Migrants and Social Networks: Old Ideas, Lasting Myths and New Findings*

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Abstract: This paper considers social network effects for migrants on labour market outcomes. Much of the empirical literature has to rely on very indirect evidence since the typical investigator observes neither the social network, nor whether the labour market outcome was a consequence of actual network use. By contrast, our analysis is based on a large scale UK data set in which individuals report social network use as a job search method, and whether the job match was the result of social network use. We examine social network effects for immigrants in the UK and highlight the role played by confounding factors namely local labour market characteristics.
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1 Introduction

Decentralised labour markets are full of search frictions. Currently unemployed individuals search for jobs, employed individuals search for better jobs, and firms with vacancies search for employees. Social networks, spanned by relatives, friends and acquaintances are important informal channels through which information about job opportunities are transmitted.[1] It is well known that such networks are particularly important to immigrants, since they often lack country specific skills such as language or knowledge of institutions, and as new arrivals are newcomers to the local labour market.[2]

While network theory is well-developed, empirical investigations are often hampered by the lack of suitable data. The principal challenge for the empirical analyses of network effects is the fact that neither the network, nor the actual use of the network, nor the causal connection of the outcome to network use are commonly observed. The common approach is then to assume that (A.i) a specific individual is part of a postulated network; in the migrant context it is typically assumed that networks are defined by ethnicity or country or region of origin,[3] (A.ii) that this individual will actually make use of this network, i.e. be an active network user, and (A.iii) that the achieved labour market outcome is directly linked to the use of the network. The typical mode of analysis is then to regress labour market outcomes on measures of characteristics of the assumed network, which are in turn proxied by geographic attributes. More generally, social space is proxied by geographical space. Recent examples of this approach are Munshi (2003), Patacchini and Zenou (2004), and Dustmann et al (2010).

In contrast to this, our empirical analysis is based on a data set in which unemployed respondents report on whether they use social networks to search for jobs, and recently employed respondents are asked whether obtaining this job was the result of having used the social network. Below we use as a convenient shorthand the event indicator SN for the former, and REF for the latter. Hence we do not have to invoke assumptions (A.ii) and (A.iii). At the same time examining the events $\{SN = 1\}$ and $\{REF = 1\}$ enables us to examine the validity of such assumptions, at least in the country-specific UK context. Moreover, following common practice and making assumption (Ai), i.e. the social networks of migrants are exclusively defined by ethnicity, and relating the events $\{SN = 1\}$ and $\{REF = 1\}$ to standard measures of the characteristic of the assumed network, we can investigate the extent to which conventional

[1] Indeed Granovetter (1995) and Ioannides and Datcher Loury (2004) report that between 30% and 60% of jobs in the US are found through social networks.

[2] It is also well known that network membership positively influences the migration decision, and that, typically, migrants prefer to settle in localities in the host country in which members of their network already reside.

[3] For instance, Munshi(2003) considers the case of Mexican migration to the US. Finding that migrants from the same region of origin cluster in distinct destinations justifies assumption (i). However, due to lack of data, other investigations work at far larger levels of aggregation and have to make assumption (i). For instance, Patacchini & Zenou (2004) and Dustmann et al. (2010) assume that networks are exclusively ethnicity based, i.e. all members of the same ethnic group are members of the same network.

measures of social networks are good proxies for their use. At the same time we are able to confirm empirically some observations that have been made in the theoretical literature.

To be more specific, we use the UK Special Licence Quarterly Labour Force Survey (SLQLFS) in which individuals are observed at a high level of geographic disaggregation, namely the Local Authority (LAD) level. This enables us to control for many local labour market characteristics, enriched by Census data, which potentially confound analyses of network effects at higher level of geographic aggregation. The sampling design is such that migrants are well represented. We distinguish between several groups of non-white foreign born individuals, namely Indians, Pakistanis, Bangladeshis, Black Caribbeans and Black Africans. These are the principal ethnic minority migrant groups which are the usual focus of policy concerns in the UK. It is well known that ethnic minority groups have a tendency to cluster geographically in urban enclaves (but also that the extent of this, while substantial, is smaller than in the US).

The outline of the paper is as follows. After considering some of the related literature next, in Section 2 we consider evidence from 2001 Census. Based on this census, for each ethnic group g, we select the top 15 LADs in terms of populations. This defines the spatial units used in the subsequent SLQLFS-based analysis. We provide evidence of clustering, segregation, as well some characterisations of the LADs. As a preliminary descriptive analysis, and to establish benchmarks for the subsequent investigation, we examine regressions of labour market outcomes on network characteristics, such as relative size, commonly encountered in the empirical literature. Moreover, we reveal the importance of controlling for locality-level characteristics, as well as for the endogeneity of network size. In Section 3 we present the survey data the principal part of our analysis is based on. In particular, we consider the effects of social networks on labour market outcomes in Section 4. Our basic decomposition relating outcomes and network characteristics makes clear the importance to consider the constituent parts; hence, the analysis of outcomes is conditioned on social network use and employment. Section 5 examines the effects of network use on wages. We summarise our conclusions in section 6.

1.1 The Related Literature

The theoretical literature on social network, as surveyed in e.g. Jackson (forthcoming), has identified two main channels through which informal networks can affect labour market outcomes of network members. The network can transmit information about job opportunities to its unemployed members, and informational asymmetries about job applicants' quality are reduced when employed network members make referrals and recommend fellow network members to their employers. The two channels have in common that the size and the quality of the network[4] should matter for labour market outcomes, and we consider

[4]Whilst the theoretical literature has explicitly considered the quality issue (e.g. Calvo-Armengol and Jackson (2004, 2007)), this has largely been neglected in the empirical literature. An exception is Wahba and Zenou (2005).

both in our empirical investigation. For instance, Montgomery (1991) assumes assortative matching and shows that individuals who possess social ties to those in high-paying jobs obtain better matches and thus higher wages than less well connected job seekers. Focussing instead on lower ability workers, the same mechanism is used in Datcher Loury (2006) to show that only workers who do not obtain better job offers through formal channels use social networks as a last resort to find better jobs, and hence network users obtain lower wages.

In our empirical investigation we are agnostic about the precise channels which link labour market outcomes of network users and network characteristics. Most empirical investigations have to take a stand on this, and focus on one channel in opposition to others, since network use is usually not observed in their data nor whether a job was in fact obtained through the network. We do not have to disentangle such linkages from the myriad of possible confounding effects which plague the empirical literature since these two key pieces of information are reported in our survey.

One of the principal challenges for empirical analyses is the fact the network is never observed. The empirical literature has therefore focused on population subgroups which are well known to be cohesive and clustered geographically, i.e. ethnic minorities and immigrants. Hence group membership is equated with active network membership. For instance, Munshi (2003) considers network effects for Mexican migrants to the US, Falcon and Melendez (1996) consider Latinos and Blacks in the US, Battu et al consider ethnic minorities in the UK. We consider network effects of migrants as well.

