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Eleonora Patacchini and Yves Zenou

Centre for Research and Analysis of Migration
Department of Economics, University College London
Drayton House, 30 Gordon Street, London WC1H 0AX

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Eleonora Patacchini* and Yves Zenou†

* Università di Roma "La Sapienza", EIEF and CEPR
† Stockholm University

Non-Technical Abstract

This paper explores the relationship between residential proximity of individuals from the same ethnic group and the probability of finding a job through social networks, relative to other search methods. Using individual-level data from the UK Labour Force survey and spatial statistics techniques, we find that (i) the higher is the percentage of a given ethnic group living nearby, the higher is the probability of finding a job through social contacts; (ii) this effect decays very rapidly with distance. The magnitude, statistical significance and spatial decay of such an effect differ depending on the ethnic group considered. We provide an interpretation of our findings using the network model of Calvó-Armengol and Jackson (2004).

Keywords: Ethnic minorities, population density, social interactions, weak and strong ties, spatial statistics.

JEL Classification: A14, C21, J15, R12, R23.

Centre for Research and Analysis of Migration
Department of Economics, Drayton House, 30 Gordon Street, London WC1H 0AX
Telephone Number: +44 (0)20 7679 5888
Facsimile Number: +44 (0)20 7679 1068

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Abstract

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†Università di Roma "La Sapienza", EIEF and CEPR. E-mail: Eleonora.Patacchini@uniroma1.it

‡Corresponding author. Stockholm University, Department of Economics, 106 91 Stockholm, Sweden, IFN, and GAINS. E-mail: yves.zenou@ne.su.se.

1 Introduction

Networks of personal contacts mediate employment opportunities, which flow through word-of-mouth and, in many cases, constitute a valid alternative source of employment information to more formal methods. Such methods have the advantage that they are relatively less costly and may provide more reliable information about jobs compared to other methods. The empirical evidence reveals that around 50 percent of individuals obtain or hear about jobs through friends and family (Granovetter, 1974; Corcoran et al., 1980; Holzer, 1988; Montgomery, 1991; Gregg and Wadsworth, 1996; Addison and Portugal, 2001; Ioannides and Loury, 2004; Wahba and Zenou, 2005; Goel and Lang, 2009; Ioannides and Topa, 2010; Pellizzari, M., 2010; Topa, 2011). The recent study by Bayer et al. (2008) documents that people who live close to each other, that is, in the same census block, are more likely to work together than those in nearby blocks. Do these (positive) effects extend to ethnic groups in the labor market?

Because usually ethnic minorities experience higher unemployment rates, one may think that ethnic enclaves may be harmful to labor-market outcomes of minorities. Indeed, having fewer connections to employed workers makes it more difficult to receiving information about jobs and therefore reduces the chance of obtaining a job (see, e.g., Hellerstein et al. 2008).

On the other hand, the hiring of new workers via employee referral is supposed to be important for understanding ethnic divisions of labor because it creates a built-in bias toward incumbents: members of a particular ethnic group concentrate in specific jobs and when new employment opportunities become available at their workplace, they pass this information along to social contacts, often of the same race and ethnic background.

For the US, some evidence can be found in Conley and Topa (2002). They examine the spatial distribution of unemployment in Chicago using different social and economic distance metrics. Their results indicate a clear dominance of the racial/ethnic distance metric and of the racial/ethnic composition variables in explaining the spatial correlation of unemployment. More direct evidence can be found in Falcon (2007) and Falcon and Melendez (2001). They show that Latinos in Boston are more likely to use personal networks to gain employment relative to other job search methods. Elliott (2001) finds that Latinos, especially newly arrived immigrants, are more likely than native-born Whites to enter jobs through insider referrals. He also finds that the correlation between insider referrals and ethnically homogeneous jobs is positive and significant only for native-born Blacks. Mouw (2002), using longitudinal data, finds that Black workers who used personal contacts to find employment did no worse compared to where they used formal methods. Munshi (2003) attempts to identify network effects among Mexican migrants in the U.S. labor market and to test whether the network improves labor market outcomes for its members. He finds that the same individual is more likely to be employed and to hold a higher paying nonagricultural job when his network is exogenously larger.

There are very few papers investigating this issue for Europe. Exceptions include Frijters et. al (2005) and Battu et al. (2011), both for the UK. They find that, though personal networks are a popular method of finding a job among ethnic minorities, they are not necessarily the most effective method in finding a job. Using data on both legal and illegal migrants in eight Italian cities in 2009, Boeri et al. (2011) show that residential segregation can be harmful to employment when the fraction of migrants is above 15-20% of the total local population.

In this paper, we look at the acquisition and transmission of job information by job seekers through their social contacts. We first present as a theoretical background the dynamic model of Calvó-Armengol and Jackson (2004) who explicitly model social networks as graphs. If workers are linked to each other, then they exchange information about jobs. Strong ties are direct friends while weak ties are friends of friends of any length (Granovetter, 1983; Calvó-Armengol et al., 2007; Patacchini and Zenou, 2008). In this framework, the individual probability of finding a job increases with the number of strong ties and weak ties. However, the farther away is a weak tie, the lower is the individual probability of finding a job.

A precise test of this model requires detailed information on all social contacts between individuals over time, which is unfortunately not available. However, one can use this mechanism and approximate the *social proximity* by the *geographical proximity.* Since ethnic communities tend to be more socially cohesive, a reasonable conjecture is that the density of people living in the same area is a good approximation for the number of direct friends one has, i.e. *strong ties*, especially if the areas are not too large and if people belong to the same ethnic group.[1] In the same spirit, the density of individuals living in neighboring areas will be a measure of friends of friends, i.e. *weak ties.* Ethnicity is thus the chosen dimension along which agents' social contacts develop. Using this framework, one can thus look at the relationship between ethnic employment density and the probability of finding a job through social contacts and use *spatial data analysis techniques* to investigate the spatial scale of the effects. We collect some evidence for Europe, where these issues are scarcely investigated.[2]

[1] A similar approximation of the social space (approximated by the physical space) is used in Wahba and Zenou (2005) for the case of Egypt.

[2] Although immigration-related issues are now at the forefront of the political debate in Europe, detailed data on ethnic minorities are still not available (see, e.g., Bisin et al. 2011).

Consistently with the theoretical model, we find that the higher is the percentage of a given ethnic group living nearby, the higher is the probability of finding a job through social contacts. We also find that such an effect is, however, quite localized. It decays very rapidly with distance, losing significance beyond approximately 60 minutes travel time. One possible concern in our analysis is that these correlations capture the effects of *unobserved characteristics* of areas highly populated by ethnic minorities that also affect job search methods, such as tastes for discrimination, spatial mismatch, etc. Our qualitative results remain unchanged if we instrument the contemporaneous level of ethnic population density with its value lagged in time. As labor market conditions evolve over time, our assumption is that the factors that influenced the pattern of settlement of ethnic minorities in the past are unrelated with employment prospect today, apart from their effect through present-day ethnic population density.[3]

Our results can be understood within the more general existing literature on the *cumulative causation* of immigrant inflows where not only employment outcomes but also geographic origin is shared by immigrants in the same national group living in proximity. Social scientists have indeed long noted that international migration is characterized by a strong internal momentum: once a particular migration stream has been initiated, it tends to persist and grow over time and often in the same location. This is referred by sociologists to as a process of "cumulative causation" whereby social networks connecting migrants to nonmigrants make the process of migration "self-perpetuating" (Walker and Hannan, 1989; Massey, 1990). Massey and Espinosa (1997) have suggested that the persistence of migration in space and time stems from two fundamental processes: human and social capital accumulation. The former operates among individuals and the latter through the social networks in which they are embedded. Massey and Zenteno (1999) postulate that each act of migration creates social capital among those to whom the migrant is related. Once someone migrates, the costs and risks of international movement fall for that person's friends and relatives, inducing some of them to migrate, which further expands the network of people with ties to migrants, yielding more social capital, which induces new people to migrate, further expanding the network, and so on. The steady accumulation of social capital through the progressive expansion of interpersonal networks yields another powerful feedback loop that results in the cumulative causation of migration over time.[4]

There is also an important literature in economics on the importance of networks for outcomes such as the probability of immigration and the location decisions of recently-

[3]Such an approach has also been used by Rice et al. (2006).

