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Network Matching Efficiency along the Economic Cycle: Direct and Indirect Ties

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Network matching efficiency along the economic cycle: Direct and indirect ties

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Abstract

There is a large consensus in the literature on the major role of social networks as a helpful instrument to find a job. In this paper, we study the social network matching rate along the economic cycle both from a theoretical and empirical perspective. Using the French Labor Force Survey for the period 2003-2012, we find that the relationship between the network matching rate based on direct ties and the job finding rate is decreasing and convex as predicted by our theoretical setup. Results are completely modified when we consider a measure of the network matching rate based on indirect ties related to the share of peers in a job. In this case, we find a linearly increasing relation between the network matching rate and the job finding rate. This underlines not only the heterogeneous ways through which network membership may influence the individuals' performance on the labor market, but also the different behaviors of these driving factors along the economic cycle.

Keywords: employment; network matching rate; direct and indirect ties; job finding rate; immigrants

JEL: J24; J61; J15; A14; D85

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1 Introduction

Big companies are increasingly using their own workers to find new hires, saving time and money. Referred candidates are twice as likely to land an interview as other applicants. For those who make it to the interview stage, the referred candidates have a 40 percent higher chance of being hired compared with other applicants (see Brown, Setren, and Topa (2016)). This new hiring trend presents though some major problems.

First of all, as noted by Brown, Setren, and Topa (2016) using US data, 63.5 percent of employees recommended candidates of the same sex, while 71.5 percent favored the same race or ethnicity. This is likely to have long run effects in terms of diversity and skill variety within firms. Second, people who are disconnected from the labor market, *i.e.* long-term unemployed, are even less likely to find a job in this new context. Third, during expansions, when the labor market is tight, employees are less likely to have friends seeking for jobs. When employment opportunities are abundant, people are less likely to need a referral to find a suitable job.

Our paper deals with this last concern, *i.e.* the varying role of the network matching rate along the economic cycle. A particular focus is made on the immigrant population since peer effects have been shown to be of major relevance for this population subgroup[1]. Moreover, we show that networks seem to play along different dimensions for natives and immigrants. The original contribution of this paper is not only to analyze the progression of the network matching rate along the economic cycle,[2] but also to expand the traditional definition of the network matching rate, which is based on direct recommendations from social ties, to a larger definition based on indirect ties. This new definition internalizes the fact that the employability of an individual from a given origin in a given job may be influenced by the presence of his peers in this job. We show that the behavior of both indicators completely differs along the economic cycle. While the probability of finding a job through direct recommendations decreases convexly as the job finding rate increases, the probability of being employed in a job where there is a a large share of the individual's peers linearly increases with the job finding rate.

The evidence that many workers become aware of available jobs through word-of-mouth has led to an increasing number of theoretical studies, which have explored the importance of social networks for various labor market outcomes (see Calvo-Armengol (2004); Calvo-Armengol and Jackson

[1]See McKenzie and Rapoport (2010) for location decisions and Waldinger (1996), Munshi (2003) or Patel and Vella (2013) for labor market outcomes.

[2]To our knowledge, this has only been done with UK data by Galeotti and Merlino (2014).

(2004); Calvo-Armengol and Zenou (2005); Calvo-Armengol and Jackson (2007) or Galeotti and Merlino (2014)). The empirical economic literature reveals that around 50% of individuals obtain or hear about jobs through friends and family in developed countries (for studies on US data see Holzer (1987); Holzer (1988), Montgomery (1991), Granovetter (1995) or Brown, Setren, and Topa (2016); on Portuguese data see Addison and Portugal (2002); on Swedish data see Kramarz and Nordström-Skans (2014)). Most of these studies assume that the intensity of information flow in the network is exogenous, an assumption that prevents the analysis of how incentives in networking relate to different labor market conditions. Working with UK data, Galeotti and Merlino (2014) estimate that the probability that a worker finds a new job via his connections is an increasing function of the separation rate when the separation rate is low, while it decreases when the separation rate is high, leading then to an inverted U-shape profile.

In this paper we present a theoretical setup inspired from Galeotti and Merlino (2014) and Beaman (2012) showing the existence of two contradictory effects when analyzing the share of unemployed finding their job through friends or relatives. On the one hand, during economic expansions, there is a relative increase in the share of job offers that are received directly (without networking) by unemployed individuals, since the vacancy rate increases. This effect should reduce the probability of finding a job through networks. On the other hand, as the vacancy rate rises, employed workers in the network receive more often job offers that they are going to transmit towards unemployed members. This rises the probability that an unemployed worker in the network receives a job offer through the network. Intuitively the first effect should be dominant for initial increases in the vacancy rate, when the value of this rate is likely to be relatively low. In this scenario, the share of employed people in the network is still low. For initial high values of the vacancy rate, additional increases should push up the share of individuals who finds a job through social interactions since a very large share of network members is employed and they will transmit the information they receive on job offers.

This theoretical setup provides an economic rationale for our empirical analysis which is based on French data over the period 2003-2012. We distinguish between one traditional indicator of the network matching rate, based on recommendations of direct ties, and an extended indicator, which internalizes the fact that among the immigrant group peer effects operate along the geographical origin dimension. The former closely follows the definition proposed in Galeotti and Merlino (2014). The network matching rate is defined as the proportion of workers in a region who claim having found their job through social interactions (friends, relatives or colleagues). This traditional indicator corresponds to what we will refer as direct ties, since it implies a direct recommendation from a friend, relative or colleague.[3]

The second indicator of the network matching rate corresponds to indirect ties, since the individual does not benefit from a direct recommendation to find a job, but rather from a positive externality related to his geographical origin. Because of their geographical origin, individuals implicitly belong to a social network that increases their employment probability in a job where there is already a large share of their peers because communication and cultural issues are simplified among individuals from the same geographical origin. When an individual from a given origin finds a given job, he creates a positive externality in other people from the same origin since their employability in that job may be improved due to the presence of their peers.

Using these two indicators, we investigate the variation of the network matching rate along the economic cycle[4]. When using direct recommendation as a measure of the network matching rate, as in Galeotti and Merlino (2014), our estimations reveal that for the observed values of the job finding rate in France, there is a convex decreasing relation between the probability that the individual finds a job through these social interactions and the job finding rate. These results are also perfectly consistent with the predictions of the theoretical setup proposed in this paper.

Our conclusions are strongly modified when we consider a wider definition internalizing the positive externality associated with the fact of being a member of a social network. When we internalize this positive externality, we find an increasing relationship between the network matching rate and the job finding rate. Social networks still favor the employability of their members even during economic expansions. This positive influence on the individual's employability does not come from a direct recommendation, but rather from an indirect network effect.

The remainder of our paper is organized as follows. The next section presents a framework providing theoretical foundations to our empirical analysis. Section 3 describes the database and provides some descriptive statistics. Section 4 explains the econometric approach and the main estimation results are presented in Section 5. Section 6 concludes.

[3]It can also match with the notion of strong ties introduced by Granovetter (1973) which corresponds to the socialization process that takes place inside the family or close friends, while weak ties correspond rather to random encounters outside the family or friends.

[4]We do not deal with network investment issues in this paper. Implicitly we assume that along the economic cycle, the individual does not make strategic choices to spend more or less time with network members depending on their employment status. The number of contacts of the individual and the time spent with each of them are assumed exogenous and constant.

2 Theoretical framework

The objective of our paper is to analyze the relationship between the network matching rate and the job finding rate. Social networks are expected to be very helpful when searching for a job. However, this role is likely to change depending on labor market conditions. This section proposes a theoretical setup, inspired from Galeotti and Merlino (2014) and Beaman (2012), which seeks to highlight the economic mechanisms behind our empirical findings.

2.1 Labor Market

We consider that the economy is composed by S independent networks. The number of members in each network is denoted N_t and, as in Galeotti and Merlino (2014), all these members are assumed to be employed at the beginning of the period. Following Beaman (2012), we make the simplifying assumption that all individuals within a network are connected. Networks are made up of individuals that only exchange with each other and have no contact outside their own network. Individuals belonging to different networks do not actually communicate together. We consider that a local labor market corresponds to one network and we ignore potential interactions or congestion problems associated with the presence of other networks in the economy. Implicitly we assume that our economy is composed by S independent local labor markets (*i.e.* networks) and we will analyze the progression of the network matching rate along the economic cycle for one of these local labor markets, which is assumed to be representative of all the others.
The considered labor market (*i.e.* networks) is then composed of N_t individuals. Economic cycles can be characterized by the dynamics of the labor market and two parameters characterize the turnover in this market:

- First, the time invariant parameter δ with $\delta \in (0, 1)$ stands for the job separation rate at the beginning of the period. A random sample of workers loses their job at the beginning of each period with probability δ. The number of individuals loosing their job is given by δN_t. If an individual loses his job, he becomes a job seeker. The probability that an individual will keep his job is equal to $(1 - \delta)$, so the number of individual keeping their job equals $(1 - \delta)N_t$.

- The second parameter stands for the direct job offer arrival rate or, rather, the probability that the individual receives directly a job offer. For simplicity we denote $a \in (0, 1)$ the probability of receiving a direct job offer, while $(1 - a)$ will stand for the probability of receiving an indirect job offer via the network. This job arrival process is assumed to be independent across agents. If an agent is unemployed and receives job information, he accepts the position. If the individual in the network who receives the information on a vacant job is employed and has not lost the job (with probability $1 - \delta$), the individual passes along the information to a randomly selected network member.[5] If this member is employed, the vacant job is lost. If the individual receiving the information on the job offer has lost his job, he will occupy the job in the next period. Job seekers receive then information on a job offer directly or indirectly. In both cases, the individual keeps this job offer.

Both parameters δ and a are assumed to vary exogenously along the economic cycle. Relationships allow group members to exchange information on vacant jobs. The employment dynamics of each network, that is of each local labor market, depends on its specific characteristics (network size and composition) as well as the dynamics of the labor market (job separation rate and job vacancy rate).

2.2 Matching function

The matching function within a particular local labor market is denoted by $M(.)$. This function summarizes the number of effective matches arising following the random contacts between vacant jobs and individuals having lost their job:

$$M(a, N_t) = a\delta N_t + (1 - a)\delta N_t \phi(N_t, a) \tag{1}$$

where δN_t stands for the number of individuals having lost their job at the beginning of the period and receiving information on a vacant job either directly ($a\delta N_t$ in the matching function) or indirectly through social interactions ($(1 - a)\delta N_t \phi(N_t, a)$ in the matching function). The function $\phi(N_t, a)$ is interpreted as the probability of hearing of a job through social interactions and depends on both the size of the social network and the labor market conditions. The probability that a given job seeker finds a job is then determined by the job offers he directly receives plus the job offers received indirectly through friends and relatives.

