

# Neighborhoods, networks and unemployment: the role of neighborhood disadvantage and local networks for taking up work

Leen Vandecasteele, University of Lausanne & NCCR LIVES

Anette Eva Fasang, Humboldt University of Berlin and WZB Berlin Social Science Center

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## *Abstract*

We bring together research on social networks and neighborhood disadvantage to examine how they jointly affect unemployed individuals' probability of re-entering employment. Data from the UK Household Longitudinal Study "Understanding Society" provides information on the proportion of friends who live in the same neighborhood and is linked with small-scale administrative information on specific dimensions of neighborhood deprivation. Results indicate that neighborhood employment-deprivation prolongs unemployment, but only for individuals who report that all of their friends live in the same neighborhood. Living in an advantaged neighborhood with all of one's friends in the neighborhood increases chances to exit unemployment. In contrast, neighborhood location is not associated with unemployment exit if one's friends do not live in the same neighborhood. We conclude that neighborhood effects on exiting unemployment critically depend on individuals' social embeddedness in the neighborhood. Not just residing in a disadvantaged neighborhood, but actually living there with all one's friends, prevents individuals from re-entering employment. This opens new avenues for theorizing neighborhood effects as social rather than geographic phenomena, and highlights that the effects of neighborhood socio-economic characteristics are conditional on the level of interaction residents have within their neighborhood.

## *Key words:*

unemployment, social network, local unemployment, local disadvantage, neighborhood deprivation

## ***Introduction***

Neighborhoods are an important context of social stratification. Living in a neighborhood with concentrated poverty reduces educational attainment, well-being, increases problem behaviors, crime and limits employment chances (Sampson et al., 2002, Wodtke et al., 2011). It has been convincingly demonstrated that neighborhood disadvantage prolongs unemployment (Buck, 2001, Dawkins et al., 2005, Musterd et al., 2003, Miltenburg and van de Werfhorst, 2017). The reasons why, and the conditions under which neighborhoods influence unemployment duration remain less clear. Residents of disadvantaged neighborhoods may be more likely to be unemployed for several reasons: employer *discrimination* based on neighborhood, a *spatial mismatch* resulting from a lack of local jobs coupled with poor transportation connections, a lack of local *institutional* and social services that may help in the job search, lack of access to resourceful *networks* that hold information about job opportunities, or neighborhood peer influences that undermine an effective job search. Theoretical mechanisms that connect neighborhood disadvantage and resident's life chances have been difficult to disentangle in empirical population-level research.

In this paper, we examine how social ties in the neighborhood and neighborhood deprivation jointly affect the probability to exit unemployment. We address two research questions: First, we follow the conventional approach to neighborhood effects and ask, whether neighborhood deprivation per se decreases the probability to exit unemployment. Second we bring together neighborhoods and networks to examine, in a population-wide longitudinal study, how social network location measured as the proportion of friends in the neighborhood moderates the association between neighborhood disadvantage and the probability of re-employment. Social relations are important cornerstones in understanding how context-level determinants affect individual outcomes (Erbring and Young, 1979). Neighborhood socio-economic status matters if neighbors provide access to information about job opportunities, practical help or act as role models in the job search process. Hence, unemployment could be prolonged in neighborhoods with concentrated disadvantage that lack these resources.

Until recently the literatures on neighborhood and network effects developed largely separately (see Desmond and An, 2015). On the one hand, the neighborhood literature has documented how residential neighborhoods affect the life chances and choices of their inhabitants, but it has rarely incorporated detailed measures of social networks and social interaction (Galster, 2012, Sampson et al., 2002, Topa and Zenou, 2015). On the other hand, the social networks literature has focused on the types and structure of social ties and how these affect socio-economic outcomes, largely without concern for their geographical location (Burt, 2004, Portes, 1998, Granovetter, 1973). Integrated studies of social networks and neighborhoods are often called-for, but empirical work is rare (Papachristos et al., 2013, Topa and Zenou, 2015, Fernandez and Su, 2004, Desmond and An, 2015), and empirical population-wide survey evidence is non-existent to our knowledge. Existing studies are either cross-sectional (Miltenburg, 2015, Desmond and An, 2015) or based on administrative records of specific groups (Papachristos et al., 2013), but do not rely on population-wide longitudinal survey data with information on network and neighborhood characteristics.

We use the UK Household Longitudinal Study “Understanding Society” to test whether the impact of neighborhood disadvantage on the probability of re-employment is moderated by

the location of residents' social networks, measured as the proportion of friends in the neighborhood. The data uniquely combine geographically localized measurements of respondents' friendship networks and small-scale neighborhood information specifically on employment-deprivation of neighborhoods with the possibility to examine unemployment longitudinally.

Our study contributes to the literature on neighborhood-effect heterogeneity (Wodtke et al., 2016) and is the first to find clear evidence with population-wide data that neighborhood effects on employment depend on the co-location of social networks. Specifically, we find that locally concentrated networks moderate the effect of neighborhood disadvantage: they act as multipliers of the beneficial effects of resourceful neighborhoods and of the detrimental effects of disadvantaged neighborhoods on the probability to exit unemployment. This finding extends previous work that theoretically elaborates the downsides of locally concentrated social ties and highlights that the benefits of locally concentrated social ties are confined to resourceful environments (Portes, 1998, Fasang et al., 2014). At the same time, individuals who have a larger share of friends outside of the neighborhood are largely immune to the effects of neighborhood disadvantage. We argue that it is not simply where individuals reside, but where they live, i.e. where they spend time and with whom they interact, that matters for the impact of neighborhood characteristics on socio-economic outcomes. This opens new avenues for theorizing neighborhood effects as social rather than geographic phenomena, and highlights that the effects of neighborhood socio-economic characteristics are conditional on the level of interaction residents have within their neighborhood.

### ***Background: Neighborhoods, networks and unemployment***

We first review theory and evidence on neighborhood effects on employment (2.1), followed by a discussion of theoretical mechanisms and empirical findings that link networks in neighborhoods to employment outcomes, before (2.2) summarizing our main hypotheses (2.3).

#### *Neighborhoods and employment*

Previous research has suggested several mechanisms through which neighborhood disadvantage can affect life chances (Galster, 2012, Jencks and Mayer, 1989, Sampson et al., 2002, Sharkey and Faber, 2014). For employment, four main mechanisms have been distinguished: spatial mismatch, neighborhood discrimination, local institutional services, and social interaction.

First, the *spatial mismatch* hypothesis (Kain, 1968) attributes lower employment chances for residents of neighborhoods that are geographically distant from suitable jobs to three reasons: information, commuting and moving (Ihlanfeldt and Sjoquist, 1998). The further the job opportunities are away, the less likely a jobseeker is to know about them. Many low-level jobs are advertised locally or require local knowledge for successfully obtaining them. While more distant jobs come with higher commuting costs in terms of money and time, poorer areas are often less well-served by public transport and have lower rates of car ownership. Additionally, high housing costs and housing discrimination can impede relocation to neighborhoods with job opportunities. Consequently, the rise in inner-city poverty in the United States is believed to be related to a spatial mismatch resulting from jobs shifting to the suburbs (Wilson, 1987). The spatial mismatch has

also been argued to play a role outside of the United States. In the United Kingdom lower-paid employees have been found to work closer to home while social housing residents and manual workers are less likely to move (Houston, 2005).

Second, job applicants may be *discriminated* against based on living in a neighborhood with a bad reputation. The neighbourhood thereby serves as a signal for an applicant's unobservable future productivity. Field experiments have shown that employers prefer and are more likely to interview applicants from certain neighborhoods (Bunel et al., 2016, Tunstall et al., 2014).

Third, the *institutional mechanism* focuses on a lack of local services that foster individuals' opportunities to find and maintain employment (Galster, 2012), including private, non-profit and public organizations. While job centers and welfare organizations can directly aid job searches, medical services and childcare centers are important to ensure employees' physical health and care for children while their parents are at work.