[4]See Massey et al. (1998) for a review of this literature.

arrived immigrants. For example, using the 1990 Census data, Card (2001) studies the effects of immigrant inflows on occupation-specific labor market outcomes. He finds that *intercity mobility rates* of natives and earlier immigrants are insensitive to immigrant inflows. However, occupation-specific wages and employment rates are systematically lower in cities with higher relative supplies of workers in a given occupation. Using variation in the fraction of immigrants across different cities, Altonji and Card (1991) study the effects of immigration on the labor-market outcomes of the less-skilled natives. They find that a one percentage point increase in the share of immigrants in a city generates a one percent increase in the supply of labor to industries in which less-skilled natives are employed. More recently, Munshi and Wilson (2011) examine the role played by local identity, or the attachment to a home-town, in restricting occupational choice and mobility. They find that the effect of historical competition on participation in socializing institutions (such as churches and parochial schools) grows stronger over the course of the twentieth century, emphasizing the idea that small differences in initial conditions can have large long-term effects on institutions and economic choices.

Our analysis helps understand the role of local ethnic social networks on labor-market outcomes of workers from the same ethnicity and more generally how ethnic enclaves and the "cumulative causation" of immigrant inflows work in the real world. Remarkably, we find that these network effects are very localized and work differently depending on the ethnic group studied. For instance, we find that the employment status of a Chinese immigrant is strongly correlated with the size of the Chinese population living in proximity, as opposed to the size of the Pakistani population also living in proximity, or to the size of Chinese immigrant communities living in another town. Interestingly, no statistically significant effects are found for Indian and Pakistani workers. As mentioned above, our analysis has, however, some limitations, mainly because the individual social contacts (i.e. the exact social network topologies) are not known. As a result, our analysis should be taken with caution. Nevertheless, it presents a novel approach to this complex issue, which is able to provide some evidence on ethnic network effects and their spatial dimension in Europe.

The paper is structured as follows. The next section expose the model of Calvó-Armengol and Jackson (2004). We clarify the link between the model and our empirical analysis in Section 3 and describe our data in Section 4. Section 5 discusses estimation issues and presents our empirical model and the estimation results. In Section 6, we collect additional empirical evidence. Finally, Section 7 concludes.

2 Theoretical analysis

The aim of our theoretical framework is to understand how *strong* and *weak* ties affect the labor-market outcomes of workers. Indeed, given a network structure, we would like to see how the size of strong and weak ties affects the individual probability of obtaining a job and thus the employment rate in the economy.

In the model, the main problem for each worker is to obtain information about jobs. Each worker is embedded in a network of social relationships, and her *direct friends* are her *strong ties* while *the friends of her friends* of any length are her *weak ties*. This worker can hear about a job either *directly* (if by chance she sees the job advertisement) or *indirectly* because one of her friends who belongs to her social network is employed, knows about this job and transmits the information to the worker. Observe that it is assumed that the probability of hearing directly about a job is the same for someone who is employed and for someone who is unemployed.

2.1 Some notations and definitions from graph theory[5]

Denote by n the number of individuals in a given social network $\mathbf{g}$, with $n = U + E$ (U and E are respectively the unemployment and the employment levels in the network). Therefore $N = \{1, \dots, n\}$ is a set of individuals connected in some network relationship. A network is thus a list of unordered pairs of players $\{i, j\}$. These links are represented by a graph $\mathbf{g}$, where $g_{ij} = 1$ if i is friend with j (denoted by ij) and $g_{ij} = 0$ otherwise (*unweighted* graphs/networks). In our framework, links are taken to be reciprocal, so that $g_{ij} = g_{ji}$ (*undirected* graphs/networks). By convention, $g_{ii} = 0$. The set of i's direct contacts is: $N_i(\mathbf{g}) = \{j \neq i \mid g_{ij} = 1\}$, which is of size $n_i(\mathbf{g})$.

One of the key features of networks/graphs is that not only *direct* but also *indirect* links that matter.

Definition 1 *A path of length k from i to j in the network $\mathbf{g}$ is a sequence $\langle i_0, i_1, ..., i_k \rangle$ of players such that $i_0 = i$, $i_k = j$, $i_p \neq i_{p+1}$, and $g_{i_p i_{p+1}} = 1$, for all $0 \leq p \leq k - 1$, that is, players i_p and i_{p+1} are directly linked in $\mathbf{g}$. If such a path exists, then individuals i and j are path-connected.*

In words, a *path* between two individuals i and j is an ordered set of agents $(i, i_1, ..., i_k, j)$ of N, where an agent can appear several times, such that $i \neq j$. We say that a path belongs to the network $\mathbf{g}$ if $g_{ii_1} g_{i_1 i_2} ... g_{i_k j} \neq 0$.

[5] For a more complete overview of these definitions, see Wasserman and Faust (1994) and Jackson (2008).

Definition 2 *An individual i holds a* ***strong tie*** *with an individual j if $g_{ij} = 1$. An individual i holds a* ***weak tie*** *with an individual j if individuals i and j are path-connected. The length k of this (weak) tie is defined by the length of the path between individuals i and j.*

2.2 The model

We now described the model of Calvó-Armengol and Jackson (2004). Time evolves in discrete periods indexed by t. The vector s_t describes the employment status of the workers at time t. If individual i is employed at the end of period t, then $s_{it} = 1$ and if i is unemployed then $s_{it} = 0$.

A period t begins with some agents being employed and others not, as described by the vector $\mathbf{s}_{t-1} = (s_{1t-1}, ..., s_{nt-1})$ that describes the status of all workers from the last period. Next, information about job openings arrives. In particular, any given individual hears about a job opening with probability a that is between 0 and 1. This job arrival process is independent across individuals. If the individual is unemployed, then she will take the job. However, if the individual is already employed then she will pass the information along to a friend, picked at random among her unemployed friends. As stated above, the graph or network $\mathbf{g}$ summarizes the links of all agents, where $g_{ij} = 1$ indicates that i and j know each other (strong tie), and share their knowledge about job information, while $g_{ij} = 0$ indicates that they do not know each other.

Observe that if an employed worker hears about a job but all her friends (i.e. direct links) are already employed, then the job is lost. We focus here on a model where wages are exogenous and identical for all workers. So there is no room in this model for an employed worker to exploit a job offer in order to increase her current wage.

Finally, the last thing that happens in a period is that some agents lose their jobs. This happens randomly according to an exogenous breakup rate, δ, which is between 0 and 1. We are able to write the probability $\mathbb{P}_{ij}$ of the joint event that individual i learns about a job and this job ends up in individual j's hands. It is equal to:

$$\mathbb{P}_{ij}(\mathbf{s}) = \begin{cases} a & \text{if} \quad s_i = 0 \text{ and } i = j \\ a / \sum_{k:s_k=0} g_{ik} & \text{if} \quad s_i = 1,\ s_j = 0, \text{ and } g_{ij} = 1 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where the vector $\mathbf{s}$ describes the employment status of all the individuals at the beginning of the period. In (1), a is the probability of obtaining a job information without using friends and relatives. Three cases may then arise. If individuals i and j are unemployed ($s_i = s_j = 0$), then the probability that j will obtain a job is just a since individual i will never transmit any information to j. If individual i is already employed and her friend j is not ($s_i = 1$, $s_j = 0$), then individual i transmits this job information to all her direct unemployed neighbors, who total number is $\sum_{k:s_k=0} g_{ik}$. We assume that all unemployed neighbors are treated on equal footing, meaning that the employed worker who has the job information does not favor any of her direct neighbors. As a result, the probability that an unemployed worker j is selected among the $\sum_{k:s_k=0} g_{ik}$ unemployed direct neighbors of an employed worker j is given by: $a/\sum_{k:s_k=0} g_{ik}$. Finally, if individual j is employed, then she does not need any job information, at least in the current period.

2.3 Impact of strong ties on employment probabilities

The first result obtained by Calvó-Armengol and Jackson (2004) is not surprising and has also been showed in a static framework (see Calvó-Armengol, 2004, and Calvó-Armengol and Zenou, 2005).

Proposition 1 *The higher $n_i(\mathbf{g})$, the number of strong ties individual i has, the higher is her individual probability of finding a job.*

Indeed, if an individual has more strong ties, then she is more likely to hear on average about more jobs through her friends and relatives but her chance of finding a job directly does not increase since a is not affected by the size of the network. This result is quite intuitive since, when the number of direct connections increases, the source of information about jobs is larger and people find it easier to obtain a job through their friends and relatives. This is the first prediction of our model, which implies that workers have a greater chance of finding a job, the higher is the number of their strong ties. Observe that the individual probability of finding a job through strong ties for individual j is obviously not given by (1) since $\mathbb{P}_{ij}(\mathbf{s})$ is the probability that only one individual, i, who hold a strong tie with j, and who is aware of some job, will transmit this information to individual j. To determine the individual probability of obtaining a job for j, one has to do the calculation for all the direct friends of i.

