spatial (dis)connectedness of build-up areas to decide which area type is appropriate. This means, for

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[7] We tested several other markers to see whether our results are robust to definitions of our key indicators and the main findings were replicated (see Section 4.2.1).

[8] This builds on the assumption that the distance of employment centres to the LSOA centroid are randomly distributed. This may, however, not be the case. Distances in sparsely populated or rural areas, e.g., tend to be greater and this could lead to an underestimation of the local unemployment rate in low density areas. To alleviate these concerns, we also undertook estimations dropping (a) individuals living in low density areas, and (b) men living in London or in the South East. The results were robust to these restrictions.

Table 4: Listing of Control variables with description

Variables	Description
Variables	*Description*
Time-varying explanatory variables	
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)
Married	Dummy: 1 if married, 0 otherwise
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
ue-high	Dummy: 1 if the neighbourhood[*] belongs to the 25th percentile with the highest unemployment rate, 0 otherwise
Time-constant explanatory variables	
Post-sec. educ.	Dummy: 1 if individual has a degree or other higher degree, 0 otherwise
notukborn	Dummy: 1 if individual was not born in England, Scotland, Wales or Northern Ireland, 0 otherwise
humcap 1[‡]	Dummy: 1 if *i)* the individual was employed in the initial period and was working in a professional occupation or in a managerial & technical occupation or *ii)* if the individual was unemployed in the initial period and was working in a professional occupation or in a managerial & technical occupation in the last job, 0 otherwise.
humcap 2[‡]	Dummy: 1 if *i)* the individual was employed in the initial period and was working in a skilled (non-) manual occupation or *ii)* if the individual was unemployed in the initial period and was working in a skilled (non-) manual occupation in the last job, 0 otherwise.
humcap 3[‡]	Dummy: 1 if *i)* the individual was employed in the initial period and was working in a partly skilled or unskilled occupation or *ii)* if the individual was unemployed in the initial period and was working in a partly skilled or unskilled occupation in the last job, 0 otherwise.

[‡] Identification according to Registrar General's Social Class. [*] Regional identifier are LSOA, MSOA and LAD, see Section 3.

Table 5: Descriptive statistics

	Total$_t$	Higher-Paid$_t$	Low-Paid$_t$	Unemployed$_t$
young	0.130	0.130	0.128	0.161
old	0.151	0.144	0.176	0.179
married	0.619	0.649	0.561	0.234
health1	0.011	0.010	0.010	0.023
health2	0.022	0.019	0.032	0.050
health3	0.071	0.064	0.100	0.078
health4	0.147	0.146	0.159	0.101
health5	0.750	0.761	0.699	0.748
lonse	0.303	0.328	0.194	0.275
ntsarea 1	0.221	0.224	0.192	0.317
ntsarea 2	0.319	0.305	0.362	0.417
ntsarea 3	0.460	0.471	0.447	0.266
humcap 1	0.504	0.594	0.151	0.239
humcap 2	0.352	0.317	0.479	0.500
humcap 3	0.145	0.089	0.369	0.261
Post-sec. educ.	0.480	0.560	0.167	0.261
notukborn	0.137	0.129	0.183	0.083

Source: Understanding Society (2014), Waves 1-4, 2009-2013. *N*=6,552

instance, that not all addresses in the region London are also classified as falling into the NTS area type "Inner or outer London metropolitan area" as this depends on whether or not it is connected to the bulk of the metropolitan area addresses.

Descriptions of all variables used in the econometric models and basic descriptive statistics are reported in **Table 4** and **Table 5**, respectively.

4. Econometric Model

4.1 The baseline model

The aim of this study is to analyse the effect of the previous labour market position on employment and earnings prospects. An appropriate statistical model for this complex problem is a correlated dynamic random-effects probit model, as it has been suggested by Stewart (2007) and as it also has been applied in a low-pay study by Knabe and Plum (2013). Random-effects panel models which account for the initial conditions problem will derive consistent estimators at

sample sizes of at least $N=1,000$ observations if the number of waves is four or higher (see Arulampalam and Stewart 2009); these are properties which are satisfied by our sample.

The statistical representation of the model is as follows (see Stewart 2007). The observed binary outcome variables are defined as:

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

and,

$$y_{2it} = \begin{cases} 1 & \text{if the person is higher-paid employed,} \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

and,

$$y_{3it} = \begin{cases} 1 & \text{if the person is low-paid employed,} \\ 0 & \text{otherwise.} \end{cases} \tag{3}$$

Note that the labour market positions are mutually exclusive; each observation can only be in one of the three labour market positions. The model is defined as:[9]

$$y_{1it} = \mathbf{1}\{y_{2i(t-1)}\gamma_{11} + y_{3i(t-1)}\gamma_{12} + \text{ue-high}_{i(t-1)}y_{1i(t-1)}\delta_{11} + \text{ue-high}_{i(t-1)}y_{2i(t-1)}\delta_{12} + \text{ue-high}_{i(t-1)}y_{3i(t-1)}\delta_{13}$$
$$+ x_{it}'\beta_1 + z_i'\varphi_1 + \grave{q}_i + u_{1it} > 0\} \tag{4}$$

and if $y_{1it} = 0$,

$$y_{2it} = \mathbf{1}\{y_{2i(t-1)}\gamma_{21} + y_{3i(t-1)}\gamma_{22} + \text{ue-high}_{i(t-1)}y_{1i(t-1)}\delta_{21} + \text{ue-high}_{i(t-1)}y_{2i(t-1)}\delta_{22} + \text{ue-high}_{i(t-1)}y_{3i(t-1)}\delta_{23}$$
$$+ x_{it}'\beta_2 + z_i'\varphi_2 + \grave{o}_{2i} + u_{2it} > 0\} \tag{5}$$

