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How helpful are social networks in finding a job along the economic cycle? Evidence from immigrants in France[☆]

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ABSTRACT

Around 50% of individuals obtain or hear about jobs through social networks. This hiring trend may become problematic when the labor market is tight and people need less social contacts to find a job. Using a one-period static model where network members may receive job offers directly from the firm or indirectly through employed members in the network we show that the share of new hires finding a job through social connections (*ie network matching rate*) decreases with the job finding rate. Using French data for the period 2003–2012, we test this prediction with immigrants, a population subgroup for whom networks play a major role in occupational decisions. We propose two network matching rate indicators, one based on direct recommendations and another one internalizing the positive externality on the employment probability induced by peers. We find a decreasing relationship between the network matching rate and the job finding rate. Social connections are less helpful for finding jobs during economic expansions.

1. Introduction

Around 50% of individuals in developed countries obtain or hear about jobs through friends and family (for studies on US data, see Holzer, 1987, Holzer, 1988, Montgomery, 1991, Granovetter, 1995 or Brown et al., 2016; on Portuguese data, see Addison and Portugal, 2002; on Swedish data, see Kramarz and Nordström-Skans, 2014).[1] Referrals are increasingly used by big companies to find new hires, saving time and money. Firms are more likely to hire applicants referred by current employees than non-referred applicants (see Ioannides and Datcher-Loury, 2004, or Topa, 2011, for a survey). Using data from one US firm, Brown et al. (2016) estimate that 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. Using field experiments, Pallais and Glassberg-Sands (2016) find that referrals contain positive information about workers' performance and persistence that is not contained in workers' observable characteristics. Moreover, referrals perform particularly well when working directly with their referrers.[2]

This hiring trend presents some major problems. First, as reported by Ioannides and Datcher-Loury (2004), the acquired social contacts

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[1] 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, 2004; Calvo-Armengol; Zenou, 2005; Calvo-Armengol and Jackson, 2007; Galeotti; Merlino, 2014).

[2] The literature on social networks is very large. A detailed survey on the taxonomy of "macro" and "micro" characteristics of social networks and their role in determining learning, diffusion, decisions and resulting behaviors is presented in Jackson et al. (2017). Among many others, social ties influence geographic mobility (see David et al., 2010; Alesina et al., 2015), criminal behavior (Matsueda and Anderson, 1998; Warr, 2002; Glaeser et al., 1996), financial integration (Bhattacharya et al., 2018), equity markets (Lyocsa et al., 2019), the diffusion of freedom of expression, exchange of ideas and rules (Mukherjee and Dutta, 2018), the stringency of procedural formalism in the housing market (Bonleu, 2019) and electoral outcomes (Cruz et al., 2017).

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develop along dimensions such as race, ethnicity, religious affiliation and education. Brown et al. (2016) find that 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 adverse effects in the long run in terms of diversity and skill variety within firms. Second, people who are disconnected from the labor market, *ie* long-term unemployed, are even less likely to find a job in this context. Third, during expansions, when the labor market is tight, employees are less likely to have friends seeking jobs. When employment opportunities are abundant, people are less likely to need social contacts to find a suitable job.

Our paper empirically analyzes changes along the economic cycle in the probability of finding a job through friends, relatives or formers colleagues. To illustrate the economic rationale behind our empirical results, we propose a simple one-period static model inspired from Beaman (2012), Galenianos (2014), Galeotti and Merlino (2014), Stupnytska and Zaharieva (2015) and Schmutte (2016), where the economy is composed of a finite number of independent networks or labor markets. Both job destruction and job finding rates are exogenous. Members of the network only exchange with each other and have no contact outside their own network. They may receive job offers directly from the firm or indirectly through employed members in the network. The model predicts a decreasing relationship between the share of new hires that have found a job through social connections (*ie network matching rate*) and the job finding rate. Intuitively, during expansion periods, there are more job offers that are posted. This allows network members to receive offers directly rather than through their social connections. The network matching rate behaves then in a counter-cyclical way, decreasing during economic expansions.[3]

We test this result using the French Labor Force Surveys 2003–2012. We focus on immigrants, since peer effects have been shown to be of major relevance for immigrants' location decisions (see McKenzie and Rapoport, 2010) and for labor market outcomes (see among others Waldinger, 1996, Munshi, 2003 or Patel and Vella, 2013).[4] Furthermore, we provide descriptive evidence on the fact that social networks operate along different dimensions for natives and immigrants. The share of immigrants finding a job through social connections is shown to be more dependent on the economic cycle than that of natives, confirming the major relevance of networks for immigrants' labor market outcomes.

