Social Interactions and the Labor Market*

Yves Zenou†

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Abstract

To better understand the way social networks operate in the labor market, we propose two simple models where individuals help each other finding a job. In the first one, job information flows between individuals having a link with each other and we show that an equilibrium with a clustering of workers with the same status is likely to emerge since, in the long run, employed workers tend to be friends with employed workers. In the second model, individuals interact with both strong and weak ties and decide how much time they spend with each of them. As in Granovetter, this model stresses the strength of weak ties in finding a job because they involve a secondary ring of acquaintances who have contacts with networks outside ego's network and therefore offer new sources of information on job opportunities. We then discuss some policy implications showing how these models can explain why ethnic minorities tend to experience higher unemployment rate than workers from the majority group.

Key words: Social interactions, weak and strong ties, dyads, homophily.

JEL Classification: A14, J15, J64, Z13.

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†Stockholm University, Department of Economics, 106 91 Stockholm, Sweden, and GAINS, Université du Maine. E-mail: yves.zenou@ne.su.se.

1 Introduction

A large body of research, first in sociology, then in physics, and more recently in economics, has studied the importance of social networks in different activities. For example, the decision of an agent whether to buy or not a new product, attend a meeting, commit a crime, find a job is often influenced by the choices of his or her friends and acquaintances (be they social or professional). The emerging empirical evidence on these issues motivates the theoretical study of network effects. For example, job offers can be obtained from direct, and indirect, acquaintances through word-of-mouth communication. Also, risk-sharing devices and cooperation usually rely on family and friendship ties. Spread of diseases, such as AIDS infection, also strongly depends on the geometry of social contacts. If the web of connections is dense, we can expect higher infection rates.[1]

In the present paper, we focus on the role of social networks in the labor market. Indeed, 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, 1973, 1974; Corcoran et al., 1980; Holzer, 1988; Montgomery, 1991; Gregg and Wadsworth, 1996; Addison and Portugal, 2002; Ioannides and Loury, 2004; Wahba and Zenou, 2005; Ioannides and Topa, 2010; Pellizzari, 2010; Topa, 2011). For example, 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.

We investigate the role of social networks in the labor market by presenting two different approaches, which both have a dynamic perspective. We first present the model of Calvó-Armengol and Jackson (2004) who explicitly model social networks as graphs.[2] The authors study the evolution over time of employment statuses of n workers connected by a network of relationships. Individuals exchange job information only with their strong ties (as defined by their direct friends) while weak ties (as defined by friends of friends) will indirectly help them by providing job information to their strong ties. They are able to determine how the network of relationships influences these outcomes. It is shown that, in steady-state, there

[1] There is a growing literature on networks. See, in particular, Goyal (2007), Jackson (2008), de Martí and Zenou (2011), Ioannides (2012) and Jackson and Zenou (2013) for overviews.

[2] See also Boorman (1975), Calvó-Armengol (2004), Calvó-Armengol and Zenou (2005), Fontaine (2008) and Cahuc and Fontaine (2009).

is a positive correlation in employment status between two path-connected workers. This result is not trivial since, in the short run, the correlation is negative (see Boorman, 1975; Calvó-Armengol, 2004; Calvó-Armengol and Zenou, 2005). Indeed, in a static model, if an employed worker is directly linked to two unemployed workers, then if she is aware of a job, she will share this job information with her two unemployed friends. These two individuals, who are path-connected (path of length two), are thus in competition with each other and only one of them (randomly chosen) will obtain the job and be employed while the other will remain unemployed. So their employment status will be negatively correlated. This leads to homophily and clustering and thus the quality of the network is the main determinant of individual's outcomes.

We then present the model of Zenou (2011, 2012).[3] Individuals belong to mutually exclusive two-person groups, referred to as dyads and two individuals belonging to the same dyad hold a strong tie to each other. Individuals can also meet weak ties outside of the dyad. Building on Granovetter (1973, 1974, 1983)'s idea that weak ties are superior to strong ties for providing support in getting a job, this model develops a social interaction model where workers can obtain a job through either their strong or weak ties. In this model, it is better to meet weak ties because a strong tie does not help in the state where all best friends are unemployed. But a weak tie can help leaving unemployment in any state because that person might be employed. So there is an asymmetry that is key to the model and that explains why some workers (for example, ethnic minorities) may be stuck in poverty traps having little contact with weak ties (for example, the majority group) that can help them escape unemployment.

The paper unfolds as follows. In the next section, we provide some evidence on the importance of social networks in the labor market in France and in the UK. In Section 3, we expose the model of Calvó-Armengol and Jackson (2004) while, in Section 4, the one of Zenou (2011, 2012). Finally, Section 5 concludes and discuss some policy implications.

2 Evidence on social networks in the labor market in France and in the UK

We first present some evidence for France using the TeO (Trajectoire et Origine) survey. This survey was performed between September 2009 and February 2009 by researchers from

[3] See also Calvó-Armengol et al. (2007) and Patacchini and Zenou (2008) for the same type of models but for criminal activities.