The probability of receiving job information through an employed network member is represented by the ratio between the total number of jobs which are available in the network to be passed, *i.e.*

[5]We assume that all job offers are symmetric, so the employed individual has no interest in quitting his job and accept the current job offer. In our framework, we do not model the quitting behavior and job separations can only arrive through exogenous shocks.

the number of job offers received by network members who are already employed $a(1-\delta)N_t$, and the number of potential recipients, *i.e.* those who are unemployed at the beginning of the period after the exogenous breakup has occurred δN_t:

$$\phi(N_t, a) = \frac{a(1-\delta)N_t}{\delta N_t} = \frac{(1-\delta)a}{\delta} \tag{2}$$

This paper focuses on the number of individuals receiving a job offer indirectly through social networks, *i.e.* network matching rate. During expansion periods, the vacancy rate increases, leading to two contradictory effects on the network matching rate:

- On the one hand, the number of matches resulting from the unemployed receiving a direct job offer increases, *i.e.* $a\delta N_t$, while the number of matches explained by networks, *i.e.* $(1-a)\delta N_t\phi(N_t, a)$, decreases, since $(1-a)$ falls.

- On the other hand, even if the number of employed workers in the network remains unchanged, these people receive more job offers that they transmit to other network members as a rises:

$$\frac{\partial\phi(N_t, a)}{\partial a} = \phi\prime(N_t, a) = \frac{(1-\delta)}{\delta} > 0 \tag{3}$$

Therefore, the effect of a on the network matching rate cannot be signed:

$$\frac{\partial M}{\partial a} = \delta N_t - \delta N_t\phi(N_t, a) + (1-a)\delta N_t\phi\prime(N_t, a) \tag{4}$$

This derivative includes three terms, two of which capture the impact of social networks. The first term, δN_t, represents the impact of an increase in the probability of hearing about a job, a, on the number of matches. If a increases by one marginal unity, M increases by the same marginal unit leading to δN_t new matches. The second term, $-\delta N_t\phi(N_t, a)$, stands for the complementary impact of the increase in a. An increase by one marginal unit in the probability of receiving a direct job offer decreases by the same amount the probability of receiving this job offer indirectly through a network. Therefore, the number of matches created through the networks decreases by $-\delta N_t\phi(N_t, a)$. The third term, $(1-a)\delta N_t\phi\prime(a)$, shows that when the probability of receiving direct job offers increases, employed members of the network are going to receive more job offers that will be transmitted to other members. So the probability of receiving a job offer via social networks is increased when a raises.[6]

[6] The increase in the vacancy rate "a" increases the total number of matches, that is $\frac{\partial M}{\partial a} > 0$ since $1-\phi(N_t, a) > 0$ and $(1-a)\phi\prime(N_t, a) > 0$.

We seek to shed light on how the share of individuals finding a job through social networks evolves along the economic cycle, where we will use a as an indicator of the economic cycle. The relative size of the terms $-\delta N_t \phi(N_t, a)$ and $(1-a)\delta N_t \phi\prime(N_t, a)$ of equation (4) drives the relationship between the probability of finding a job through social networks and the economic cycle. Two possible scenarios may arise:

- If $\delta N_t((1-a)\phi\prime(a) - \phi(N_t, a)) < 0$, the direct effect coming from the fact that, as a increases, there is a relative decrease in the number of job offers perceived through networks, dominates over the indirect effect associated with an increase in the number of offers arriving through network members.

- If $\delta N_t((1-a)\phi\prime(a) - \phi(N_t, a)) > 0$, the positive indirect effect associated with the increase in the number of job offers transmitted through the network dominates the direct effect associated with the decrease in $(1-a)$. In this scenario, the probability of finding a job through social networks should increase during economic expansions.

The impact of an increase in a on the probability of finding a job through social interactions is then theoretically ambiguous. The reduction in $(1-a)$ is simultaneously associated with an increase in $\phi(N_t, a)$, implying an undetermined sign for the net impact. We expect that for low values of a, the direct impact coming from a reduction in $(1-a)$ will dominate the indirect impact coming from the fact that employed network members will transmit more job offers, since for low values of a the share of employed workers in the network will be lower than for high values of a. Conversely, when a is high, the indirect effect will be more likely to dominate since most people in the network will be employed.

Using our setup, we can determine the value of a for which there is a switch from one scenario to another, that is, we need to find the value of a for which $\delta N_t(1-a)\phi\prime(N_t, a) = \delta N_t \phi(N_t, a)$:

$$\begin{aligned}(1-a)\frac{(1-\delta)}{\delta} &= \frac{(1-\delta)a}{\delta} \\ a &= \frac{1}{2}\end{aligned}$$

For $a < 1/2$ the direct effect dominates over the indirect effect and the network matching rate decreases as a increases. Conversely, for $a > 1/2$ the indirect effect is dominant and the probability of finding a job through social interactions will increase during the economic expansion.

Overall, the opposite effects of $(1-a)$ and $\phi(N_t, a)$ suggest the existence of a non-monotonic relationship between the network matching rate and the economic cycle. For low values of a, additional increases should lead to a decrease in the number of individuals finding a job through social networks. For high values of a, additional increases foster an increase in the number of individuals finding a job through social interactions. This leads to a theoretical U-shaped progression of the network matching rate along the economic cycle. In what follows, we turn to an empirical analysis investigating the relationship between the network matching rate and the job finding rate in France, which corresponds to our economic cycle indicator.

3 Data and descriptive statistics

We use data from the French Labor Force Surveys (LFS) for the period going from 2003 to 2012. For this period we have consistent and reliable information on occupations, on whether the individual has found his job through social interactions (*i.e.* network matching rate), country of birth and year of arrival in France for immigrants. We stop our analysis in 2012 since afterwards there is no detailed information on the respondent's country of birth and therefore we cannot exploit heterogeneity across origins among immigrants to estimate our relationship.[7] The LFS was launched in 1950 and established as an annual survey in 1982. We start our analysis in 2003 which is the year when the LFS was redesigned as a continuous survey with quarterly interviews of people. Participation is compulsory and all individuals living in the same dwelling and older than 15 are surveyed.[8]

The main topics covered by the LFS concern employment, unemployment, underemployment, hours of work, wages, duration of employment and unemployment (length of service), discouraged workers, industry, occupation, status in employment, education/qualification, and secondary jobs. The French LFS provides the occupation for each employed individual among a list of 350 possible occupations such as "gardener", "messenger", "clerk in banking activities", or "financial manager". We focus on the employed population between 15 and 64 years old. For all our analysis we adopt the region as the unit of analysis for two main reasons. First, the job finding rate (which will be our cycle indicator) is defined at the the regional level. Second, it allows to guarantee a sufficient number of observations even when considering detailed categories of immigrants. France

[7] In contrast with most papers on migration (see Ortega and Verdugo (2014) or Patel and Vella (2013)), we rely on survey data and not census data. Indeed, the French database resulting from matching French Census with individual social security data ("Declaration Annuelle Donnees Sociales") fails to provide some of the information we require for our analysis. For example, occupations are not consistently reported.

[8] The collection method has always been a face-to-face interview. Since 2003, a telephone interview has been employed for intermediate surveys (2nd to 5th).

includes 22 regions. We consider a two-digit definition of occupations for the econometric analysis so as to exploit variability across 22 regions and 24 occupations.[9] Concerning immigrants, we consider the nine following groups of birth country : (1) North Africans: Algerian, Tunisian, Morrocan, (2) Africans: all other African countries, (3) Turkish: Turkey, (4) South-East-Asian: Vietnamese, Cambodian, Laotian, (5) South-Europeans: Italian, Portuguese, Spanish, Greek, (6) Northern Europeans: German, Belgian, Dutch, Luxembourg, Irish, Danish, British, Swiss, Austrian, Norwegian, Swedish, (7) Eastern Europeans and Russians, (8) South-Americans and (9) North-Americans.

INSERT TABLE 1

After pooling all the year-specific datasets, we obtain a sample comprising 231,316 respondents for the period 2003-2012. Among them, 24,374 are foreign born. As shown in Table 1, this workforce is very unequally distributed across regions, with Ile de France being by far the most abundant region, followed by Rhone Alpes, Nord-Pas-de-Calais, Provence-Alpes Cote d'Azur (PACA) and Pays de la Loire. The average share of immigrants in the employed population equals 10.5%. Six regions have a proportion of immigrant workforce above the average: Corse (21.4%), Ile de France (21.1%), PACA (16.1%), Languedoc-Roussillon (16.1%), Rhône-Alpes (10.6%) and Alsace (10.6%). Moreover, the internal composition of the immigrant population strongly differs across regions. While in Ile de France 27% of the immigrant workforce is European, 53% African and around 20% from other origins, in PACA these proportions are equal to 26%, 64% and 10% and in Rhône-Alpes they are equal to 39%, 45% and 16%. Finally, the proportion of employed individuals claiming to have found a job through social connections varies from 33% in Corse, 28.5% in PACA or 25.7% in Ile de France, to 18.6% in Basse Normandie, 19.9% in Auvergne or 20% in Poitou-Charentes.

We consider two different indicators of the network matching rate. First, we define the network matching rate as the share of individuals in a region claiming having found their job trough social interactions.[10] This indicator captures direct social interactions since the individual benefits from a recommendation of a friend, relative or colleague. Our second indicator considers rather indirect

[9]We exclude from our sample farmers, civil servants, military and clergymen.

[10]The LFS precisely asks "How did you find the job in the firm?". Among the possible answers there is "through family relations, personal relations or professional relations". The network matching rate is then defined as the ratio between the number of employed people having found their job through through friends, family or colleagues and the total number of employed.

social interactions, since we will not require to benefit from a direct job recommendation. We define it only over the immigrant population. It measures the proximity between jobs occupied by recently arrived immigrants (with less than 5 years of residence in the host country) and the most popular job among their peers in the region. Our indicator is inspired from the one proposed in Patel and Vella (2013), but here we take into account the whole ranking of occupations of established immigrants from a particular origin in a region[11]. This indicator allows us to take into account the heterogeneity in the degree of dispersion among jobs for individuals from different geographical origins.

INSERT FIGURE 1

Figure 1 displays the progression between 2003 and 2012 of both real GDP growth and the share of employed natives and immigrants that declares having found a job through friends, relatives or colleagues. On the left-hand side of the y-axis we represent the proportion of individuals (natives and immigrants, respectively) claiming to have found a job through social interactions, while on the right-hand side we represent real GDP growth. Two conclusions can be drawn from this figure. First, the network matching rate is clearly more important for the immigrant population than for the native population, confirming that peer effects are particularly relevant for the former subgroup. Second, while the network matching rate of natives has decreased smoothly since 2007, that is since the beginning of the recession period, for immigrants the decrease in real GDP growth seems rather associated with an increase in the network matching rate (see 2005 and 2009-2011). As this figure suggests that the network matching rate does not operate along the same dimensions for natives and immigrants, we will systematically implement our analysis distinguishing between both groups.