2.4 Impact of weak ties on employment probabilities

We would now like to study the impact of weak ties (as defined by Definition 2) on the individual probability of finding a job. Calvó-Armengol and Jackson (2004) show that, in steady-state, there is a positive correlation in employment status between two path-connected workers. As we will see, this result is not at all easy to obtain since, in the short run, the correlation is negative. Indeed, in a static model, if an employed worker is directed linked to two unemployed workers, then if she is aware of a job, she will share this job information with her two unemployed friends (see (1)). These two persons, who are path-connected (path of length two) are thus in competition and one (randomly chosen) will obtain the job and be employed while the other will stayed unemployed. So their employment statuses will be negatively correlated (see Calvó-Armengol, 2004, and Calvó-Armengol and Zenou, 2005).

Let us now give the intuition why this negative correlation result does *not* hold in a dynamic labor-market model. Consider the star-shaped network described in Figure 1 with three individuals, i.e. $n = 3$ and $g_{12} = g_{23} = 1$. Suppose the employment status of these three workers from the end of the last period is $\mathbf{s}_{t-1} = (0, 1, 0)$. In the figure, a black node represents an employed worker (individual 2), while unemployed workers (1 and 3) are represented by white nodes. Conditional on this state $\mathbf{s}_{t-1}$, the employment states s_{1t} and s_{3t} are negatively correlated. As stated above, this is due to the fact that individuals 1 and 3 are "competitors" for any job information that is first heard by individual 2.

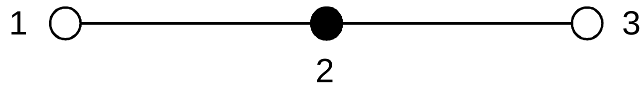


Figure 1: Employment correlations in a star-shaped network

Despite this negative (conditional) correlation in the short run, individual 1 can benefit from individual 3's presence in the longer run. Indeed, individual 3's presence helps improve individual 2's employment status. Also, when individual 3 is employed, individual 1 is more likely to hear about any job that individual 2 hears about. These two aspects counter the local (conditional) negative correlation, and help induce a positive correlation between the employment status of individuals 1 and 3.

In what follows, we describe how we obtain this long-run positive correlation. Consider again the network described in Figure 1 but without imposing any employment status to workers. In that case, there are eight possible employment states: $000, 100, 010, 001, 110, 101, 011, 111$, where for example 000 means that individuals $1, 2$, and 3 are unemployed. As a result, the state of the economy s_t evolves following a Markov process $\mathcal{M}(a, \delta)$ where a is the job-arrival rate that takes place in the first half of each period, while δ is the job-destruction rate that takes place in the second half of each period. We gather the Markov transitions into a matrix $\mathbb{P}_{ij} = \Pr\{s_{t+1} = i \mid s_t = j\}$, where $i, j \in \{000, 100, 010, 001, 110, 101, 011, 111\}$, i.e., rows correspond to $t + 1$ while columns correspond to t (the columns sum up to one as in all Markov matrices).

As highlighted above, an important issue in this case is the short-run negative correlation versus the long-run strictly positive correlation. To sort out the short and longer run effects, we divide a and δ both by some larger and larger factor, so that we are looking at arbitrarily short time periods. We call this the "sub-division" of periods. More precisely, instead of analyzing the Markov process $\mathcal{M}(a, \delta)$, we can analyze the associated Markov process $\mathcal{M}(a/T, \delta/T)$, that we name the *$T-$period subdivision* of $\mathcal{M}(a, \delta)$, with steady state distribution μ^T. We show that there exists some T' such that, for all $T \geq T'$, the employment statuses of any path-connected agents are positively correlated under μ^T. Consider $\mathcal{M}(a/T, \delta/T)$. For this Markov process, at every period, every shock (be it a job arrival a/T or a job breakdown δ/T) is very unlikely when T is high enough. Having two or more shocks in every such period is thus much less unlikely. Instead of analyzing $\mathcal{M}(a/T, \delta/T)$, we analyze an approximated Markov process $\mathcal{M}^*(a/T, \delta/T)$ where we only keep track of one-shock transitions, and disregard transitions involving two or more shocks. We denote by μ^{*T} the corresponding steady-state distribution. The higher T, the closer are the transitions of the approximated Markov process $\mathcal{M}^*(a/T, \delta/T)$ to that of the true Markov process $\mathcal{M}(a/T, \delta/T)$, and so the closer is μ^{*T} to μ^T.

Calvó-Armengol and Jackson (2004) show that, with a high enough $T-$period subdivision, for n individuals and any social network structure, we have:

Proposition 2 *Under fine enough subdivisions of periods, the unique steady-state long-run distribution on employment is such that the employment statuses of any path-connected agents are positively correlated.*

The proposition shows that, despite the short-run conditional negative correlation between the employment of competitors for jobs and information, in the longer run any interconnected workers' employment is positively correlated. This implies that there is a clustering of agents by employment status, and employed workers tend to be connected with employed workers, and vice versa. The intuition is clear: conditional on knowing that some set of agents are employed, it is more likely that their neighbors will end up receiving information about jobs, and so on. The benefits from having other agents in the network outweigh the local negative correlation effects, if we take a long-run perspective.

Proposition 3 *The longer the length of two-path connected individuals (i.e weak ties), the lower is the correlation in employment statuses between these two individuals.*

Indeed, the correlation between two agents' employment is (weakly) decreasing in the number of links that each an agent has, and the correlation between agents' employment is higher for direct compared to indirect connections. The decrease as a function of the number of links is due to the decreased importance of any single link if an agent has many links. The difference between direct and indirect connections in terms of correlation is due to the fact that direct connections provide information, while indirect connections only help by indirect provision of information that keeps friends, friends of friends, etc., employed. In other words, the longer the path in the social network between two individuals, the weaker is the effect of job transmission.

2.5 Interpreting the model in terms of ethnic minorities

The model of Calvó-Armengol and Jackson (2004) has no ethnic component since it is assumed that all individuals are ex ante identical. It shows, however, that there is a *clustering of workers with the same employment status* in equilibrium since, in the long run (i.e. steady state), employed workers mostly tend to be friends with employed workers. This is because weak ties (friends of friends of any length) indirectly help individuals by providing job information to their strong ties, which, in turn, help them become employed. As a result, in this framework, if, because of some initial condition, some ethnic minority workers are employed, then in steady-state they will still be employed because both their strong and weak ties will also be employed.

To illustrate this issue, let us consider a network with four workers, i.e. $n = 4$. Figure 2 depicts the value of unemployment probabilities of worker 1, and the correlations between workers 1 and 2, and between workers 1 and 3, in the long-run steady state for $a = 0.10$ and $\delta = 0.015$. These results are calculated using numerical simulations repeated for a sufficiently long period of time. When there is no social network so that no information is exchanged between workers, the unemployment rate of each agent is just equal to its steady-state value, i.e. $\delta/(a + \delta) = 0.13$. Thus, the probability of being unemployed for each worker is 13.2 percent, given that they cannot rely on other workers to obtain information about jobs and the only chance they can have of obtaining a job is by direct methods. Imagine now that one link is added in this network so that workers 1 and 2 are directly linked to each other. Steady-state unemployment decreases substantially for workers 1 and 2, from 13.2 percent to 8.3 percent. When more links are added, the unemployment rate for each worker decreases even more from 13.2 percent when there are no links to 5 percent when the social network is complete. This table also shows the positive correlation between employment statuses of different workers already mentioned before. As stated above, this model can provide a rationale for why ethnic minorities, who tend to have friends who are of the same ethnicity (see, for example, Sigelman, 1996; Cutler et al., 1999; McPherson et al., 2001; Jackson, 2008; Currarini et al., 2010), have difficulties in finding a job. Since employment statuses between direct and indirect friends of the same network are correlated, then, like a disease, unemployment will spread among all individuals belonging to this network. Similarly, if ethnic minorities can help each other finding a job because some of them have been successful upon their arrival in the host country, then we will find a positive correlation between the size of the network friends and the individual probability of finding a job, as in Proposition 1.