The existing body of empirical evidence about network effects on labour market outcomes concerns principally the US (e.g. Granovetter (1983, 1995), Holzer (1988), and Ioannides and Datcher Loury (2004)). When specialised to migrant and ethnic minority networks it is also well known that segregation and geographic clustering in the US is substantial. By contrast, the particular geographic focus of our investigation is the UK, which has also been considered in related work. [5] We briefly discuss some relevant aspects of this work and delineate our approach. Frijters et. al. (2005) seek to explain the determination of the principal job search method. Using Roy type models, individuals make a mutually exclusive choice from a set of alternatives, and social network search is one possible choice. Efficiency is judged with reference to the associated unemployment durations. It is questionable whether modelling the choice problem as one between mutually exclusive alternatives is the most appropriate for sets which include social networks, given the social network search is usually considered to be cheap and can be done alongside more formal methods. Similarly, Battu et al. (2005) use a multinomial logit model to explain the choice of the job search method. Both teams of authors compare migrants and natives, and base

[5] Complementary empirical work, not discussed here for reasons of space, is based on the Ethnic Minority Survey. While the level of geographic resolution is the ward, so smaller than LADs, the sample sizes are too small to permit comparisons between distinct immigrant groups. Moreover, social network use for job search and job mathcing are not observed. The literature has thus mainly focused on language proficiency and questions of cultural identity and assimilation.

their investigation on the standard LFS. We consider different labour market outcomes, are not concerned with the optimality of a chosen search method, and use the SLQLFS which allows us to control carefully for potentially confounding locality effects.

Rather than using individual level data, Patacchini and Zenou (2008) aggregate LFS data at the level of LADs, and construct an annual panel for 301 LADs spanning ten years. Unlike our data, they do not observe social network use (SN), nor actual job finding methods (REF), and hence focus on unemployment rates of specific migrant groups in LADs. Proxying social space by geographic space, they consider the distance between LADs, and construct migrant group densities as a function of distance. The estimating equation relates LAD level employment rates to these banded population densities, lagged employment and LAD fixed effects, and the measuring of the network effect is based on assumptions A.i to A.iii discussed above.

In a cross-country comparative analysis, Pellizzari (2010) uses data from the European Community Household Panel and regresses log hourly wages on the indicator REF indicator and individual controls. No attempt is made to control for network characteristics, nor whether social network use could fail in delivering a job. He reports a wage penalty in the case of the UK.

Ethnicity based networks are also considered in Dustmann et a. (2010) in a setting that focuses on job referrals. Assuming that job referrals provide more precise information about the quality of an applicant than unsolicited applications, it is immediate that the larger the share of network members working at a firm, the larger is the hiring from this network (here the ethnic group). Using German social security employee-employer data for four metropolitan areas in 1990-2001, the authors regress at firm level labour market outcomes on employment shares, and firm and individual fixed effects.

2 Evidence from the Census

Our analysis focuses on the five principal immigrant groups in the UK defined in terms of ethnicity, namely Indians (I), Pakistanis (P), Bangladeshis (B), Black Caribbeans (C) and Black Africans (A). Since social networks commonly operate locally, and these migrant groups are well known to cluster spatially, we consider the immigrants in the smallest spatial unit available to us in the UK Special Licence Quarterly Labour Force Survey (SLQLFS), which is the Local Authority (LAD) which represent local government areas in Great Britain.[6] As a shorthand we refer to immigrant i of ethnic group g in locality l.

Locality level characteristics are most accurately captured by the Census to which we turn first. The objectives of this Section are threefold. (i) to define the localities using immigrant population shares in 2001, which will be analysed in the subsequent sections; (ii) to describe the principal characteristics of these

[6]These LADs differ vastly in terms of population density and geographic coverage. For instance, the city of Southampton is one LAD, while London consists of 32 LADs. See the Data Appendix for a more detailed discussion.

localities, which will be merged with our survey data; and (iii) to provide a preliminary analysis of the type usually undertaken in the empirical literature, which relates individual labour market outcomes to measures of network characteristics, such as measures of relative network size. This exercise will also serve as a benchmark for the subsequent analysis, whilst at the same time elucidating the extent to which locality effects can confound network effects.

2.1 Spatial Concentration

For an observer to be able to isolate any systematic effects of locally operating social networks on labour market outcomes, the network needs to be sufficiently dense. We therefore consider, for each of the three immigrant groups g, the top 15 LADs which host the largest immigrant populations in 2001. The Census does not distinguish between foreign born and British born co-ethnics, but the 2% sample of the Census (SAM) does, hence we use the latter to determine the LADs. Table 1 reports the results. Column 1 ranks the LADs by the size immigrant population of group g in SAM2001, which itself is reported in Column 3. Column 4 reports the Census population counts but cannot distinguish between whether the individual is foreign or British born. A comparison between these two columns reveals that the population rankings are very similar. We defer the discussion of the results for the entire SLQLFS and our working sample to the next Section. As all selected LADs turn out to lie in England, we will benchmark each group against English LADs.

The Table confirms that the immigrant groups are spatially highly clustered as for each group g the top 5 LADs contain more than 25%, and the top 15 LADs about 50% of each group's population. Moreover, a comparison of LAD names shows that there is only very limited overlap in the LADs between the different ethnic groups, so the groups tend to segregate spatially. In particular, Blacks are well known to settle predominately in London. All selected LADs are located in London, the midlands, and the north.

Table 2 reports selected characteristics for these LADs,[7] focusing on measures of deprivation, including the government provided deprivation index, the locality level unemployment rate u_l and the group specific unemployment rate $u_{g,l}$ in that locality. It is evident that immigrants from the five ethnic groups live in some of the most deprived LADs (Manchester, Hackney, Tower Hamlets, Newham). Almost all of the LADs exhibit higher than average deprivation, incidence of social housing, and both local and group specific unemployment u_l and $u_{g,l}$. However, there are important difference between the groups. Specifically, Indians experience lower unemployment rates in the localities than other residents, $u_{g=I,l} < u_l$, and often perform better than the LAD average across England of $\mu_{\bar{l}} = 5.46$ (the exception is Sandwell). By contrast, the other ethnic im-

[7] Wages (year 2003) and vacancies (year 2004) are derived from nomsiweb.co.uk. House prices (year 2003) and deprivation index (2004) are from the website http://www.communities.gov.uk. The % of council houses and LAD unemployment rate are derived from the 2001 Census (ONS). The foreign born ethnic unemployment rate is computed using SAM 2001.

migrant groups perform dramatically worse, both locally and nationwide, their unemployment rates $u_{g,l}$ being between two (Kirklees) and five times (Tower Hamlets) the average rate $\mu_{\bar{l}}$.

We follow the literature and assume that networks are ethnicity and locality based. As regards measures of the relative size of the network, several measures have been proposed and we consider three such measures.[8] We define the first exposure measure as the population share of group g in locality l of the total population in l (n_l), and the second as the population share of group g in locality l of the total group g population (n_g),

$$Exp1_{g,l} = \frac{n_{g,l}}{n_l} \text{ , } Exp2_{g,l} = \frac{n_{g,l}}{n_g} \text{ and } Exp3_{g,l} = \frac{Exp1_{g,l}}{n_g/n}\frac{1}{100}. \tag{1}$$

The third measure normalises the first by the share of the ethnic group g in the total population (n).

By construction, $Exp2_{g,l}$ correlates perfectly with the population rank reported in the Table, and by construction $Exp1_{g,l}$ and $Exp3_{g,l}$ are highly correlated. The correlation between $Exp1_{g,l}$ and $Exp2_{g,l}$ across all selected LADs is .56, but the table also shows that whilst there are some LADs in which the three group predominate as a population (e.g. Brent, Newham, Ealing), in other LADs large ethnic subpopulation also coincide with a large white population (e.g. Manchester).