The variable y_{1it} (and y_{2it}, respectively) refers to the labour market position of individual $i = 1,\ldots,N$ at time $t = 1,\ldots,T$. Factors that are held to influence the labour market position are split into time-varying (x_{it}) and time-constant variables (z_i). Moreover, it is assumed that the labour market position in the previous period (i.e., y_{2it-1} and y_{3it-1}, respectively) has an impact on the current position. To capture the effect of living in a neighbourhood with a high unemployment level, the binary indicator ue-high$_{i(t-1)}$ is included (it assumes a value of 1 if the individual lives in a neighbourhood with high unemployment and 0 otherwise) and interacted

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[9] To evaluate the impact of the ordering of the dependent variables, we estimated the model also with a different ordering of the dependent variables. This change did not affect the conclusions.

with the lagged neighbourhood indicator variables.[10] Hence, being unemployed in $t-1$ and living in a neighbourhood with a low unemployment level is chosen as the reference category. As noted by Heckman (1981a), individuals may not only differ in observable but also in unobservable characteristics; therefore, individual-specific time-constant error terms $\grave{o}_{ji}$ with $j \in \{1, 2\}$ are included. The time-specific idiosyncratic error term is denoted u_{jit}.

Random-effects models assume that the individual-specific time-invariant error terms $\grave{o}_{ji}$ are uncorrelated with the time-varying explanatory variables x_{it}. To relax this strict assumption, we follow Mundlak (1978) and Chamberlain (1984) and include the time-means of the time-varying explanatory variables with $\grave{o}_{ji} = \bar{x}_i \pi_j + \kappa_{ji}$. Implementing this into equations **(4)** and **(5)** leads to:

$$y_{1it} = \mathbf{1}\{ y_{2i(t-1)}\gamma_{11} + y_{3i(t-1)}\gamma_{12} + \text{ue-high}_{i(t-1)} y_{1i(t-1)}\delta_{11} + \text{ue-high}_{i(t-1)} y_{2i(t-1)}\delta_{12} + \text{ue-high}_{i(t-1)} y_{3i(t-1)}\delta_{13}$$
$$+ x'_{it}\beta_1 + z'_i\varphi_1 + \bar{x}_i\pi_1 + \kappa_{1i} + u_{1it} > 0\}$$
(6)

And if $y_{1it} = 0$,

$$y_{2it} = \mathbf{1}\{ y_{2i(t-1)}\gamma_{21} + y_{3i(t-1)}\gamma_{22} + \text{ue-high}_{i(t-1)} y_{1i(t-1)}\delta_{21} + \text{ue-high}_{i(t-1)} y_{2i(t-1)}\delta_{22} + \text{ue-high}_{i(t-1)} y_{3i(t-1)}\delta_{23}$$
$$+ x'_{it}\beta_2 + z'_i\varphi_2 + \bar{x}_i\pi_2 + \kappa_{2i} + u_{2it} > 0\}$$
(7)

However, it is likely that the labour market position in the initial period is not randomly distributed and in fact correlated with the random-effects, referred to in the literature as the initial conditions problem (Heckman 1983b). To address the initial conditions problem, we follow Wooldridge's (2005) suggestion, i.e., we condition the dynamic sequence of the estimation on the outcome in the initial period.[11] Referring to the individual-specific time-invariant error term of equation **(6)** and **(7)**, κ_{ji} takes the following form (see Wooldridge 2005):

$$\kappa_{ji} = a_{0j} + y_{2i0}\tau_{j1} + y_{3i0}\tau_{j2} + \alpha_{ji}$$
(8)

Plugging equation **(8)** into equation **(6)** and **(7)** leads to:

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[10] We use the lagged neighbourhood indicator to avoid interrelation of the current labour market position with the current conditions in the neighbourhood. For mover, the local conditions of the destination neighbourhood are used.
[11] There exist several strategies to take care of the initial conditions problem. Arulampalam and Stewart (2009) show that the prominent methods proposed by Heckman (1981b), Orme (1996) and Wooldridge (2005) produce comparable results for panels T>2 and N>1000.

$$y_{1it} = \mathbf{1}\{y_{2i(t-1)}\gamma_{11} + y_{3i(t-1)}\gamma_{12} + \text{ue-high}_{i(t-1)}y_{1i(t-1)}\delta_{11} + \text{ue-high}_{i(t-1)}y_{2i(t-1)}\delta_{12} + \text{ue-high}_{i(t-1)}y_{3i(t-1)}\delta_{13}$$
$$+ x_{it}'\beta_1 + z_i'\varphi_1 + \bar{x}_i\pi_1 + a_{01} + y_{2i0}\tau_{11} + y_{3i0}\tau_{12} + \alpha_{1i} + u_{1it} > 0\}$$
(9)

and if $y_{1it} = 0$,

$$y_{2it} = \mathbf{1}\{y_{2i(t-1)}\gamma_{21} + y_{3i(t-1)}\gamma_{22} + \text{ue-high}_{i(t-1)}y_{1i(t-1)}\delta_{21} + \text{ue-high}_{i(t-1)}y_{2i(t-1)}\delta_{22} + \text{ue-high}_{i(t-1)}y_{3i(t-1)}\delta_{23}$$
$$+ x_{it}'\beta_2 + z_i'\varphi_2 + \bar{x}_i\pi_2 + a_{02} + y_{2i0}\tau_{21} + y_{3i0}\tau_{22} + \alpha_{2i} + u_{2it} > 0\}$$
(10)

As normalizations for the random-effects error terms, it is assumed that $\alpha_{ji} \sim N(0, \sigma_{\alpha_j}^2)$ and the two random-effects may be correlated with the correlation parameter ρ_α. For identification it is assumed that the idiosyncratic error terms are standard-normal distributed, i.e., $u_{jit} \sim N(0,1)$.