In our study, the job finding rate is used as an indicator of the economic cycle. Based on the estimations of Hairault, Barbanchon, and Sopraseuth (2015) and given the strictness of the employment protection legislation in France, we argue that the job finding rate at the regional level is a good indicator of the economic cycle, *i.e.* it summarizes well the evolution of labor market conditions. The job finding rate in period t, which is defined as the probability of transition from unemployment to employment, is calculated using quarterly data (which is the highest frequency available in the French LFS) at the regional level on the flows of workers into and out of unemployment between $t-1$ and t.[12] In order to reduce time aggregation biases, we calculated the

[11] Patel and Vella (2013) only consider the most popular job.

[12] We thank Idriss Fontaine for providing us with all the prepared data to compute the job finding rates. For

job finding rate according to equation (5) of Shimer (2012), which is meant to take into account the problem that, while data is available only at discrete date, the underlying environment keeps changing over time. Taking yearly averages, we obtain an average job finding rate per region.[13]

4 Econometric Analysis

We implement our analysis by steps. First of all, we consider the definition of the network matching rate used in Galeotti and Merlino (2014). We propose both an estimation based on a cell approach in which the dependent variable equals the proportion of workers who claim having having found their job through social connections, and an estimation based on individual data in which the dependent variable is the probability that the individual has found his job through social interactions. We estimate the varying role of the network matching rate along the economic cycle for the whole population, natives and immigrants. Moreover, we test the robustness of our results over the skilled population. In a second step, we propose an alternative measure of the network matching rate exploiting the fact that peer effects are of major importance among immigrants. Thus, it internalizes the positive externality of social networks related to geographical origin on the individual's employability.

While our first indicator captures direct social ties, since it implies that the individual obtained his job thanks to a direct recommendation from a friend, relative or colleague, the second indicator corresponds rather to a measure of indirect social interactions explained by the fact of having a common geographical origin. As we work with survey data (which implies limited sample sizes compared to census data), we build our indicators using stock variables rather than flows. Concerning the first indicator, when implementing the cell approach, we consider for every year the ratio between the number of individuals declaring having found their job through social interactions and the total number of employed people in the cell. When implementing the individual data approach, we consider the number of individuals declaring having found the job through social networks. For the second indicator, our reference population per year is the stock of immigrants

further details, see Fontaine (2016).

[13] In our study we consider a unique job finding rate per region, without distinguishing by worker skill level. Considering the job finding rate by skill level has at least two major drawbacks. On the one hand, mobility across regions differs between skilled and unskilled workers, which is likely to affect the estimation of the job finding rate. On the other hand, while high-skilled workers may apply to low-skilled positions and be hired on them, the opposite is unlikely to happen. The job finding rate of high-skilled workers must then be necessarily higher than that of low-skilled workers.

with less than 5 years of residence duration in France. We measure how far they are employed from the most popular job of their peers in their region of residence.

In the first step, we estimate to which extent the network matching rate defined at the region level varies along the economic cycle for different population subgroups: all the population, native population and foreign-born population. We adopt the specification proposed by Galeotti and Merlino (2014) and estimate the following linear regression:

$$N_{got} = \gamma_0 + \gamma_1 a_{gt} + \gamma_2 a_{gt}^2 + \gamma_t + \gamma_o + \gamma_{ot} + \epsilon_{got} \tag{5}$$

where N_{got} stands for the share of people from region g and origin o who found their job thanks to social connections, and a_{gt} represents the job finding rate in region g at date t.[14] This variable is introduced using a quadratic profile to allow for a non monotonic relation between the network matching rate and labor market conditions. We control for year and origin fixed effects (γ_t and γ_o, respectively). The formers allow to control for aggregate shocks while origin fixed effects capture systematic differences in the distribution of different origins across regions. This allows to take into account for systematic differences in the network size across origins. We also consider an origin-year fixed effect γ_{ot} so as to allow for differential trends across origins, which may induce different evolutions on the size of the network across origins.[15] Because serial correlation within a particular labor market may be a concern, in all regressions we adjust standard errors for clustering of observations at the region level. We also use weighted regressions with weights equal to the population in the corresponding region-origin-year cell.[16]

We replicate the same estimations using individual data. We define the network matching rate as the probability that the individual i has found the job through social interactions and estimate the following linear probability model:

$$P_{iogjt} = \gamma_0 + \gamma_1 a_{gt} + \gamma_2 a_{gt}^2 + \gamma_t + \gamma_o + \gamma_j + \gamma_{ot} + \gamma_{oj} + \gamma_{jt} + \epsilon_{ogjt} \tag{6}$$

[14] In Appendix A we present estimations obtained when using as dependent variable N_{gjot} the share of people from region g in job j from origin o who found their job through social interactions.

[15] Due to the low intra-region variation along time of the job finding rate, we are unable to introduce regional fixed effects alone or interacted with any other characteristics (origin or year), since these effects will actually capture the effect of the regional job finding rate.

[16] To control for composition effects we have also implemented weighted OLS regressions with weights equal to the average population size in the cell during the period 2003-2012. Because our estimation results are not essentially modified when we control for composition effects, we do not report in the paper these estimations. They are though available from the authors upon request.

where a_{gt} represents the job finding rate in the region of residence of the individual at date t. We control for year, origin and job fixed effects (γ_t, γ_o and γ_j, respectively).[17] We also consider fixed effects year-origin, job-year and job-origin (γ_{ot}, γ_{jt} and γ_{oj}, respectively). In all regressions we adjust standard errors for the clustering of observations at the region-job level. Moreover, we use weighted OLS regressions taking weights provided by the LFS.

One limit of this measure of the network matching rate is that it only considers direct recommendations (*i.e.* direct ties). Thus, it abstracts from potential positive externalities that the massive presence of individuals of certain geographical origin in a certain job may have on the employability of their peers (*i.e.* indirect ties). The individual does not need then an explicit recommendation from a friend or relative already employed in that job, the fact of being a peer increases his chances to obtain the job. In an involuntary way, the individual belongs to a social network associated with his own geographical origin that is going to increase his chances to get a job (because it facilitates communication, reduces cultural distance, etc). To internalize this externality, we focus in a second step on immigrants, a population subgroup for which peer effects are of major importance. We adopt an alternative measure of the network matching rate which is inspired from the one proposed in Patel and Vella (2013) to measure the importance of social networks on immigrants' occupational choices. In their paper, Patel and Vella (2013) consider the probability that the immigrant is employed in the most popular job among his peers in the corresponding federal state. We generalize here this indicator and we consider the whole set of occupations where established immigrants from origin o in region g are present. These jobs are ranked from the most popular to the least popular. More precisely, if in region g, people from origin o are present in M different types of jobs, we will give a rank equal to M to the job where the number of people from origin o is the most numerous, a rank equal to $M-1$ to the job where the number of people from origin o is the second most numerous, and so on. The last job in the ranking will be the occupation in the region where the number of people from o is the least numerous and its rank equals 1. Therefore, in every region, for every year and for every considered origin, we will have a specific set of occupations ranked from M for the most popular job to 1 for the least popular job of the considered origin in the region.

We then define for every recently arrived immigrant i a variable $Dist_{iogjt}$ capturing the distance between the ranking of the job where he is employed and the most popular job among his estab-

[17] Again we only control for origin when dealing with the whole population or with the immigrant population. The objective is to control for systematic differences in network size across origins.

lished peers in the region. The distance should be smaller the closer the recently arrived immigrant is employed with respect to the most popular job of his peers in the region. Distance is then defined as:

$$Dist_{iogjt} = RPopular_{ogt} - R_{iogjt} \tag{7}$$

where $RPopular_{ogt}$ stands for the ranking of the most popular job of individuals from origin o in region g in date t, *i.e.* if in period t individuals from origin o in region g are present in $M = 20$ different jobs in the region, the ranking of the most popular job for this population subgroup will be equal to $RPopular_{ogt} = 20$. R_{iogjt} stands for the ranking of the job where the recently arrived immigrant i from origin o in region g is employed. We normalize between 0 and 1 this distance and compute our proximity indicator $ExJobI_{iogjt}$ as one minus the normalized distance:

$$ExJobI_{iogjt} = 1 - \frac{Dist_{iogjt} - Min\{Dist_{ogjt}\}}{Max\{Dist_{ogjt}\} - Min\{Dist_{ogjt}\}} \tag{8}$$

The closer $ExJobI_{iogjt}$ is to unity, the closer the recently arrived immigrant is to the most popular job of his peers in the region. We then estimate the following equation:

$$ExJobI_{iogjt} = \gamma_0 + \gamma_1 a_{gt} + \gamma_2 a_{gt}^2 + \gamma_t + \gamma_j + \gamma_o + \gamma_{ot} + \gamma_{oj} + \gamma_{jt} + \epsilon_{ogjt} \tag{9}$$

where a_{gt} represents the job finding rate in region g at date t. We control for aggregate shocks through year fixed effects γ_t. We control for systematic differences across jobs and origins through the introduction of job and origin fixed effects, γ_j and γ_o respectively. We allow aggregate shocks to be origin-specific and job-specific (γ_{ot} and γ_{jt} respectively), and we control for the potential tendency of some origins to cluster into certain types of jobs by considering origin-job fixed effects γ_{oj}. We adjust standard errors for the clustering of observations at the region-job level. We also use weighted regressions with weights provided by the LFS.

5 Results

5.1 Network matching effects based on direct ties

In a first step, we use the traditional definition of the network matching rate based on direct ties. The French LFS explicitly asks employed individuals if they have found their current job through friends, relatives or colleagues. As in Galeotti and Merlino (2014), we use this question to build the classic network matching rate indicator. In columns (1)-(8) from Table 2, we present estimation results based on the region-origin cell approach of equation (5). The dependent variable is the proportion of individuals in a region declaring having found their job through social connections. To identify the relationship between the network matching rate and the job finding rate we exploit the relationship between yearly changes in the share of individuals declaring having found their job through social networks and yearly changes in the job finding rate.[18]

In columns (9)-(16) from Table 2, we present linear probability estimation results from equation (6) based on individual data. We estimate the relationship between the probability that the individual has found the job through a direct recommendation of a social connection and the job finding rate. We introduce as control variables the age and age squared of the individual, sex, educational level and marital status. Panel A of Table 2 considers all individuals while Panel B considers only individuals having at least secondary education (*i.e.* skilled individuals). Moreover, within each panel, we implement separate regressions over the whole population, the native population, the immigrant population and the recently arrived immigrant population with less than 5 years of residence.

The first eight columns of Panel A suggest that, when considering all individuals, natives and recently arrived immigrants the regional network matching rate negatively correlates with the job finding rate. When considering the whole stock of immigrants, a non-monotonic U-shaped relationship arises though between both variables. Results are modified when we consider the subgroup of skilled workers. The relationship between the regional network matching rate and the job finding rate becomes non-monotonic and follows an U-shaped progression for all considered groups, except from recently arrived immigrants for which the relationship remains rather linearly negative.