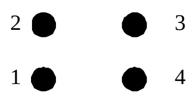
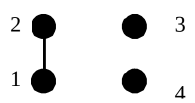
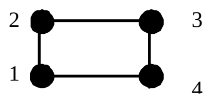
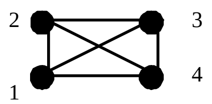
	Probability of being unemployed for individual 1	Correlations in employment statuses between 1 and 2	Correlations in employment statuses between 1 and 3
	0.132	–	–
	0.083	0.041	–
	0.063	0.025	0.019
	0.050	0.025	0.025

Figure 2: Employment correlations as a function of network structure

In the Calvó-Armengol and Jackson framework, there are no general-equilibrium effects. Indeed, in the model, a, the arrival rate of jobs to each individual (excluding referrals), is considered *constant* and *exogenous*. Consider, however, the existence of a (more-or-less) fixed pool of jobs available to low-skilled individuals in immigrant communities. Here, employees have an incentive to pass on information to members of one's own network, but not to individuals of the other networks. Job-offer arrivals could thus be completely endogenous to the networks. In this context, individuals embedded in larger networks are more likely to capture jobs initially. This increases the fraction of employed individuals in the "networked" group and reduces the availability of jobs to the group of individuals who do not have access to networks (by reducing the ex ante arrival rate of offers). In an extreme case, all jobs go to "networked" individuals and immigrants in the unconnected group may never have the chance to hear from new jobs.

There is another (unmodelled) advantage of having a larger network. Strong and weak ties provide some sort of insurance. Indeed, even if a worker does have a job now, the network is valuable as an insurance device that decreases the probability of remaining unemployed in the case this worker had a negative shock to her current status. Risk-averse individuals will certainly value this. In developing countries, which often have no formal institution to make insurance mechanisms operational, it has been widely documented that households use social networks as an informal insurance (Fafchamps and Lund, 2003). Interestingly, using survey data from the rural Philippines, Fafchamps and Gubert (2007) show that occupation is not a major determinant of risk-sharing links. In contrast, *geographic proximity* is strongly related to risk-sharing networks. This may be because it facilitates monitoring and enforcement. As a result, larger networks may increase the employment prospects of workers belonging to the same network because the network may serve as an insurance device for exogenous variations of the job-destruction rate δ over time.

3 Bridging the model to the empirics

Let us summarize our theoretical results. We have shown that:

(*i*) The individual probability of finding a job is increasing in the number of strong ties each individual has (Proposition 1);

(*ii*) The individual probability of finding a job is increasing in the number of weak ties each individual has (Proposition 2);

(*iii*) The longer the length of weak ties, the lower the individual probability of finding a job (Proposition 3).

Let us now approximate the *social proximity* by the *geographical proximity*, drawing a link between the social and geographical spaces. We believe that this approximation makes sense because the two spaces (social and geographic) are highly correlated. For example, individuals in established immigrant communities typically provide information, seed capital, shelter, and legal sponsorship to other immigrants from the same origin communities (family or friends). In this way, not only employment outcomes but also geographic origin is shared by immigrants in the same national group living in proximity (e.g. Mexicans from a particular town in rural Michoacan may tend to live in the same neighborhood in East Los Angeles). This is the idea of ethnic enclaves that have positive (employment) effects on the local ethnic community. Ethnic minorities living with large numbers of employed neighbors of the same ethnicity are more likely to have jobs than ethnic minorities residing in areas with fewer employed neighbors. This latter finding is consistent with earlier findings on Swedish (Edin et al., 2003), Danish (Damm, 2009) and U.S. immigration (Andersson et al., 2009) and draws at least partially on the notion that enclaves enable immigrants to form social networks that effectively make them act as intermediaries in getting jobs. Recently, Bayer et al. (2008) have shown how the social and the geographical space are highly correlated. Specifically, they examine the propensity of a pair of individuals to *work* in the *same location*, comparing such propensities for pairs of individuals who reside on the same versus nearby blocks. They take the propensity to work in the same location as an indication that one member of the pair provided a referral (or more generally information) to the other member about jobs available in her place of work. Their results indicate the existence of significant social interactions at the block level; residing on the same versus nearby blocks increases the probability of working together by over 33 percent. As a consequence, individuals are about 6.9 percentage points more likely to work with at least one person from their block of residence than they would be in the absence of referrals. Beside the specific studies on the labor market outcomes of ethnic minorities and ethnic networks (such as the ones cited in the Introduction), there is a rich socio-economic literature on patterns of relations among individuals, documenting that social networks appear to be fairly homogeneous with regard to certain socio-demographic attributes. Indeed, individuals are likely to associate with people who are similar, i.e., *assortative matching* or *homophily*. This tendency is particularly strong among ethnic groups.[6,7] Therefore, because of all these arguments, we believe that it is reasonable to assume that the density of individuals of a given ethnic group is a good approximation for the social contacts that each individual of that ethnicity is exposed to. Looking at the importance of social networks for the acquisition and transmission of information about jobs, a more precise measure of the relevant social contacts is the density

[6] See e.g. Moody (2001), Marmaros and Sacerdote (2006), Bayer et al. (2007).

[7] It has also been shown that investments in public goods, tastes for redistribution, and other forms of civic behavior are more common in racially or ethnically homogenous communities (see Alesina and La Ferrara , 2005, for an overview of this literature).

of *employed workers* having the same ethnicity living nearby.

Take an individual with a given set of characteristics (family, age, education, gender...), living in area a and belonging to race r. Our conjecture is that the density of employed people living in the same area is a good approximation of the number of direct friends one has, i.e. *strong ties*, especially if the areas are not too large and if people belong to the same ethnic group (Topa, 2001). In the same spirit, the density of employed individuals living in neighboring areas will be a measure of friends of friends, i.e. *weak ties*. Using this approach, other things being equal (i.e. fixing the characteristics of the area) the theoretical predictions are as follows.

(*i*) The higher is the percentage of type$-r$ employed workers living in area a, the higher is the individual probability of finding a job for an individual of type$-r$ living in area a (Proposition 1).

(*ii*) The higher is the percentage of type$-r$ employed workers living in the neighboring areas of a, the higher is the individual probability of finding a job for an individual of type$-r$ living in area a (Proposition 2).

(*iii*) This effect should decrease with the distance between area a and its neighboring areas (Proposition 3).

4 Data

Our data source is the UK Labour Force Survey (LFS). This survey was conducted every two years from 1975-1983, then annually until 1992 and quarterly since that date. In the present study, we use the Quarterly Labour Force Survey from 1992 until 2009.[8] It is an address-based household survey (including about 60,000 households), which allows us to get rich individual-level information at a local level, i.e. the local authority, as well as information on ethnicity at a level of disaggregation suitable for our purposes. The *local authority* is the finer level of spatial disaggregation of the English local government structure.[9] For the purposes of our analysis, ethnicity has to be defined in a narrow way. For example, the

[8]The data are available through the Office of National Statistics (ONS). We acknowledge the original data creators, depositors or copyright holders, the funders of the Data Collections and the UK Data Archive. They bear no responsibility for their further analysis or interpretation.

[9]In England, there is indeed a mix of single-tier and two-tier local government. Our definition of "local authority" considers single-tier (unitary) authorities together with the lower-tier authorities in areas of two-tier local government. For example, in London there are 33 local authorities (London boroughs).

density of Asian people living nearby cannot be a good approximation of the social contacts of a Black-Caribbean person. This is due to important cultural (and language) differences between these groups. Therefore, in order to ensure a relative cultural homogeneity within each ethnic group, our investigation has been performed separately for the different ethnic minorities that can be unambiguously identified in our data, namely "Black Caribbean", "Black African", "Indian", "Pakistani", "Bangladeshi" and "Chinese".[10] Ethnic minorities, however, are not over-sampled in the survey design. Because of the resulting small sample sizes per local areas of each specific ethnic minority group in each quarter, we pool individuals for the different quarters across years.

Excluding local areas with too low sample sizes of ethnic minorities (or too low sample sizes in adjacent areas), we are left with a final sample of 15,008 ethnic minority individuals who are employed distributed over 49 local authorities in the UK. These areas are located in London, in the West Midlands, in Yorkshire and in Merseyside.[11,12] We report in Table 1 some summary statistics. Indians are the largest group representing slightly more than 2% of the total population, followed by Pakistanis (1.4%), Black African and Black Caribbeans (1%), Chinese and Bangladeshis (0.5%). Pakistani and Bangladeshi are the groups that seem to face more difficulties in finding a job.[13] Chineses show the highest self-employment rate.

[*Insert Table* 1 *here*]

In our empirical analysis, we define as employed each individual in paid work, including self-employed and those under government schemes.[14,15] The density of own-race employed individuals leaving nearby is the ratio between employed individuals and resident individuals in the work-force (years 16-64) for each race in each local authority.

[10] We exclude mixed-ethnicity individuals. The ethnicity question has been re-defined during the years and these mixed categories were the groups mostly affected by these changes.