2.2 Employment Outcomes and Network Characteristics

To what extent do network characteristics influence labour market outcomes of network users such as obtaining a job through the network? The principal problem in the empirical literature is the fact that typically neither network use nor the actual job matching method is observed, so researchers usually regress labour market outcomes, such as the employment indicator of immigrant i of group g in locality l, e_{igl}, on individual characteristics (X_i), locality specific characteristics (Z_l), and measures of network characteristics ($N_{g,l}$) such as the exposure measures. I.e. the common practice is to estimate a regression of the type

$$\Pr\left\{e_{igl} = 1 \middle| \left[X_i Z_l N_{gl}\right]\right\}. \tag{2}$$

Alternatively, the regression is often run at the level of the locality. Below we examine in Section 4 what can be learned from such a regression about the importance of social networks.

Here, we simply implement the usual approach using the individual level SAM 2001 in order to establish some benchmarks. Table 4 reports the results of various experiments using the three exposure measures (1) and linear probability models. Column 1 reports the results of a naive OLS in which employment outcomes are regressed on individual characteristics (X_i), in Column 2 we add

[8] For instance, Borjas (2005) and Warman (2005) consider measures 1 and 3, Munshi (2003) and Damm (2009) consider versions of the second measure.

locality level characteristics (Z_l), and Column 3 considers the potentially remaining endogeneity of exposure and uses instrumental variables. In particular, following the reasoning in Card and Lewis (2005), we instrument relative stocks with historical changes in relative stocks[9] (e.g. we instrument $Exp1_{g,l,2001}$ with $Exp1_{g,l,1991} - Exp1_{g,l,1981}$): areas that experienced larger relative changes in the past are areas which are more exposed today, while present shocks are unlikely to be correlated with changes in the past. Across all exposure measures, the results are fairly similar. The naive OLS suggests that exposure has typically a highly significant negative impact on employment outcomes. However, the estimate is confounded by local characteristics, and including our measures Z_l substantially reduces the magnitude of the exposure coefficient. Controlling for the endogeneity of exposure (the instrument being relevant in the first stage) reduces the magnitude of the first and third exposure coefficient. In all experiments the IV estimate is statistically insignificant. Across all experiments the ethnicity dummies are very similar, and stable once Z_l is included. In particular, Black immigrants experience significantly worse employment outcomes.

It is possible that a particular observed network effect is simply due to the selection of particular spatial units. For instance, Orepopolous (2003) finds that neighbourhood quality no longer plays little role in the US once neighbourhoods are not selected. To this end, we have repeated the experiments 1-3 for all LADs. It turns out that the same qualitative and quantitative results obtain. While naive OLS results in a seeming significant effect, this is annihilated in the subsequent refinements. Column 4 of the Table only reports the IV estimate for reasons of space.

Finally, we estimate a "fixed" effect model in Column 5, where we include white migrants and fixed LAD effects. In Column 6, we set the exposure of white migrants to zero and find that our previous results hold.

We conclude that, following the usual interpretation in the literature based on (2), network size, as measured by exposure, is not a determinant of labour market outcomes, at least at the level of LADs once locality characteristics and the endogeneity of the network measure are controlled for. Of course, an important caveat is that network size could be relevant for spatial units that are smaller than LADs.

3 The SLQLFS

The principal part of the analysis in this paper is based on individual level survey data taken from the UK Special Licence Quarterly Labour Force Survey (SLQLFS) for the quarters January-March 2003 to July-September 2009, which, unlike the standard edition of the LFS, contains information at Local Authority (LAD) level.[10] Migrants and ethnic minorities are well captured by this survey

[9]To be precise, the main difference between our and Card and Lewis' implementation is that we use changes to predict stocks, while they use stocks to predict changes.

[10]Earlier micro data at LAD level is not available. Although Patacchini and Zenou (2004) consider the period 1993-2003, they use macro data at the LAD level which have been aggre-

since sampling is stratified. Table 1 compares the pooled SLQLFS sample for our period in the selected 75 LADs to both SAM2001 and the Census in Table 3, but considers only male immigrants aged 16-64 in the labour force. The population shares in the three data sets are in good agreement; some differences are partly attributable to the passage of time, and the stratification of the SLQLFS.

We benchmark the experiments based on SAM 2001 for the restricted LADs with the dataset used in the subsequent analysis, the SLQLFS in Table 4. The by now familiar pattern obtains, the significant naive OLS point estimate being annihilated by the refinements. Moreover, SAM 2001 and SLQLFS yield also quantitatively very similar results.

We turn to our sample selection rules. As we are concerned with labour market outcomes, we follow the literature and consider only males aged between 16 and 64. Focussing on waged employment, we drop the self-employed. In order to isolate network effects and to be able to ignore learning effects, we consider only recent unemployment spells and recent job matches; i.e. the network reports discussed below are only available for individuals with recent transitions. To be precise, unemployed who in the first quarter of their survey were unemployed for more than twelve months are dropped, and a recent transition from unemployment to employment must have happened in the last twelve months.[11] We also exclude individuals with job-to-job transitions from our analysis, since their labour market outcomes and the effects of the network are likely to be substantially different to individuals who seek to transit or have transited from unemployment to employment. In our analysis of employment effects we pool the two groups of recently unemployed and recently employed, since both are subgroups of a population with strong labour market attachments but also have experienced episodes of unemployment; it also turns out that they are fairly similar in terms of observable characteristics. Finally, we exclude persons who have moved within the period covered by the network report since it is not clear whether this report refers to the old or the new network. We control for outliers in the wage data by excluding individuals who report hourly wages below £1 or above £99.

Our analysis is spell-based since wage data are only available in waves 1 and 5, and in order to reduce high frequency noise and measurement error. Although an individual can contribute potentially more than one spell if his labour market status changes frequently during the 5 quarter observation window, this occurrence is fairly small Therefore it is not practical to implement standard panel data modelling.

Note that our data is not representative of migrants in the population, and that the focus on recently unemployed and recent escapees from unemployment means that the majority of the sample is, by design, unemployed. Column 6 of Table 1 compares our sample to the pooled SLQLFS and the census counts. Again, the population shares are well reproduced. Our sample of male immi-

gated by the data providers (ONS).

[11] Until Spring 2005, the reference period of this question for the employed was 3 months or less rather than 12 months or less. Robustness checks excluding observations before this period were conducted.

grants having experienced recently labour market transitions consists thus of 204 Indians, 182 Pakistanis, 151 Bangladeshis, 74 Caribbeans and 154 Africans.

Table 5 reports some summary statistics for our immigrant sample of recent labour market transitions by ethnic group. The foreign born ethnic minorities are similar across many of the reported covariates. One principal difference is in terms of years since migration and thus age, which reflects the difference in the timing of the distinct migration waves to the UK. Bangladeshis perform the worst in terms of education and hourly wage rate. London hosts a large share of immigrants, and specifically the majority of Black immigrants, which emphasises the role of the city as a pole of attraction.