INSERT TABLE 2

Estimations from columns 5 to 8 of Panel A and B reveal that the introduction of the square of the job finding rate strongly modifies the value of the estimated coefficients. To understand the impact of a marginal change in the job finding rate on the share of people that declares finding a job through direct recommendation of social connections, we estimate the predicted marginal effects. More precisely, Figures 2 and 3 provide the estimated values of the derivative of equation

[18]While the network matching rate in period t corresponds to the stock of individuals declaring having found their job through social connections in period t, the job finding rate in period t is computed based on the unemployment to employment transitions between period $t-1$ and t.

(5) with confidence intervals at the 95 percent level:

$$\frac{\partial \ N_{got}}{\partial \ \text{Job finding rate}} = \widehat{\gamma}_1 + 2\widehat{\gamma}_2 a_{gt} \tag{10}$$

The term $\frac{\partial \ N_{got}}{\partial \ \text{Job finding rate}}$ changes along the job finding rate distribution since the derivative depends on a_{gt}. The analysis of the marginal effects along the distribution of the job finding rate reveals for which values of the job finding rate we are in the decreasing part of the U-shape, at the inflexion point and in the increasing part.[19]

Figure 2 reveals that when considering the whole population, natives and immigrants, the relationship between the regional network matching rate and the job finding rate is always decreasing. The negative values of the marginal effects approach zero as we move up in the job finding rate distribution, suggesting a decreasing convex relation between the regional network matching rate and the job finding rate. For recently arrived immigrants, the estimated marginal effects are negative but not significantly different from zero along the job finding rate distribution.

Conclusions are slightly modified when we exclusively focus on the skilled population. As revealed by Figure 3 for all skilled individuals and for skilled natives, the values of the marginal effects are significantly negative until the 6th decile of the job finding rate distribution and then they become not significantly different from zero. We conclude that for these population subgroups the relationship between the regional network matching rate and the job finding rate along the cycle is decreasing and convex, reaching the inflexion point at the top of the job finding rate distribution. Conclusions are different for skilled immigrants and recently arrived skilled immigrants. For the former subgroup, the values of the marginal effect are systematically significantly negative but increasing along the job finding rate distribution, pointing to a decreasing convex relation between the network matching rate and the job finding rate. For recently arrived immigrants, the marginal effect of the job finding rate is negative but not significantly different from zero (apart from the very top of the job finding rate distribution where it becomes slightly significant and negative).

INSERT FIGURE 2

INSERT FIGURE 3

Estimation results from linear probability models in columns (9)-(16) of Table 2 confirm these findings. As revealed by Panel A, whatever the population subgroup we consider (the whole

[19]Negative values of the marginal effects indicate that we are in the decreasing part of the curve. When the marginal values reach zero, we will be in the inflexion point and for positive marginal effects we are in the increasing part of the U-shaped progression.

population, natives, immigrants or recently arrived immigrants), a negative relationship between the probability of finding a job through direct ties and the job finding rate arises. This relationship seems to follow an U-shaped progression when considering either the whole population or the population of immigrants. These conclusions also hold when focusing exclusively on skilled people in Panel B of the table.

To shed some light on whether the statistically significant quadratic coefficients obtained in columns (9)-(16) imply an actual U-shaped progression of the probability of finding a job through social networks for the observed values of the job finding rate in France, we graphically represent the estimated marginal effects in Figures 4 and 5.

Figure 4 considers the estimated marginal effect along the job finding rate distribution for all workers, natives, immigrants and recently arrived immigrants, independently of their skills. For all population groups, the estimated values of the marginal effects are negative, significant and increase towards zero along the job finding distribution observed in France. While the zero value is not reached for all workers, natives and immigrants, suggesting a decreasing and convex relation between the network matching rate of these population subgroups and the job finding rate, for recently arrived immigrants marginal effects become not significantly different from zero at the top of the job finding rate distribution, suggesting that for this population subgroup the relationship is effectively decreasing, convex and reaches the inflexion point for high values of the job finding rate. Figure 5 replicates the same exercise but considers only the skilled population. We reach essentially the same conclusions except for recently arrived immigrants, for whom the marginal effects are no longer significantly different from zero.

INSERT FIGURE 4

INSERT FIGURE 5

Combining results from Table 2 with Figures 2, 3, 4 and 5, we conclude that there is a negative and convex relationship between our indicator of the network matching rate based on direct ties and the job finding rate. This conclusion holds when considering all workers, natives and immigrants whatever their skill level. For recently arrived immigrants (those with less than 5 years of residence) results are less clear-cut. The analysis based on individual data, which offers more observations for this population subgroup than the analysis based on cells, suggests the existence of a negative and convex relationship between the probability that a recently arrived immigrant has found a job through a direct recommendation and the job finding rate. This conclusion does not hold though if we consider skilled recently arrived immigrants, for which the relation is not actually significant.[20] We conduct in Appendix A several additional tests in order to assess the robustness of our results. In the first place, we define our indicator of the network matching rate based on direct ties using a cell approach where cells are defined at the region-job-origin level (see Table A.1). We still find a negative relationship between the network matching rate and the job finding rate that seems to follow an U-shaped progression when considering all workers and immigrants.

As a second robustness test, we propose a fractional response model estimation. More precisely, our estimates could be affected by the presence of mass points in our dependent variable at values 0 and 1. To take into account the presence of these mass points, Table A.2 in Appendix A proposes a fractional response model (see Papke and Wooldridge (2008)) of the network matching rate replicating the cell approach proposed in Table 2. Fractional response estimates are largely consistent with findings reported in Table 2.

As a third robustness test, we replicate our estimations in Table 2 but consider only regions having a proportion of immigrants below the average. This allows us to ensure that the estimated effects are not driven by a reduced number of regions having an over-representation of the immigrant population. From Table 1, we see that the regions with a large proportion of immigrants are: Alsace, Ile de France, Languedoc-Roussillon, PACA, Rh$\hat{o}$ne-Alpes.[21] We exclude now these regions from our estimations. Table A.3 in Appendix A shows that when considering low immigrant populated regions, we still find for all workers, natives and immigrants a decreasing relation between the network matching rate and the job finding rate. This relationship is decreasing and convex when considering immigrants or skilled workers (both natives or immigrants). Concerning the recently immigrant population subgroup, coefficients are negative but not significantly different from zero. This lost in precision is probably explained by the important reduction in the number of observations.[22] All in all, our main conclusions still hold when considering regions having a lower proportion of immigrants, suggesting that estimated effects are not driven by a small number of regions having a large share of immigrants.

Estimation results concerning immigrants must be interpreted with caution since, due to the large number of origins we consider (9 different origins), the proportion of region-origin-year cells

[20]For the analysis based on cells, marginal effects for recently arrived immigrants are not significant.

[21]Due to its insularity and particular economic structure essentially based on tourism, Corse is not considered in this analysis.

[22]When considering regions having a proportion of immigrants below the average, the number of recently arrived immigrants is reduced from 2293 to 855 and from 1171 to 377 for recently arrived skilled immigrants..

adopting the zero value is around 30%. Table A.2 proposes a fractional response estimation to deal with this issue. However, we propose an alternative method that consists in aggregating immigrants into 3 large origins: African immigrants, European immigrants and Other origins. Estimation results are provided in Table A.4 in Appendix A and concerns only the cell approach (since when exploiting heterogeneity across individuals we are not confronted with the problem of lack of observations). They are perfectly consistent with estimations reported in Table 2. We find a decreasing and convex relationship between the network matching rate and the job finding rate when considering all immigrants (skilled or not). For the recently arrived subgroup coefficients are not significantly different from zero.

All in all, combining the whole set of estimation results in Table 2, in Figures 2, 3, 4, 5 and various robustness tests, we can conclude that the probability that immigrants find a job through direct ties decreases during economic expansions, as the job finding rate rises. The relationship is decreasing and convex. This holds for both all immigrants and skilled immigrants, but does not hold for recently arrived immigrants, for whom the relationship is rather linearly decreasing and becomes non-significant when considering an aggregate approach based on cells. When considering the whole population (immigrants and natives together) or natives alone, the relationship remains continuously decreasing and convex.

5.2 Network matching effects based on indirect ties

Social networks have been proved to be a major driver of immigrants' occupational choices (see among others Waldinger (1996), Munshi (2003) or Patel and Vella (2013)). In results available upon request, we find that, in France, many recently arrived immigrants do not find their job through a direct recommendation from a social tie, but they are though flowing towards the most popular job among their peers in the region, suggesting an imitating behavior.[23] On the basis of this finding, our alternative indicator internalizes the positive externality on the employability of an individual in a given job generated by the massive presence of peers in that job. This alternative indicator will allow us to test the consistency of our previous results based on direct ties.

Our indicator is inspired from the one proposed in Patel and Vella (2013), but is not exactly the same. While in their paper the authors consider the probability that an individual chooses the

[23] In these results we also show that the most popular job for individuals from a given origin varies across regions, suggesting that there is not a comparative advantage that could be determining individuals' occupational choices (this conclusion is also reached in Patel and Vella (2013)). Moreover, we propose an IV analysis to control for the fact that immigrants may sort into occupations whose demand is growing. IV estimations confirm our main conclusions.

most popular job of his peers in the corresponding federal state, in our paper we take into account the fact that different origins may be more or less concentrated among jobs across regions. To do so, we define an indicator that considers the whole ranking of jobs where established immigrants are present and how recently arrived immigrants allocate across them. Our indicator measures the proximity between the ranking of the job in which the recently arrived immigrant is employed and the most popular job of his peers in that region. Note that the ranking of the job refers to the "popularity scale of jobs" defined by region, origin and year.

Estimation results of equation (9) are summarized in columns (1)-(8) of Table 3. Higher job finding rates are associated with linear increases in the proximity between the job occupied by a recently arrived immigrant from origin o in region g at time t and the most popular job of his already established peers in the region at time t. Quadratic coefficients are not significant, underlining the linear nature of the relationship between our indirect indicator of the network matching rate and the job finding rate. During expansion periods, immigrants tend to be employed in jobs where their peers are relatively more numerous, pointing to the positive externality social networks in the employability of immigrants.

Indirect ties seem then to operate along different dimension with respect to direct ties. While in expansion periods there is a decrease in the probability that the individual obtains a job through a direct recommendation, the probability of obtaining a job where there is a large share of people coming from the same origin as the individual increases during expansions. Social interactions continue then to positively influence the probability of finding a job even during expansion periods but in an indirect way. This type of indirect ties has often been ignored by the literature studying the network matching rate, which considers a traditional indicator based on direct recommendation.

INSERT TABLE 3

The analysis of the estimated marginal effects in Figure A.1 (Appendix A) confirms this conclusion. Marginal effects are positive and significant (although slightly decreasing) from the 3rd decile of the observed job finding rate distribution in France. There is thus an increasing positive relation between the job finding rate and the proximity to the most popular job, confirming regression results in Table 3.

As a robustness tests, columns (9)-(12) repeat the same estimation but consider, on the one hand, regions having a proportion of immigrants above the average (columns (9)-(10)) and, on the other hand, regions having a proportion of immigrants below the average (columns (11)-(12)).