[11] Ethnic minorities are mainly concentrated in London (slightly less than a half), in the West Midlands, in Yorkshire and Humberside and in the North West and Merseyside (Cabinet Office, 2003). In contrast, only about a tenth of all White people live in London, and about 4 per cent in the West Midlands.

[12] Not all the areas contain large enough sample sizes of all ethnic groups.

[13] The particularly low employment rate of Pakistani and Bangladeshi is partly due to the extremely low employement rate of female (about 20% in both groups). The figures reported in Table 1 are consistent with other studies on the labor market performance of ethnic minorities in the UK (see e.g. Dustmann et al., 2003). We restric here our sample to the total population aged 16-64.

[14] It does not include unpaid family workers.

[15] Because our analysis requires a high level of disaggregation by ethnic groups and by geographical areas, we cannot further disaggregate our data by sex, type of employment, sector or education level because of small sample sizes of each cell in each area.

We measure distance between areas by the average road journey time (in minutes) between the centres of the areas.[16] Indeed, driving times is a relative good representation of how agents' contacts develop and is better than other measures of proximity, such as physical distance or contiguity (see, e.g. Conley and Topa, 2002). The estimated road journey time between areas in the sample varies between 9.7 minutes and 514 minutes, with a median journey time of approximately 198 minutes. This spatial approach is essential to implement the test of our point (iii) above. Let us be more precise. In the original Calvó-Armengol and Jackson (2004) model the length of ties is measured by the path connecting individuals (see definitions 1 and 2). Since we approximate the social space by the physical space, to measure ties of different lengths we create *proximity bands* based on driving time between areas and we measure the population density by ethnic group within each proximity band. To be specific, for each local authority l in our sample, we create new variables containing the densities of ethnic population within 20 minutes driving time from local authority l; within 20-40 minutes, and so on. We assume that the population of each local authority is concentrated at the economic centre of the local authority, so that each time band (e.g., 20-40 minutes) contains the population densities of all areas whose centre is in the band (e.g., within 20-40 minutes from the centre of local authority l).[17] By comparing estimates across rings, it is possible to assess the impact of the density of own-race employed individuals living nearby and how far this effect extends.

The target variable in our theoretical framework is the probability of finding a job through social network contacts. In the LFS, the recently employed workers (i.e. those who are in their current job for no more than three months before 2005 and twelve months after 2005) were asked which job search method was used to obtain their current job, among the following list of possibilities: "reply to a job advertisement", "Jobcentre or jobmarket", "private employment agencies", "hearing from someone who worked there", "direct applications", "some other way". Table 2 shows that more than 20% of ethnic minority individuals found a job from hearing from someone who worked there. For Bangladeshi, almost 50% of the jobs are found through this method. Although there is no evidence that ethnic minorities necessarily benefit from this method more than whites (the percentage here is slightly less

[16] Distances in travel times and kilometers are estimated using Microsoft Autoroute 2002. The Microsoft Autoroute software computes the driving time between two locations on the basis of the most efficient route given the road network in 2002, and allowing for different average speeds of travel depending on the type of road.

[17] The analysis has also been performed assuming that the population is evenly distributed within the area (see, Rosenthal and Strange, 2008 and Rice and al., 2006, for details on this approach). The results remain qualitatively unchanged.

than 30%), the information about jobs provided by social contacts is a non-negligible factor for the labor market prospects of ethnic minorities.

In order to help establish the representativeness of our sample, it is important to compare these figures with the UK-wide pattern of job finding methods. In their tables 1 and 2, Battu et al. (2011) investigate similar issues using the same data sources (Labour Force Survey) for the UK. Although they refer to a slightly different period (1998-2001) and include only males, the data are for all the UK and not only for some areas (like in our study). They find very similar shares. Observe that, contrarily to Battu et al. (2011) who investigate the immigrant characteristics that associate with the type of job search method, we do not focus here on this aspect. Immigrant characteristics (sex, age, marital status, time since arrival in the UK, etc...) are used as controls in our analysis, i.e. we look at the relationship between ethnic population density and the probability of finding a job through social networks (relative to other search methods) *given* the immigrant characteristics.

[*Insert Table* 2 *here*]

5 Empirical strategy and estimation results

5.1 Empirical strategy

Our aim is to study whether and to what extent network size positively impacts on the individual probability of finding a job through social contacts for ethnic minorities as well as to uncover differences between ethnic groups. As mentioned above, we use the density of own-ethnic employed workers living nearby as a proxy for the size of each individual social network. This choice is motivated by the lack of data on the precise contacts each individual has. This can be a viable alternative but it comes at a cost. The assessment of the existence of a causal effect of local ethnic employment rate on individual labor market outcomes is a difficult empirical exercise. The main problem is the possible presence of *unobservable area characteristics* that can be responsible for an *endogenous sorting of individuals into areas*. For example, if the more able ethnic minority workers manage to live in more dynamic labor markets, with higher employment rates, and if these individuals are also the ones who benefit the most from job information provided by friends, then our estimates will be upward biased. In this paper, we address these concerns in two ways. First, we include *area fixed effects*. Our spatial unit of analysis is the local authority and we use fixed effects at the level of NUTS3 area, which are wider areas but far smaller that a region. By doing so, a large number of unobserved differences between areas are controlled for. Second, we use an *instrumental variable* strategy. We instrument the contemporaneous local authority ethnic employment density by its value lagged in time, as reported in the 1991 Census. As labor market conditions evolve over time, our assumption is that the factors that influenced the pattern of settlement of ethnic minorities in the past are unrelated with employment prospect today (and job search method efficacy), apart from their effect through the present-day ethnic density variable. Such a strategy has been extensively used in the literature. In fact, most of the literature uses the existence of immigrant communities and the assumption that the size of existing ethnic networks matter to generate instruments about the location of immigrants (see, for instance, Walker and Hannan, 1989; Altonji and Card, 1991; Massey and Zenteno, 1999; and Card, 2001).

Another issue is that high (low) employment rate areas are usually surrounded by high (low) employment rate areas. Traditional studies on the relationship between local employment rates and individual labor-market outcomes ignore possible spillover effects at the local level, i.e. the effect of the levels of the variables in neighboring areas. In this paper, we explicitly look at this issue. We take into account the geographical location of the areas and use *spatial data analysis techniques* to appreciate the range of action of the effects. Importantly, by creating ethnic employment density proximity bands, we define the relevant local community affecting individual employment prospects in a flexible way.

There are, of course, other possible identification strategies to tackle the issue of endogenous sorting of individuals into areas. Scandinavian studies have used *natural experiments* through placement policies that randomly allocate immigrants to locations (see Edin et al., 2003, or Åslund et al., 2010, for Sweden and Damm, 2009, for Denmark). Others have used very *detailed data* on location and jobs. For example, Bayer et al. (2008) take advantage of the use of data from the US Census, disaggregated at the level of the city block. City blocks are then grouped into small sets of adjacent areas and they then condition on block group fixed effects in their regression analysis to isolate block-level variation in neighbor attributes. Their identifying assumption is the absence of correlation in unobservables across blocks within block groups. Boeri et al. (2011) adopt an IV strategy based on the use of the physical characteristics of the buildings in different Italian urban structures. Others have used a more *structural approach*,[18] like e.g. Dennis Epple and his co-authors (see, in particular, Epple and Sieg, 1999; Epple et al., 2001; Epple et al., 2009). Their approach seeks to explain how members of a given total population, defined in terms of the distribution of individuals' demographic characteristics, allocate themselves via the housing market to

[18] For an overview on this approach, see Ioannides (2012, Chap. 3).

distinct communities. In particular, Epple et al. (2009) develop a model for the market of public housing that captures excess demand for public housing and rationing in equilibrium. They characterize the equilibrium and show that a unique equilibrium exists if the housing authority follows an equal treatment policy and does not discriminate based on current residence. They then develop a maximum likelihood estimator and estimate the parameters of the model based on a unique restricted use panel data set of low-income households in Pittsburgh.

As stated above, our strategy is different because we have neither a natural experiment nor data with such level of geographical detail and we do not use a completely structural approach. Instead, we condition on NUTS3 fixed effects (larger areas) and then investigate the spatial scale of the effects within each area using data at a lower (the lowest available) level of spatial disaggregation, which is the local authority level.