Note that the composite error term is $v_{jit} = u_{jit} + \alpha_{ji}$ and is correlated over time in the following way $\lambda_j = corr(v_{jit}, v_{jis}) = \dfrac{\sigma_{\alpha_j}^2}{\sigma_{\alpha_j}^2 + \sigma_{u_j}^2}$ for each $t \neq s$. The variance-covariance matrix of the random-effects error terms, then, takes the following form:

$$V_\alpha = \begin{pmatrix} \sigma_{\alpha_1}^2 & \cdot \\ \rho_\alpha \sigma_{\alpha_1} \sigma_{\alpha_2} & \sigma_{\alpha_2}^2 \end{pmatrix}$$
(11)

Furthermore, it may be that the idiosyncratic shocks are correlated between both processes. The variance-covariance matrix of the idiosyncratic shocks takes the following form:

$$V_u = \begin{pmatrix} \sigma_{u_1}^2 & \cdot \\ \rho_u & \sigma_{u_2}^2 \end{pmatrix}$$
(12)

To allow for correlation in the idiosyncratic shocks, a dynamic bivariate random effects probit model is applied. The individual outcome probabilities are:

$$P_{it}(\alpha_1^*, \alpha_2^*) = \left\{\Phi\left[\mu_1\right]\right\}^{y_{1it}} \left\{\Phi_2\left[-\mu_1, (2y_{2it}-1)\mu_2, -(2y_{2it}-1)\rho_u\right]\right\}^{(1-y_{1it})}$$
(13)

and Φ refers to the cumulative univariate normal distribution function and Φ_2 refers to the cumulative bivariate normal distribution function and

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$$\mu_j = y_{2i(t-1)}\gamma_{j1} + y_{3i(t-1)}\gamma_{j2} + \text{ue-high}_{i(t-1)}y_{1i(t-1)}\delta_{j1} + \text{ue-high}_{i(t-1)}y_{2i(t-1)}\delta_{j2} + \text{ue-high}_{i(t-1)}y_{3i(t-1)}\delta_{j3}$$
$$+ x_{it}^{'}\beta_j + z_i^{'}\varphi_j + \bar{x}_i\pi_j + a_{0j} + y_{2i0}\tau_{j1} + y_{3i0}\tau_{j2} + \sigma_{\alpha_j}\alpha_j^{*}.$$

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

$$L_i = \int_{\alpha_1^{*}}\int_{\alpha_2^{*}}\left\{\prod_{t=1}^{T}P_{it}(\alpha_1^{*},\alpha_2^{*})\right\}g(\alpha_1^{*})g(\alpha_2^{*})\mathrm{d}\alpha_1^{*}\mathrm{d}\alpha_2^{*} \qquad (14)$$

and $g(\alpha_j^{*})$ are the probability density functions which need to be integrated out. Using random numbers based on primes numbers (also called Halton draws, see Train 2009), two times R standard uniform distributed draws $\tilde{\alpha}_j^{r} \in \{0,\ldots,1\}$ are derived and transformed by the inverse cumulative standard normal distribution $\Phi^{-1}\left(\tilde{\alpha}_j^{r}\right)$. In the simulation, $\alpha_1^{r} = \sigma_{\alpha_1}\tilde{\alpha}_1^{r}$ and $\alpha_2^{r} = \sigma_{\alpha_1}\rho_\alpha\tilde{\alpha}_1^{r} + \sigma_{\alpha_2}\sqrt{1-\rho_\alpha^2}\tilde{\alpha}_2^{r}$ (see Alessie et al., 2001). For each draw the likelihood is derived for each observation, multiplied over all individuals and time-points and finally averaged over all draws:

$$MSL = \prod_{i=1}^{N}\frac{1}{R}\sum_{r=1}^{R}\left\{\prod_{t=1}^{T}P_{it}(\alpha_1^{r},\alpha_2^{r})\right\} \qquad (15)$$

In this application, we use 100 Halton draws. This concludes the full description our baseline econometric model. All estimations are undertaken in the statistical data analysis program Stata 13.1 and using the command **bireprob** (Plum 2015). We report coefficients from probit models, and seeing as these do not lend themselves easily to interpretation, we will also report the partial effects of low-pay employment.[12]

4.2 Robustness tests

4.2.1 Alternative labour market indicators

Our local labour market indicator is a binary variable based on a measure of the proportion of jobseekers to "users of employment centres" in the LSOA. More specifically, the measure

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[12] Average partial effects (APE) may be interpreted as the difference in percentage points of becoming unemployed, respectively higher-paid employed, between someone who was low-paid employed in the previous period compared to someone who was unemployed. Following Stewart's (2007) suggestion we first derive the partial effects for each individual, and then calculate the mean over the sample. We do this separately for individuals who live in high and low unemployment areas. Indication for a steppingstone effect of low-pay is found if the unemployment risk is reduced and the chances of becoming higher-paid employed are increased.