Fourth and most importantly for our study, the *social interaction mechanism* refers to the influence of social connections in the neighborhood.<sup>1</sup> Neighborhoods may facilitate getting a job if resources and information are successfully shared among residents, and if neighbours act as positive role models. One important mechanism of neighborhood stratification is selection into neighborhoods or residential sorting. If individuals with similar characteristics tend to live in the same neighborhood, then inequalities between neighborhoods boil down to inequalities between individuals. In fact, studies have argued that much of the neighborhood effect is attributable to selection (Dietz, 2002; Ginther et al., 2000). Others have argued that inequalities between social groups in residential re-location patterns is in itself an important aspect of spatial stratification. It has been shown that a large part of residential sorting across the lifecycle is captured by variables such as race, ethnicity and socio-economic position (Sampson, 2008). While our study empirically accounts for the most plausible confounders in a longitudinal set-up, selection on unobservable characteristics that relate to both neighborhood location and networks usage is still a possibility. Extensive theoretical accounts of the detrimental impact of neighbourhood disadvantage on employment have proven more difficult to disentangle in empirical population-level research. Studies on spatial mismatch have used indicators measuring distance to jobs controlling for other neighbourhood disadvantage characteristics (Mouw, 2000, Ihlanfeldt and Sjoquist, 1998). Neighborhood discrimination and stigma have been examined in field experiments sending out job applications from different localities (Bunel et al., 2016, Tunstall et al., 2014). The social interaction mechanism, however, is often assumed to be at play without being explicitly modeled. Qualitative research provides hints about the reasons behind neighborhood disadvantage, but quantitative studies usually show that neighborhoods matter without including explicit indicators to address why that is the case. Because the social interaction mechanism is the focus of our study, we subsequently bring together insights from the neighborhood and social networks literatures to hypothesize how social interactions and neighborhoods jointly affect the probability of re-employment.

#### *Neighborhood social ties and employment outcomes*

In both the neighborhood effects and social networks literatures, there are two main ways through which neighbors potentially affect employment outcomes, which we summarize as: resource-

sharing and norm-setting. *Resource-sharing* refers to instrumental support in finding employment by exchanging information and resources in networks (Granovetter, 1995, Granovetter, 1973, Lin, 1999). Research in four large urban areas in the United States, for instance, showed that 40–50% of jobs are obtained through social networks (Mouw, 2002). Neighbours potentially provide information about job opportunities; psychological support and practical help or directly recommend a candidate for a job.

*Norm-setting* goes beyond tangible support through resource-sharing and refers to how social interaction can set behavioral standards. Through social learning from peers and role models individuals adjust their aspirations and behavior. This mechanism is known under different names and sub-dimensions in the neighborhoods literature, including contagion theories, collective socialization (Jencks and Mayer, 1989) or social cohesion and social control (Sampson et al., 2002, Galster, 2012). While interacting with professionally successful neighbours can motivate job searches, a lack of local positive role models could foster a ‘culture of unemployment’ (Wilson, 1987), e.g. by reducing the social stigma attached to welfare use (Moffitt, 1983). In line with the norm-setting function of social interaction, network scholars, prominently Portes (2014), have drawn attention to potential downsides of dense and concentrated social networks: they could bring about downward leveling norms, excessive claims on group members, and impaired judgment due to excessive trust in group members (Morgan and Sorensen, 1999, Portes, 2014).

Whether neighborhoods prove useful for getting a job crucially depends on the resources and role models available in its social networks as well as the type of social ties an individual establishes with co-residents. Distinguishing between a mediating and moderating relationship between local networks and neighborhood effects is important to illuminate the theoretical mechanisms through which neighborhoods affect socio-economic outcomes.

Social networks are *mediators* of neighborhood disadvantage if they are variables on the causal pathway from neighborhood deprivation to employment; for example, if residence in a deprived vs. affluent neighborhood affects the size, composition, or geographical location of residents’ social networks, and these social network characteristics affect employment. In this study, we focus on the local concentration of friendship ties in the neighbourhood as proxies for neighbourhood social interaction. A mediating role of neighborhood social networks implies that individuals in disadvantaged neighborhoods have more locally concentrated friends. Social-isolation theories of neighborhood effects argue that residents of deprived neighborhoods are cut off from outside social networks and institutions that provide access to job information (Jencks and Mayer, 1990, Wilson, 1987, Wilson, 1996). For instance, Tigges, Brown and Greene (1998) report that neighborhood poverty reduces the size of the social network of their residents as well as their overall level of social contact. Most prior work on neighborhood effects similarly treats social isolation as a neighborhood characteristic.

In contrast, a *moderating role* of social networks implies a differential effect of neighbourhood disadvantage depending on whether people have social ties in their neighbourhood or not. The mechanisms of resource-sharing and norm-setting crucially depend on social interaction in the neighbourhood. Local friends in disadvantaged neighborhoods may be less able to support the job search process due to their limited resources, e.g. in terms of the type of job they hold or the extent and quality of connections to individuals in power positions. Similarly, a lack of employed role

models, downward-leveling norms, and oppositional cultures likely are powerful barriers to exiting unemployment for people with their social ties primarily in areas of concentrated disadvantage. At the same time, residents who don't interact within their immediate surroundings but whose social networks extend beyond the neighbourhood, will be less exposed to, and less dependent on the resources and norms shared in disadvantaged neighbourhoods. Desmond and An (2015) examined the relationship between neighborhood disadvantage and social network disadvantage and reported individual heterogeneity. Many residents of poor neighborhoods were embedded in more advantaged networks. In the subsequent analyses, we therefore examine whether neighborhood deprivation has less detrimental consequences for residents who have social networks outside of their neighborhood.

### *Previous research*

Previous research supports that residents of high-poverty neighborhoods rely more heavily on less educated and poorer informal contacts compared to residents of affluent neighborhoods (Elliott, 1999). A study evaluating job networks among Moving to Opportunity participants found that the job networks of residents who remained in concentrated poverty neighborhoods are less diverse than those of individuals who moved to more mixed neighborhoods (Kleit, 2002). Oesch and von Ow (2017) combined survey and administrative data in Switzerland to show that middle-aged job seekers with high prior earnings primarily find a new job through work-related ties, whereas job seekers with poor employability rely more heavily on communal contacts. Cingano and Rosolia (2012) found that a one standard-deviation increase in the employment rate of the network of an unemployed person reduces unemployment duration by about 8%. The closed homogeneous networks in high poverty neighbourhoods may not only limit access to job information but also shape perceptions of opportunities (Galster and Killen, 1995).

While these and other studies suggest that neighborhood effects on employment could be related to social networks, quantitative studies usually show that neighborhoods matter without including indicators to address why that is the case. Indicators of neighborhood composition, such as the employment or poverty rate, are used as distant proxies of social interactions (Cutler and Glaeser, 1997, Oregon and Quigley, 1996, Weinberg et al., 2004, Dawkins et al., 2005).

Existing empirical evidence that locally concentrated social ties act as multipliers of local resources is often confined to specific sites and urban areas, uses distant proxies for social interaction, and is cross-sectional. Importantly, most studies only test a mediating role of social networks in neighborhood effects but disregard potential moderating effects. This is surprising, because, as outlined above, the theoretical rationales of resource-sharing and norm-setting through social interaction in neighborhoods suggest moderating rather than mediating effects. An exception is Miltenburg (2015), who examined, in a cross-sectional study, the moderating role of neighborhood social integration on the relationship between neighborhood's socio-economic position and resident's income and found no moderating effect. Miltenburg and van de Werfhorst (2017) demonstrate effect heterogeneity of neighborhood disadvantage on the transition to employment for individuals in different household constellations, using household constellation as a proxy for social ties in the neighborhood. Specifically, they deduce that parents spend more time in the neighborhood and likely have a denser, more locally concentrated social network than

childless individuals, especially when children are young. Findings indeed show that neighborhood disadvantage particularly depresses job opportunities for single parents and parents of young children.