5.2 Empirical model and estimation results

For each ethnic group $r = W, BC, BA, I, P, B, C$,[19] we estimate the following regression model:

$$y_{i,l}^r = \alpha_1 X_{i,l}^r + \sum_{\sigma} \gamma_{\sigma}^r d_{\sigma,l}^r + \eta_c + \varepsilon_{i,l}^r, \tag{2}$$

where $y_{i,l}^r$ denotes the probability of finding a job through social contacts for individual i of type r in local authority l, $X_{i,l}^r$ is a set of control variables both at the individual i and local area l level that are likely to influence employment prospects of ethnic group r, and $d_{\sigma,l}^r$ denotes the employment rate of ethnic group r in local authority l within the proximity bands σ. The error term is composed of an area-specific fixed effect, η_c and a white noise error component, $\varepsilon_{i,a}^r$.

Table 3 collects the descriptive statistics for our set of control variables, for each ethnic group separately and for whites.

[*Insert Table* 3 *here*]

Table 4 reports the probit results from the estimation of (2) with four proximity bands: up to 20 min, 20 to 40 min, 40 to 60 min, 60 to 80, min, and our set of control variables, for each ethnic group in a separate panel. Looking at the table, the local employment density

[19] W stands for "White", BC for "Black Caribbean", BA for "Black African", I for "Indian", P for "Pakistani", B for "Bangladeshi" and C for "Chinese".

shows a positive effect on the probability of finding a job through social contacts, which is the greatest within 20 minutes driving time. This effect then decreases quite sharply with travel time and there is impact beyond approximately 60 minutes. This pattern remains unchanged across the different ethnic minority groups. If the ethnic employed population density is taken as a measure of the strength of social contacts, these results are consistent with our theoretical mechanisms. Indeed, the theoretical mechanism postulates that such contagion/spillover effects can be explained by the diffusion of information between adjacent areas. This means that strong ties (i.e. employed population density of the same ethnic group within 20 minutes driving time) have a greater positive impact on the probability of finding a job through friends than weak ties of length 2 (i.e. employed population density of the same ethnic group within 20 to 40 minutes driving time), which, in turn, has a higher impact than weak ties of length 3 (i.e. employed population density of the same ethnic group within 40 to 60 minutes driving time), etc.

The results show, however, important differences between ethnic groups both in terms of magnitude and statistical significance of the effects. For two of the Asian groups, Indian and Pakistani, the effects are not statistically significant. Instead, the four other groups display high and statistically significant effects. Interestingly, the effects are higher for the Chinese and the Bangladeshi groups than for the Black Caribbeans and Black Africans, confirming the idea that Chinese and Pakistani form close-knit networks. Focusing on the estimates of the spatial decay, Bangladeshis and Chineses also show higher rates of attenuation. In particular, the effects are quite localized for the Chineses since a one point percentage increase in the density of the Chinese employed population within 20 minutes driving time increases the Chinese probability of finding a job through social contacts by roughly 0.13 percentage points. This is more than twice the impact of the density of the Chinese employed population living 40 minutes away, and almost 6 times that of the density of the Chinese employed population living at 60 minutes.

The last panel of Table 4 shows the results that are obtained when the analysis is run on the white sample. The effect are extremely small in magnitude and statistical significant only for distances within 20 minutes (significant at only 10%). This confirms our idea that networks approximated by local population density mainly work for ethnic minorities but not for whites. In light of the model, this means that social networks are particularly strong and localized for the Chinese and Pakistani ethnic minorities. It does not mean, however, that whites do not use social networks for finding a job. It just means that the density of similar workers is *not* a good approximation for the social networks of white workers.

[*Insert Table* 4 *here*]

As mentioned before, a major concern of our empirical analysis can be described as follows. If local authorities that attract ethnic workers also have exogenously determined characteristics (not directly observables) that affect employment and the success of job search methods, then the employed population density variables might be correlated with the error term. In that case, instead of social networks, we may capture some unobserved characteristics of workers if, for example, the higher the (unobserved) ability of ethnic minorities, the more likely they live in areas with high employment rates and find a job through friends and relatives. Such a mechanism would lead to an overestimation in a standard OLS regression. We address this problem by using an instrumental variable approach. We instrument the contemporaneous level of ethnic employment population density by its value lagged in time. For each area (and each band) and each ethnic group, we take the corresponding population density reported in the 1991 Census. As labor market conditions evolve over time, our assumption is that the factors that influenced the pattern of settlement of ethnic minorities in the past are unrelated with employment prospect (and job search method efficacy) today, apart from their effect through the present-day ethnic population variable.[20]

Table 5 has the same structure as Table 4 and contains our IV results. Although the estimated effects are slightly lower in magnitude and less precisely estimated, the results confirm the main findings of Table 4.

Observe that our approach is likely to identify a Local Average Treatment Effect or LATE (Imbens and Angrist, 1994). Specifically, our estimates are identified by the subgroup of the ethnic population whose residential decision is affected by the presence of ethnic network ties. Those are the individuals who have weaker ties to the native population and are more likely to require assistance from the ethnic network. Therefore, this is the group that probably self-select the most to live in large immigrant ghettos in order to benefit from same-ethnicity networks. Note that this may actually be the LATE of policy interest for populations with fragile or uncertain attachment to the native labor markets. Intuitively, an ethnic minority individual who has completely assimilated to the white's norm and has a very extensive network of friends and professional contacts in the native population is almost observationally equivalent to a native, and we may not be very concerned about her outcomes in terms of policy any longer.

[20]The analysis has also been performed by excluding individuals surveyed in 1992 in order to ensure the instrument exogeneity. The results remain qualitatively unchanged.

[*Insert Table* 5 *here*]

6 Additional results

In this section, we investigate further our findings. As noted before, the small sample sizes of each ethnic group individuals in each area (local authority) prevent us to perform our analysis by type of employment, occupation or industrial sector. In other words, we cannot provide concluding results about the nature of the relationship between ethnic population density and employment prospect. For example, it can be driven by agglomeration of co-ethnic workers in specific activities or in self-employment. We cannot look at those issues here. However, we can perform two further exercises. Firstly, we can investigate if the effect of ethnic networks varies with the time since arrival in UK. In Tables 4 and 5 we used this information as a control. However, one might think that ethnic networks are much more important for recently-arrived immigrants, because they rely exclusively on family and friends in the same community to obtain information about jobs. As they stay longer in the country, immigrants develop broader networks including natives and individuals in other national groups. Table 6 shows the results of our analysis when considering only the subsample of individuals in the bottom quartile in terms of years since arrival in the UK.[21] We find that the our results are stronger for more recently arrived immigrants. In line with the expectations, this evidence points to the fact that more recently-arrived immigrants tend to rely more on local ethnic networks for finding a job.

Interestingly, using data on political refugees resettled in the U.S., Beaman (2012) shows that the relationship between social network size and labor market outcomes is heterogeneous and depends on the vintage of network members: an increase in network size can negatively impact some cohorts in a network while benefiting others. Her empirical results indicate that an increase in the number of social network members resettled in the same year or one year prior to a new arrival leads to a deterioration of outcomes, while a greater number of tenured network members improves the probability of employment.

[*Insert Table* 6 *here*]

Our second exercise, instead, looks at the differences between formal and informal methods of job findings. It is indeed interesting to know whether the importance and spatial

[21] In Table 6 and 7 we report the IVs results. OLS results are similar and remain available upon request.

attenuation of the effects of ethnic networks on the probability of finding a job differs between jobs found through formal or informal methods. Table 7 shows the results of our analysis when considering jobs obtained using the methods "replay to a job advertisement" and "direct applications" (grouped together). We can see that most of our results lose statistical significance. The effect of the ethnic network remains important only for the Chineses. Furthermore, the effect is spatially much less far reaching since it is virtually 0 after 20 minutes travel time. Indeed, the probability of finding a job through formal methods does not seem to be affected by the density of the ethnic population living nearby. These findings support our theoretical model based on ethnic networks as a channel of information sharing.

[*Insert Table* 7 *here*]

7 Concluding remarks

Using individual-level data from the UK Labour Force Survey, we look at the employment prospects of ethnic minorities by adding to the traditional determinants of employment rates (sex, age, education, years since arrival in UK, percentage of high-skilled leaving nearby, etc...) local ethnic employment density bands based on travel-time between areas. Such a specification allow us to define the relevant local community in a flexible way. Using sub-regional area-fixed effects and an IV approach, we find that the higher is the percentage of employed workers from a given ethnic group living nearby, the higher is the probability of finding a job through social networks. This effect decays, however, very rapidly with distance, losing significance beyond approximately an hour travel time. We argue that local social interactions between people of the same ethnicity can explain this positive relationship and its spatial trend. Conjecturing that the social space is highly correlated to the physical space for ethnic minorities in relatively small areas, we present a theoretical framework based on Calvó-Armengol and Jackson (2004), which shows that the individual probability of finding a job increases with the number of strong ties and weak ties, and the longer the length of weak ties, the lower is this probability. Our data are, however, limited for delivering conclusive results about the mechanisms at the basis of the complex relationship between employment and ethnicity. Our purpose here is to highlight that peer effects might be an important part of the story. If ethnic employment density is interpreted as a proxy for the strength of social contacts in delivering information about jobs, then our analysis suggests that they are quite localized and are relevant in explaining the spatial distribution of ethnic employment.