Turning to the indicators of social network use (SN), the survey contains two complementary questions. Unemployed individuals are asked about their main and secondary search methods in the past four weeks, and this question is repeated in each wave if the individual remains unemployed. We therefore define as social network users those individuals who report having 'asked relatives, friends and acquaintances' at least once during their observed unemployment spell. As regards the recently employed individuals, we consider first only those who transited into employment after wave one. Hence they are unemployed in wave one, and we thus observe the report on the job search method. Workers who recently found employment are asked about the main method through which they obtained the current job. We assume that the event of successfully obtaining the job through the social network, i.e. $\{REF = 1\}$, is described by the answer of having 'hearing from someone who worked there'. Finally we also include those individuals who have found a job in wave one through the social network, and postulate naturally that $\{SN = 1\}$ for this group for the preceding unemployment spell. For individuals with $\{REF = 0\}$ we do not know whether they have used social networks during search, so we cannot include them. It turns out that this inclusion does not introduce biases in our multivariate analyses below but increases efficiency. The data Appendix contains more detailed description of alternative job search and actual matching methods.[12]

Table 6 reports, by population subgroup, the incidence of social network use among the recently unemployed and, conditional on social network use, the incidence of obtaining the job through the social network. As regards the recently employed, we consider in Panel B only those individuals who found a job after wave 1, since this gives us an unbiased estimate of the success probability of finding a job through the social network $\Pr\{REF = 1|SN = 1\}$. The sample we use in our multivariate analysis of marginal effects oversamples successful social network users in order to improve estimation efficiency, as we include individuals

[12]For the unemployed, we could consider a more stringent definition of social network use. We define 'intensive' social network users as those individuals who have used social networks as their main job search method. Our main sample thus includes both intensive and extensive users. However, the share of intensive social network users among the unemployed is less than 10% and hence fairly small. The principal reason for not focussing on intensive users throughout is the fact that the REF indicator relates to overall social network use, and does not permit making a distinction between intensive and extensive network use during job search.

who found jobs through their social network in wave 1. The success probability is thus upwardly biased, and reported here in Panel C only for completeness.

These simple bivariate cross-tabulations help to quantify the extent to which some of the common working assumptions made in the empirical literature, such as A.ii and A.iii discussed in the Introduction, are met in the case of the UK. Panel A shows that a large share of non-white unemployed migrants do use social networks to search for jobs, so the incidence of network use is substantial but far from universal. Hence not everyone uses social networks despite the fact that such use is often considered to be fairly cheap. Variation exists between the migrant groups, as Pakistanis report the largest (68%), and Indians the lowest incidence (48%). Panel B considers the sample of migrants who found employment after wave 1. Compared to the sample of unemployed, the incidence of using social networks as a job search method is in fact higher for all groups. However, the most important result of Panel B is the low success rate among social network users in obtaining their job through the social network, which ranges between 37 and 50%. The sample for Panel C contains the oversample of successful social network users, and thus leads to an upward bias of the success rates. Despite this, the success rate only doubles.

Finally, Table 7 considers the individual characteristics of social network users across all ethnic groups, as well as, conditional on having transited into employment, of successful social network users. The table reveals that across the three ethnic immigrant groups Pakistanis and Bangladeshis exhibit a significant above average use of social networks. Moreover, it is less established and lower skilled immigrants who are more likely to use social networks, and to do so successfully.

4 Analysis: The Effects of Social Networks on Employment

We turn to our principal questions of interest, i.e. how important are social networks for labour market outcomes? What can we learn about networks from usual regressions of the type $\Pr\{e_{igl} = 1 | [X_i Z_l N_{gl}]\}$? Denoting social network use by SN_{igl} and job matching through the network by the event $\{REF_{igl} = 1\}$, it is immediate that this probability can be decomposed as follows:

$$\begin{aligned}
\Pr\{e_{igl} = 1 | [X_i Z_l N_{gl}]\} \quad = \quad & \Pr\{(e_{igl} = 1 \text{ and } REF_{igl} = 1) | SN_{igl} = 1, [X_i Z_l N_{gl}]\} \\
& \times \Pr\{SN_{igl} = 1 | [X_i Z_l N_{gl}]\} \\
& + \Pr\{(e_{igl} = 1 \text{ and } REF_{igl} = 0) | SN_{igl} = 1, [X_i Z_l N_{gl}]\} \\
& \times \Pr\{SN_{igl} = 1 | [X_i Z_l N_{gl}]\} \\
& + \Pr\{(e_{igl} = 1 \text{ and } REF_{igl} = 0) | SN_{igl} = 0, [X_i Z_l N_{gl}]\} \\
& \times \Pr\{SN_{igl} = 0 | [X_i Z_l N_{gl}]\} \qquad (3)
\end{aligned}$$

Hence the regression (2) is problematic to truly identify network effects on employment outcome since it is possible that the network effects are confounded by e.g. locality level effects. In particular we have shown already in Table 6 that the likelihood of network failures, either in obtaining a job altogether or despite using social networks matching through other methods, $\Pr\{(e_{igl} = 1 \text{ and } REF_{igl} = 0) \, | SN_{igl} = 1\}$, are substantial, and the Table 4 has revealed the importance of controlling for Z_l.

The decomposition (3) reveals that our principal question of interest is in fact multi-facetted. Our interest here is in how successful is social network use in securing employment; i.e. probability of obtaining employment through social network.

$$\Pr\{REF_{igl} = 1 | e_{igl} = 1, SN_{igl} = 1, [X_{is} Z_l N_{gl}]\}, \tag{4}$$

To estimate the above equation we need to control for network use and employment. Thus, we estimate the above equation using a bivariate sample selection model. In the first stage we correct for two selections: social network use SN and employment e . In the second step, REF is estimated via simple OLS where the correction terms are included as additional regressors. Excluded covariates for the employment equation are Z_l and for social network use is religion.

Table 8 reports the results of the implementations of the above equations. First, considering the relevance of relative network size on employment outcomes (Column 2), as measured by the three exposure measures, as shown across all estimating equations and estimation methods, none of the exposure measures are significant. Secondly, in the case of social network use (Column 3), relative network size is again statistically insignificant. By contrast, measures which relate to socio-economic cohesion and interaction, such as religion exhibit positive explanatory power. Column 4 shows that controlling for selectivity into employment and social network use, network size is not a determinant of transiting into employment using social network. Thus, we don't find evidence that social network characteristics affect the probability of successfully getting a job through social network use.

To sum up, our findings suggest that network size at LAD level doesn't explain employment in the UK for the 5 main ethnic immigrant groups.

5 Analysis: The Effects of Social Networks on Wages

In this section, we focus on a different labour market outcome namely wages. Here since we know who has used social networks to get a job we do not need to make any assumptions about network use. We assume that the better the network, the more likely network members would use it. Hence we do not have to worry about what network characteristics constitute better network since this information is already contained in the network use decision.

We base our analysis on SLQLFS 2003-10 for all LADs to maximise sample size given that wages are reported in waves 1 and 5 only and information on

REF is only collected from recent employees (those who have been employed in the last twelve months)[13]. We use white immigrants as a reference group. We first run OLS estimates of log hourly wages as a function of REF.