considers only those users who can reach the nearest 5-10 employment locations (travelling on foot, by public transport or by bicycle) within reasonable time. As the definition for reasonable time is somewhat arbitrary, we investigated the robustness of our findings to restricting the time threshold for accessibility to 20 minutes (Model 2) and 40 minutes (Model 3). We expect that these adjustments lead to an overestimation of the unemployment rate due to an underestimation of the active population (i.e., "users of employment centres"), in particular in rural areas where the time to reach the employment centres may be above the respective 20/40 minutes thresholds. The definition of a neighbourhood as facing high unemployment if it belongs to the 25th percentile of the distribution with the highest unemployment rate, too, is somewhat arbitrary. The differentiation is based on the assumption that the variation within the same type of neighbourhood is small compared to the variation between groups. To relax this assumption we also estimate the model using a continuous marker of local unemployment (in logarithmic form as the distribution is skewed to the left), see Model 4.

4.2.2 Alternative scales of the neighbourhood

There is little to no theoretical guidance regarding at which geographical scale neighbourhood effects may be expected to operate, and we opted for using indicators at a more immediate scale than previous research. Whilst this has the advantage that we can more confidently interpret any local effects we observe as neighbourhood effects that operate via social interaction with local people such as stigmatization or role models (and, more technically, it also means that we do not have to worry about clustering in our statistical modelling), potential caveats include that people may have chosen to live in a specific neighbourhood because of the employment prospects it offers, and that the neighbourhood is too tightly drawn seeing as people increasingly work farther away from where they live.

To alleviate some of these concerns we also undertook all analyses using local labour market indicators at two alternative, less immediate scales. The first alternative marker is our LSOA-level labour market indicator aggregated to the scale of Middle Layer Super Output Areas (MSOA)[13]. LSOA are nested within MSOA which allowed us to aggregate the LSOA-level information provided in the Accessibility Statistics. In this analysis, MSOAs in the 25th highest

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[13] There are 6,791 MSOAs in England, and they comprise between 5k and 15k individuals.

percentile of the ratio of jobseekers to 16-74 year-olds with access to employment centres in the MSOA in the respective year are defined as high unemployment neighbourhoods (Model 5). The second alternative marker is at the level of Local Authority Districts (LAD, N=381 in England) and uses official annual district-level unemployment statistics provided by the Office for National Statistics (ONS). We define a district as having high unemployment if it belongs to the 25th percentile with the highest unemployment rate of males[14] in the respective year (Model 6). Note that the unemployment rate at this scale does not consider whether or not there are accessible jobs in the area.

4.2.3 Testing the local labour market effect

Without further restrictions, any neighbourhood effect that we identify will be driven by neighbourhoods transitioning into or out of low local unemployment over time, people moving to a different neighbourhood, and other principally unobserved changes in the neighbourhood. One of these principally unobserved neighbourhood characteristics is whether the area faced major changes such as population growth or decline, for instance, as a consequence of housing developments. Seeing as such major changes tend to prompt boundary changes in our immediate neighbourhoods, we restrict the sample to respondents whose LSOA boundaries were not redrawn between the 2001 and 2011 Censuses (Model 7). To more directly assess the extent to which unobserved neighbourhood characteristics may be driving the results, we restrict the sample to respondents who live in the same neighbourhood throughout the observation period (thus net-out the neighbourhood fixed effect) (Model 8). To minimize the effect of unobserved local characteristics as well as major local change, we also drop movers and those who live in an LSOA whose boundary has changed (Model 9).

A further specification (Model 10) tests the persistence of local labour market conditions by keeping constant the labour market characteristics that applied to the respondent in the initial period. The rationale is that if neighbourhoods frequently change from high to low unemployment over the observation period, the neighbourhood specific findings may be transitory and we should not interpret the effects for a specific type of neighbourhood.

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[14] The data are made available through the NOMIS website, see https://www.nomisweb.co.uk/. The statistics are provided for the whole population and separately for men and women. Seeing as our sample only contains men, the LAD level unemployment rates of males only are used.

4.2.4 Testing the labour market position effect

Next, we estimate our baseline models on the basis of samples which exclude specific groups of the population for whom we hypothesize stronger or weaker labour market position effects. First, we drop from our sample individuals who live in low density areas with a population size below 25k. The rationale is that rural areas experience a lower level of employment transitions - there will be a lower number of available jobs, including those at a higher pay level - and by removing this group we would expect the labour market effect to attenuate downwards (Model 11). By contrast, removing from the sample those who live in London or the South East of England, i.e., regions with major impact on the British economy and above-average wages, may attenuate the labour market effect upwards (Model 12) seeing as the bulk of the labour market transitions to higher-paid employment could be happening in this area. By removing from the estimation sample individuals who have roots outside Britain[15] we also expect the labour market effect to be attenuated downward; ethnic minorities have been shown to perform better on the British labour market than their native counterparts (Model 13). Last but not least, we exclude from the sample individuals who have post-secondary education seeing as they have been shown to face lower risks of unemployment and low-pay. Whilst we control for education in our baseline model, differences may be more structural; we expect stronger persistence in unemployment and low-pay employment (Model 14).