Our results are consistent with the view that ethnic minorities' success or failure in the labor market is influenced by the characteristics of the social networks in their local neighborhoods. Ethnic minorities living with large numbers of employed neighbors of the same ethnicity are more likely to have jobs than ethnic minorities residing in areas with fewer employed neighbors. This latter finding is consistent with earlier findings on Swedish (Edin et al., 2003), Danish (Damm, 2009) and U.S. immigration (Andersson et al., 2009) and draws at least partially on the notion that enclaves enable immigrants to form social networks that effectively make them act as intermediaries in getting jobs.

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Table 1: Sample description

	Black African	Black Caribbean	Indian	Pakistani	Bangladeshi	Chinese	Total
In total population	1.10	1.01	2.15	1.41	0.55	0.53	6.75
In total ethnic population	16.30	14.96	31.85	20.89	8.15	7.85	100
of which							
Employed	54	60	61	32	33	47	
Self-employed	4	6	2	9	5	11	

Notes. All Figures are percentages. For British, the percentages of employed and self-employed are 65 and 9 respectively

Table 2: Method used to find a job

	Black African	Black Caribbean	Indian	Pakistani	Bangladeshi	Chinese	British
Reply to a job advertisement	32	30	25	29	17	12	29
Jobcentre, jobmarket	10	7	10	7	8	12	7
Private employment agencies	16	8	15	4	8	15	8
Hearing from someone who worked there	20	27	21	22	46	23	27
Direct applications	17	14	17	32	13	27	18
Some other ways	5	8	12	6	8	11	11
N. Obs.	2446	2246	4780	3135	1223	1178	222,384

Notes. All Figures are percentages, except those in the last row.

Table 3: Descriptive statistics

	Black African	Black Caribbean	Indian	Pakistani	Bangladeshi	Chinese	British
Female	0.41 (0.49)	0.37 (0.48)	0.35 (0.48)	0.23 (0.42)	0.21 (0.41)	0.40 (0.49)	0.47 (0.50)
Age	36.02 (14.65)	35.10 (15.55)	33.12 (16.03)	30.84 (13.65)	30.02 (13.30)	31.12 (14.06)	38.01 (16.02)
Education qualification high	0.27 (0.48)	0.28 (0.48)	0.31 (0.49)	0.21 (0.42)	0.18 (0.39)	0.25 (0.48)	0.35 (0.027)
Married	0.41 (0.49)	0.40 (0.24)	0.36 (0.23)	0.29 (0.21)	0.33 (0.47)	0.47 (0.50)	0.61 (0.49)
Years in the UK	15.05 (13.13)	15.60 (11.02)	14.23 (13.07)	11.67 (10.99)	10.07 (10.04)	9.80 (8.88)	-
Born in UK	0.52 (0.50)	0.49 (0.50)	0.44 (0.50)	0.34 (0.47)	0.32 (0.47)	0.36 (0.48)	-
Local unemployment rate	0.11 (0.05)	0.11 (0.05)	0.11 (0.05)	0.12 (0.07)	0.11 (0.07)	0.11 (0.04)	0.11 (0.05)
Proportion of high-skilled population	0.19 (0.08)	0.19 (0.08)	0.19 (0.08)	0.18 (0.08)	0.18 (0.09)	0.19 (0.07)	0.19 (0.08)

Notes. Means and standard deviations (in parentheses) are reported. “Education qualification high” is a dummy taking value 1 if the respondent has A-level or above qualification. “Proportion of high-skilled population” is the percentage of people having A-level or above qualification in the local authority.

Table 4: Probability of Finding a Job Using Social Networks

	Black African	Black Caribbean	Indian	Pakistani	Bangladeshi	Chinese	British
Own ethnic group employment density							
…within 20 min	0.0788** (0.0328)	0.0678** (0.0319)	0.0298 (0.0219)	0.0037 (0.0046)	0.1099** (0.0509)	0.1271** (0.0599)	0.0005* (0.0003)
… within 20-40 min	0.0640** (0.0287)	0.0603** (0.0239)	0.0157 (0.0116)	0.0016 (0.0030)	0.0495** (0.0234)	0.0405** (0.0195)	0.0003 (0.0002)
… within 40-60 min	0.0495** (0.0231)	0.0462** (0.0217)	0.0103 (0.0096)	0.0011 (0.0020)	0.0218** (0.0100)	0.0223** (0.0110)	0.0001 (0.0001)
… within 60-80 min	0.0189 (0.0134)	0.0075 (0.0074)	0.0068 (0.0062)	0.0007 (0.0012)	0.0097 (0.0099)	0.0113 (0.0101)	0.0001 (0.0002)
female	0.0755 (0.0576)	0.0160 (0.0117)	-0.0314** (0.0116)	0.0038 (0.0071)	-0.0113 (0.0127)	0.0381* (0.0202)	0.0516** (0.0245)
age	-0.1302** (0.0651)	-0.1002** (0.0503)	-0.1227*** (0.0383)	-0.1455** (0.0658)	-0.1222** (0.0614)	-0.1292** (0.0652)	-0.0805*** (0.0210)
age^2	0.0003*** (0.0001)	0.0002** (0.0001)	0.0017*** (0.0005)	0.0055*** (0.0018)	0.0029* (0.0015)	0.0011* (0.0006)	0.0001*** (0.00001)
Education Qualification high	-0.0769*** (0.0290)	-0.0894*** (0.0319)	-0.1022*** (0.0302)	-0.1569*** (0.0459)	-0.1956*** (0.0669)	-0.1363** (0.0664)	-0.2093*** (0.0269)
Married	0.0302 (0.0291)	0.0230 (0.0275)	0.0016 (0.0055)	-0.0019 (0.0051)	0.0033 (0.0101)	0.0017 (0.0095)	0.1013** (0.0508)
Years in the UK	0.0005* (0.0003)	0.0004* (0.0002)	0.0001* (0.0001)	0.0002* (0.0001)	0.0007* (0.0004)	0.0003* (0.0002)	-
Born in UK	0.1867** (0.0914)	0.2013** (0.0989)	0.2546** (0.1254)	0.2122** (0.1066)	0.2647** (0.1332)	0.3001** (0.1511)	-
Local unemployment rate	-0.0042** (0.0019)	-0.0040** (0.0020)	-0.0041** (0.0022)	-0.0079** (0.0036)	-0.0030* (0.0016)	-0.0026* (0.0014)	-0.0134** (0.0067)
Proportion of high-skilled population	-0.0010 (0.0009)	-0.0015* (0.0008)	-0.0129* (0.0073)	-0.0199* (0.0115)	-0.0269* (0.0159)	-0.0150 (0.0096)	-0.0115** (0.0057)
NUTS3 area fixed effects	yes	Yes	yes	yes	yes	yes	yes

Notes. Probit estimation results. Marginal effects at the sample means and clustered standard errors (in parentheses) are reported; time dummies are included; * significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Probability of Finding a Job Using Social Networks - IV estimates -