INED and INSEE and the final sample comprises 15,862 individuals between 17 and 60 years old. Employed individuals were asked about the main job search method used in finding their current jobs while those currently unemployed were also asked about the job search method they were using to find a job, but they were allowed to list more than one job search method, i.e. respondent reports yes or no to a list of job search methods.

Table 1 shows that one fourth (25.4%) of all employed workers obtained their current jobs through friends and relatives. It also shows that the main search methods used by the unemployed are "friends and relatives" (79.7%). This is accordance with other studies. Compared to the U.S., approximately 50% of all workers currently employed found their jobs through friends and relatives (Montgomerry, 1991). Holzer (1987, 1988) found that, among the young unemployed, 80% are using "friends and relatives". Among employed men, 35% obtained their jobs through friends and relatives compared to 21% for women, and 57% of young employed workers (15-19 year old) have obtained their current jobs through social networks.

[*Insert Table* 1 *here*]

If we differentiate by nationality, Table 2 shows that French unemployed workers tend to use more their social networks than non-French workers. Interestingly, in Table 3, we see that the most successful workers who find their jobs through their social networks are the non-French Europeans while non-European immigrants who use a lot their social networks have a lower chance of finding with this method as compared to direct applications.

[*Insert Tables* 2 and 3 *here*]

If we look at the UK (Tables 4 and 5; see Battu et al., 2011) the picture is slightly different. These tables utilizes data drawn from twelve consecutive waves of the Quarterly Labour Force Survey (QLFS) – the first wave is the December 1998 to February 1999 wave while the last wave is the September 2001 to November 2001 wave. Each wave covers around 60,000 households incorporating around 150,000 individuals. Only males of working age (aged 16 to 65) are used in these tables.

Table 4 shows the primary job search methods used of unemployed individuals. By far the two most commonly used methods are institutional and adverts, with less than 10% of the unemployed having friends and family as their main job search method (personal networks). This general ranking has been found elsewhere (Gregg and Wadsworth, 1996) and the relative unimportance of personal networks in the UK has also been found by Fritjers et al. (2005). There are also important differences across different ethnic groups. Friends and family are used more heavily by Indians, Pakistanis, Bangladeshis and 'Others' compared to

Whites and Blacks. 14.2% of the Pakistani/Bangladeshi group have friends and family as their primary job search method. Blacks (Black-Caribbean and Black-African) are the least likely to use personal networks (9.6% of them use personal networks) and are the most likely to resort to the institutional method. The Pakistani/Bangladeshi ethnic group are also less likely to use adverts compared to the other ethnic groups.

[*Insert Table* 4 *here*]

Table 5 shows what job search method was successful — not necessarily what they were using as their primary job search method. The job search methods that generated the greatest success for the newly employed were in order of importance institutional, personal networks and adverts. Direct applications were only deemed successful for around 15% of respondents. Nearly 30% of respondents were successful using personal networks. From Table 5 it is clear that although Indians, Pakistanis, Bangladeshis and 'Others' used personal networks the most (Table 4), there is little evidence that they benefited from this method more so than whites. This is consistent with the French evidence displayed in Table 3.

[*Insert Tables* 5 *here*]

3 Social Interactions and the Labor Market: A first model

We would like to propose a first theoretical framework based on the paper by Calvó-Armengol and Jackson (2004).

3.1 Some notations and definitions from graph theory[4]

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 $N = \{1, \ldots, n\}$ is a set of individuals connected in some network relationship. A network is 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 $n_i(\mathbf{g})$.

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

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 $g_{ii_1} g_{i_1 i_2} ... g_{i_k j} \neq 0$.

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.*

3.2 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 λ 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:

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

where the vector $\mathbf{s}$ describes the employment status of all the individuals at the beginning of the period. In (1), λ 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 λ 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: $\lambda / \sum_{k: s_k = 0} g_{ik}$. Finally, if individual j is employed, then she does not need any job information, at least in the current period.

3.3 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 λ 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. 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. See, for example, Calvó-Armengol (2004).

3.4 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 $\mathbf{s}_{t-1} = (0, 1, 0)$, where "0" means unemployed and "1" employed. 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.

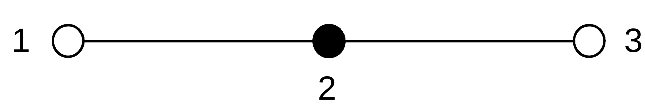


Figure 1: Employment correlations in a star-shaped network

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 λ 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 $\mathcal{M}(\lambda, \delta)$, we can analyze the associated Markov process $\mathcal{M}(\lambda/T, \delta/T)$, that we name the $T-$*period subdivision* of $\mathcal{M}(\lambda, \delta)$, 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 $\mathcal{M}(\lambda/T, \delta/T)$. For this Markov process, at every period, every shock (be it a job arrival λ/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 $\mathcal{M}(\lambda/T, \delta/T)$, we analyze an approximated Markov process $\mathcal{M}^*(\lambda/T, \delta/T)$ 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 $\mathcal{M}^*(\lambda/T, \delta/T)$ to that of the true Markov process $\mathcal{M}(\lambda/T, \delta/T)$, 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.

3.5 Clustering and homophily

The model of Calvó-Armengol and Jackson (2004) shows 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.