In this paper we present a large population-wide longitudinal study to isolate how network location measured as the proportion of friends in the neighborhood moderates the association between neighborhood disadvantage and the probability to exit unemployment.

### *Summary of hypotheses*

Based on the considerations above we hypothesize that residence in a disadvantaged neighborhood compared to an advantaged neighborhood is associated with a lower probability to exit unemployment (H1). Further, we expect that the association between neighborhood disadvantage and the probability of re-employment is more negative among residents who have exclusively local friendship networks compared to residents who also have friends outside of their own neighborhood (H2). We thus hypothesize neighborhood-effect heterogeneity by the location of residents' social networks. Note that if effect heterogeneity exists, evaluating only the main effects of both neighborhood disadvantage and a local concentration of friends would be misleading. In particular, averages might suggest null effects, when in reality neighborhood disadvantage and a local concentration of friends facilitate unemployment exits under some conditions but hamper them under others.

### ***Data and methods***

We use nationally representative longitudinal data from the United Kingdom Household Longitudinal Study (UKHLS), *Understanding Society*. Understanding Society started to collect data annually in 2009 for a stratified and clustered random sample of 39,802 households, which corresponds to about 100,000 individuals. All household members aged 16 and above are eligible for interview, and original sample members and their children are followed when they move to new households. During our observation window (2010-2012), the UK experienced a surge in unemployment from around 5.5 percent to around 8 percent following the international financial crisis (Gregg and Wadsworth, 2010). The extent to which individuals have been able to exit unemployment and which local factors proved beneficial or detrimental in this process provides insights that may extend to other countries affected by the crisis.

### *Study design and analysis sample*

Our analysis sample comprises original sample members who participated in the first two waves of the survey (2009 and 2010) were personally interviewed, aged 17-55 and unemployed in the 2011 wave, when we measure network location and neighbourhood deprivation. We follow these individuals if they received personal or proxy interviews in 2012 where we measure the outcome variable, whether an unemployment exit occurred or not. Out of N=1327 cases, we lose 230 cases (17 percent) to attrition in wave 4 and an additional 63 cases (5.7 percent) to item-specific nonresponse in waves 2-4, which we excluded through listwise deletion. The final sample size amounts to 1034 cases and the analysis is weighted with the longitudinal weight. Overall

Understanding Societies has been found highly representative of the population covered in census data. Compared to other large-scale panel studies, attrition is moderate and only slightly selective with somewhat higher drop-out probabilities for younger age groups, men, black people, people on lower incomes, and in the West Midlands (Lynn and Borkowska, 2018). Since these groups are also disproportionately affected by unemployment, we account for their higher attrition probability with the longitudinal weight. Due to the availability of the neighborhood variable, our analysis is confined to England.

Our research design uses three observation points Table S.1 in the supplementary material shows the core variables assessed at each of the three time points. We select all unemployed individuals at the 2011 wave and measure our central variables—neighborhood deprivation and network location—in the same wave. We measure a number of social background characteristics in 2010 known to affect the selection into neighborhoods and assess re-employment at wave 2012. Our design thereby accounts for the temporal ordering of confounders (t-1) before treatment (t) before outcome (t+1). Note that the selection of years and our longitudinal approach was limited by the fact that network location was only available in waves 1 and 3.

### *Variables and measurement*

We estimate to what extent neighbourhood effects on unemployment exit are mediated and moderated by network location. The outcome is an indicator variable whether respondents have entered paid employment at wave 2012 or not.

Neighbourhoods are defined on the basis of Middle Layer Super Output Areas (MSOA) delineated by the UK Office of National Statistics for the collection and publication of small area statistics. They were designed to have similar population sizes and be socially homogenous (ONS, 2018). There are 6791 MSOAs in England, with a minimum population of 5,000 and a maximum of 15,000. The average population of MSOAs in England and Wales was 7,878 with 95% of MSOAs having a population between 5,443 and 11,579 (ONS, 2012).

The key independent variable, percent employment-deprived in the neighbourhood, is a sub-dimension of the English Index of Multiple Deprivation 2010 (IMD), an administrative data source of 38 separate indicators covering seven domains of deprivation (McLennan et al., 2011)<sup>2</sup>. Neighborhood employment-deprivation is conceptualised as the percentage of the working-age population in the neighborhood that is involuntary excluded from the labour market. Calculated from seven indicators, this variable provides a more accurate account of the proportion of people involuntarily out of work than a single indicator of claimants of jobseeker allowance would. Included are claimants of the following allowances over four quarters of the year: jobseeker's allowance, incapacity benefit, severe disablement allowance and employment support allowance. In addition, they include participants in New Deal (aged 18-24 and 25+) not receiving jobseeker's allowance and participants in New Deal for Lone Parents aged 18+ (McLennan et al., 2011).

The combined count of employment-deprived individuals of working age (women aged 18-59 and men aged 18-64) per Lower Layer Super Output Area (LSOA) forms the numerator of an employment-deprivation rate, expressed as a proportion of the full working age population in the LSOA. We aggregated the employment-deprivation rate to the MSA-level using the method recommended by the Department of Communities and Local Government (DCLG) at the Office

of National Statistics. Averages of LSOA-level scores have been population-weighted using adjusted 2008 mid-year estimates, provided by DCLG. We linked this census-based employment-deprivation rate to the MSOA-areas in wave 2011 of our dataset. Note that employment-deprivation does correlate with other dimensions of deprivation, but each of the dimensions are distinct and have shown different relationships with outcomes (for details see McLennan et al., 2011).

The mediating and moderating variable, network location, was measured using a self-report of the proportion of the respondent's friends that live in the local area. This indicator was measured in 2011, the third wave of our temporal sequencing. We distinguish three categories: whether "less than half", "more than half" or "all friends" live in the same neighbourhood.

We measure an extensive set of covariates at the 2010 wave to control for confounding of neighbourhood residence and unemployment exits (Table S.1), including self-reported employment status ("in paid employment", "unemployed", "inactive"), age and gender of the respondent. Educational level was measured as "university degree", "other higher qualification", "A level & equivalent", "GCSE & equivalent", "other qualification" and "no qualification". Race is included as "White", "Asian", "Black", "Other", and "don't know/missing". Marital status of the respondent covers the categories "single, never married", "married or cohabiting", "separated, divorced, widowed". Further, we control for household income and composition including the number of employed individuals, and the number of adults and children under age 16 in the household.

In addition to the central independent variables measured in 2011, neighbourhood deprivation and proportion of friends in the neighbourhood, we control for several other characteristics of friendship networks and residential area at 2011: the total number of close friends<sup>3</sup>, urban versus rural area and duration of residence at the current home in years. We performed a supplementary analysis including conscientiousness as a personality trait that potentially affects both, which neighbourhood individuals reside in and their likelihood to be unemployed. Unfortunately, conscientiousness was only measured in 2011, the same time point when neighbourhood deprivation and network location was measured and is therefore potentially affected by neighbourhood deprivation, our "treatment" variable. Controlling for conscientiousness does not affect our results and was therefore omitted from the final analyses.

Table 1 and Table S.2. and S.3. shows descriptive sample statistics of all variables included in the analyses. About 38% of the unemployed in our study had more than half of their friends in the neighbourhood, indicating that social networks are partly geographically based, but there is substantial heterogeneity in network location across residents. This is true for residents of both the deprived and less deprived neighbourhoods and calls for a conditional analysis of neighbourhood effects across network location.