	Black African	Black Caribbean	Indian	Pakistani	Bangladeshi	Chinese	British
Own ethnic group employment density							
…within 20 min	0.0673*	0.0662**	0.0218	0.0028	0.0927*	0.1224**	0.0003
	(0.0351)	(0.0333)	(0.0243)	(0.0049)	(0.0516)	(0.0612)	(0.0003)
… within 20-40 min	0.0577*	0.0558**	0.0142	0.0012	0.0447*	0.0383*	0.0001
	(0.0299)	(0.0278)	(0.0149)	(0.0040)	(0.0250)	(0.0213)	(0.0002)
… within 40-60 min	0.0483*	0.0456*	0.0088	0.0010	0.0233*	0.0211*	0.0001
	(0.0255)	(0.0240)	(0.0100)	(0.0033)	(0.0132)	(0.0121)	(0.0001)
… within 60-80 min	0.0101	0.0057	0.0040	0.0008	0.0087	0.0099	0.0001
	(0.0162)	(0.0098)	(0.0034)	(0.0014)	(0.0101)	(0.0106)	(0.0002)
female	0.0790	0.0150	-0.0298*	0.0030	-0.0121	0.0368	0.0525**
	(0.0590)	(0.0155)	(0.0166)	(0.0096)	(0.0142)	(0.0225)	(0.0260)
age	-0.1293**	-0.0980*	-0.1244***	-0.1379**	-0.1215**	-0.1333**	-0.0816***
	(0.0654)	(0.0510)	(0.0399)	(0.0689)	(0.0620)	(0.0660)	(0.0247)
age^2	0.0003**	0.0002**	0.0019***	0.0065***	0.0032*	0.0012*	0.0002***
	(0.0001)	(0.0001)	(0.0005)	(0.0025)	(0.0017)	(0.0007)	(0.0001)
Education Qualification High	-0.0605**	-0.0666**	-0.0855***	-0.1234***	-0.1328**	-0.0999**	-0.1879***
	(0.0300)	(0.0316)	(0.0288)	(0.0404)	(0.0645)	(0.0504)	(0.0214)
Married	0.0313	0.0243	0.0015	-0.0022	0.0044	0.0027	0.1094**
	(0.0302)	(0.0288)	(0.0059)	(0.0059)	(0.0114)	(0.0100)	(0.0545)
Years in the UK	0.0005*	0.0004*	0.0001*	0.0002*	0.0007*	0.0003*	-
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0004)	(0.0002)	
Born in UK	0.1800*	0.1920*	0.2415*	0.2100*	0.2588**	0.2930*	-
	(0.0947)	(0.1021)	(0.1271)	(0.1150)	(0.1369)	(0.1542)	
Local unemployment rate	-0.0065**	-0.0060**	-0.0055**	-0.0087**	-0.0050*	-0.0038*	-0.0159**
	(0.0034)	(0.0031)	(0.0025)	(0.0044)	(0.0026)	(0.0020)	(0.0075)
Proportion of high-skilled population	-0.0019	-0.0018	-0.0138*	-0.0231*	-0.0286*	-0.0169	-0.0128**
	(0.0015)	(0.0015)	(0.0075)	(0.0122)	(0.0165)	(0.0109)	(0.0068)
NUTS3 area fixed effects	yes	yes	yes	yes	yes	yes	yes

Notes. Probit estimation results. Marginal effects at the sample means and clustered standard errors (in parentheses) are reported; time dummies are included; * significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Probability of Finding a Job Using Social Networks - IV estimates –

-More recently arrived immigrants-

	Black African	Black Caribbean	Indian	Pakistani	Bangladeshi	Chinese
Own ethnic group employment density						
…within 20 min	0.1052***	0.0866***	0.0426	0.0222**	0.1250**	0.1482**
	(0.0370)	(0.0320)	(0.0350)	(0.0101)	(0.0541)	(0.0621)
… within 20-40 min	0.0943***	0.0698***	0.0317	0.0105	0.0674**	0.0505**
	(0.0349)	(0.0250)	(0.0271)	(0.0088)	(0.0331)	(0.0252)
… within 40-60 min	0.0721**	0.0505**	0.0199	0.0061	0.0356**	0.0277**
	(0.0326)	(0.0224)	(0.0201)	(0.0055)	(0.0169)	(0.0130)
… within 60-80 min	0.0209	0.0157	0.0070	0.0005	0.0150	0.0115
	(0.0218)	(0.0198)	(0.0049)	(0.0027)	(0.0140)	(0.0125)
Female	0.0691	0.0130	-0.0210	0.0101*	-0.0103	0.0376
	(0.0599)	(0.0169)	(0.0201)	(0.0060)	(0.0155)	(0.0249)
Age	-0.1100**	-0.0909**	-0.0791***	-0.1075**	-0.0921**	-0.0899**
	(0.0539)	(0.0445)	(0.0290)	(0.0519)	(0.0400)	(0.0450)
age^2	0.0003**	0.0003**	0.0015***	0.0076***	0.0030**	0.0011*
	(0.0001)	(0.0001)	(0.0005)	(0.0027)	(0.0014)	(0.0006)
Education Qualification High	-0.0510**	-0.0602**	-0.0777**	-0.0900**	-0.1136**	-0.0901**
	(0.0245)	(0.0306)	(0.0330)	(0.0438)	(0.0558)	(0.0450)
Married	0.0460	0.0402	0.0180*	0.0043	0.0100	0.0032
	(0.0439)	(0.0366)	(0.0102)	(0.0075)	(0.0121)	(0.0125)
Local unemployment rate	-0.0076**	-0.0069**	-0.0041*	-0.0085**	-0.0042*	-0.0037*
	(0.0037)	(0.0033)	(0.0024)	(0.0042)	(0.0023)	(0.0021)
Proportion of high-skilled population	-0.0025	-0.0022	-0.0146*	-0.0245	-0.0298*	-0.0198
	(0.0020)	(0.0019)	(0.0077)	(0.0185)	(0.0170)	(0.0123)
NUTS3 area fixed effects	Yes	yes	yes	yes	yes	yes

Notes. Probit estimation results. Marginal effects at the sample means and clustered standard errors (in parentheses) are reported; time dummies are included; * significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: Probability of Finding a Job Using More Formal Methods - IV estimates -

	Black African	Black Caribbean	Indian	Pakistani	Bangladeshi	Chinese	British
Own ethnic group employment density							
…within 20 min	-0.0330 (0.0322)	-0.0359 (0.0373)	-0.0129 (0.0210)	0.0015 (0.0099)	-0.0102 (0.0251)	0.0257** (0.0122)	-0.0011 (0.0007)
… within 20-40 min	-0.0285 (0.0255)	-0.0255 (0.0329)	-0.0111 (0.0169)	0.0011 (0.0077)	-0.0045 (0.0129)	0.0185 (0.0145)	-0.0004 (0.0003)
… within 40-60 min	-0.0204 (0.0202)	-0.0214 (0.0284)	-0.0090 (0.0123)	-0.0010 (0.0053)	-0.0025 (0.0135)	0.0072 (0.0113)	-0.0002 (0.0002)
… within 60-80 min	-0.0109 (0.0116)	0.0008 (0.0189)	-0.0064 (0.0095)	-0.0003 (0.0022)	-0.0005 (0.0108)	-0.0066 (0.0109)	-0.0001 (0.0002)
female	-0.0587 (0.0499)	-0.0123 (0.0165)	0.0102 (0.0199)	-0.0054 (0.0109)	0.0099 (0.0140)	-0.0203 (0.0206)	-0.0326** (0.0168)
age	-0.1293** (0.0654)	-0.1095** (0.0515)	-0.1205*** (0.0385)	-0.1398** (0.0656)	-0.1166** (0.0569)	-0.1253** (0.0601)	-0.0909*** (0.0254)
age^2	0.0010** (0.0004)	0.0006** (0.0001)	0.0022*** (0.0006)	0.0069*** (0.0021)	0.0030** (0.0015)	0.0018** (0.0008)	0.0007*** (0.0002)
Education Qualification High	0.0355** (0.0182)	0.0456** (0.0222)	0.0621*** (0.0243)	0.1013** (0.0450)	0.1118** (0.0521)	0.0767* (0.0465)	0.2312*** (0.0621)
Married	-0.0231 (0.0430)	-0.0264 (0.0400)	-0.0087 (0.0105)	-0.0002 (0.0077)	-0.0037 (0.0150)	-0.0015 (0.0123)	-0.0984** (0.0490)
Years in the UK	-0.0002 (0.0003)	-0.0001 (0.0004)	-0.0001 (0.0001)	-0.0002* (0.0001)	-0.0003 (0.0004)	-0.0005* (0.0002)	-
Born in UK	-0.0801 (0.0915)	-0.0848 (0.0977)	-0.1243 (0.1260)	-0.1090 (0.1100)	-0.1511 (0.1468)	-0.1669 (0.1555)	-
Local unemployment rate	-0.0030 (0.0033)	-0.0051 (0.0064)	0.0032* (0.0018)	0.0063* (0.0035)	0.0026 (0.0032)	0.0023 (0.0019)	0.0091** (0.0045)
Proportion of high-skilled population	0.0021 (0.0018)	0.0019 (0.0016)	0.0121* (0.0067)	0.0160 (0.0131)	0.0128 (0.0116)	0.0117 (0.0104)	0.0356** (0.0099)
NUTS3 area fixed effects	yes	yes	yes	yes	yes	yes	yes

Notes. Probit estimation results. Marginal effects at the sample means and clustered standard errors (in parentheses) are reported; time dummies are included; * significant at 10%; ** significant at 5%; *** significant at 1%. Formal methods include "private employment agencies" and "direct applications".