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 $\lambda = 0.10$ and $\delta = 0.015$.

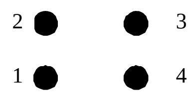
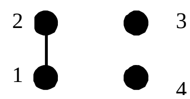
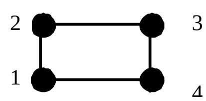
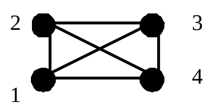
	Probability of being unemployed for individual 1	Correlations in employment statuses between 1 and 2	Correlations in employment statuses between 1 and 3
	0.132	–	–
	0.083	0.041	–
	0.063	0.025	0.019
	0.050	0.025	0.025

Figure 2: Employment correlations as a function of network structure

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. $\delta/(\lambda+\delta) = 0.13$. 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.

3.6 The case of dyads

To better understand the model, consider the simplest possible network, i.e. a dyad so that $n = 2$, and $g_{12} = g_{21} = 1$. Dyads, which consist of paired individuals, can be in three different states:[5]

(i) both members are employed −we denote the number of such dyads by d_2;

(ii) one member is employed and the other is not (d_1);

(iii) both members are unemployed (d_0).

There are thus three states, up to relabelling: $(0,0),(0,1)$ and $(1,1)$ corresponding to dyads d_0, d_1 and d_2. We order them in increasing order for the partial coordinate-wise order. The total population is normalized to 1.

We here assume that *time is continuous*. This simplifies a lot the analysis because, in the continuous time Markov process, the probability of a two-state change is zero (small order) during a small interval of time t and $t+dt$. This means, in particular, that both members of a dyad cannot change their status at the same time. For example, two unemployed workers cannot find a job at the same time, i.e. during t and $t+dt$, the probability assigned to a transition from a d_0-dyad to a d_2-dyad is zero. Similarly, two employed workers (d_2-dyad) cannot both become unemployed, i.e. switch to a d_0-dyad during t and $t+dt$. This is similar to the model above with the $T-$*period subdivision* of $\mathcal{M}(\lambda,\delta)$ when T was high enough.

As above, the state of the economy s_t evolves following a Markov process $\mathcal{M}(\lambda,\delta)$ where λ is the job arrival rate and δ is the job-destruction rate. We gather the Markov transitions into a matrix $m_{ij} = \Pr\{s_{t+1} = i \mid s_t = j\}$, where $i,j \in \{(0,0),(0,1),(1,1)\}$. Thus $d_0(t)$ is the fraction of the population of size 1 which is in state $(0,0)$ in period t and thus $d_0(t)$ is the total number of members of the population in state $(0,0)$ in period t. Similarly, $d_2(t)$ is the fraction of the population of size 1 which is in state $(1,1)$ in period t and $d_2(t)$ is the total number of members of the population in state $(1,1)$ in period t. Finally, $d_1(t)$ is the fraction of the population of size 1 which is in state $(0,1)$ in period t and $d_1(t)$ is the total number of members of the population in state $(0,1)$ in period t.

In steady state, the population normalization means that

$$2d_0^* + 2d_1^* + 2d_2^* = 1 \tag{2}$$

[5] The inner ordering of dyad members does not matter.

and the employment and unemployment rates are:

$$\begin{cases} e^* = 2d_2^* + d_1^* \\ u^* = 2d_0^* + d_1^* \end{cases} \tag{3}$$

It is readily checked that the net flow of dyads from each state between t and $t + dt$ is given by:

$$\begin{cases} \overset{\bullet}{d}_2(t) = 2\lambda d_1(t) - 2\delta d_2(t) \\ \overset{\bullet}{d}_1(t) = 2\lambda d_0(t) - (\delta + 2\lambda)\, d_1(t) + 2\delta d_2(t) \\ \overset{\bullet}{d}_0(t) = \delta d_1(t) - 2\lambda d_0(t) \end{cases}$$

Indeed, between a small interval of time t and $t + dt$, the variation of dyads composed of two employed workers is equal to the number of d_1-dyads in which the unemployed worker has found a job minus the number of d_2-dyads in which one of the two employed workers has lost her job. What is crucial here is that workers can find a job either directly (at rate λ) or through their dyad friend if she is employed and has heard about a job opportunity (at rate λ). All the other equations have a similar interpretation. These dynamic equations reflect the flows across dyads. Graphically,

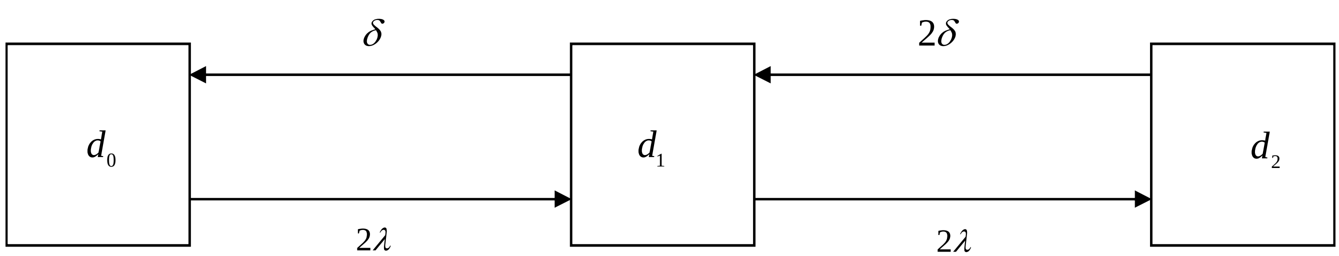


Figure 3: Flows in the labor market in Calvó-Armengol and Jackson (2004)