Table 1. Descriptive Sample Characteristics

	Scale Range	Mean (SD)/ Proportion
<b>Percent employment-deprived in neighbourhood 2011</b>	1.8 – 35.6	13(6.4)
<b>Proportion of friends in neighborhood 2011</b>		
Half or less		61.7
More than half		22.6
All friends		15.7
<b>Total number of close friends 2011 (centered)</b>	-4.2-10.8	0(3.4)
<b>Self-reported employment status 2010</b>		
In paid employment		25.3
Unemployed		42.6
Inactive		32.1
<b>Age 2010, M(SD)</b>	16 - 54	34.5 (11.6)
<b>Gender</b>		
Male		52.1
Female		47.9
<b>Education 2010</b>		
No qualification		13.4
University Degree		13.9
Other higher qualification		8.1
A level & equivalent		20.9
GCSE & equivalent		31.1
Other qualification		12.5
<b>Race</b>		
White		58.8
Asian		15.6
Black		11.0
Other		6.7
Don't know or missing		7.9
<b>Marital status 2010</b>		
Single, never married		50.2
Married or cohabiting		39.5
Separated, divorced or widowed		10.4
<b>Net monthly income in household 2010</b>	0 - 67408.5	1092 (2205.7)
<b>Number of employed in household 2010</b>	0 - 5	0.9 (1)
<b>Number of adults in household 2010</b>	1 - 8	2.4 (1.2)
<b>Number of kids in household 2010</b>	0 - 8	0.9(1.2)
<b>Region 2011</b>		
North East		5.4

North West	13.2
Yorkshire and the Humber	10.4
East Midlands	8.4
West Midlands	10.5
East of England	8.9
London	24.9
South East	10.9
South West	7.4
<b>Urban/rural area 2011</b>	
Urban area	90.5
Rural area	9.5
<b>Duration at residence 2011</b>	
up to 3 years	28.2
4-7 years	20.4
8-14 years	21.7
15 years or more	24.2
missing	5.5
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<b>Number of observations:</b>	1034
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### *Methods*

Logistic regression models were conducted on the probability to exit unemployment between wave 2011 and wave 2012. The moderating impact of network location on the effect of neighbourhood deprivation on exiting unemployment is included via an interaction term between employment-deprivation of the neighbourhood  $n$  and the proportion of an individual's friends located in the neighbourhood of residence  $n$ . The model is specified as follows:

$$\text{logit}(\pi_i) = \beta_1 + \beta_2 x_{2n} + \beta_3 x_{3in} + \beta_4 x_{2n} x_{3in} + \zeta_i$$

We did not estimate multilevel models since most (81.5%) MSOA's contain only a single observation, and few (5%) contain more than two.<sup>4</sup>

We report odds ratios and average marginal effects. Standard errors are clustered at the neighborhood level (2011 wave). Odds ratios cannot be straightforwardly compared across nested models and between groups of an interaction (Mood, 2010). Therefore, we calculated average marginal effects (AME) of neighborhood IMD across the three groups of neighborhood integration.<sup>5</sup> The average marginal effect produces the average change in probability of unemployment exit with a one percent increase in employment-deprived residents in the neighborhood. This change is calculated for all sample members and then averaged. We report the AME's as well as the AME contrast scores compared to the reference category of 'half or less of my friends reside in the neighborhood' along with the significance of the associated Chi-square test. The AME's of the control variables refer to average effects. Furthermore, we graph predicted probabilities of unemployment exit by neighborhood deprivation and network location, and at the mean of the other covariates. This allows us to visualize how the estimated effect of changing neighborhood location changes with the relative location of one's friends.<sup>6</sup>

## **Results**

Table 2 reports the average marginal effects for the probability to exit unemployment between waves 2011 and 2012. The models proceed in several steps. First, in Model 1, we only include the percentage of employment-deprived in the neighbourhood adjusted for temporally precedent controls to test our main hypotheses, whether the probability to exit unemployment is lower in more deprived neighborhoods. Model 2 adds the proportion of friends in the neighborhood, followed by Model 3 that additionally takes into account the interaction between network location and employment-deprivation in the neighbourhood.

The AME's in Model 1 show that an increase of one percent employment-deprived residents in the neighborhood is on average associated with a 0.6% reduction in the probability to exit employment in 2012. When proportion of friends in the neighborhood is added in Model 2, the effect of neighborhood deprivation does not change quantitatively and remains significant. Consequently, the effect of neighborhood deprivation is not mediated by the location of close social ties. In other words, the lower employment uptake for individuals in disadvantaged neighborhoods is not explained by having more locally concentrated friends. Instead, in Model 3, the significant and negative interaction term between neighborhood deprivation and having all friends in the same neighborhood suggests a moderating effect of a strong local concentration of friends in the neighborhood for the association between neighborhood deprivation and re-employment. Local networks as moderators index effect heterogeneity in neighborhood effects across individuals with different types of personal networks.

Table 4 shows the AME's calculated for the subgroups of network location. For people with less than half of their friends in the neighborhood, a one percent increase in employment-deprived individuals in the neighbourhood does not significantly reduce their likelihood of re-employment (AME= -0.002;  $p=0.620$ ). In contrast, for residents with all their friends in the neighborhood the decrease in the re-employment probability amounts to 1.6% with a one percent increase of employment-deprived co-residents in neighborhood deprivation (AME= -0.016;  $p=0.004$ ). For residents with more than half of their friends in the neighbourhood the average reduction in re-employment amounts to 1% (AME= -0.001;  $p=0.095$ ). Hence, having many friends in the neighbourhood is particularly detrimental for individuals who have no friends outside of their own disadvantaged neighbourhood. Living in a deprived neighbourhood and having all of one's friends in the same neighbourhood considerably reduces the chance of re-employment compared to living in an advantaged neighbourhood and having all of one's friends there. That is, even if residents of disadvantaged neighborhoods have the same level of locally concentrated networks as residents of advantaged neighborhood, these networks do not increase their chances of exiting unemployment in the same way. By contrast, living in a disadvantaged compared to living in an advantaged neighbourhood is not associated with a change in the probability of re-employment for individuals who have locally dispersed friendship networks.

Table 2. Average Marginal Effects for exiting unemployment between t2 and t3.

	M1	M2	M3 <sup>6</sup>
<b>Percent employment-deprived in neighbourhood 2011</b>	-0.006*	-0.006*	-0.002
<b>Proportion of friends in neighborhood 2011</b> (Ref.: <i>Half or less</i> )			
More than half		-0.003	
All friends		0.105*	
<b>Interaction</b>			
More than half of friends X Percent unemployment-deprived in neighbourhood			-0.008
All friends X Percent unemployment-deprived in neighbourhood			-0.014*
<b>Employment status 2010</b> (Ref.: <i>In paid employment</i> )			
Unemployed	-0.207***	-0.204***	-0.204***
Inactive	-0.184***	-0.177**	-0.180***
<b>Education</b> (Ref.: <i>No qualification</i> )			
University Degree	0.186**	0.211***	0.206***
Other higher qualification	0.089	0.105+	0.102+
A level & equivalent	0.168**	0.176***	0.173***
GCSE & equivalent	0.118*	0.124**	0.123*
Other qualification	0.047	0.054	0.054
<b>Gender</b> (Ref.: <i>Male</i> )			
Female	-0.053+	-0.060+	-0.055+
<b>Age 2010</b>	-0.002	-0.002	-0.002
<b>Race</b> (Ref.: <i>White</i> )			
Asian	0.021	0.026	0.024
Black	0.061	0.072	0.070
Other race	0.093	0.094	0.086
Race: Don't know or missing	-0.055	-0.053	-0.043
<b>Number of employed in household 2010</b>	0.033	0.036	0.032
<b>Number of adults in household 2010</b>	-0.004	-0.005	-0.002
<b>Number of kids in household 2010</b>	-0.016	-0.015	-0.014
<b>Marital Status 2010</b> (Ref.: <i>Single, never married</i> )			
Married or cohabiting	0.039	0.043	0.041
Separated, divorced or widowed	0.044	0.044	0.045
<b>Net monthly income in household 2010</b>	0.000+	0.000	0.000+