We propose two alternative indicators of the network matching rate. On one hand, we consider an indicator based on the probability of finding a job through social interactions (friends, relatives or colleagues). This traditional indicator, also employed in Galeotti and Merlino (2014), corresponds to what we will refer to as direct ties, since it implies a direct recommendation from a friend, relative or colleague.[5] On the other hand, we propose an indicator in which the individual does not benefit from a direct recommendation, but rather from a positive externality related to her 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. The importance of these occupational niches for immigrants has been analyzed recently by Hamilton et al. (2018), Eckstein and Peri (2018) and Liang and Zhou (2018).

We investigate the variation of the network matching rate for immigrants along the economic cycle. Whether we consider the direct recommendation or the alternative indicator that exploits indirect ties of immigrants related with their geographical origin as a measure of the network matching rate, our estimations reveal that the relation between the probability that the individual finds a job through social interactions and the job finding rate is decreasing, confirming the prediction of the theoretical framework.[6]

The role of networks along the economic cycle is studied in Galenianos (2014). Using a search model with social networks, the author predicts that while higher use of referrals increases aggregate matching efficiency and the proportion of jobs found through a referral, a higher efficiency of the matching function increases aggregate matching efficiency but reduces referrals. Moreover, a higher unemployment rate reduces the flow of referrals. Arbex et al. (2016) propose a theoretical setup in which the complementarity of networks and direct search by the unemployed amplifies the short run response of the economy to a technological shock. In Cahuc and Fontaine (2009) social networks can be over-utilized or under-utilized, with respect to an efficient allocation. Moreover, the existence of different job search methods can give rise to a higher job search intensity than the efficient one.

These studies assume that the intensity of the information flow in the network is exogenous, an assumption that prevents the analysis of how incentives in networking relate to different labor market conditions. Galeotti and Merlino (2014) propose a theoretical framework in which workers invest in forming referral networks taking into account labor market conditions before matching in the labor market (*ie* networks are a set of links that persist once formed).[7] Using UK data, they find that the network matching rate is increasing in 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. The counter-cyclical movement in referral-based searches is rationalized by Schmutte (2016) in a model of frictional job matching in which the intensity at which referrals are used is endogenously determined (with unemployment, vacancies and the wage rate) and exhibits a non-monotonic relation with labor market tightness. Whether referrals are converted to jobs is inversely related to the intensity of use of referrals.

In contrast with this literature, our paper does not endogeneize incentives in networking depending on labor market conditions. We abstract from potential influences coming from workers' strategic behavior depending on returns to network investment related to labor market conditions. Instead, the number of contacts of the individual and time spent with each of them are assumed exogenous and constant along the economic cycle. The predicted relationship between the job finding rate and the network matching rate captures then the structural relation between both variables. However, in line with previous papers endogeneizing the intensity of the information flow in the network, we still find a counter-cyclical progression of the network matching rate

[3] In contrast with Calvo-Armengol (2004) and Calvo-Armengol and Zenou (2005), we do not consider the network size but the probability of finding a job thanks to a social contact (network matching rate). Calvo-Armengol (2004) establishes a general nonmonotonicity result on information flow and unemployment with respect to network size in symmetric networks. In Calvo-Armengol and Zenou (2005) when the network size increases the unemployed workers hear about more vacancies through their social network. However, above a certain critical value, job matches decrease with network size.

[4] Peer effects are also widely recognized as very influential in migration decisions (see McKenzie and Rapoport, 2010; Dolfin; Genicot, 2010; Beine et al., 2011; Giulietti et al., 2018; Bertoli and Moraga, 2015; Mourao, 2016).

[5] It could also match with the notion of strong ties introduced by Granovetter (1973) which corresponds to the socialization process that takes place within the family or close friends, while weak ties correspond rather to random encounters outside the family or friends. See also Goel and Lang (2017).

[6] As remarked in Mourao et al. (2017), similar underlying mechanisms apply when analyzing migration decisions along the electoral cycle. Better economic conditions the year before elections tend to reduce migration rates.