In steady state, $\overset{\bullet}{d}_2(t) = \overset{\bullet}{d}_1(t) = \overset{\bullet}{d}_0(t) = 0$ so that (using (2)):

$$d_0^* = \frac{\delta^2}{2\left(2\lambda^2 + 2\lambda\delta + \delta^2\right)} \tag{4}$$

$$d_1^* = \frac{\lambda\delta}{2\lambda^2 + 2\lambda\delta + \delta^2} \tag{5}$$

$$d_2^* = \frac{\lambda^2}{2\lambda^2 + 2\lambda\delta + \delta^2} \tag{6}$$

and thus the employment probability converges to

$$e^*(\text{dyad}) = 2d_2^* + d_1^* = \frac{2\lambda^2 + \lambda\delta}{2\lambda^2 + 2\lambda\delta + \delta^2} \tag{7}$$

Let us better understand this result. Denote by $s = (s_1, s_2)$ the state of the dyad and observe that d_0^* corresponds to $\{s_1 = 0, s_2 = 0\}$, d_2^* to $\{s_1 = 1, s_2 = 1\}$ and d_1^* to either $\{s_1 = 0, s_2 = 1\}$ or $\{s_1 = 1, s_2 = 0\}$. The latter implies that in steady state the fraction of people who will be in state $\{s_1 = 0, s_2 = 1\}$ is $d_1^*/2 = \frac{\lambda\delta}{2\left(2\lambda^2+2\lambda\delta+\delta^2\right)}$, and the fraction of people who will be in state $\{s_1 = 1, s_2 = 0\}$ is $d_1^*/2 = \frac{\lambda\delta}{2\left(2\lambda^2+2\lambda\delta+\delta^2\right)}$. As a result, the steady-state joint distribution is given by:

	$s_2 = 0$	$s_2 = 1$
$s_1 = 0$	$\frac{\delta^2}{2\left(2\lambda^2+2\lambda\delta+\delta^2\right)}$	$\frac{\lambda\delta}{2\left(2\lambda^2+2\lambda\delta+\delta^2\right)}$
$s_1 = 1$	$\frac{\lambda\delta}{2\left(2\lambda^2+2\lambda\delta+\delta^2\right)}$	$\frac{\lambda^2}{2\lambda^2+2\lambda\delta+\delta^2}$

(8)

The marginal probability to be employed is either to belong to a d_1-dyad or a d_2-dyad and is thus equal to

$$\frac{\lambda\delta}{2\left(2\lambda^2+2\lambda\delta+\delta^2\right)} + \frac{\lambda\delta}{2\left(2\lambda^2+2\lambda\delta+\delta^2\right)} + \frac{2\lambda^2}{2\lambda^2+2\lambda\delta+\delta^2} = \frac{2\lambda^2+\lambda\delta}{2\lambda^2+2\lambda\delta+\delta^2}$$

which is (7).

Let us now calculate the employment rate of isolated workers (i.e. not linked by a network). We easily obtained:

$$e^*(\text{isolated}) = \frac{\lambda}{\lambda+\delta}$$

As a result,

$$e^*(\text{dyad}) > e^*(\text{isolated})$$

The probability of being employed is therefore higher for a worker in a dyad than for an isolated agent, reflecting the fact that an agent may hear about a job opportunity from the other agent.

Let us now calculate the correlation in employment status between the two individuals in a dyad. We have:

$$Cor\left(s_1 = 1, s_2 = 1\right) = \frac{Cov\left(s_1 = 1, s_2 = 1\right)}{\sqrt{Var\left(s_1 = 1\right) Var\left(s_2 = 1\right)}}$$

where

$$
\begin{aligned}
Cov\left(s_1=1,s_2=1\right) &= \mathbb{E}\left(s_1=1,s_2=1\right)-\left[\mathbb{E}\left(s_1=1\right)\right]\left[\mathbb{E}\left(s_2=1\right)\right] \\
&= 2d_2^*-\left(e^*\right)^2=\frac{2\lambda^2}{2\lambda^2+2\lambda\delta+\delta^2}-\frac{\left(2\lambda^2+\lambda\delta\right)^2}{\left(2\lambda^2+2\lambda\delta+\delta^2\right)^2} \\
&= \frac{\lambda^2\delta^2}{\left(2\lambda^2+2\lambda\delta+\delta^2\right)^2}
\end{aligned}
$$

$$
\begin{aligned}
Var\left(s_1=1\right) &= \mathbb{E}\left(s_1=1\right)-\left[\mathbb{E}\left(s_1=1\right)\right]^2=\frac{2\lambda^2+\lambda\delta}{2\lambda^2+2\lambda\delta+\delta^2}-\left(\frac{2\lambda^2+\lambda\delta}{2\lambda^2+2\lambda\delta+\delta^2}\right)^2 \\
&= \frac{\lambda\delta\left(2\lambda+\delta\right)\left(\lambda+\delta\right)}{\left(2\lambda^2+2\lambda\delta+\delta^2\right)^2}=Var(s_2=1)=\mathbb{E}\left(s_2=1\right)-\left[\mathbb{E}(s_2=1)\right]^2
\end{aligned}
$$