<b>Urban/rural area 2011</b> ( <i>Ref.: Urban area</i> )			
Rural area	-0.001	0.006	0.010
<b>Region 2011</b> ( <i>Ref.: North East</i> )			
North West	-0.014	-0.009	-0.016
Yorkshire and the Humber	-0.027	-0.021	-0.028
East Midlands	-0.028	-0.018	-0.031
West Midlands	0.009	0.010	0.001
East of England	0.032	0.050	0.043
London	-0.067	-0.054	-0.064
South East	0.056	0.072	0.065
South West	-0.070	-0.059	-0.066
<b>Duration at residence 2011</b> ( <i>Ref.: up to 3 years</i> )			
4-7 years	-0.059	-0.056	-0.053
8-14 years	-0.067	-0.065	-0.074+
15 years or more	-0.096*	-0.099*	-0.101*
missing	0.068	0.070	0.050
<b>Total number of close friends 2011 (centred)</b>	0.009*	0.009*	0.009*
<b>Number of Observations</b>	1,034	1,034	1,034

\*\*\* p<0.001, \*\* p<0.01, \* p<0.05, + p<0.1

Table 3. Average Marginal Effects for exiting unemployment across the categories of ‘proportion friends in neighborhood’

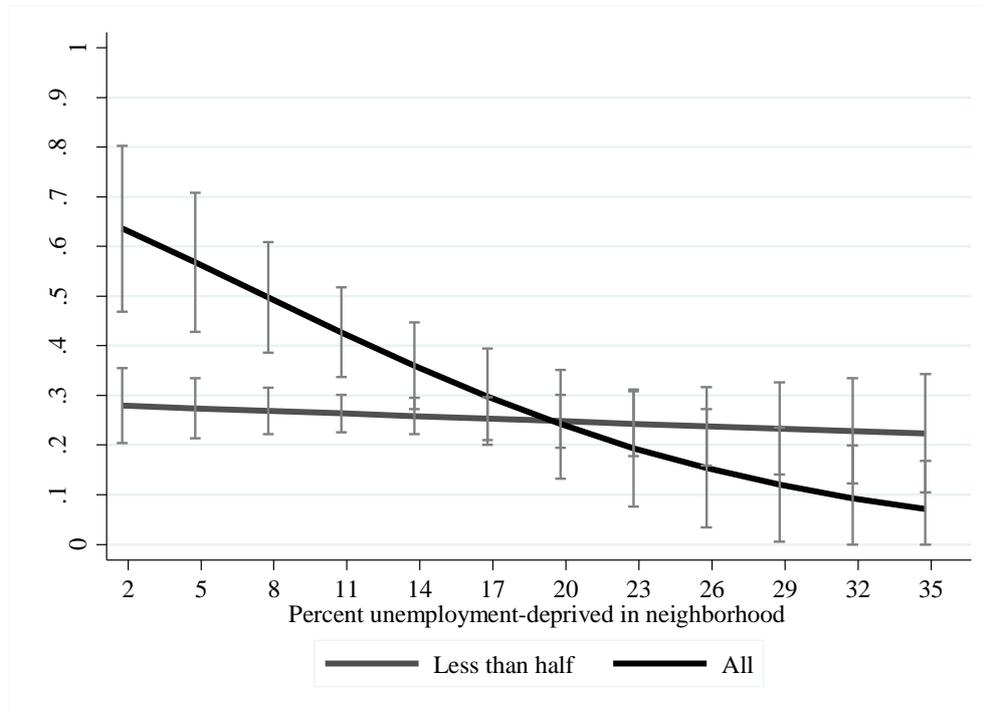
Proportion of friends in neighborhood	AME of percentage employment-deprived in neighborhood	AME contrast scores (relative to ref. category)
Less than half	-0.002	-
More than half	-0.010+	-0.008
All	-0.016**	-0.014*

\*\*\* p<0.001, \*\* p<0.01, \* p<0.05, + p<0.1

Figure 1 shows the predicted probabilities for exiting unemployment by percent employment-deprived individuals in the neighborhood and proportion of friends in the neighborhood. Neighborhood employment-deprivation much more strongly reduces the probability of unemployment exit for people with all their friends in the neighborhood than for the other two groups (Figure 1). For individuals with half or less of their friends in the neighborhood, neighborhood deprivation does not change the probability to exit unemployment. Residents of neighborhoods with low employment-deprivation have a higher probability to exit unemployment if they have all their friends in the neighborhood. In contrast, residents of employment-deprived neighborhoods with strong locally concentrated social networks in these neighborhoods have a lower chance to exit unemployment compared to residents of these neighborhoods with less locally

concentrated social networks.

Figure 1. Predicted Probabilities for exiting unemployment between wave 2011 and wave 2012 by neighborhood deprivation and proportion of friends in the neighbourhood (less than half, versus all)<sup>7</sup>



### ***Discussion***

We brought together the literatures on social networks and neighborhood disadvantage to address two research questions: 1) does neighborhood deprivation lower the probability to exit unemployment? 2) does a local concentration of friends in the neighborhood moderate the effect of neighborhood deprivation on the probability to exit unemployment?

Findings based on the UK Household Longitudinal Study substantiate previous research that neighborhood deprivation is associated with prolonged unemployment. In addition to what was possible in previous research, our findings based on population-wide longitudinal data suggest that neighborhood-level employment-deprivation reduces the probability of finding a job only for individuals who have no friends outside of the neighborhood (controlling for total number of friends). Living in an advantaged neighborhood and having all of one's friends locally speeds up re-employment, whereas living in a deprived neighborhood and having all of one's friends in that deprived neighborhood delays re-employment. By contrast, we find no evidence that neighborhood-level employment-deprivation is associated with re-employment for individuals who have at least some friends outside their own neighborhood.

Our study thereby highlights the moderating role of networks that is in line with both the resource-sharing and norm-setting function of social interaction in neighborhoods. Indeed, the

mechanisms of resource-sharing and norm-setting crucially depend on social interaction in the neighbourhood. If residents don't interact within their immediate surroundings but have social ties that spread outside of the neighbourhood, they are less exposed to the resources and norms shared in the neighbourhood.

Our findings add locational specificity to the more general sociological argument that bridging, or horizon-expanding ties outside of the immediate network of a respondent are particularly valuable for socio-economic attainment (Morgan and Sorensen, 1999): bridging ties might not be a necessary condition but rather a proxy for resource-access in deprived environments; indeed if an individual is located in a resource-rich environment, locally dense networks are potentially more helpful.

Our findings point to social interaction as an important mechanism in explaining why neighborhood deprivation affects employment chances. Indeed, the unemployed with less than half of their friends in the neighborhood, experience no effect of neighborhood disadvantage on their employment uptake even though they are equally distant to jobs (spatial mismatch), with an equally stigmatizing postcode (neighborhood discrimination) and the same access to local institutional resources. One challenge for further research is to explore how neighborhood mechanisms may interact with each other.

Our results hint at two possible policy directions. Firstly, the beneficial effects of local friends are found in mixed and advantaged neighborhoods, so any policies aiming at neighborhood de-segregation and social mixing might provide employment benefits for the residents. Furthermore, for the most deprived neighborhoods, initiatives that help less locally concentrated networks to develop (e.g. sport teams or other interest groups with membership across neighborhoods).

The findings of our study need to be interpreted in the context of several limitations.