Columns (9)-(12) reveal the underlying forces behind our alternative indicator of the network matching rate for the whole population of immigrants.[24]. When considering regions with a large proportion of immigrants (columns (9)-(10)), we find the same results as when considering all regions (columns (1)-(8)), that is, in expansion periods recently arrived immigrants from origin o region g are increasingly employed in jobs that are the most popular among their peers in the region. In contrast, when considering regions with a low proportion of immigrants, the relationship is no longer significant. This result seems consistent with the nature of our alternative indicator of the network matching rate, which is based on the existence of indirect ties related with the importance of a particular nativity group in a job. In order to positively influence the employability of an individual in a job, the share of his peers in that job must be sufficiently high, which is less likely to happen in regions characterized by a low presence of immigrants.

To become effective, the network matching rate founded on indirect ties requires then a sufficiently large number of immigrants in the region and in the job. Aggregate effects reported in columns (1)-(8) of Table 3 are actually driven by regions having a large proportion of immigrants. In regions with a low proportion of immigrants, the effects are insignificant.

All in all, when we consider a larger definition of the network matching rate based on indirect ties, conclusions are modified with respect to the case where we define the network matching rate on the basis of a direct recommendation from a social connection. While with the standard definition of the network matching rate, our results are perfectly consistent with Galeotti and Merlino (2014) with a decreasing and convex progression in the probability to find a job through social connections along the economic cycle, when considering an alternative definition of the network matching rate based on indirect ties, we find a linearly increasing relation between the network matching rate and the job finding rate.

6 Conclusion

Referrals play a major and an increasing role in recruiting policies of big companies. The efficiency of the network matching rate is though likely to be modified along the economic cycle, since the labor market tension tends to increase during expansions and decrease during recessions. In this paper, we follow an approach close to Galeotti and Merlino (2014) and analyze the variation of the network matching rate along the economic cycle using the job finding rate as an indicator of

[24]The loss in the number of observations when considering only skilled immigrants prevents us from making a focus on this population subgroup.

market conditions.

Using the job separation rate, Galeotti and Merlino (2014) estimate for the UK a non-monotonic hump-shaped relationship between the network matching rate and the job separation rate. Working with French data, we reach close conclusions. When using the same network matching indicator as in Galeotti and Merlino (2014), we conclude that for the observed values of the job finding rate, the relationship between the network matching rate and the job finding rate is decreasing and convex. These findings are perfectly consistent with our theoretical setup, which predicts that the probability of finding a job through social networks decreases during the initial stages of the economic expansions, when the vacancy rate is still relatively low. It is necessary to have higher values of the vacancy rate to observe an increase in the share of individuals finding their jobs through friends and relatives.

One of the limits of this traditional indicator of the network matching rate is that it only considers direct ties (*i.e.* direct recommendation), but it abstracts from indirect ties related with the positive externalities that the presence of individuals from certain geographical origin in a certain job may have on the employability of their peers. We internalize this externality by proposing an alternative measure of network matching rate based on the immigrant population (a population subgroup for whom peer effects have proved to be of major importance). We conclude that when externalities are internalized, the relationship between the economic cycle and the network matching rate is reverted and becomes strictly positive. During economic expansions, the probability of finding a job due to the fact of belonging to a network increases.

Overall, we conclude that direct and and indirect ties capture actually different impacts of the social network on the individual's probability to find a job. Moreover, the progression of the impact of direct and indirect ties differs along the economic cycle. For future research, it would be of interest to study to what extent our results on the relationship between the economic cycle and the network matching rate generalize to other European countries.

Compliance with Ethical Standards

The authors declare that they have no conflict of interest

References

Addison, J., and P. Portugal. 2002. "Job search methods and outcomes." *Oxford Economic Papers* 54 (3): 505–533.

Beaman, L. 2012. "Social Networks and the Dynamics of Labor Market Outcomes: Evidence from Refugees Resettled in the U.S." *Review of Economic Studies* 79 (1): 128–161 (January).

Brown, M., E. Setren, and G. Topa. 2016. "Do Informal Referrals Lead to Better Matches? Evidence from a Firm's Employee Referral System." *Journal of Labor Economics* 34 (1): 161–209 (January).

Calvo-Armengol, A. 2004. "Job Contact Networks." *Journal of Economic Theory* 115:191–206.

Calvo-Armengol, A., and M. Jackson. 2004. "The Effects of Social Networks on Employment and Inequality." *American Economic Review* 94:27–46.

———. 2007. "Networks in Labor Markets: Wage and Employment Dynamics and Inequality." *Journal of Economic Theory* 132:426–454.

Calvo-Armengol, A., and Y. Zenou. 2005. "Job Matching, Social Network and Word-of-mouth Communication." *Journal of Urban Economics* 57:500–522.

Fontaine, I. 2016. "French Unemployment Dynamics: a "Three-State" Approach." *Revue d'Economie Politique* 126:835 – 869.

Galeotti, A., and L.P. Merlino. 2014. "Endogenous job contact networks." *International Economic Review* 55 (4): 1201–1226.

Granovetter, M. 1973. "The Strength of Weak Ties." *American Journal of Sociology* 78 (6): 1360–1380.

Granovetter, M.S. 1995. *Getting a Job: a Study of Contacts and Careers.* 2nd. MA. Harvard University Press.

Hairault, J.O, T. Le Barbanchon, and T. Sopraseuth. 2015. "The Cyclicality of the Separation and Job Finding Rates in France." *European Economic Review* 76 (May): 60–84.

Holzer. 1988. "Search method use by unemployed youth." *Journal of Labor Economics* 6 (1): 1–20.

Holzer, H. 1987. "Informal job search and black youth unemployment." *American Economic Review* 77 (3): 446–452.

Kramarz, F., and O. Nordström-Skans. 2014. "When Strong Ties are Strong: Networks and Youth Labor Market Entry." *The Review of Economic Studies* 81 (3): 1164–1200.

McKenzie, D., and H. Rapoport. 2010. "Self-Selection Patterns in Mexico-U.S. Migration: The Role of Migration Networks." *The Review of Economics and Statistics* 92 (4): 811–821.

Montgomery, J. 1991. "Social networks and labor-market outcomes: Toward an economic analysis." *American Economic Review* 81 (5): 1408–18.

Munshi, K. 2003. "Networks In The Modern Economy: Mexican Migrants In The U.S. Labor Market." *The Quarterly Journal of Economics* 118 (2): 549–599 (May).

Ortega, J., and G. Verdugo. 2014. "Immigration and the Occupational Choice of Natives: A Factor Proportions Approach." *Labour Economics* 29:14–27.

Papke, L.E., and J.M. Wooldridge. 2008. "Panel data methods for fractional response variables with an application to test pass rates." *Journal of Econometrics* 145:121–133.

Patel, K., and F. Vella. 2013. "Immigrant Networks and Their Implications for Occupational Choice and Wages." *Review of Economics and Statistics* 95:1249–1277.

Shimer, R. 2012. "Reassessing the Ins and Outs of Unemployment." *Review of Economic Dynamics* 15 (2): 127–148.

Waldinger, R. 1996. *Still the Promised City?* Boston University Press.

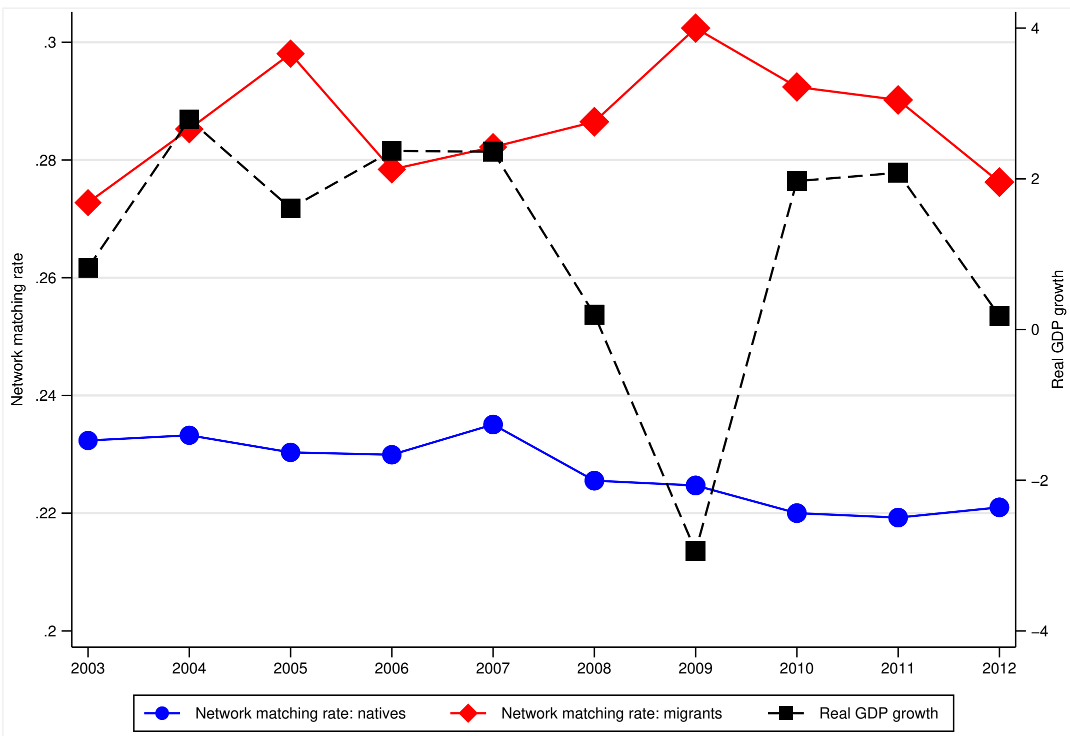
7 Tables and Figures

Table 1: Descriptive statistics of the sample by region

Region	Network matching rate	Proportion of immigrants	Origin of immigrants Europe	Africa	Other	Number of observations
Ile-de-France	0.257	0.211	0.271	0.533	0.196	44,184
Champagne-Ardenne	0.216	0.065	0.328	0.473	0.199	7,411
Picardie	0.230	0.058	0.351	0.501	0.148	8,382
Haute-Normandie	0.239	0.045	0.313	0.541	0.146	8,703
Centre	0.223	0.066	0.412	0.443	0.145	8,947
Basse-Normandie	0.186	0.024	0.276	0.555	0.169	6,045
Bourgogne	0.229	0.069	0.489	0.402	0.109	7,436
Nord-Pas-de-Calais	0.232	0.046	0.398	0.478	0.123	18,547
Lorraine	0.232	0.080	0.507	0.286	0.208	8,512
Alsace	0.237	0.106	0.449	0.307	0.244	8,288
Franche-Comté	0.204	0.072	0.333	0.468	0.200	6,477
Pays de la Loire	0.225	0.032	0.208	0.546	0.245	13,731
Bretagne	0.207	0.029	0.308	0.474	0.218	8,389
Poitou-Charentes	0.200	0.041	0.536	0.374	0.090	6,507
Aquitaine	0.239	0.079	0.409	0.456	0.136	8,771
Midi-Pyrénées	0.204	0.082	0.319	0.517	0.164	7,907
Limousin	0.209	0.058	0.364	0.489	0.148	4,971
Rhône-Alpes	0.221	0.106	0.386	0.455	0.159	21,646
Auvergne	0.199	0.058	0.443	0.357	0.200	5,159
Languedoc-Roussillon	0.256	0.113	0.277	0.624	0.099	6,492
Provence-Alpes Côte d′Azur	0.285	0.161	0.260	0.643	0.097	14,296
Corse	0.330	0.214	0.490	0.499	0.011	515
All regions	0.235	0.105	0.322	0.508	0.171	231,316

Source: Data from Labor Force Surveys 2003-2012.