Thus

$$
Cor\left(s_1=1,s_2=1\right)=\frac{\lambda\delta}{\left(2\lambda+\delta\right)\left(\lambda+\delta\right)}>0
$$

The employment status of two employed individuals is *positively correlated*: if one agent is employed, the probability that the other agent is employed is positive since they help each other finding a job. Furthermore, when $\delta=0$, i.e. no destruction rate, the correlation is equal to zero since, as soon as $\lambda>0$, everybody will end up employed independently of her partner in the dyad. The same intuition applies to $\lambda=0$ where everybody will end up unemployed. Observe, finally, that the correlation $Cor\left(s_1=1,s_2=1\right)$ increases with δ and decreases with λ if and only if $2\lambda^2>\delta^2$. Indeed, if λ is larger than δ, i.e. people hear more about jobs than jobs are destroyed, then when the destruction rate δ increases, individuals tend to be more often unemployed and thus help each other more to find a job since λ is relatively high. As a result, their correlation employment status increases. The same reasoning applies for a decrease in λ.

4 Social Interactions and the Labor Market: A second model

Let us now described the model by Zenou (2011, 2012) where the network is simplified since we only consider dyads. We can, however, study other aspects of the labor market.

4.1 The model

Consider again a population of individuals of size one. Time is continuous and individuals live for ever. As in Section 3.6, we assume that individuals belong to mutually exclusive two-person groups, referred to as *dyads*. We say that two individuals belonging to the same dyad hold a *strong tie* to each other. We assume that dyad members do not change over time. A strong tie is created once and for ever and can never be broken. Thus, we can think of strong ties as links between members of the same family, or between very close friends. We assume repeated random pairwise meetings over time. Matching can take place between dyad partners or not. At time t, each individual can meet a weak tie with probability $\omega(t)$ (thus $1-\omega(t)$ is the probability of meeting her strong-tie partner at time t).[6] We assume these probabilities to be constant and exogenous, not to vary over time and thus, they can be written as ω and $1-\omega$. Compared to the previous model, the definition of weak and strong ties is different. Here it is really the intensity of the relationship that defines weak and strong ties, given that weak ties change over time while strong ties don't.[7] In the previous model, strong and weak ties did not change over time; they were defined by the closeness of the relationship (length of the links) in the network. In his seminal papers, Granovetter (1973, 1974, 1983) defines *weak ties* in terms of lack of overlap in personal networks between any two agents, i.e. weak ties refer to a network of acquaintances who are less likely to be socially involved with one another. Formally, two agents A and B have a weak tie if there is little or no overlap between their respective personal networks. Vice versa, the tie is *strong* if most of A's contacts also appear in B's network.

To summarize, we refer to matchings inside the dyad partnership as *strong ties*, and to matchings outside the dyad partnership as *weak ties* or random encounters. Within each matched pair, information is exchanged, as explained below.

As in Section 3.6, individuals can be in either of two different states: employed (state 1) or unemployed (state 0) and there are therefore three different states: both members are employed (dyad d_2), one member is employed and the other is not (dyad d_1) and both members are unemployed (dyad d_0).

Let us now describe how job is transmitted. Each job offer is taken *to arrive only to employed workers*, who can then direct it to one of their contacts (through either strong

[6] If each individual has one unit of time to spend with her friends, then $\omega(t)$ can also be interpreted as the percentage of time spent with weak ties.

[7] Observe that strong ties and weak ties are assumed to be substitutes, i.e. the more someone spends time with weak ties, the less he has time to spend with her strong tie.

or weak ties).[8] This is the main difference with Section 3.6 where both workers could hear about a job. Here it is only the person who is employed that can hear about a job and then transmit it to her dyad partner. To be more precise, employed workers hear of job vacancies at the exogenous rate λ while they lose their job at the exogenous rate δ. All jobs and all workers are identical (*unskilled labor*) so that all employed workers obtain the same wage. Therefore, employed workers, who hear about a job, pass this information on to their current matched partner, who can be a strong or a weak tie. Thus, information about jobs is essentially obtained through social networks. This information transmission protocol defines a Markov process. The state variable is the relative size of each type of dyad.

It is readily checked that the net flow of dyads from each state between t and $t + dt$ is given by:

$$\begin{cases} \dot{d}_2(t) = h(e(t))d_1(t) - 2\delta d_2(t) \\ \dot{d}_1(t) = 2g(e(t))d_0(t) - [\delta + h(e(t))]\, d_1(t) + 2\delta d_2(t) \\ \dot{d}_0(t) = \delta d_1(t) - 2g(e(t))d_0(t) \end{cases} \tag{9}$$

where $h(e(t)) \equiv [1 - \omega + \omega\, e(t)]\, \lambda$ and $g(e(t)) \equiv \omega\, e(t)\lambda$ and where the employment rate $e(t)$ is given by (3).