Despite the longitudinal design and the unusually rich information available in Understanding society we cannot rule out that our findings are biased by unobserved heterogeneity due to unaccounted selection into neighborhoods. Unemployed people located in deprived neighborhoods may be different from the unemployed in affluent neighborhoods on unobserved characteristics (e.g. personality traits) that make them interact less successfully with – and benefit less from – their local friends. Placed in affluent neighborhoods, these same individuals would similarly interact less successfully with local friends and hence not experience positive employment effects from having a high proportion of friends in an affluent neighborhood. In addition, future research should examine whether the reinforcing impact of social interactions on neighborhood advantage and disadvantage extends to individuals who are not unemployed and spend less time in their neighborhood. Importantly, the relative importance of resource-sharing and norm-setting in the moderating effect of network location for neighborhood disadvantage should be further disentangled in future research.

To inform the theoretical mechanisms at work behind the moderating effect of a local concentration of friends for neighborhood disadvantage, future research requires more information on employment outcomes and social networks in conjunction with detailed neighborhood characteristics. Our study goes beyond previous research with the localized measure of friendship networks, but the central network indicator remains rather crude. Future studies

should include information on the types of ties, strong or weak (Granovetter, 1973), the overall network structure, that is how friends are connected to each other and create closed or open social structures (Coleman, 1988, Morgan and Sorensen, 1999, Burt, 2001), as well as the specific resources and exchange relationships of network members. Furthermore, re-employment remains a crude outcome and information on type of employment, wage, occupational status upon re-employment could deepen our insight in the role of neighborhoods and networks.

Our analysis concentrates on a specific historical period, 2010-2012 in which unemployment was high following the 2008 recession. Findings could be similar in other liberal restrictive welfare states, for example the United States, with relatively strong residential segregation in times of high unemployment following economic recessions. Future research should investigate to what extent these relationships hold in times of lower unemployment in the United Kingdom, and expand comparisons with other structural and policy contexts. The extent and duration of unemployment assistance, active labor market policies and overall levels of residential segregation likely affect the strength of the associations. Arguably, a local concentration of friends in disadvantaged neighborhoods will have weaker effects on re-employment in more egalitarian contexts with more extensive state policies to compensate for unemployment and activate re-employment.

To conclude, beyond what was possible in previous studies, the detailed measurement of network location via the proportion of friends in the neighborhood combined with the specific dimension of employment-deprivation in neighborhoods enabled us to contribute to the literature in two ways. First, previous studies have theoretically argued that locally concentrated social ties act as multipliers of the beneficial effects of resourceful environments and the detrimental effects of disadvantaged environments on socio-economic outcomes. This has been empirically shown for parental networks in school environments for educational outcomes (Fasang et al., 2014). Our study shows that a similar moderating and multiplying effect of locally concentrated social ties also exists in the context of neighborhood disadvantage and unemployment. Secondly, our findings underline an important role of locally concentrated social ties in explaining the mechanisms through which neighborhood disadvantage affects individuals' life chances. It is not simply where individuals reside, but where they live, that is where they spend time and with whom they interact, that matters for the impact of neighborhood characteristics on socio-economic outcomes. It therefore is promising to theorize neighborhood effects as social rather than geographic phenomena.

## ***Endnotes***

<sup>1</sup> Social connections are often loosely conceptualized as social capital referring to both individual-level social ties and macro-level norms of reciprocity and trust that are generally assumed to benefit individuals and societies at large (Coleman, 1986, Granovetter, 1973, Putnam, 1995).

. Note that the 2010 English Index of Multiple Deprivation is based on 2001 geographical boundaries, while our individual data uses 2011 boundaries, which may lead to small discrepancies. About 2% of the MSOA-boundaries have been adjusted between 2001 and 2011, usually because of population size changes (ONS, 2012).<sup>3</sup> This variable was top-coded at 15 close friends

<sup>4</sup> Note that our research question on the interaction between network location and neighbourhood disadvantage does not lend itself to an instrumental variable or fixed effects approach: we lack a convincing instrument, have a complex interacted “treatment” variable, and a limited number of observation periods. Event history analysis is also not viable, as it would further reduce case numbers to individuals for whom we can observe the exact duration of unemployment. We therefore adopt a carefully temporally ordered design to control for pre-treatment confounders and estimate the interacted effect of networks and neighborhoods on the probability to exit unemployment.

<sup>5</sup> Odds ratios showed the same level of significance as AME in our analysis, the table is available in the supplementary material.

<sup>6</sup> In order to be able to assess the interaction effect, the average marginal effects for the neighbourhood deprivation index have been calculated across the categories of the proportion of friends variable. We report the AME contrast scores compared to the reference category of ‘half or less of my friends reside in the neighborhood’ along with the significance of the associated Chi<sup>2</sup> test (Mize, 2019). The AME’s of the control variables refer to average effects.

<sup>7</sup> The STATA-package uses the Delta-method for estimating confidence intervals (Long and Freese, 2006), which resulted in a few slightly negative confidence intervals at percentages of unemployment-deprived over 28. We fixed the lower bound of these confidence intervals at 0.

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## References

- BRATTBAKK, I. & WESSEL, T. 2013. Long-term Neighbourhood Effects on Education, Income and Employment among Adolescents in Oslo. *Urban Studies*, 50, 391-406.
- BUCK, N. 2001. Identifying neighbourhood effects on social exclusion. *Urban Studies*, 38, 2251-2275.
- BUNEL, M., L'HORTY, Y. & PETIT, P. 2016. Discrimination based on place of residence and access to employment. *Urban Studies*, 53, 267-286.
- BURT, R. S. 2001. Structural holes versus network closure as social capital. In: LIN, N., COOK, K. S. & BURT, R. S. (eds.) *Social Capital: Theory and Research*. Aldine de Gruyter.
- BURT, R. S. 2004. Structural holes and good ideas. *American Journal of Sociology*, 110, 349-399.
- CINGANO, F. & ROSOLIA, A. 2012. People I Know: Job Search and Social Networks. *Journal of Labor Economics*, 30, 291-332.
- COLEMAN, J. S. 1986. Social theory, social research, and a theory of action. *American journal of Sociology*, 91, 1309-1335.
- COLEMAN, J. S. 1988. Social capital in the creation of human capital. *American journal of sociology*, 94, 95-120.
- CUTLER, D. M. & GLAESER, E. L. 1997. Are ghettos good or bad? *Quarterly Journal of Economics*, 112, 827-872.
- DAWKINS, C. J., SHEN, Q. & SANCHEZ, T. W. 2005. Race, space, and unemployment duration. *Journal of Urban Economics*, 58, 91-113.
- DESMOND, M. & AN, W. 2015. Neighborhood and Network Disadvantage among Urban Renters. *Sociological Science*, 2, 329 - 349.
- ELLIOTT, J. R. 1999. Social isolation and labor market insulation: Network and neighborhood effects on less-educated urban workers. *Sociological Quarterly*, 40, 199-216.
- ERBRING, L. & YOUNG, A. A. 1979. Individuals and Social Structure. Contextual Effects as Endogenous Feedback. *Sociological Methods & Research*, 7, 396-430.
- FASANG, A. E., MANGINO, W. & BRÜCKNER, H. 2014. Social Closure and Educational Attainment. *Sociological Forum*, 29, 137-164.
- FERNANDEZ, R. M. & SU, C. 2004. Space in the study of labor markets. *Annual Review of Sociology*, 30, 545-569.
- GALSTER, G., ANDERSSON, R. & MUSTERD, S. 2010. Who is affected by neighbourhood income mix? Gender, age, family, employment and income differences. *Urban Studies*, 47, 2915-2944.
- GALSTER, G. C. 2012. The mechanism(s) of Neighbourhood Effects: Theory, Evidence, and Policy Implications. In: VAN HAM, M., MANLEY, D., BAILEY, N., SIMPSON, L., & MACLENNAN, D. (ed.) *Neighbourhood Effects Research: New Perspectives*. Springer Science+Business Media B.V.
- GALSTER, G. C. & KILLEN, S. P. 1995. The geography of metropolitan opportunity: A reconnaissance and conceptual framework. *Housing Policy Debate*, 6, 7-43.
- GINTHER, D., HAVEMAN, R. & WOLFE, B. 2000. Neighborhood attributes as determinants of children's outcomes: how robust are the relationships? *Journal of Human Resources*, 603-642.