5. Results

5.1 The baseline model

Results of the baseline model can be found in **Table 6**. The first column refers to the probability of becoming unemployed and the second column to the conditional probability of becoming higher-paid employed. We only report relevant information on the random effects parameters, the coefficients for the respondent's lagged labour market position and the interaction dummies between them and the lagged level of unemployment in the neighbourhood as they are required to derive the steppingstone effect of low pay.[16] The reference category is being unemployed in a neighbourhood with low unemployment.

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[15] Understanding Society includes an ethnic minority boost sample which is excluded in this robustness test. Our baseline sample over-represents individuals who self-identify as an ethnic minority or whose parents or grandparents were born outside the UK.

[16] Tables reporting results for the complete models can be obtained from the authors upon request.

With respect to the risk of becoming unemployed (column 1), the results suggest that higher-pay and low-pay employment in a neighbourhood with low unemployment significantly reduces the risk of becoming unemployed compared to the reference category of being already unemployed. Furthermore, there is no statistically significant effect of living in a neighbourhood with high unemployment on the risk of becoming unemployed for those on higher pay $\left(\text{ue-high}_{(t-1)} \times \text{higher-pay}_{(t-1)} = -0.038, \text{ p-}val = 0.82\right)$, nor is there an effect of living in such a neighbourhood for the low-paid employed $\left(\text{ue-high}_{(t-1)} \times \text{low-pay}_{(t-1)} = 0.220, \text{ p-}val = 0.29\right)$. However, the risk of remaining unemployed is significantly increased for those living in neighbourhood with high unemployment compared to those living in areas with low unemployment $\left(\text{ue-high}_{(t-1)} \times \text{unemployed}_{(t-1)} = 0.562, \text{ p-}val = 0.01\right)$.

With respect to the conditional probability of entering higher pay (column 2), the results suggest that for those who live in a neighbourhood with low unemployment there is no difference between the different labour market positions. However, there is a statistically significant reduction in the likelihood of becoming higher-paid employed when living in a neighbourhood with a high unemployment rate for the higher-paid employed $\left(\text{ue-high}_{(t-1)} \times \text{higher-pay}_{(t-1)} = -0.192, \text{ p-}val = 0.01\right)$ compared to a neighbourhood with a low unemployment rate, indicating the scarcity of higher-paid jobs in such areas. This effect is exacerbated for those who were unemployed in the previous period: There is a statistically significant reduction in the chances of becoming higher-paid employed associated with living in a neighbourhood with high unemployment $\left(\text{ue-high}_{(t-1)} \times \text{unemployed}_{(t-1)} = -1.027, \text{ p-}val < 0.01\right)$.

The random-effects parameters for these models (bottom panel) suggest that individuals also differ in their unobserved characteristics: Whilst 16.2% of the variance in the error term is explained by the random-effects error term in the unemployment equation (albeit, this is not significantly different from zero at the 10% level), 67.6% to the composite variance is explained by the random-effects error term in the higher pay equation, and this is significantly different from zero at the 1% level. Moreover, the random-effects are negatively correlated $\left(\rho_\alpha = -0.438\right)$, which is also significantly different from zero at the 5% level. A negative correlation indicates that individuals who are less likely to become unemployed are more likely to become higher-paid employed. The empirical results also suggest that the idiosyncratic shocks are not correlated.

Table 6: Correlated random effects probit regression of lagged labour market position on current labour market position, by level of local unemployment. B-coefficients and Average Partial Effects (APE).

Dependent variable:	*unemployed in t*	*higher-paid employed in t*
higher-pay$_{t-1}$	-1.106	0.205
	(0.465)	(0.260)
low-pay$_{t-1}$	-0.993	-0.147
	(0.404)	(0.274)
unemployed$_{t-1}$	*reference category*	
ue-high$_{t-1}$ × higher-paid$_{t-1}$	-0.038	-0.192
	(0.170)	(0.090)
ue-high$_{t-1}$ × low-pay$_{t-1}$	0.220	-0.152
	(0.207)	(0.101)
ue-high$_{t-1}$ × unemployed$_{t-1}$	0.562	-1.027
	(0.219)	(0.345)
λ_1	0.162	
	(0.198)	
λ_2	0.676	
	(0.051)	
ρ_α	-0.438	
	(0.174)	
ρ_u	-0.097	
	(1.049)	
log likelihood	-1401.099	
N	4,914	
APE*: Local unemployment rate	*low*	*high*
Unemployed	-0.140	-0.249
	(0.119)	(0.161)
Higher-paid	0.089	0.358
	(0.126)	(0.144)

Source: Understanding Society (2014), Waves 1-4, 2009-2013. Standard errors in parenthesis. Estimations include additional covariates (and their mean values) as listed in Table 4, and year dummies. Coefficients are adjusted according to the suggestion of Arulampalam (1999). * Average partial effect of becoming unemployed, resp. higher-paid employed, for someone who was low-paid employed in the previous period compared to someone unemployed, differentiated by level of neighbourhood unemployment. *Reading example*: the probability of becoming unemployed in a neighbourhood with low unemployment is 14.0 percentage points lower, on average, for someone who was low-paid employed compared to someone unemployed.

To facilitate interpretation of the results, we also report the average partial effects (see **Table 6**, bottom panel). This shows that for those living in neighbourhoods with low unemployment, entering low-pay employment is associated with an, on average, 14.0 percentage points lower risk of subsequent unemployment compared to someone who is already unemployed. Furthermore, the chances of climbing up the pay distribution are improved by 8.9 percentage points, on average. However, in both cases, the average partial effects are in the mean not significantly different from zero at the 10% level.