Let us explain in details these equations. Take the first one. Then, during a small interval of time, the variation of dyads composed of two employed workers ($\dot{d}_2(t)$) is equal to the number of d_1-dyads in which the unemployed worker has found a job (through either her strong tie with probability $(1 - \omega)\lambda$ or her weak tie with probability $\omega e(t)\lambda$) minus the number of d_2-dyads in which one of the two employed workers has lost her job. In the second equation, the variation of dyads composed of one employed and one unemployed worker ($\dot{d}_1(t)$) is equal to the number of d_0-dyads in which one of the unemployed workers has found a job (only through her weak tie with probability $g(e(t))$ since her strong tie is unemployed and cannot therefore transmit any job information) minus the number of d_1-dyads in which either the employed worker has lost her job (with probability δ) or the unemployed worker has found a job with the help of her strong or weak tie (with probability $h(e(t))$) plus the number of d_2-dyads in which one the two employed has lost her job. Finally, in the last equation, the variation of dyads composed of two unemployed workers ($\dot{d}_0(t)$) is equal to the number of d_1-dyads in which the employed worker has lost her job minus the number of d_0-dyads in which one of the unemployed workers has found a job

[8] See also Montgomery (1991) who considers a different model of information transmission in social networks where workers do not pass along information about job opportunities, but rather refer other workers to their employers.

(only through her weak tie, with probability $g(e(t))$). These dynamic equations reflect the flows across dyads. Graphically,

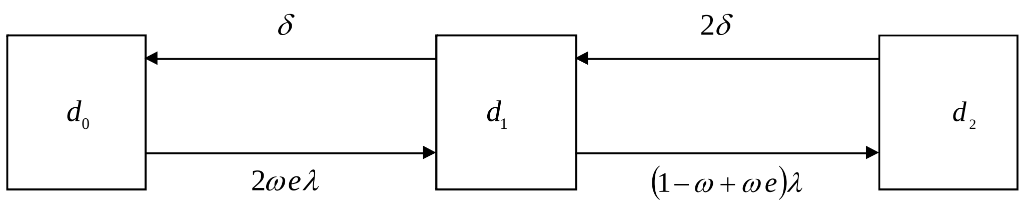


Figure 4: Flows in the labor market

4.2 Steady-state equilibrium and comparative statics analysis

In steady state, $\dot{d}_2(t) = \dot{d}_1(t) = \dot{d}_0(t) = 0$ so that, using (2) and (3), we have the following result.

Proposition 4 *If*

$$\frac{\delta}{\lambda} < \frac{\omega + \sqrt{\omega\left(4 - 3\omega\right)}}{2} \tag{10}$$

there exists a steady-state equilibrium $\mathcal{I}$ where $0 < e^* < 1$ is defined by

$$e^* = \frac{\sqrt{\lambda\left[\lambda + 4\delta\left(1 - \omega\right)\right]} - 2\delta + 2\lambda\omega - \lambda}{2\lambda\omega} \tag{11}$$

and $0 < d_0^* < 1/2$ by

$$d_0^* = \frac{\delta^2}{\lambda^2\omega + \lambda\omega\sqrt{\lambda\left[\lambda + 4\delta\left(1 - \omega\right)\right]}} \tag{12}$$

Also, the other dyads are given by:

$$d_1^* = \frac{2\lambda\omega e^*}{\delta} d_0^* \tag{13}$$

$$d_2^* = \frac{\lambda^2\omega\left(1 - \omega + \omega e^*\right)e^*}{\delta^2} d_0^* \tag{14}$$

Let us study the impact of social interactions (captured by ω) on the different endogenous variables. We have the following important result.

Proposition 5 *Assume*

$$\frac{\delta}{\lambda} < \sqrt{\frac{\omega}{6}} \tag{15}$$

Then, increasing the percentage of weak ties ω *decreases the number of* d_0-*dyads and increases the employment rate* e^* *in the economy, i.e.*

$$\frac{\partial d_0^*}{\partial \omega} < 0 \qquad , \qquad \frac{\partial e^*}{\partial \omega} > 0$$

The effects of ω *on* d_1^* *and on* d_2^* *are, however, ambiguous.*

We show here that by increasing the probability of meeting *new workers* (i.e. weak ties), the steady-state employment rate increases. This is not a trivial result, since, by increasing ω, we have different and opposite effects on the job formation/destruction process. On the one hand, we increase the probability of getting out of unemployed dyads, while, on the other hand, we potentially give up the information of an employed partner in favor of a link with an unemployed one. This result is non trivial since strong and weak ties are substitutes. In this model, it is indeed better to meet weak ties because a strong tie does you no good in state d_0 since your best friends are all unemployed. But a weak tie can do you good in any state because that person might be employed. So there is an *asymmetry* that is key to the model and that can explain why some workers may be stuck in poverty traps (i.e. d_0 dyads) having little contact with weak ties that can help them leaving the d_0 dyad. This result formally demonstrates the Granovetter's informal idea of the *strength of weak ties* in finding a job.