- GRANOVETTER, M. 1973. The Strength of Weak Ties. *American Journal of Sociology*, 78, 1360-1380.
- GRANOVETTER, M. 1995. *Getting a Job: A Study of Contacts and Careers*, University of Chicago Press.
- GREGG, P. & WADSWORTH, J. 2010. Employment in the 2008–2009 recession. *Economic & Labour Market Review*, 4, 37-43.
- HOUSTON, D. 2005. Employability, skills mismatch and spatial mismatch in metropolitan labour markets. *Urban Studies*, 42, 221-243.
- IHLANFELDT, K. R. & SJOQUIST, D. L. 1998. The spatial mismatch hypothesis: a review of recent studies and their implications for welfare reform. *Housing policy debate*, 9, 849-892.
- JENCKS, C. & MAYER, S. E. 1989. Growing Up in Poor Neighborhoods: How Much Does It Matter? *Science*, 243, 1441-1445.
- JENCKS, C. & MAYER, S. E. 1990. *The social consequences of growing up in a poor neighborhood, Inner-city poverty in the United States*.
- KAIN, J. F. 1968. Housing Segregation, Negro Employment, and Metropolitan Decentralization. *The Quarterly Journal of Economics*, 82, 175-197.
- KLEIT, R. G. 2002. Job search networks and strategies in scattered-site public housing. *Housing Studies*, 17, 83-100.
- LIN, N. 1999. Social Networks and Status Attainment. *Annual Review of Sociology*, 25, 467-487.
- LONG, S. J. & FREESE, J. 2006. *Regression Models for Categorical Dependent Variables Using Stata, Second Edition*, Taylor & Francis.
- LYNN, P. & BORKOWSKA, M. 2018. Some Indicators of Sample Representativeness and Attrition Bias for BHPS and Understanding Society. Understanding Society at the Institute for social and economic research.
- MCLENNAN, D., BARNES, H., NOBLE, M., DAVIES, J., GARRATT, E. & DIBBEN, C. 2011. *The English Indices of Deprivation 2010*. London: Department of Communities and Local Government.
- MILTENBURG, E. M. 2015. The Conditionality of Neighbourhood Effects upon Social Neighbourhood Embeddedness: A Critical Examination of the Resources and Socialisation Mechanisms. *Housing Studies*, 30, 272-294.
- MILTENBURG, E. M. & VAN DE WERFHORST, H. G. 2017. Finding a Job: The Role of the Neighbourhood for Different Household Configurations over the Life Course. *European Sociological Review*, 33, 30-45.
- MIZE, T. D. 2019. Best practices for estimating, interpreting, and presenting nonlinear interaction effects. *Sociological Science*, 6, 81-117.
- MOFFITT, R. 1983. An economic model of welfare stigma. *The American Economic Review*, 73, 1023-1035.
- MOOD, C. 2010. Logistic Regression: Why We Cannot Do What We Think We Can Do, and What We Can Do About It. *European Sociological Review*, 26.
- MORGAN, S. L. & SORENSEN, A. B. 1999. Parental networks, social closure, and mathematics learning: A test of Coleman's social capital explanation of school effects. *American Sociological Review*, 64, 661-681.

- MOUW, T. 2000. Job relocation and the racial gap in unemployment in Detroit and Chicago, 1980 to 1990. *American Sociological Review*, 65, 730-753.
- MOUW, T. 2002. Are black workers missing the connection? The effect of spatial distance and employee referrals on interfirm racial segregation. *Demography*, 39, 507-528.
- MUSTERD, S., OSTENDORF, W. & DE VOS, S. 2003. Neighbourhood effects and social mobility: A longitudinal analysis. *Housing Studies*, 18, 877-892.
- OESCH, D. & VON OW, A. 2017. Social Networks and Job Access for the Unemployed: Work Ties for the Upper-Middle Class, Communal Ties for the Working Class. *European Sociological Review*, 33, 275-291.
- ONS 2012. 2011 Census: Population and Household Estimates for Small Areas in England and Wales, March 2011. Office for National Statistics.
- ONS 2018. Beginner's guide to UK geography. Office for National Statistics.
- OREGAN, K. M. & QUIGLEY, J. M. 1996. Teenage employment and the spatial isolation of minority and poverty households. *Journal of Human Resources*, 31, 692-702.
- PAPACHRISTOS, A. V., HUREAU, D. M. & BRAGA, A. A. 2013. The Corner and the Crew: The Influence of Geography and Social Networks on Gang Violence. *American Sociological Review*, 78, 417-447.
- PORTES, A. 1998. Social Capital: Its origins and applications in modern sociology. *Annual Review of Sociology*, 24, 1-24.
- PORTES, A. 2014. Downsides of social capital. *Proceedings of the National Academy of Sciences*, 111, 18407-18408.
- PUTNAM, R. 1995. Bowling Alone: America's Declining Social Capital. *Journal of Democracy*, 6, 65-78.
- SAMPSON, R. J. 2008. Moving to inequality: Neighborhood effects and experiments meet social structure. *American journal of sociology*, 114, 189-231.
- SAMPSON, R. J., MORENOFF, J. D. & GANNON-ROWLEY, T. 2002. Assessing "neighborhood effects": Social processes and new directions in research. *Annual Review of Sociology*, 28, 443-478.
- SHARKEY, P. & FABER, J. W. 2014. Where, When, Why, and For Whom Do Residential Contexts Matter? Moving Away from the Dichotomous Understanding of Neighborhood Effects. *Annual Review of Sociology, Vol 40*, 40, 559-579.
- TIGGES, L. M., BROWNE, I. & GREEN, G. P. 1998. Social isolation of the urban poor: Race, class, and neighborhood effects on social resources. *Sociological Quarterly*, 39, 53-77.
- TOPA, G. & ZENOU, Y. 2015. Neighborhood and Network Effects. *Handbook of Regional and Urban Economics: Elsevier B. V.*
- TUNSTALL, R., GREEN, A., LUPTON, R., WATMOUGH, S. & BATES, K. 2014. Does Poor Neighbourhood Reputation Create a Neighbourhood Effect on Employment? The Results of a Field Experiment in the UK. *Urban Studies*, 51, 763-780.
- WEINBERG, B. A., REAGAN, P. B. & YANKOW, J. J. 2004. Do neighborhoods affect hours worked? Evidence from longitudinal data. *Journal of Labor Economics*, 22, 891-924.
- WILSON, W. J. 1987. *The truly disadvantaged*, Chicago, The University of Chicago Press.
- WILSON, W. J. 1996. *When Work Disappears: The World of the New Urban Poor*, New York.

- WODTKE, G. T., ELWERT, F. & HARDING, D. J. 2016. Neighborhood Effect Heterogeneity by Family Income and Developmental Period. *American Journal of Sociology*, 121, 1168-1222.
- WODTKE, G. T., HARDING, D. J. & ELWERT, F. 2011. Neighborhood Effects in Temporal Perspective: The Impact of Long-Term Exposure to Concentrated Disadvantage on High School Graduation. *American Sociological Review*, 76, 713-736.
- ZENOU, Y. 2002. How do firms redline workers? *Journal of Urban Economics*, 52, 391-408.