Figure 1: The network matching rate over time: migrants versus natives



Source: data on the network matching rate comes from French Labor Force Surveys (2003-2012). Data on GDP growth is provided by the French National Statistical Institute.

Note: the y-axis on the left hand side stands for the share of natives and immigrants (separately) that declares having found a job through social interactions. The y-axis on the right-hand side stands for real GDP growth rate.

Table 2: Estimates of the network matching rate based on direct ties.

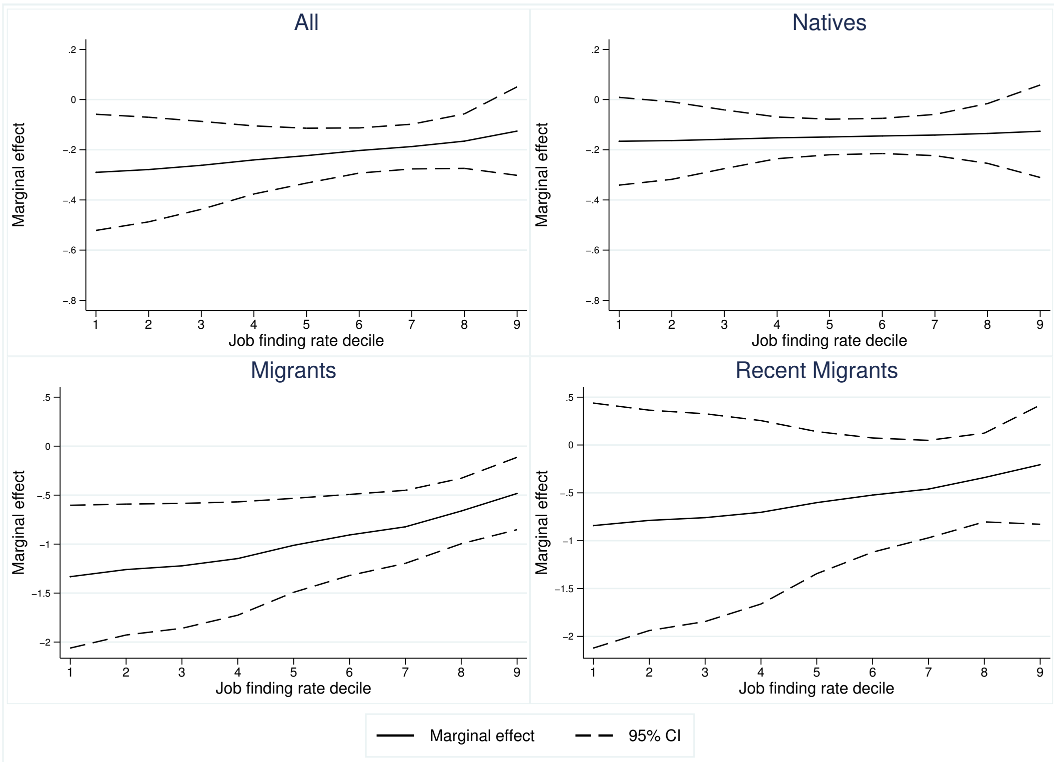
Dependent variable: network matching rate

	Share of individuals having found their job through direct ties (cell-approach)								Probability that the individual has found his job through direct ties (individual data approach)							
	All	Natives	Immigrants	Recent Immigrants	All	Natives	Immigrants	Recent Immigrants	All	Natives	Immigrants	Recent Immigrants	All	Natives	Immigrants	Recent Immigrants
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: All Individuals																
Job finding rate	-0.199***	-0.144***	-0.782***	-0.428*	-0.517	-0.221	-2.682**	-1.853	-0.223***	-0.177***	-0.713***	-0.600***	-0.685***	-0.444**	-2.358***	-2.862*
	(0.044)	(0.036)	(0.192)	(0.247)	(0.371)	(0.315)	(0.998)	(1.937)	(0.031)	(0.030)	(0.094)	(0.217)	(0.201)	(0.201)	(0.555)	(1.475)
Job finding rate^2					0.570	0.137	3.495*	2.618					0.829**	0.478	3.024***	4.126
					(0.650)	(0.581)	(1.691)	(3.400)					(0.347)	(0.350)	(0.990)	(2.603)
Fixed effects																
Origin	YES	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Job	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Origin*Year	YES	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES
Origin*Job	NO	NO	NO	NO	NO	NO	NO	NO	YES	NO	YES	YES	YES	NO	YES	YES
Job*Year	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Individual controls (age, age^2, married, female, education)	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,801	220	1,581	765	1,801	220	1,581	765	231,156	206,786	24,370	2,293	231,156	206,786	24,370	2,293
R-squared	0.300	0.138	0.262	0.336	0.302	0.138	0.269	0.336	0.025	0.018	0.077	0.299	0.026	0.018	0.077	0.300
Panel B: Skilled Individuals																
Job finding rate	-0.253*	-0.239*	-0.408***	-0.357**	-1.959**	-1.930**	-2.126***	-0.033	-0.192***	-0.162***	-0.590***	-0.544*	-0.673**	-0.500*	-2.632***	1.782
	(0.131)	(0.133)	(0.098)	(0.158)	(0.764)	(0.779)	(0.706)	(1.806)	(0.034)	(0.035)	(0.126)	(0.285)	(0.261)	(0.264)	(0.887)	(2.442)
Job finding rate^2					3.055**	3.023**	3.144**	-0.594					0.864*	0.607	3.745**	-4.163
					(1.206)	(1.220)	(1.232)	(3.232)					(0.466)	(0.470)	(1.639)	(4.203)
Fixed effects																
Origin	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO	YES	YES	YES	NO	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Job	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Origin*Year	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO	YES	YES	YES	NO	YES	YES
Origin*Job	YES	NO	NO	NO	YES	NO	NO	NO	YES	NO	YES	YES	YES	NO	YES	YES
Job*Year	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Individual controls (age, age^2, married, female, education)	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Observations	440	220	220	180	440	220	220	180	105,086	95,572	9,514	1,171	105,086	95,572	9,514	1,171
R-squared	0.084	0.073	0.205	0.102	0.121	0.109	0.239	0.102	0.024	0.018	0.093	0.426	0.024	0.018	0.094	0.427

Source: authors' calculations, data from Labor Force surveys 2003-2012.

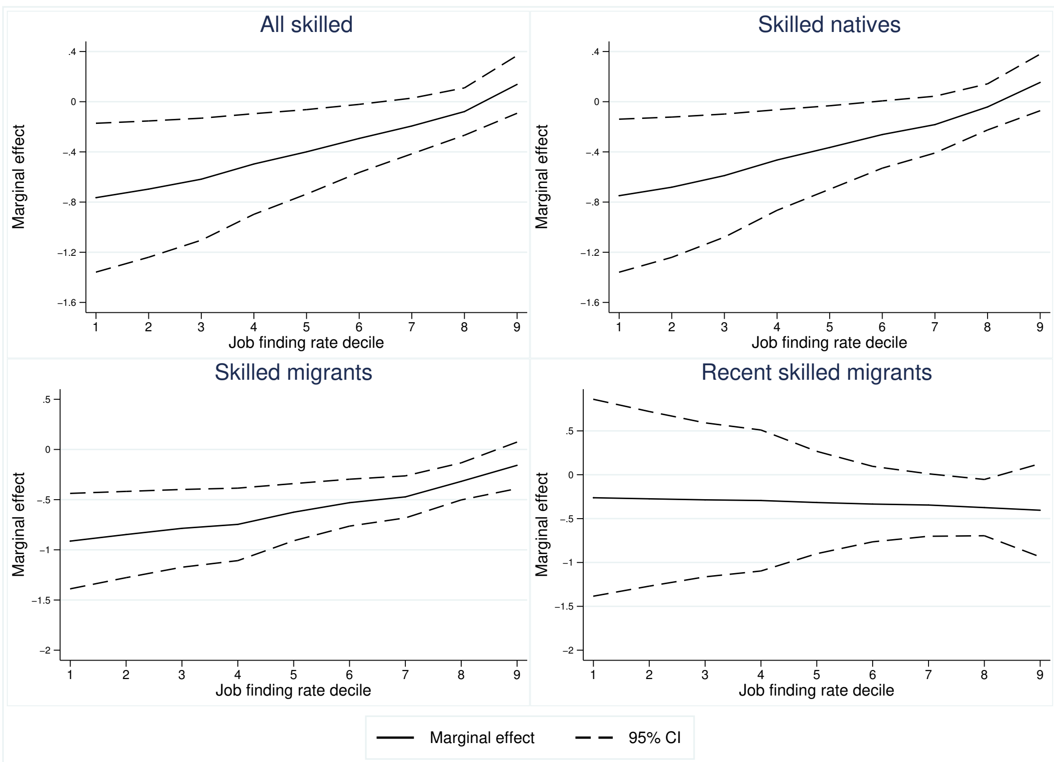
Note: estimates from linear regression models, with robust standard errors clustered at the region level in columns (1)-(8) and at the region-job level in columns (9)-(16). Weights equal total population of the corresponding region-origin cell for columns (1)-(8) and standard individual weights provided by the French Labor Force Survey for columns (9)-(16). Significance levels are $***(p < 0.01), **(p < 0.05) and *(p < 0.1)$. In panel A, origin fixed effects correspond to North Africans, Africans, Turkish, South-East-Asians, South-Europeans, North Europeans, East Europeans, South-Americans and North-Americans. In panel B, origin fixed effects distinguish between natives and immigrants since when considering the skilled population we need to aggregate all immigrants' origins to ensure a sufficient number of observations.