For those living in neighbourhoods with high unemployment, differences in the probabilities are more pronounced. The risk of future unemployment is reduced by 24.9 percentage points, on

average, if instead of staying unemployed the individual enters low-pay employment. Furthermore, the conditional probability of becoming higher-paid employed is 35.8 percentage points, on average, higher for low-paid than for unemployed individuals. This effect is significantly different from zero at the 1% level.

Overall, then, we find heterogeneity in labour market state dependence conditional on the unemployment level in the neighbourhood. The results suggest that there is a steppingstone effect of low pay which is particularly marked in neighbourhoods with high unemployment. In these places, the risk of future unemployment is lowered and the prospects of becoming higher-paid employed are substantially increased when individuals enter low-pay employment compared to when they remain unemployed.

5.2 Robustness tests

Results of robustness tests are reported next. **Table 7** and We furthermore argued that other unobserved neighbourhood characteristics may be driving the results and therefore restricted the sample to non-movers only (Model 8). Whilst the baseline results are confirmed in this sample, none of the apparent reductions in the steppingstone effect are statistically significant. The same is true when we combine the restrictions from Model 7 and Model 8 (see Model 9).

Figure 1 present results from tests aimed at scrutinizing our operationalisation of local unemployment, and **Table 8** report the results from tests aimed at bringing to the fore more clearly the steppingstone effect in the two types of neighbourhood. For ease of comparing the results with the baseline model we report average partial effects (APE).

The results presented in **Table 7** show that the findings from the baseline model hold when we change the accessibility thresholds applied (Models 2-3); low pay acts as a steppingstone to higher-pay employment in neighbourhoods with high unemployment and the effect sizes are in the same ballpark. Using a continuous marker of local unemployment also confirms that the steppingstone effect is higher the higher the local unemployment rate (see **Figure 1**, Model 4): at a local unemployment rate of 5.7%, which is the mean local unemployment rate of high unemployment neighbourhoods when using a binary indicator as in the baseline model, the chances of becoming higher-paid employed is, on average, 21.5 percentage points higher for someone who was low-paid employed compared to someone unemployed. This difference is, on average, statistically significant different from zero at the 10% level. The steppingstone effect is

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confirmed also when we draw the neighbourhood boundaries less tightly (Model 5), and when we change the definition of local unemployment as well as drawing the area unit even less tightly (Model 6). Although we observe sizeable differences in the size of the steppingstone effect at the LAD compared to the LSOA level, only the difference in becoming higher-paid employed in a neighbourhood with a high unemployment level is statistically significant from zero at the 1% level.

Table 7: Correlated random effects probit regression of lagged labour market position on current labour market position, by level of local unemployment. Testing the local labour market indicator. Average Partial Effects (APE)

	Baseline	Alternative labour market indicators		Alternative scales of neighbourhood	
	Model 1	Model 2	Model 3	Model 5	Model 6
			Low local unemployment rate		
Unemployed	-0.140	-0.125	-0.127	-0.133	-0.125
	(0.119)	(0.108)	(0.112)	(0.110)	(0.105)
Higher-paid	0.089	0.082	0.075	0.102	0.091
	(0.126)	(0.114)	(0.118)	(0.114)	(0.109)
			High local unemployment rate		
Unemployed	-0.249	-0.224	-0.226	-0.231	-0.194
	(0.161)	(0.147)	(0.150)	(0.151)	(0.144)
Higher-paid	**0.358**	**0.301**	**0.331**	**0.276**	**0.233**
	(0.144)	(0.133)	(0.134)	(0.135)	(0.137)
N	1,638	1,638	1,638	1,638	1,638

Source: Understanding Society (2014), Waves 1-4, 2009-2013. Standard errors in parenthesis. Bold numbers are significantly different from zero in the mean at least at the 10% level of significance.
Model 2: Composite travel mode, employment centres accessible within 20 minutes.
Model 3: Composite travel mode, employment centres accessible within 40 minutes.
*Model 5:* Local unemployment measured at Middle Super Output Area (MSOA) level.
Model 6: Local unemployment measured at local authority district (LAD) level.

With respect to testing the steppingstone effect in the two types of neighbourhoods (see Table 8), we hypothesized that the local labour market effects may be driven by unobserved neighbourhood characteristics. Dropping individuals in neighbourhoods that have undergone structural changes (as reflected in their neighbourhood boundaries having been re-drawn), suggests that some of the steppingstone effect is associated with such changes (Model 7): whilst there are no statistically significant differences in the reduction to the unemployment risk or the increase in the chance to be higher-pay employed in low unemployment neighbourhoods, in high unemployment neighbourhoods, the risk of entering unemployment reduces by 12 percentage points to 13 percentage points (statistically significant at the 1% level).

We furthermore argued that other unobserved neighbourhood characteristics may be driving the results and therefore restricted the sample to non-movers only (Model 8). Whilst the baseline results are confirmed in this sample, none of the apparent reductions in the steppingstone effect are statistically significant. The same is true when we combine the restrictions from Model 7 and Model 8 (see Model 9).