Table 9 Column 1 shows a significant wage penalty of around 12% for those immigrants who found their jobs through social networks. Controlling for locality effects in Column 2, and interacting REF with the ethnic immigrant group dummies in Column 3, we still find a negative penalty. In Column 4, we explore whether the estimated REF is the outcome of potential self-selection into participation; hence we estimated a regression adding Heckman-type selection correction term. The coefficient of the Mill's ratio is negative, but it is neither economically nor statistically significant.
It is possible that the choice of social networks as a job search method is likely to be a function of expected labour market outcomes, such as wages. After all, who would use this method if it were independent of the sought outcome? Considering then both social network use and wages can give rise to a simultaneity bias. In particular, the bias is prominent in a (Roy-model) situation in which individuals have to make one mutually exclusive choice of job search method from a given set. However, this concern is significantly lessened in our empirical application, since individuals can and do use several search methods at the same time, and using social networks as a job search method is fairly cheap. We explore this hypothesis by using IV estimation to model wages where we instrument REF using the average REF for group g in locality l and education group s. This instrument is meant to capture traditions of social network use among the ethnic immigrant group residing in a given locality and belonging to a certain skill level and is arguably uncorrelated with the error term in the individuals' wage equation.[14]. Column 4 reports the results of the IV estimates of wages as a function of the instrumented REF (finding a job through social networks) and shows that after controlling for endogenity, we find a wage penalty of around 18% for those who obtained their jobs through social networks.

To sum up our preliminary analysis in this section suggests that immigrants face a wage penalty as a result of using social network. This might be explained by the limited choices facing immigrants when searching for jobs or it could be due to compensating wage differential. For example, migrants might accept jobs offered through the network because, despite the lower wage, it is a quicker way to exit unemployment. Further analysis is needed to explain this finding.

[13]Dellatre and Sabatier (2007) have pointed out that network effects could disappear over time if employers learn about the worker's productivity. We don't have this problem since we examine recent hires.

[14]For reasons of sample size, only two education groups are considered: high and low educated. Highly educated migrants are those who left formal education after the age of 17

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A Data Appendix

A.1 Local Authority Districts (LADs)

Local government in the UK is represented by Local Authority Districts (LADs). In Great Britain, there are a total of 408 LADs (354 districts in England, 22 in Wales and 32 Coucil Areas in Scotland). These areas are not uniform in terms of population and size: there are populated LADs such as Birmingham (about 980,000 individuals according to 2001 Census) and areas far less populous, such as City of London (less than 8,000 persons in 2001). The average population, according to the last Census, is about 140,000. The largest LADs in terms of geographical extension are situated in Scotland, where the population density is the lowest of Great Britain. By contrary, most of the 32 London boroughs, as well as many regional centres such as Southampton and Leicester, are relatively small in terms of size, but with the highest population densities.

As discussed extensively in Section 2, we have selected, for each ethnic immigrant group g, the top 15 LADs in terms of population sizes. Tables 1 and 2 have reported the names of these LADs, as well as some selected LAD characteristics. A comparison of LAD names across immigant groups reveals that these not only spatially cluster, but also segregate. This is made visual in Figure 1, which depicts a map of these LADS.

Pop. Rank	LAD	SAM 2001	Census 2001	SLQLFS 2003-9	Sample
		Indian			
Pop. Rank	LAD	SAM 2001	Census 2001	SLQLFS 2003-9	Sample
1	Leicester	638	34,976	948	52
2	Brent	476	23,851	428	17
3	Harrow	432	22,040	472	18
4	Ealing	402	24,800	498	18
5	Birmingham	366	27,341	547	19
% England top 5		**0.26**	**0.26**	**0.23**	**0.32**
% England top 15		**0.51**	**0.52**	**0.47**	**0.53**
Total top 15		**4,538**	**265,735**	**5,878**	**204**
		Pakistani			
Pop. Rank	LAD	SAM 2001	Census 2001	SLQLFS 2003-9	Sample
1	Birmingham	550	52,260	945	44
2	Bradford	341	33,619	824	47
3	Kirklees	161	13,254	283	12
4	Manchester	146	11,691	237	18
5	Luton	138	8,687	182	5
% England top 5		**0.30**	**0.33**	**0.33**	**0.40**
% England top 15		**0.50**	**0.54**	**0.56**	**0.57**
Total top 15		**2,260**	**196,506**	**4,204**	**182**
		Bangladeshi			
Pop. Rank	LAD	SAM 2001	Census 2001	SLQLFS 2003-9	Sample
1	Tower Hamlets	379	32,591	723	66
2	Newham	165	10,771	259	13
3	Birmingham	129	10,326	187	16
4	Camden	82	6,253	79	4
5	Luton	65	3,868	90	7
% England top 5		**0.42**	**0.45**	**0.44**	**0.47**
% England top 15		**0.58**	**0.62**	**0.64**	**0.67**
Total top 15		**1,140**	**87,814**	**1,917**	**151**
		Caribbean			
Pop. Rank	LAD	SAM 2001	Census 2001	SLQLFS 2003-9	Sample
1	Birmingham	156	22,140	230	12
2	Lambeth	117	14,124	107	6
3	Brent	107	12,221	86	8
4	Croydon	106	11,224	124	7
5	Lewisham	104	13,333	109	8
% England top 5		**0.25**	**0.28**	**0.23**	**0.29**
% England top 15		**0.49**	**0.55**	**0.52**	**0.52**
Total top 15		**1,139**	**142,455**	**1,473**	**74**
		African			
Pop. Rank	LAD	SAM 2001	Census 2001	SLQLFS 2003-9	Sample
1	Southwark	319	18,868	390	18
2	Lambeth	276	14,752	286	18
3	Newham	228	15,268	247	12
4	Lewisham	206	10,998	317	24
5	Hackney	169	11,409	193	8
% England top 5		**0.35**	**0.31**	**0.21**	**0.19**
% England top 15		**0.59**	**0.59**	**0.38**	**0.36**
Total top 15		**2,002**	**137,251**	**2,624**	**154**