[7] Merlino (2014) proposes an extension of Galeotti and Merlino (2014) in which workers can affect the arrival rate of job offers by searching more intensively. Workers decide whether to use formal or informal searches when firms are passive. Merlino (2019) complements this paper by studying the interaction between firms' decisions to open vacancies and workers investment in social networks to find jobs. The transmission of information in the network generates positive search externalities so that, in equilibrium, vacancy creation and socialization are strategic complements.

along the economic cycle. This suggests that endogenous incentives to network tend simply to reinforce the already existing counter-cyclical pattern between the network matching rate and the economic cycle.

The remainder of our paper is organized as follows. The next section presents a theoretical framework shedding light on the relationship between the economic cycle and the network matching rate. Section 3 describes the database and variables and provides some descriptive statistics. Section 4 explains the econometric approach while the main estimation results are presented in Section 5. Section 6 presents concluding comments and discusses the limits of our approach.

2. Theoretical framework

2.1. Labor market

We consider a one-period static model inspired from Beaman (2012), Galenianos (2014), Galeotti and Merlino (2014), Stupnytska and Zaharieva (2015) and Schmutte (2016). The economy is composed of S independent networks. The number of members in each network is denoted N_t and all these members are assumed to be employed at the beginning of the period.[8] Following Beaman (2012), we make the assumption that all individuals within a network are connected. This eliminates the distinction made by Calvo-Armengol and Jackson (2004) between direct and indirect connections. In our framework, 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 ignore potential interactions or congestion problems associated with the presence of other networks in the economy Fig. A.1.[9]

The dynamics of each of the S labor markets are characterized by two parameters. On the one hand, $\delta \in (0,1)$ stands for the job separation rate at the beginning of the period and can thus be interpreted as an aggregate economic shock. A random sample of workers loses their job at the beginning of each period with probability δ. The number of individuals losing their job is given by δN_t. If a worker loses the job, the worker becomes a job seeker. The probability that an individual keeps the job equals $(1-\delta)$, so the number of individuals keeping their job equals $(1-\delta)N_t$.

On the other hand, $a \in (0,1)$ stands for the probability that the individual directly receives a job offer from an employer, while $(1-a)$ will stand for the probability of receiving a job offer via the network. If an agent is unemployed and receives information on a job vacancy, the agent 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, the individual passes along the information to a randomly selected network member.[10] If this member is employed, the vacant job is lost. If the member has lost her job, the member will occupy the vacant job in the next period. Job seekers receive information on a job offer directly from a firm or indirectly through a network member. In both cases, the individual keeps this job offer.

Both parameters δ and a are assumed to be exogenous. We will analyze how changes in a affect the probability of the unemployed finding jobs through social contacts. Contrary to Galeotti and Merlino (2014) or Schmutte (2016), in our setup individuals cannot decide to invest more or less effort/time on networking depending on labor market conditions. The predicted relationship between the job finding rate and the network matching rate will then capture the structural relation between both variables. We abstract from potential influences coming from workers' strategic behavior depending on returns to network investment related to labor market conditions.

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:

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

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 from a firm ($a\delta N_t$ in the matching function) or indirectly through social interactions ($(1-a)\delta N_t \varphi(N_t,a,\delta)$ in the matching function). The function $\varphi(N_t,a,\delta)$ is interpreted as the probability of hearing of a job through social interactions and depends on both the size of the social network and labor market conditions.

The total number of jobs which are available in the network to be passed, *ie* the number of job offers received by network members who are already employed, equals $a(1-\delta)N_t$. The number of potential recipients, *ie* those who are unemployed at the beginning of the period after the exogenous breakup has occurred, equals δN_t. If employees send offers at random, then the number of offers received by a given job seeker follows a binomial that converges to a Poisson. The probability of receiving at least one offer through the network is $\varphi(N_t,a,\delta) = 1 - e^{-\frac{a(1-\delta)N_t}{\delta N_t}} = 1 - e^{-\frac{(1-\delta)a}{\delta}}$ where $\frac{\partial \varphi(N_t,a,\delta)}{\partial a} > 0$ and $\frac{\partial^2 \varphi(N_t,a,\delta)}{\partial a^2} < 0$.