**Supplementary Materials**

Table S.1: Study design: Temporal sequencing

<u>Wave 2010</u>	<u>Wave 2011</u> <u>Unemployed</u>	<u>Wave 2012</u>
Employment status Age Gender Education Race Marital status Household income Number of people employed in household Number of adults in household Number of kids	Neighborhood deprivation % friends in area Number of close friends Region Urban vs rural area Duration of residence at current home	Return to paid employment versus remaining unemployed

Table S2. Median and mean number of close friends by proportion of friends in neighborhood

Proportion friends in neighborhood	Median	Mean
	number close friends	number close friends
Half or less	3	4.55
More than half	3	4.88
All	3	3.86

Table S.3. Distribution of friends in area by neighbourhood deprivation (N cell size, row percentage)

<i>Neighborhood deprivation</i>	<i>Proportion of friends in neighborhood</i>			Total
	Half or less	More than half	All	
Least deprived tertile	100 64.10 %	37 23.72%	19 12.18%	156 100.00
Mid deprived tertile	168 59.36%	72 25.44%	43 15.19%	283 100.00
Most deprived tertile	370 62.18%	125 21.01%	100 16.81%	595 100.00
Total	638 61.70	234 22.63	162 15.67	1,034 100.00

Table S.4. Distribution of friends in area by employment deprivation (N cell size)

<i>Proportion of friends in neighborhood</i>	<b>Outcome Unemployed</b>			<b>Outcome Employed</b>		
	Least deprived tertile	Mid deprived tertile	Most deprived tertile	Least deprived tertile	Mid deprived tertile	Most deprived tertile
Half or less	59	103	275	41	65	95
More than half	16	50	103	21	22	22
All	10	27	77	9	16	23

Table S.5. Odds Ratios for exiting unemployment between wave 2011 and wave 2012.

	<b>M1</b>	<b>M2</b>	<b>M3</b>
<b>Percent employment-deprived in neighbourhood 2011</b>	0.965*	0.966*	0.991
	(0.936 - 0.996)	(0.936 - 0.997)	(0.956 - 1.027)
<b>Proportion of friends in neighborhood 2011 (Ref.: Half or less)</b>			
More than half		0.981	1.774
		(0.638 - 1.508)	(0.700 - 4.494)
All friends		1.777*	5.233**
		(1.086 - 2.907)	(1.751 - 15.640)
<b>Interaction</b>			
More than half of friends X Percent unemployment-deprived in neighbourhood			0.950 (0.875 - 1.031)
All friends X Percent unemployment deprived in neighbourhood			0.918* (0.848 - 0.994)
<b>Total number of close friends 2011 (centered)</b>	1.052* (1.003 - 1.104)	1.052* (1.004 - 1.103)	1.052* (1.004 - 1.102)
<b>Employment status 2010 (Ref.: In paid employment)</b>			
Unemployed	0.349*** (0.210 - 0.580)	0.350*** (0.209 - 0.585)	0.348*** (0.207 - 0.586)
Inactive	0.399*** (0.237 - 0.673)	0.412*** (0.244 - 0.695)	0.400*** (0.237 - 0.675)
<b>Education (Ref.: No qualification)</b>			
University Degree	2.986** (1.453 - 6.133)	3.471*** (1.671 - 7.208)	3.422** (1.624 - 7.210)
Other higher qualification	1.777 (0.840 - 3.763)	1.989+ (0.932 - 4.244)	1.966+ (0.909 - 4.253)
A level & equivalent	2.724** (1.398 - 5.306)	2.915** (1.491 - 5.701)	2.896** (1.457 - 5.754)
GCSE & equivalent	2.101* (1.107 - 3.987)	2.218* (1.162 - 4.233)	2.212* (1.137 - 4.302)
Other qualification	1.383 (0.673 - 2.840)	1.460 (0.706 - 3.018)	1.461 (0.695 - 3.071)
<b>Gender (Ref.: Male)</b>			
Female	0.740 (0.517 - 1.060)	0.707+ (0.493 - 1.014)	0.724+ (0.504 - 1.040)
<b>Age</b>	0.988 (0.968 - 1.008)	0.989 (0.968 - 1.009)	0.990 (0.970 - 1.010)
<b>Race (Ref.: White)</b>			
Asian	1.129 (0.626 - 2.035)	1.162 (0.647 - 2.089)	1.145 (0.634 - 2.071)

Black	1.396	1.484	1.472
	(0.726 - 2.685)	(0.770 - 2.859)	(0.768 - 2.822)
Other race	1.649	1.666	1.609
	(0.849 - 3.204)	(0.853 - 3.254)	(0.821 - 3.151)
Race: Don't know or missing	0.717	0.722	0.772
	(0.303 - 1.696)	(0.309 - 1.685)	(0.333 - 1.785)
<b>Number of employed in household 2010</b>	1.206	1.233	1.206
	(0.925 - 1.572)	(0.943 - 1.614)	(0.922 - 1.577)
<b>Number of adults in household 2010</b>	0.976	0.969	0.989
	(0.795 - 1.198)	(0.788 - 1.192)	(0.804 - 1.218)
<b>Number of kids in household 2010</b>	0.915	0.915	0.922
	(0.779 - 1.076)	(0.777 - 1.077)	(0.783 - 1.087)
<b>Marital Status 2010</b> ( <i>Ref.: Single, never married</i> )			
Married or cohabiting	1.248	1.280	1.263
	(0.776 - 2.006)	(0.789 - 2.077)	(0.783 - 2.039)
Separated, divorced or widowed	1.284	1.283	1.296
	(0.655 - 2.517)	(0.655 - 2.512)	(0.661 - 2.541)
<b>Net monthly income in household 2010</b>	1.000+	1.000	1.000+
	(1.000 - 1.000)	(1.000 - 1.000)	(1.000 - 1.000)
<b>Urban/rural area 2011</b> ( <i>Ref.: Urban area</i> )			
Rural area	0.996	1.033	1.059
	(0.583 - 1.701)	(0.602 - 1.773)	(0.622 - 1.803)
<b>Region 2011</b> ( <i>Ref.: North East</i> )			
North West	0.924	0.948	0.916
	(0.387 - 2.207)	(0.388 - 2.315)	(0.379 - 2.212)
Yorkshire and the Humber	0.858	0.889	0.852
	(0.358 - 2.057)	(0.364 - 2.173)	(0.348 - 2.085)
East Midlands	0.856	0.905	0.837
	(0.336 - 2.181)	(0.345 - 2.370)	(0.321 - 2.182)
West Midlands	1.052	1.060	1.007
	(0.420 - 2.640)	(0.416 - 2.701)	(0.392 - 2.586)
East of England	1.190	1.311	1.263
	(0.472 - 3.004)	(0.506 - 3.397)	(0.490 - 3.254)
London	0.678	0.724	0.685
	(0.268 - 1.710)	(0.280 - 1.875)	(0.267 - 1.761)
South East	1.346	1.473	1.416
	(0.553 - 3.277)	(0.587 - 3.695)	(0.569 - 3.527)
South West	0.662	0.703	0.676
	(0.254 - 1.722)	(0.266 - 1.857)	(0.257 - 1.779)
<b>Duration at residence 2011</b>			

<i>(Ref.: up to 3 years)</i>			
4-7 years	0.721 (0.442 - 1.177)	0.730 (0.443 - 1.202)	0.744 (0.453 - 1.223)
8-14 years	0.687 (0.421 - 1.121)	0.691 (0.423 - 1.127)	0.657+ (0.400 - 1.079)
15 years or more	0.575* (0.347 - 0.951)	0.560* (0.338 - 0.927)	0.552* (0.333 - 0.914)
missing	1.421 (0.529 - 3.820)	1.438 (0.541 - 3.821)	1.298 (0.481 - 3.503)
<b>Constant</b>	1.065 (0.255 - 4.448)	0.822 (0.186 - 3.633)	0.592 (0.131 - 2.672)
Observations	1,034	1,034	1,034

Robust confidence intervals in parentheses

\*\*\* p<0.001, \*\* p<0.01, \* p<0.05, + p<0.1