Table 1: Top immigrant destinations: Evidence from the Census

Rank	LAD	$I_{dperivat}$	s.hous	wage	v_l	u_l	$u_{g,l}$	$Exp1_{g,l}$	$Exp2_{g,l}$	$Exp3_{g,l}$
					Indian					
1	Leicester	32.80	0.26	5.88	7.40	0.09	0.10	0.26	0.07	0.15
2	Brent	25.95	0.22	6.15	6.98	0.09	0.07	0.18	0.05	0.11
3	Harrow	13.50	0.10	6.27	6.26	0.06	0.05	0.22	0.04	0.13
4	Ealing	23.40	0.18	6.23	6.97	0.07	0.07	0.17	0.05	0.09
5	Birmingham	37.57	0.25	6.01	8.70	0.11	0.12	0.06	0.05	0.03
	average top 15	25.66	0.20	6.12	7.12	0.08	0.08	0.13	0.03	0.08
	st. dev top 15	8.40	0.07	0.14	0.58	0.02	0.03	0.06	0.01	0.03
					Pakistani					
1	Birmingham	37.57	0.25	6.01	8.70	0.11	0.27	0.11	0.15	0.09
2	Bradford	32.93	0.14	5.92	7.86	0.08	0.26	0.15	0.10	0.12
3	Kirklees	26.15	0.15	6.04	7.46	0.06	0.19	0.07	0.04	0.06
4	Manchester	48.91	0.37	5.97	8.50	0.11	0.21	0.06	0.03	0.05
5	Luton	23.27	0.15	6.04	6.75	0.07	0.18	0.09	0.02	0.08
	average top 15	29.87	0.21	6.07	7.39	0.08	0.20	0.07	0.04	0.06
	st. dev top 15	8.05	0.07	0.11	0.79	0.02	0.05	0.03	0.04	0.03
					Bangladeshi					
1	Tower Hamlets	45.88	0.58	6.34	6.98	0.13	0.29	0.33	0.24	0.72
2	Newham	40.41	0.34	6.09	6.91	0.14	0.23	0.09	0.08	0.19
3	Birmingham	37.57	0.25	6.01	8.70	0.11	0.27	0.02	0.08	0.05
4	Camden	34.71	0.39	6.41	7.12	0.10	0.20	0.06	0.05	0.14
5	Luton	23.27	0.15	6.04	6.75	0.07	0.21	0.04	0.03	0.09
	average top 15	32.91	0.27	6.15	7.36	0.09	0.22	0.06	0.05	0.12
	st. dev top 15	7.57	0.13	0.19	0.76	0.03	0.05	0.09	0.06	0.19
					Caribbean					
1	Birmingham	37.57	0.25	6.01	8.70	0.11	0.17	0.05	0.09	0.05
2	Lambeth	34.18	0.42	6.25	6.78	0.10	0.18	0.12	0.06	0.13
3	Brent	25.95	0.22	6.15	6.98	0.09	0.13	0.10	0.05	0.11
4	Croydon	19.85	0.17	6.24	7.09	0.07	0.08	0.08	0.05	0.08
5	Lewisham	28.55	0.36	6.23	6.41	0.10	0.12	0.12	0.05	0.13
	average top 15	29.33	0.28	6.21	6.85	0.09	0.13	0.08	0.04	0.08
	st. dev top 15	8.76	0.13	0.10	0.56	0.03	0.04	0.03	0.02	0.03
					African					
1	Southwark	35.38	0.54	6.27	6.84	0.11	0.17	0.16	0.08	0.20
2	Lambeth	34.18	0.42	6.25	6.78	0.10	0.18	0.12	0.06	0.14
3	Newham	40.41	0.34	6.09	6.91	0.14	0.20	0.13	0.07	0.16
4	Lewisham	28.55	0.36	6.23	6.41	0.10	0.15	0.09	0.05	0.11
5	Hackney	45.06	0.50	6.22	6.34	0.14	0.18	0.12	0.05	0.15
	average top 15	30.77	0.32	6.24	6.75	0.10	0.18	0.08	0.04	0.10
	st. dev top 15	7.61	0.12	0.09	0.27	0.02	0.03	0.04	0.02	0.05
					England					
	average	18.88	0.16	6.09	6.33	0.05				
	st. dev	9.16	0.08	0.15	0.72	0.02				
	min	4.17	0.05	5.54	2.64	0.02				
	max	49.78	0.58	6.70	8.70	0.14				

Table 2: Top immigrant destinations in 2001: LAD characteristics

	1.OLS	2.OLS	3.IV	4.IV	5.IV	6.IV
				all LADs	$+Exp_{wl}$	$+Exp_{wl}=0$
			A. $Exp1_{g,l}$			
$Exp1_{g,l}$	–0.114***	–0.056	–0.063	–0.043	–0.088*	–0.056
	(0.042)	(0.046)	(0.044)	(0.028)	(0.053)	(0.059)
$u_{g,l}$		–0.353***	–0.355***	–0.265***	–0.463***	–0.531***
		(0.106)	(0.106)	(0.046)	(0.142)	(0.131)
Pakistani	–0.035***	0.009	0.008	–0.003	0.023	0.030*
	(0.007)	(0.013)	(0.013)	(0.006)	(0.017)	(0.016)
Bangladeshi	–0.078***	–0.018	–0.019	–0.023***	–0.011	–0.003
	(0.010)	(0.018)	(0.018)	(0.009)	(0.021)	(0.020)
B.Caribbean	–0.064***	–0.039***	–0.040***	–0.030***	–0.035***	–0.031***
	(0.010)	(0.012)	(0.012)	(0.007)	(0.012)	(0.012)
B.African	–0.062***	–0.011	–0.011	–0.014**	–0.015	–0.005
	(0.007)	(0.015)	(0.015)	(0.006)	(0.016)	(0.014)
White					–0.024***	–0.027***
					(0.005)	(0.009)
			A. $Exp2_{g,l}$			
$Exp2_{g,l}$	–0.218***	–0.019	–0.074	–0.082	–0.172	–0.179
	(0.072)	(0.092)	(0.139)	(0.094)	(0.164)	(0.163)
$u_{g,l}$		–0.331***	–0.296**	–0.244***	–0.455***	–0.457***
		(0.115)	(0.135)	(0.054)	(0.164)	(0.159)
Pakistani	–0.023***	0.012	0.009	–0.002	0.027	0.027
	(0.006)	(0.014)	(0.016)	(0.006)	(0.017)	(0.017)
Bangladeshi	–0.062***	–0.013	–0.017	–0.021**	–0.004	–0.004
	(0.011)	(0.018)	(0.021)	(0.009)	(0.020)	(0.020)
B.Caribbean	–0.055***	–0.033***	–0.036***	–0.029***	–0.030***	–0.030***
	(0.009)	(0.012)	(0.013)	(0.007)	(0.011)	(0.011)
B.African	–0.053***	–0.010	–0.013	–0.014**	–0.006	–0.006
	(0.007)	(0.016)	(0.017)	(0.007)	(0.015)	(0.014)
Whites					–0.023***	–0.025***
					(0.006)	(0.007)
			A. $Exp3_{g,l}$			
$Exp3_{g,l}$	–0.101***	–0.053	–0.002	0.009	–0.090	–0.083
	(0.032)	(0.039)	(0.188)	(0.085)	(0.137)	(0.129)
$u_{g,l}$		–0.321***	–0.342***	–0.271***	–0.456**	–0.477***
		(0.104)	(0.131)	(0.055)	(0.203)	(0.181)
Pakistani	–0.029***	0.008	0.013	0.001	0.023	0.025
	(0.006)	(0.013)	(0.023)	(0.008)	(0.025)	(0.023)
Bangladeshi	–0.055***	–0.014	–0.012	–0.019**	–0.002	–0.001
	(0.011)	(0.017)	(0.020)	(0.008)	(0.022)	(0.021)
B.Caribbean	–0.056***	–0.039***	–0.032	–0.026***	–0.032**	–0.031**
	(0.009)	(0.011)	(0.027)	(0.008)	(0.014)	(0.014)
B.African	–0.052***	–0.012	–0.009	–0.012*	–0.006	–0.003
	(0.007)	(0.015)	(0.019)	(0.007)	(0.015)	(0.014)
Whites					–0.024***	–0.026**
					(0.008)	(0.010)X_i
X_i	yes	yes	yes	yes	yes	yes
$H_{g,l}$	no	yes	yes	yes	yes	yes
Z_l	no	yes	yes	yes	no	no
θ_l	no	no	no	no	yes	yes
N	11,079	11,079	11,079	21,081	19,167	19,167

Table 3: Employment probabilities of immigrants and network size. Notes: Based on SAM 2001 restricted for each immigrant group to the top 15 LADs, excluding Col 4. Z_l includes average wages and the incidence of social housing; $H_{g,l}$ includes the unemployment rate (reported) and the share of individuals with at least bachelor degree; X_i includes demographics and human capital variables.