Let us be more specific about this result. Here, individuals belong to mutually exclusive groups, the dyads, and weak tie interactions spread information across dyads. The parameter ω measures the proportion of social interaction that occurs outside the dyad, the inter-dyad interactions. When ω is high, the social cohesion between employed and unemployed workers is high and thus they are in close contact with each other. In this context, increasing ω induces more transitions from unemployment to employment and thus e^*, the employment rate in the economy, increases. This is true if (15) holds.[9] This condition (15) also guarantees that (10) holds, i.e. that an *interior* steady-state equilibrium exists (see Proposition 4). Condition (15) states that the job-destruction rate δ has to be sufficiently low while the job-contact rate λ and social interactions ω have to be sufficiently large. As a result, we are in a "reasonable" economy where jobs are not destroyed too fast and jobs are created at the sufficient high rate.

[9] Even if (15) does not hold, it can still be true since (15) is a sufficient condition.

4.3 Choosing social interactions

We would like now to extend the model so that ω is chosen by individuals. We assume that there is some cost of interacting with weak ties. Let c denotes the marginal cost of these interactions. The expected utility is given by:

$$EV(\omega) = e^*(\omega)y + [1 - e^*(\omega)]\, b - c\,\omega$$

where $e^*(\omega)$ is defined by (11) and y and b are the wage and the unemployment benefits. Each individual optimally chooses ω that maximizes $EV(\omega)$. The first-order condition yields:

$$\frac{\partial EV(\omega)}{\partial \omega} = \frac{\partial e^*(\omega)}{\partial \omega}(y - b) - c = 0 \tag{16}$$

We have the following result:

Proposition 6 *Assume (15). Then there exists a unique interior $\omega^* \in \left]0, 1\right[$ that maximizes $EV(\omega)$. Higher wages or lower unemployment benefits or lower interaction costs will increase the interactions with weak ties, i.e.*

$$\frac{\partial \omega^*}{\partial y} > 0 \qquad \frac{\partial \omega^*}{\partial b} < 0 \qquad \frac{\partial \omega^*}{\partial c} < 0$$

Furthermore, an increase in δ, the job-destruction rate or an increase in λ, the job-information rate induces workers to spend more time with their weak ties, i.e.,

$$\frac{\partial \omega^*}{\partial \delta} > 0 \qquad \frac{\partial \omega^*}{\partial \lambda} > 0$$

There is clear trade-off between the benefits of interacting with weak ties and the costs associated with it (see (16)). Indeed, workers want to interact with weak ties because it increases their probability of being employed (or, equivalently, the time they spend employed during their lifetime), i.e. $\frac{\partial e^*(\omega)}{\partial \omega} > 0$. Concerning the wage y and the unemployment benefit b, a higher y or b increases the value of employment and, since $e^*(\omega)$ and ω are positively related, workers will interact more with weak ties. Quite naturally, increasing the cost c of social interactions reduces the time spent with weak ties. Furthermore, when δ or λ increases, workers spend more time with their weak ties because the cross effect of δ or λ on employment is positive, i.e. $\frac{\partial e^{*2}}{\partial \omega \partial \delta} > 0$ and $\frac{\partial e^{*2}}{\partial \omega \partial \lambda} > 0$. Indeed, when δ or λ increases, the positive effect of weak ties ω on employment e^* is even stronger and thus workers rely more on their weak ties. This is an interesting result since it shows that, in downturn periods where jobs are destroyed at a faster rate, workers tend to spend more time with their weak ties because they know they will help them exit unemployment. In an economy where the flow of job information is faster, the same results occur.

5 Discussion

In this article, we have proposed two different models explaining why social networks matter in the labor market. We would like now to discuss some policy implications of these models, in particular for the ethnic minorities, using the tables presented in Section 2. We have seen in these tables that ethnic minorities tend to use a lot (especially in France) their social networks to search for a job but that their success is relatively limited and varies from one group to another. In fact, the first model (Calvó-Armengol and Jackson, 2004) can provide a first explanation rationale for why ethnic minorities, who tend to have friends who are of the same ethnicity (see, for example, Sigelman et al., 1996; Cutler et al., 1999; McPherson et al., 2001; Jackson, 2008; Currarini et al., 2010), have difficulties in finding a job. We have seen that information flows between individuals having a link with each other and that an equilibrium with a clustering of workers with the same status is likely to emerge since, in the long run (i.e. steady state), employed workers tend to be friends with employed workers (Section 3.5). In this context, if because of some initial condition some ethnic minority workers are unemployed, then in steady-state they will still be unemployed because both their strong and weak ties will also be unemployed. In other words, 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.