Figure 2: Predicted marginal effect of the job finding rate on the regional network matching rate along the job finding rate distribution



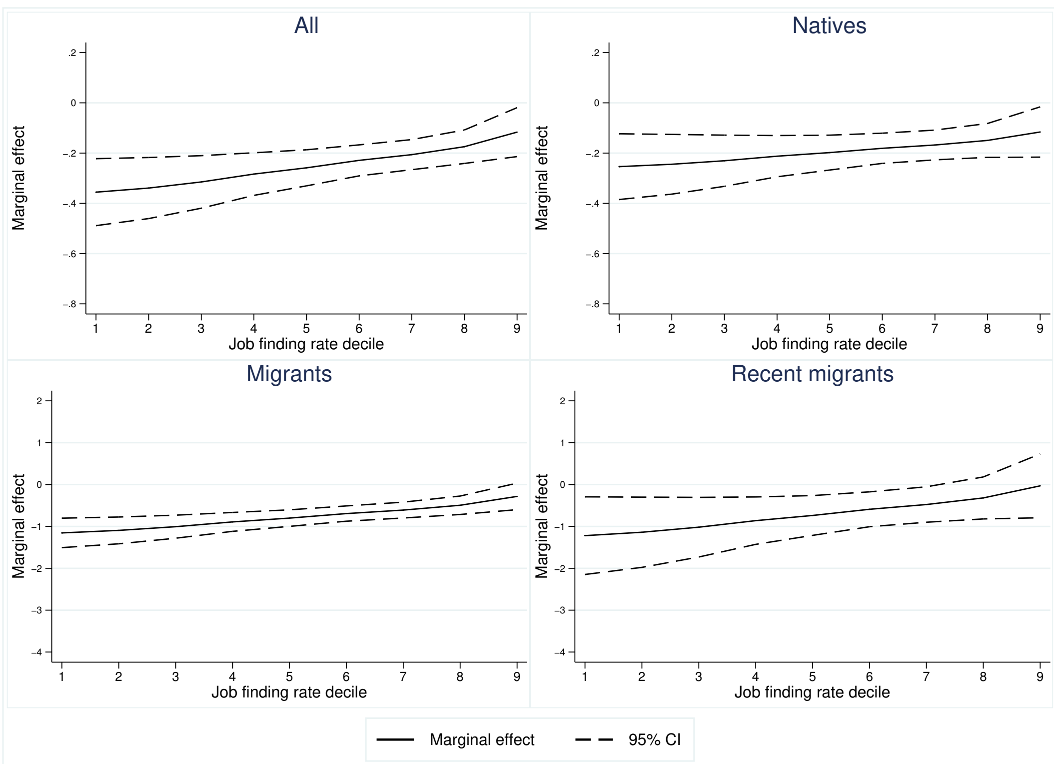
Source: authors' calculations, data from Labor Force surveys 2003-2012.

Figure 3: Predicted marginal effect of the job finding rate on the regional network matching rate of skilled employed along the job finding rate distribution



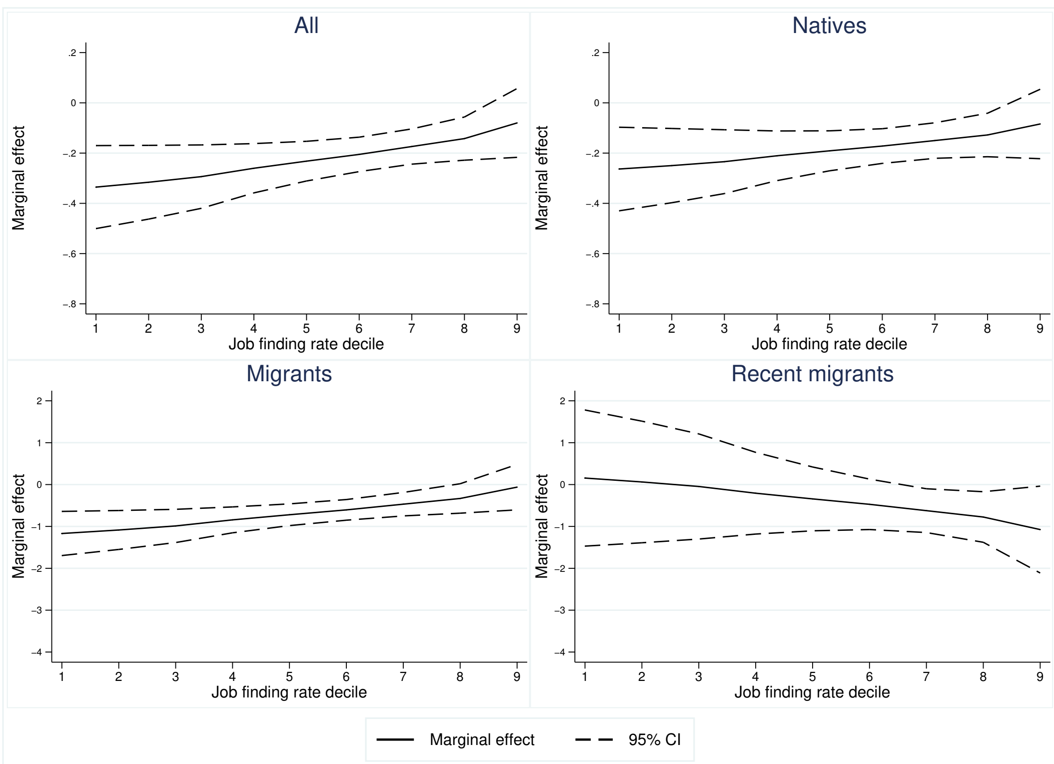
Source: authors' calculations, data from Labor Force surveys 2003-2012.

Figure 4: Individual data: predicted marginal effect of the job finding rate on the network matching rate along the job finding rate distribution



Source: authors' calculations, data from Labor Force surveys 2003-2012.

Figure 5: Individual data: predicted marginal effect of the job finding rate on the network matching rate of skilled employed along the job finding rate distribution



Source: authors' calculations, data from Labor Force surveys 2003-2012.

Table 3: Proximity of a the recently arrived individual from origin o to the most popular job among his peers in the region.

Proximity between the job of a recently arrived immigrant and the most popular job among his peers in the region

	All regions								Immigrant abundant regions		Regions with a low proportion of immigrants	
	Immigrant	Skilled immigrant	Immigrant	Skilled immigrant	Immigrant	Skilled immigrant	Immigrant	Skilled immigrant	Immigrant	Immigrant	Immigrant	Immigrant
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Job finding rate	1.087***	1.358***	1.406	2.672	1.101***	1.372***	1.450	3.046	0.865**	1.705	0.153	-0.620
	(0.267)	(0.345)	(2.098)	(3.070)	(0.269)	(0.345)	(2.105)	(3.155)	(0.366)	(3.628)	(0.334)	(2.371)
Job finding rate^2			-0.583	-2.353			-0.635	-2.997		-1.531		1.367
			(3.722)	(5.211)			(3.748)	(5.363)		(6.424)		(3.873)
Fixed effects												
Origin	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Job	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Origin*Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Origin*Job	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Job*Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls (age, age2, marri, female, educ)	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,293	1,171	2,293	1,171	2,293	1,171	2,293	1,171	1,438	1,438	850	850
R-squared	0.368	0.453	0.368	0.454	0.375	0.465	0.375	0.466	0.527	0.527	0.490	0.490

Source: authors' calculations, data from Labor Force surveys 2003-2012.

Note: estimates from linear regression models, with robust standard errors clustered at the region-job level. Individual characteristics include age, age^2, marriage, gender and education level. Significance levels are $***(p < 0.01)$, $**(p < 0.05)$ and $*(p < 0.1)$. Origin fixed effects (when considering all immigrants and not only skilled) correspond to North Africans, Africans, Turkish, South-East-Asians, South-Europeans, North Europeans, East Europeans, South-Americans and North-Americans.

A Complementary econometric results

We propose here to use as dependent variable the share of people from region g in job j from origin o who found their job thanks to social interactions, N_{gjot}. We control by year, origin and job fixed effects. We also control for year-origin, job-year and job-origin fixed effects. This allows us to control for shocks that may be origin-specific or job-specific as well as for the tendency of some origins to cluster towards certain types of jobs.

$$N_{gjot} = \gamma_0 + \gamma_1 a_{gt} + \gamma_2 a_{gt}^2 + \gamma_t + \gamma_o + \gamma_j + \gamma_{ot} + \gamma_{jo} + \gamma_{jt} + \epsilon_{got} \tag{11}$$

Because serial correlation within a particular labor market may be a concern, in all regressions we adjust standard errors for clustering of observations at the region-job level. We also use weighted regressions with weights equal to the population in the corresponding region-job-origin-year.

Table A.1: Estimates of the network matching rate at the region-job-origin level based on direct ties.

Dependent variable: network matching rate at the region-job-origin level

	All Individuals								Skilled individuals							
	All	Natives	Immigrants	Recent Immigrants	All	Natives	Immigrants	Recent Immigrants	All	Natives	Immigrants	Recent Immigrants	All	Natives	Immigrants	Recent Immigrants
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Job finding rate	-0.218***	-0.168***	-0.754***	-0.743***	-0.586***	-0.331	-2.396***	-1.943	-0.217**	-0.197*	-0.370***	-0.346	-0.587	-0.375	-2.572**	-0.548
	(0.031)	(0.030)	(0.098)	(0.222)	(0.205)	(0.204)	(0.572)	(1.877)	(0.105)	(0.115)	(0.118)	(0.487)	(0.728)	(0.776)	(1.062)	(4.153)
Job finding rate^2					0.659*	0.292	3.021***	2.219					0.660	0.317	4.023**	0.371
					(0.353)	(0.355)	(1.015)	(3.302)					(1.309)	(1.394)	(1.935)	(7.138)
Fixed effects																
Origin	YES	NO	YES	YES	YES	NO	YES	YES	YES	NO	NO	NO	YES	NO	NO	NO
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Job	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Origin*Year	YES	NO	YES	YES	YES	NO	YES	YES	YES	NO	NO	NO	YES	NO	NO	NO
Origin*Job	YES	YES	YES	YES	YES	YES	YES	YES	YES	NO	NO	NO	YES	NO	NO	NO
Job*Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	13,995	4,868	9,127	1,693	13,995	4,868	9,127	1,693	5,329	2,587	2,742	518	5,329	2,587	2,742	518
R-squared	0.206	0.225	0.183	0.441	0.206	0.225	0.185	0.441	0.176	0.163	0.284	0.638	0.176	0.163	0.287	0.638

Source: authors' calculations, data from Labor Force surveys 2003-2012. Note: estimates from weighted linear regression models, with robust standard errors clustered at the region-job level and weights equal to the population of the corresponding cell. Significance levels are $***(p < 0.01)$, $**(p < 0.05)$ and $*(p < 0.1)$. In panel A, origin fixed effects correspond to North Africans, Africans, Turkish, South-East-Asians, South-Europeans, North Europeans, East Europeans, South-Americans and North-Americans. For skilled workers, origin fixed effects distinguish between natives and immigrants since when considering the skilled population we need to aggregate all immigrants' origins to ensure a sufficient number of observations.

Table A.2: Fractional response estimates of the network matching rate based on direct ties.