	1.IV	2.IV	3.IV
		Exp_{wl}	$+Exp_{wl} = 0$
	A. $Exp1_{g,l}$		
$Exp1_{g,l}$	–0.136	0.055	0.001
	(0.088)	(0.098)	(0.116)
$u_{g,l}$	–0.457**	–0.660**	–0.592**
	(0.227)	(0.270)	(0.250)
Pakistani	0.007	0.047	0.038
	(0.027)	(0.032)	(0.031)
Bangladeshi	–0.028	0.022	0.011
	(0.035)	(0.039)	(0.038)
B.Caribbean	–0.062**	–0.031	–0.037
	(0.026)	(0.024)	(0.025)
B.African	–0.043	–0.000	–0.009
	(0.034)	(0.031)	(0.028)
Whites		–0.002	–0.005
		(0.010)	(0.017)
	A. $Exp2_{g,l}$		
$Exp2_{g,l}$	0.251	0.362	0.330
	(0.279)	(0.301)	(0.302)
$u_{g,l}$	–0.657**	–0.852***	–0.816**
	(0.305)	(0.329)	(0.318)
Pakistani	0.041	0.061*	0.058*
	(0.035)	(0.035)	(0.034)
Bangladeshi	0.012	0.033	0.030
	(0.043)	(0.039)	(0.038)
B.Caribbean	–0.030	–0.027	–0.029
	(0.028)	(0.023)	(0.023)
B.African	–0.012	0.005	0.002
	(0.040)	(0.030)	(0.029)
Whites		0.003	0.005
		(0.011)	(0.013)
	A. $Exp3_{g,l}$		
$Exp3_{g,l}$	1.125*	0.442	0.365
	(0.602)	(0.291)	(0.261)
$u_{g,l}$	–1.441**	–1.242**	–1.063**
	(0.598)	(0.502)	(0.417)
Pakistani	0.183*	0.119*	0.101*
	(0.094)	(0.062)	(0.054)
Bangladeshi	0.077	0.058	0.044
	(0.063)	(0.047)	(0.042)
B.Caribbean	0.109	–0.003	–0.010
	(0.087)	(0.032)	(0.029)
B.African	0.112	0.020	0.006
	(0.089)	(0.034)	(0.030)
Whites		0.017	0.020
		(0.018)	(0.021)X_i
X_i	yes	yes	yes
$H_{g,l}$	yes	yes	yes
Z_l	yes	no	no
θ_l	no	yes	yes
N	10,429	20,069	20,069

Table 4: Employment probabilities of immigrants and network size. Notes: Based on SQLFS 2003-10 restricted for each immigrant group to the top 15 LADs. Z_l includes average wages and the incidence of social housing; $H_{g,l}$ includes the unemployment rate (reported) and the share of individuals with at least bachelor degree; X_i includes demographics and human capital variables.

	I	P	B	C	A
Employed recently (share)	0.31	0.25	0.26	0.22	0.16
	(0.47)	(0.43)	(0.44)	(0.41)	(0.37)
Hourly wage	7.96	7.58	6.10	9.39	6.22
	(6.19)	(8.48)	(2.19)	(5.49)	(1.99)
Age	42.34	36.57	34.88	42.30	37.85
	(10.97)	(10.43)	(8.4)	(11.95)	(10.2)
Education	12.64	12.01	11.05	11.92	14.30
	(3.72)	(4.28)	(3.33)	(4.1)	(5.18)
Married (share)	0.75	0.75	0.79	0.34	0.39
	(0.43)	(0.43)	(0.41)	(0.48)	(0.49)
Number of children	2.20	4.90	6.27	1.62	2.77
	(3.07)	(4.62)	(4.53)	(2.37)	(4.2)
Years since migration	20.74	16.25	16.65	23.41	12.54
	(14.29)	(13.09)	(9.92)	(16.03)	(8.95)
Living in London (share)	0.51	0.14	0.67	0.82	1.00
	(0.5)	(0.35)	(0.47)	(0.38)	(0)
Living in council houses (share)	0.11	0.18	0.60	0.42	0.49
	(0.32)	(0.38)	(0.49)	(0.5)	(0.5)
N	204	182	151	74	154

Table 5: Summary statistics

	A. Unemployed	B. Employed: wave>= 2		C. Employed: all	
	SN=1	SN=1	REF=1 | SN=1	SN=1	REF=1 | SN=1
Indian	0.45	0.72	0.38	0.88	0.77
Pakistani	0.68	0.86	0.37	0.93	0.71
Bangladeshi	0.62	0.81	0.46	0.93	0.81
Caribbean	0.53	0.89	0.50	0.94	0.73
African	0.50	0.83	0.40	0.92	0.74

Table 6: Social network use: Incidence and success rates.

	SN=1	SN=0	REF=1	REF=0
	All	All	All	All
Age	37.85	39.66	35.46	34.88
	(10.39)	(11.05)	(9.97)	(9.4)
Education	12.22	12.74	12.46	14.24
	(4.21)	(4.03)	(3.76)	(4.03)
Years since migration	16.55	18.96	12.27	13.37
	(12.57)	(13.39)	(11.62)	(12.1)
Living in London (share)	0.52	0.69	0.48	0.69
	(0.5)	(0.46)	(0.5)	(0.46)
managers and senior officials	0.05	0.10	0.02	0.02
	(0.21)	(0.3)	(0.13)	(0.13)
professional occupations	0.04	0.11	0.03	0.11
	(0.18)	(0.32)	(0.18)	(0.31)
associate professional and technical	0.04	0.07	0.04	0.02
	(0.2)	(0.25)	(0.2)	(0.13)
administrative and secretarial	0.07	0.03	0.03	0.13
	(0.25)	(0.17)	(0.18)	(0.33)
skilled trades occupations	0.21	0.17	0.24	0.13
	(0.41)	(0.38)	(0.43)	(0.33)
personal service occupations	0.02	0.02	0.04	0.07
	(0.15)	(0.15)	(0.2)	(0.26)
sales and customer service occupation	0.09	0.07	0.09	0.09
	(0.29)	(0.25)	(0.29)	(0.29)
process, plant and machine operatives	0.20	0.18	0.15	0.16
	(0.4)	(0.38)	(0.35)	(0.37)
elementary occupations	0.28	0.25	0.37	0.29
	(0.45)	(0.43)	(0.48)	(0.46)
Indian	0.24	0.31	0.33	0.36
Pakistani	0.27	0.17	0.23	0.25
Bangladeshi	0.22	0.17	0.23	0.17
Caribbean	0.09	0.10	0.08	0.08
African	0.18	0.25	0.13	0.14
Total	493	272	131	59