Figure 1: Distribution of the local unemployment rate (left panel) and testing continuous local labour market indicator (Model 4), Average Partial Effect* (right panel)
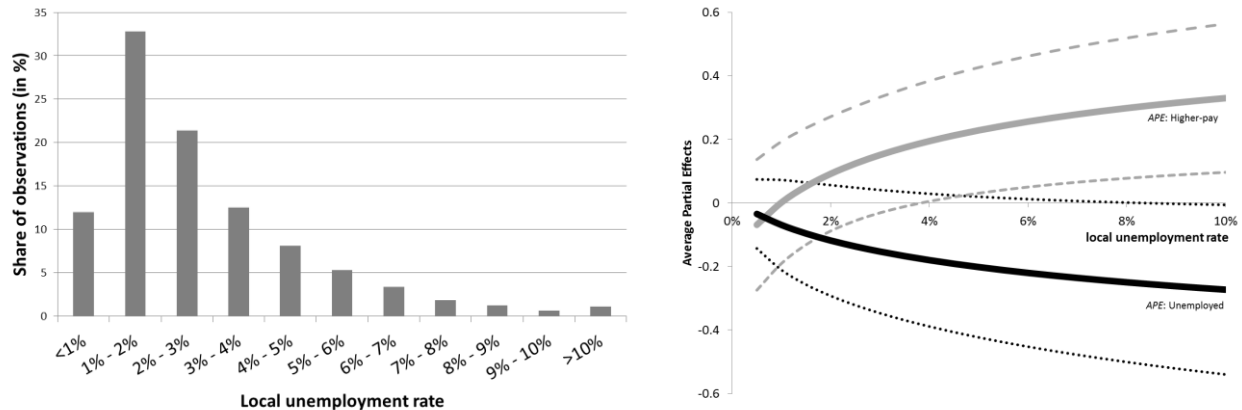
Source: Understanding Society (2014), Waves 1-4, 2009-2013. *90% confidence interval presented in the right panel. *Model 4*: using a continuous marker of local unemployment.

A further concern was that neighbourhoods may change their status across the low/high unemployment threshold over the observation period, which would mean that our classification into neighbourhood types is arbitrary. To alleviate these concerns we distributed the labour market characteristics of the neighbourhood in the initial year to all other years of observation and re-estimated the model on the sample of non-movers (Model 10). Comparing the results from Model 8 and Model 10, a statistically significant difference at the 1% level is only found for the chance to become higher-paid employed in high unemployment neighbourhoods. This indicates that neighbourhoods keep their classification for a long time period and the level of local unemployment is not randomly assigned.

Table 8: Correlated random effects probit regression of lagged labour market position on current labour market position, by level of local unemployment. Testing the local labour market and labour market position effects. Average Partial Effects (APE)

	Baseline	Local labour market effect (Model 7 - 10)				Labour market position effect (Model 11 - 14)			
	Model 1	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
					Low local unemployment rate				
Unemployed	-0.140	-0.048	-0.078	-0.040	-0.071	-0.087	-0.107	-0.121	-0.123
	(0.119)	(0.077)	(0.078)	(0.045)	(0.073)	(0.113)	(0.171)	(0.105)	(0.131)
Higher-paid	0.089	0.021	0.041	-0.007	0.055	0.037	0.103	0.120	0.144
	(0.126)	(0.084)	(0.087)	(0.063)	(0.083)	(0.135)	(0.144)	(0.110)	(0.116)
					High local unemployment rate				
Unemployed	-0.249	-0.132	-0.182	-0.091	-0.146	-0.157	-0.313	**-0.286**	-0.300
	(0.161)	(0.153)	(0.139)	(0.084)	(0.123)	(0.156)	(0.326)	(0.165)	(0.205)
Higher-paid	**0.358**	**0.300**	**0.299**	**0.233**	0.205	**0.320**	**0.402**	**0.340**	**0.395**
	(0.144)	(0.130)	(0.132)	(0.118)	(0.129)	(0.160)	(0.185)	(0.154)	(0.174)
N	1,638	1,554	1,328	1,276	1,328	1,127	1,132	1,481	852

Source: Understanding Society (2014), Waves 1-4, 2009-2013. Standard errors in parenthesis. Bold numbers are significantly different from zero in the mean at least at the 10% level of significance.

Model 7: Individuals in LSOAs without boundary change only.

Model 8: Non-movers only.

Model 9: Non-movers in LSOAs without boundary change only.

Model 10: Full sample but labour market characteristic of first year held constant (only non-movers).

Model 11: Individuals outside low density areas with a population below 25k only.

Model 12: No individuals from London and South-East of England.

Model 13: Non-Ethnic Minority Boost Sample only.

Model 14: Men without post-secondary education only.

Last but not least, we subjected the labour market position effect to greater scrutiny (see **Table 8**, Models 11-14). First, we dropped from the sample individuals who live in a low density area with a population below 25k. For these individuals we would expect a stronger steppingstone effect given the lower supply of available jobs - in particular at higher pay – in these neighbourhoods, independent of the unemployment level in the neighbourhood, lending more strength to the signalling effect of low pay. In line with our expectations, we find that the steppingstone effect is lower than in the baseline model when we drop this group (Model 11), albeit only the difference of becoming unemployed in neighbourhoods with high unemployment is statistically significant at the 1% level.

Dropping individuals who live in the economically vibrant areas of London and the South East of England, where we would expect many job transitions to take place without signalling, should positively influence the signalling effect of low pay in the remaining sample and thus lift the associated steppingstone effect. Model 13 suggests that this may be the case in particular for high unemployment neighbourhoods, where the partial effect of becoming unemployed is substantially lowered from 24.9 percentage points in the baseline model to 31.3 percentage points and the difference in the chance of becoming higher-paid employed increased from 35.8 percentage points in the baseline model to 40.2 percentage points. Note, however, that the differences compared to the baseline model are not statistically significant at conventional levels.