The second model (Section 4) can offer another explanation of employment differences between the majority and the minority group. Imagine, for example, that ethnic minority workers are discriminated against in the labor market and, because of that, tend to interact mostly with their (ethnic minority) strong ties.[10] In that case, they will have very little interaction with weak ties, especially whites and will end up experiencing high unemployment rate. This is because weak ties are an important source of job information and when ethnic minorities miss it, they end up having a higher unemployment rate than whites. This is a vicious circle since ethnic minorities experience a higher unemployment rate and mostly rely on other ethnic minority workers who also experience a high unemployment rate, etc. Since jobs are mainly found through social networks via employed friends, ethnic minorities are stuck in a "bad" labor market situation. As a result, when they found themselves in a d_0-dyad, they have nearly no chance of leaving it since the only way out is to meet an employed weak tie since their strong tie is also unemployed. As underscored by Granovetter (1973, 1974, 1983), in a close network where everyone knows each other, information is shared

[10] Other explanations could be that they interact with individuals having the same ethnicity because of preferences (Selod and Zenou, 2006; Battu et al., 2007) or because they are physically separated from the majority group (Brueckner and Zenou, 2003).

and so potential sources of information are quickly shaken down so that the network quickly becomes redundant in terms of access to new information. In contrast Granovetter stresses the *strength of weak ties* involving a secondary ring of acquaintances who have contacts with networks outside ego's network and therefore offer new sources of information on job opportunities. To summarize, when the time spent with weak ties is low, the social cohesion between employed and unemployed workers is also low and thus they are *not* in close contact with each other. Therefore, little interaction with weak ties induces more transitions from employment to unemployment and thus the unemployment rate increases.

The main difference between these two approaches is as follows. In the first one, individuals exchange job information only with their strong ties (as defined by their direct friends) while weak ties (as defined by friends of friends) will indirectly help them by providing job information to their strong ties. This leads to homophily and clustering and thus the quality of the network is the main determinant of individual's outcomes, especially for ethnic minorities. In the second approach, individuals exchange information with both their strong and weak ties but spend only a relative small fraction of time with each of them. If for some reasons (discrimination, racial preferences), ethnic minorities mainly interact with their strong ties who belong themselves to the minority group, then they may get stuck in a situation where they are all unemployed. The two approaches are complementary. In Calvó-Armengol and Jackson (2004), if because of some initial condition some black workers are unemployed, then in steady-state they will still be unemployed because both their strong and weak ties will also be unemployed. In Zenou (2011, 2012), it is discrimination and segregation that make ethnic minorities only interacting with strong ties, who are themselves likely to be unemployed.

These 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: The main job search method used by the unemployed and search method used for finding a job for the employed in France

	Direct approach	***Adverts***	***Institutional ANPE***	***Personal networks***	***Interim***	***Others***	***Total (N)***
Employed	36.4	6.8	5.3	25.4	6.2	16.2	13,274
Unemployed	68.3	68.7	76.6	79.7	43.6	38.6	2,588

All figures, except those in the final column, are percentages
Source: Enquête TeO (Ined/Insee)

Table 2: The main job search method used by the unemployed by nationality in France

	Direct approach	***Adverts***	***Institutional ANPE***	***Personal networks***	***Interim***	***Others***	***Total (N)***
French	70.8	69.3	78.3	81.6	43.9	40.7	323
European	62.8	69.5	67.7	74.2	31.1	47.1	133
Africa and Maghreb	64.7	67.2	74.7	74.3	46.7	24.3	582

All figures, except those in the final column, are percentages
Source: Enquête TeO (Ined/Insee)

Table 3: The job search method that generated success for the newly-employed at the time of the survey in France

	Direct approach	***Adverts***	***Institutional ANPE***	***Personal networks***	***Interim***	***Others***	***Total (N)***
French	37.2	6.9	5.1	24.3	5.7	16.8	2,528
European	28.6	6.4	4.0	41.9	4.6	9.7	1,135
Africa and Maghreb	35.5	5.8	6.9	26.0	11.3	12.0	1,984

All figures, except those in the final column, are percentages
Source: Enquête TeO (Ined/Insee)

Table 4: The main job search method used by the unemployed at the time of the survey in the UK

	Direct approach	***Adverts***	***Institutional***	***Personal networks***	***Total (N)***
White	11.0	33.4	44.8	10.8	10,764
Black	6.7	32.3	51.4	9.6	418
Indian	11.9	32.9	42.9	12.3	252
Pakistani/Bangladeshi	12.5	24.0	49.3	14.2	408
Other	11.4	31.6	42.9	14.1	361
Total	11.0	33.0	45.0	11.0	
Total (N)	1,339	4,021	5,496	1,347	12,203

All figures, except those in the final row and the final column, are percentages
Source: Quarterly Labour Force Survey

Table 5: The job search method that generated success for the newly-employed at the time of the survey in the UK

	Direct approach	***Adverts***	***Institutional***	***Personal networks***	***Total (N)***
White	14.6	23.6	32.8	29.0	16,466
Black	12.5	29.0	38.0	20.5	297
Indian	14.9	23.2	37.1	24.6	289
Pakistani/Bangladeshi	17.8	18.9	30.5	32.8	259
Other	19.3	18.0	34.4	28.4	384
Total	14.8	23.5	32.9	28.8	
Total (N)	2,611	4,163	5,828	5,093	17,695

All figures, except those in the final row and the final column, are percentages
Source: Quarterly Labour Force Survey