Dependent variable: Share of individuals in the region having found their job through social interactions

	All	Natives	Immigrants	Recent Immigrants	All	Natives	Immigrants	Recent Immigrants
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All Individuals								
Job finding rate	-1.122***	-0.821***	-4.016***	-2.338*	-2.769	-1.208	-12.197**	-5.539
	(0.234)	(0.198)	(0.918)	(1.303)	(2.004)	(1.768)	(5.134)	(8.720)
Job finding rate^2					2.966	0.696	15.207*	5.646
					(3.530)	(3.261)	(8.868)	(15.028)
Fixed effects								
Origin	YES	NO	YES	YES	YES	NO	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES
Job	NO	NO	NO	NO	NO	NO	NO	NO
Origin*Year	YES	NO	YES	NO	YES	NO	YES	NO
Origin*Job	NO	NO	NO	NO	NO	NO	NO	NO
Job*Year	NO	NO	NO	NO	NO	NO	NO	NO
Observations	1,801	220	1,581	765	1,801	220	1,581	765
Panel B: Skilled Individuals								
Job finding rate	-1.439**	-1.365*	-2.288***	-2.402**	-10.604***	-10.481***	-11.129***	2.352
	(0.733)	(0.743)	(0.561)	(1.102)	(3.984)	(4.045)	(3.895)	(12.389)
Job finding rate^2					16.492***	16.372***	16.275**	-8.856
					(6.309)	(6.350)	(6.833)	(22.808)
Fixed effects								
Origin	YES	NO	NO	NO	YES	NO	NO	NO
Year	YES	YES	YES	YES	YES	YES	YES	YES
Job	NO	NO	NO	NO	NO	NO	NO	NO
Origin*Year	YES	NO	NO	NO	YES	NO	NO	NO
Origin*Job	YES	NO	NO	NO	NO	NO	NO	NO
Job*Year	NO	NO	NO	NO	NO	NO	NO	NO
Observations	440	220	220	180	440	220	220	180

Source: authors' calculations, data from Labor Force surveys 2003-2012. Note: estimates from weighted linear regression models, with robust standard errors clustered at the region level and weights equal to the total population of the corresponding cell. Significance levels are $***(p < 0.01)$, $**(p < 0.05)$ and $*(p < 0.1)$. In panel A, origin fixed effects correspond to North Africans, Africans, Turkish, South-East-Asians, South-Europeans, North Europeans, East Europeans, South-Americans and North-Americans. In panel B, origin fixed effects distinguish between natives and immigrants since when considering the skilled population we need to aggregate all immigrants' origins to ensure a sufficient number of observations.

Table A.3: Estimates of the network matching rate based on direct ties: regions having a low proportion of immigrants.

Dependent variable: network matching rate in regions having a low proportion of immigrants

	Share of individuals having found their job through direct ties (cell-approach)								Probability that the individual has found his job through direct ties (individual data approach)							
	All	Natives	Immigrants	Recent Immigrants	All	Natives	Immigrants	Recent Immigrants	All	Natives	Immigrants	Recent Immigrants	All	Natives	Immigrants	Recent Immigrants
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: All Individuals																
Job finding rate	-0.092**	-0.093**	-0.074	0.066	-0.462	-0.352	-1.862**	-3.265	-0.060**	-0.063**	0.024	-0.040	-0.461***	-0.368**	-1.737***	-2.821
	(0.039)	(0.037)	(0.206)	(0.497)	(0.270)	(0.270)	(0.687)	(2.605)	(0.029)	(0.030)	(0.128)	(0.470)	(0.177)	(0.187)	(0.567)	(2.406)
Job finding rate^2					0.659	0.460	3.292**	6.119					0.713**	0.543	3.250***	5.122
					(0.468)	(0.478)	(1.274)	(4.328)					(0.316)	(0.332)	(1.069)	(4.319)
Fixed effects																
Origin	YES	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Job	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Origin*Year	YES	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES
Origin*Job	NO	NO	NO	NO	NO	NO	NO	NO	YES	NO	YES	YES	YES	NO	YES	YES
Job*Year	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Individual controls (age, age^2, married, female, education)	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,332	170	1,162	484	1,332	170	1,162	484	136,297	128,000	8,297	855	136,297	128,000	8,297	855
R-squared	0.164	0.084	0.177	0.290	0.167	0.091	0.183	0.295	0.024	0.020	0.122	0.509	0.024	0.020	0.123	0.511
Panel B: Skilled Individuals																
Job finding rate	0.004	0.007	-0.072	-0.351	-1.304*	-1.299*	-1.359*	-0.634	0.012	0.009	0.098	-0.657	-0.540**	-0.469*	-1.874*	0.778
	(0.101)	(0.098)	(0.131)	(0.369)	(0.642)	(0.637)	(0.729)	(3.258)	(0.040)	(0.042)	(0.211)	(1.063)	(0.258)	(0.268)	(1.068)	(8.122)
Job finding rate^2					2.317**	2.313**	2.326*	0.514					0.980**	0.849*	3.569*	-2.524
					(0.975)	(0.967)	(1.273)	(5.387)					(0.461)	(0.481)	(1.986)	(14.752)
Fixed effects																
Origin	YES	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Job	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Origin*Year	YES	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES	YES	NO	YES	YES
Origin*Job	NO	NO	NO	NO	NO	NO	NO	NO	YES	NO	YES	YES	YES	NO	YES	YES
Job*Year	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Individual controls (age, age^2, married, female, education)	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,106	170	936	551	1,106	170	936	551	55,784	52,847	2,937	377	55,784	52,847	2,937	377
R-squared	0.058	0.056	0.093	0.136	0.077	0.076	0.110	0.136	0.030	0.023	0.219	0.828	0.030	0.023	0.221	0.828

Source: authors' calculations, data from Labor Force surveys 2003-2012. Note: estimates from linear regression models, with robust standard errors clustered at the region level in columns (1)-(8) and at the region-job level in columns (9)-(16). Weights equal total population of the corresponding region-origin cell for columns (1)-(8) and standard individual weights provided by the French Labor Force Survey for columns (9)-(16). Significance levels are $***(p < 0.01)$, $**(p < 0.05)$ and $*(p < 0.1)$. In panel A, origin fixed effects correspond to North Africans, Africans, Turkish, South-East-Asians, South-Europeans, North Europeans, East Europeans, South-Americans and North-Americans. In panel B, origin fixed effects distinguish between natives and immigrants since when considering the skilled population we need to aggregate all immigrants' origins to ensure a sufficient number of observations.

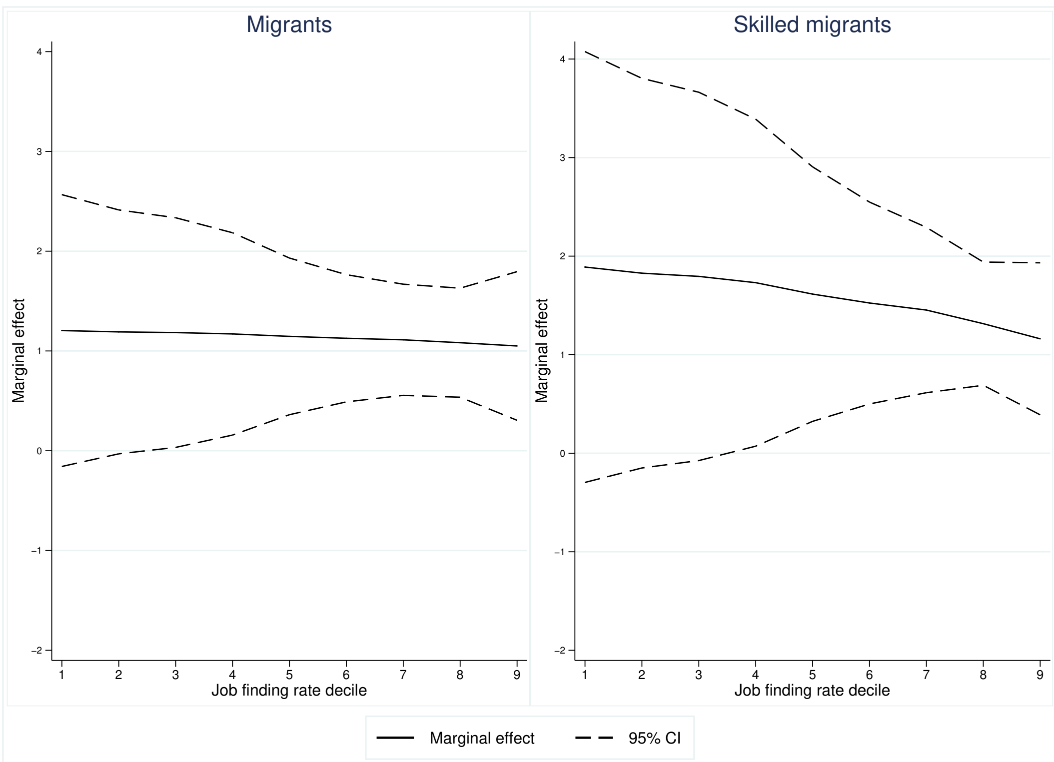
Table A.4: Estimates of the network matching rate based on direct ties: 3 origins for immigrants (African, European and Other).

Dependent variable: Share of individuals in the region having found their job through social interactions

	Immigrants	Skilled Immigrants	Recent Immigrants	Skilled Recent Immigrants	Immigrants	Skilled Immigrants	Recent Immigrants	Skilled Recent Immigrants
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Job finding rate	-0.765***	-0.522***	-0.314	-0.260	-2.996***	-3.798***	0.652	2.984
	(0.203)	(0.142)	(0.200)	(0.259)	(1.050)	(1.313)	(1.935)	(2.461)
Job finding rate^2					4.104**	5.996**	-1.774	-5.935
					(1.739)	(2.300)	(3.337)	(4.222)
Fixed effects								
Origin	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES
Job	NO	NO	NO	NO	NO	NO	NO	NO
Origin*Year	YES	YES	YES	YES	YES	YES	YES	YES
Origin*Job	NO	NO	NO	NO	NO	NO	NO	NO
Job*Year	NO	NO	NO	NO	NO	NO	NO	NO
Observations	649	595	487	347	649	595	487	347
R-squared	0.240	0.093	0.136	0.156	0.257	0.111	0.137	0.161

Source: authors' calculations, data from Labor Force surveys 2003-2012. Note: estimates from weighted linear regression models, with robust standard errors clustered at the region level and weights equal to the total population of the corresponding cell. Significance levels are $***(p < 0.01)$, $**\ (p < 0.05)$ and $*(p < 0.1)$. In panel A, origin fixed effects correspond to North Africans, Africans, Turkish, South-East-Asians, South-Europeans, North Europeans, East Europeans, South-Americans and North-Americans. In panel B, origin fixed effects distinguish between natives and immigrants since when considering the skilled population we need to aggregate all immigrants' origins to ensure a sufficient number of observations.

Figure A.1: Predicted marginal effect of the job finding rate on the proximity of a the recently arrived individual from origin o to the most popular job among his peers in the region. Nine origins.



Source: authors' calculations, data from Labor Force surveys 2003-2012.