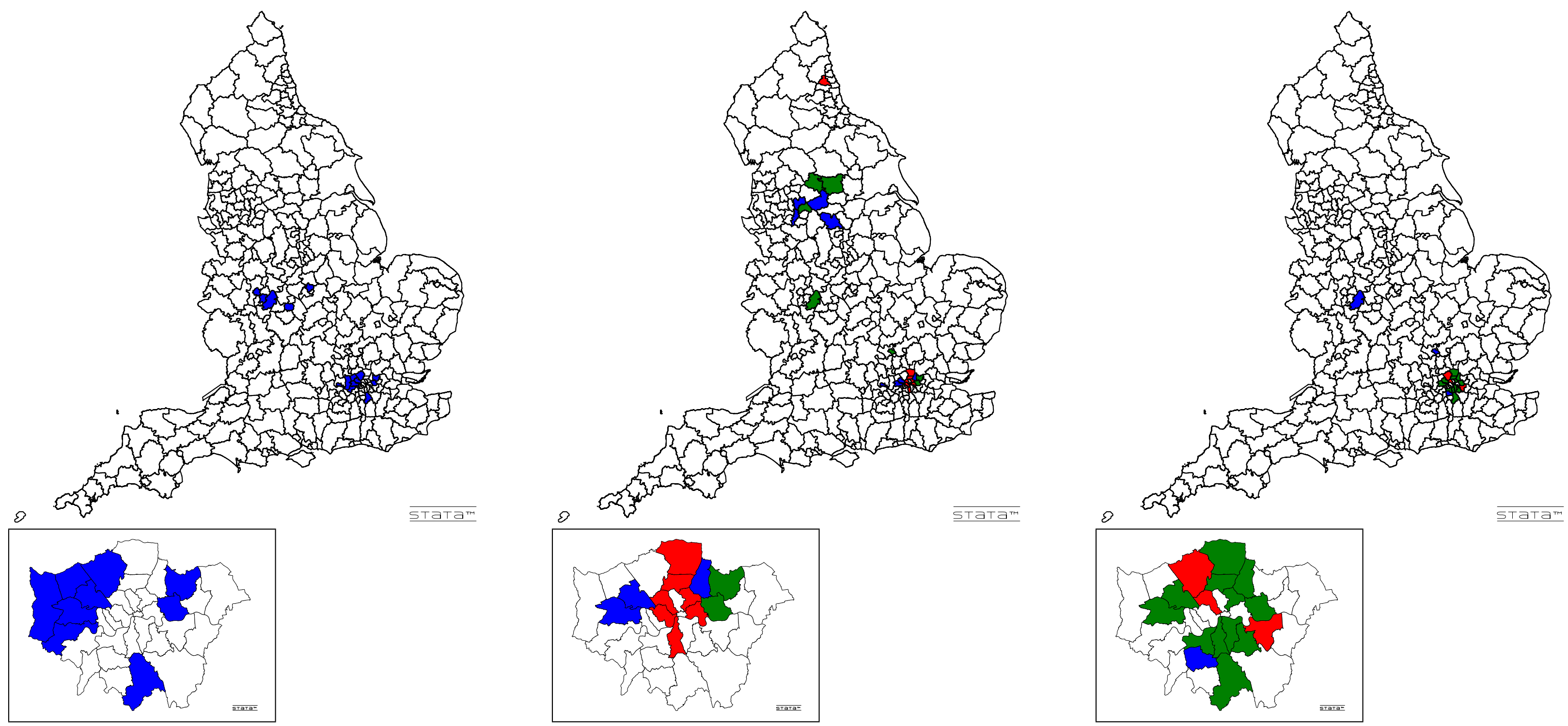
Table 7: Social network use, its success and human capital measures.

	Prob$\{E=1\}$	Prob$\{SN=1\}$	Prob$\{REF=1\}$
		A. $Exp1_{g,l}$	
$Exp1_{g,l}$	–0.371	–0.043	0.345
	(0.860)	(0.754)	(0.658)
Pakistani	–0.070	0.662**	–0.028
	(0.320)	(0.323)	(0.451)
Bangladeshi	0.113	0.592*	–0.104
	(0.359)	(0.338)	(0.418)
B.Caribbean	–0.284	0.118	–0.379
	(0.234)	(0.235)	(0.363)
B.African	–0.201	0.559	0.254
	(0.390)	(0.387)	(0.485)
λ_E			–1.703
			(1.176)
λ_{SN}			–0.024
			(1.786)
		B. $Exp2_{g,l}$	
$Exp2_{g,l}$	–1.111	–0.041	–0.789
	(0.322)	(1.327)	(1.452)
Pakistani	–0.117	0.666**	–0.113
	(0.322)	(0.322)	(0.464)
Bangladeshi	0.050	0.593*	–0.105
	(0.355)	(0.334)	(0.420)
B.Caribbean	–0.295	0.122	0.383
	(0.208)	(0.226)	(0.366)
B.African	–0.267	0.561	0.296
	(0.403)	(0.398)	(0.527)
λ_E			–1.813
			(1.298)
λ_{SN}			–0.133
			(1.804)
		C. $Exp3_{g,l}$	
$Exp3_{g,l}$	–0.588	–0.404	0.536
	(0.514)	(0.416)	(0.630)
Pakistani	–0.148	0.538*	–0.111
	(0.308)	(0.313)	(0.401)
Bangladeshi	0.085	0.561*	–0.184
	(0.324)	(0.316)	(0.380)
B.Caribbean	–0.315	0.084	0.385
	(0.204)	(0.220)	(0.350)
B.African	–0.287	0.444	0.274
	(0.382)	(0.384)	(0.456)
λ_E			–1.905
			(1.316)
λ_{SN}			–0.453
			(1.856)X_i
X_i	yes	yes	yes
$H_{g,l}$	yes	yes	yes
θ_l	no	yes	yes
N	765	765	174

Table 8: Probabilities of obtaining a job through the social network. Notes: Based on SLQLFS 2003-10 restricted for each immigrant group to the top 15 LADs. Estimates are corrected for simultaneous selection into employment (Prob$\{E = 1\}$) and social network use employment (Prob$\{SN = 1\}$). Excluded covariates for the employment equation are Z_l; for the social network use is religion membership. $H_{g,l}$ includes the share of individuals with at least bachelor degree; X_i includes demographics and human capital variables.

	1.OLS	2.OLS+int	3.OLS+lad	4.SEL	5.IV
REF	–0.115***	–0.096**	–0.102***	–0.118***	–0.183***
	(0.028)	(0.038)	(0.027)	(0.028)	(0.068)
Indian	–0.059	–0.025	0.044	–0.058	–0.058
	(0.039)	(0.046)	(0.040)	(0.038)	(0.039)
Pakistani	–0.347***	–0.353***	–0.205***	–0.343***	–0.338***
	(0.056)	(0.075)	(0.056)	(0.055)	(0.058)
Bangladeshi	–0.410***	–0.415***	–0.433***	–0.409***	–0.391***
	(0.059)	(0.076)	(0.066)	(0.058)	(0.063)
B.Caribbean	–0.166***	–0.262***	–0.111	–0.173***	–0.160**
	(0.061)	(0.073)	(0.067)	(0.063)	(0.063)
B.African	–0.308***	–0.288***	–0.240***	–0.309***	–0.309***
	(0.039)	(0.044)	(0.041)	(0.038)	(0.039)
IndianXREF		–0.144*			
		(0.080)			
PakistaniXREF		0.012			
		(0.105)			
BangladeshiXREF		–0.004			
		(0.111)			
B.CaribbeanXREF		0.264**			
		(0.118)			
B.AfricanXREF		–0.095			
		(0.084)			
Inv. Mills ratio				-0.059	
				(0.049)	
$F - stat$ IV					659.41

Table 9: Regression of wages on REF. Robust standard errors in parentheses .*** significant at 1%; ** significant at 5%; * significant at 10%. Regressors used to model participation in the selection equation are marital status, number of children below the age of 4, 9 and 16 years, possession of a house. Stock-Yogo threshold value for the IV model is 16.38 (10% maximal IV size). Sample size: 2006, except column 4 (5806)



Indian

Pakistani (blue) and Bangladeshi (red)

Overlap LADs in green.

Caribbean (blue) and African (red)

Overlap LADs in green.

Figure 1: Top 15 LADs for the ethnic groups - Insets:London
Digitalised boundaries from UKBorders http://borders.edina.ac.uk/