Dropping the ethnic minority boost sample members from our analysis (Model 13) suggests that the difference in the labour market dynamics of native British men compared with the full sample is rather small; this is also indicated by the fact that the differences in the APE to the baseline model are not statistically significant. Interestingly, however, we observe a statistically significant (at the 10% level) partial effect of picking up a low-pay employment instead of being unemployed on the risk of becoming/staying unemployed.

Our final test, see Model 14, shows little in support of the hypothesis that there are structural differences in the effects for those with and without post-secondary education which cannot be captured by including a respective indicator variable in the regression. Whilst the key results from the baseline are replicated in a sample of only those with post-secondary education, none of the differences to the baseline model are statistically significant.

6. Conclusion

Against the backlight of rising unemployment and a persistent high share of low-pay employment in many countries (OECD 2013), the aim of this research was to provide empirical evidence on whether the employment and earnings prospects of low-pay workers compared to the unemployed are improved, and how these effects – referred to as steppingstone effects - are correlated with local labour market conditions. Whilst a plethora of studies have suggested that there is state dependence in labour market processes, few have considered that opportunities for economic advancement are not distributed evenly across space. Are those who live in neighbourhoods that are characterized by high unemployment well advised to "get on their bikes" and take a job at low pay? Taking a job could mitigate the hypothesized deterioration in human capital experienced during unemployment and low pay workers may gain new skills which could help reduce their future unemployment risk and improve their earnings prospects. Or should they hang on and invest their time into looking for a better paid job? And what would be the advice to those who live in areas with high levels of employment, where staying at home may be particularly stigmatizing?

To investigate these issues empirically, we use information from the first four waves of interviews from *Understanding Society*, the new UK Household Longitudinal Study (UKHLS). The study is representative for all regions of the United Kingdom and for rural and urban areas within them. We matched the survey data with local labour market statistics at very immediate geographical scales to characterize respondents' neighbourhoods into high and low unemployment areas. Compared to local labour market characteristics used in previous research, our local labour market statistics differ in that they are much more local and that the unemployment rate is based on a measure of jobseekers to working age population in the neighbourhood who can reach employment locations on foot, by public transport and cycling. We can, therefore, look at whether the unemployed should indeed "get on their bike" as the common political rhetoric suggests (we do, however, also test alternative definitions that allow for longer travel times and different travel modes).

The empirical results suggest that there are differences in the returns to taking up low pay depending on where one lives. Whilst there is a weak (and statistically insignificant) steppingstone effect on employment and on the odds of getting into higher pay in

neighbourhoods with a low unemployment rate, the effects are sizeable and statistically robust across a great number of specifications in neighbourhoods with high unemployment.

There are a number of challenges in identifying these local interaction effects and we address these inasmuch as is feasible. One of the paramount challenges is that there may be unobserved neighbourhood characteristics that are correlated with employment opportunities and people's location choice. Economically attractive areas, for example, tend to receive a lot of investment, new property is being built and people move in. Indeed, when we undertake the analysis just for those who remained resident in the same neighbourhood, hence netting out neighbourhood fixed effects, the differences in the prospects between the unemployed and low-pay employees attenuate downwardly. The same is true when we exclude those who live in neighbourhoods that experienced boundary changes – a sign for the area having undergone major structural changes such as new housing developments having been erected – or those who live in low density areas. These results suggest that in economically vibrant areas no great distinction is made between unemployment and low-pay and both groups face comparable employment and earnings prospects.

In areas with a high local unemployment rate, however, we find strong indication for a steppingstone effect of low pay. Not only is the risk of future unemployment reduced for those who work on low pay but also is the probability of becoming higher-paid employed substantially improved. These findings hold for all alternative model specifications, including when unobserved neighbourhood characteristics are controlled for. A possible explanation is that the value of signalling ones willingness to work is positively correlated with the number of unemployed people in the neighbourhood, and with the scarcity of higher paid jobs.

We furthermore find that the steppingstone effect is higher for individuals who live in high unemployment areas outside the economically vibrant areas of London and the South East of England, and the effect is sizably reduced when we draw the neighbourhood boundaries less tightly (and relaxing the definition of the local unemployment rate and accessible employment locations). A possible explanation is that the signalling effect of low pay is stronger in communities that are less dynamic and where employment decisions are more likely to be made on the basis of personal contact and family legacy.

Overall, these findings are in contrast to previous empirical evidence presented by Stewart (2007) who concluded 'that low-wage jobs typically do not lead on to better things' [p. 529]. In the specific population and period of time that we examined here, there clearly were some groups for

whom low pay acted as a door opener. However, policy initiatives aimed at increasing the low wage sector should tread with caution. Qualitative research with residents in deprived neighbourhoods documents that low wages do not typically pay enough to maintain the family, and the costs associated with being in employment (e.g., commuting costs) put enormous pressure on workers who have to make ends meet (see, e.g., Open Society Foundations 2014). In this context, the current shifts in employment contracts towards reduced job stability (e.g., fixed-terms contracts) and uncertain payment structures (e.g., zero hour contracts) mean that the incentives to take up low-pay employment have been further reduced for exactly that part of the population for whom – according to our empirical study - the greatest benefits were had from engaging in the low pay sector. Potential solutions would include policies that increase job security, limit the use of zero-hours contracts and offer support for skills improvement and career advancement.

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