The network matching rate is therefore represented by:

$$NetMat = \frac{(1-a)\delta N_t \varphi(N_t,a,\delta)}{M(a,N_t)} = \frac{1}{1 + \frac{a}{1-a}\frac{1}{\varphi(N_t,a,\delta)}} \tag{2}$$

where the numerator stands for the number of matches that takes place through the network in period *t* and the denominator corresponds to the total number of matches in *t*. We seek to analyze the progression of the network matching rate during expansion/recession periods. Therefore, we are interested in the sign of the following derivative:

$$\frac{\partial NetMat}{\partial a} = -NetMat^2 \frac{1}{(1-a)\varphi(N_t,a,\delta)}\left(\frac{1}{1-a} - \eta_a^{\varphi}\right) \tag{3}$$

where η_a^{φ} stands for the elasticity of the probability of receiving a job offer through the network:

$$\eta_a^{\varphi} = \frac{\partial \varphi(N_t,a,\delta)}{\partial a}\frac{a}{\varphi(N_t,a,\delta)} = \frac{(1-\delta)a}{\delta}\frac{e^{-\frac{(1-\delta)a}{\delta}}}{1-e^{-\frac{(1-\delta)a}{\delta}}}$$

For a fixed network size, $a \in (0,1)$ and $\delta \in (0,1)$ it is easy to see that $\eta_a^{\varphi} < \frac{1}{1-a}$. As a consequence, the derivative $\frac{\partial NetMat}{\partial a}$ is negative, meaning that the proportion of people finding a job through social contacts is expected to decrease with the parameter a. The larger the rate at which direct offers from employer are posted, the lower the share of people that finds a job through social connections and the larger the share that finds a job through direct job offers from the employer. In what follows, we will test the relevance of this prediction on the population of immigrants using French data. The case of France is particularly interesting since, according to Hairault et al. (2015), in France the job finding rate explains more than 65% of unemployment dynamics over the past decade. This, combined with the strictness of employment protection legislation in France, justifies our focus on the job finding rate as an indicator of the economic cycle while assuming a constant δ.

[8] This simplifying assumption allows us to abstract from the former stock of unemployed workers when analyzing the number of new matches per period.

[9] As underlined by Schmutte (2016), the probability that a worker is hired through a referral is decreasing in the intensity of referral use by other workers. This within-network congestion effects as well as between-network congestion effects are not considered in our setup. With the data on hand we are unable to measure these effects. Including them in the theoretical analysis would complicate our model and would not improve the Correspondence between our theoretical and empirical analysis.

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

3. Data, variables and descriptive statistics

For our empirical analysis, we use data from the French Labor Force Surveys (LFS) for the period from 2003 to 2012. For this period we have consistent and reliable information on occupations, on whether the individual has found the job through social interactions, country of birth and year of arrival in France for immigrants. 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.[11]

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/qualifications and secondary jobs. The French LFS provides the four-digit level occupation for each employed individual.[12] We will refer to occupations as jobs all along the paper.

There are two limitations of the French LFS concerning our topic of interest. First, we have to stop our analysis in 2012, since afterwards there is no detailed information on the respondent's country of birth. Since we exploit individual's geographical origin to estimate the relationship between the network matching rate and the job finding rate, our analysis cannot go beyond 2012. Second, even if the LFS allows for consideration of new hirings by isolating people who have been in the job for less than a year, the facts of working with survey data and not census data makes this approach not possible due to the lack of observations, particularly when we consider immigrants from different origins.[13] We will, however, focus on people with less than 3 years of seniority in the job (*ie* 2 years of seniority or less in the job), which corresponds to hirings over the past two years.

We consider 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 only available at the regional level. Second, it allows us to guarantee a sufficient number of observations even when considering detailed categories of immigrants. France includes 22 regions.

For the econometric analysis we then exploit variability across regions. We consider the nine following groups of birth country: (1) North Africans: Algerian, Tunisian, Moroccan, (2) Africans: all other African countries, (3) Turkish: Turkey, (4) South-East-Asian: Vietnamese, Cambodian, Laotian, (5) South-Europeans: Italian, Portuguese, Spanish, Greek, (6) Central-North Europeans: German, Belgian, Dutch, Luxembourg, Irish, Danish, British, Swiss, Austrian, Norwegian, Swedish, (7) Eastern Europeans and Russians, (8) South-Americans and (9) North-Americans.

After pooling all the year-specific datasets, we obtain a sample comprising 232,803 respondents for the period 2003–2012. As shown in Table 1, this workforce is very unequally distributed across regions, with Ile de France being by far the most workforce 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%. The sample includes 24,485 foreign born workers. Six regions have a proportion of immigrant workforce above or equal to the average: Corse (21.5%), Ile de France (21.1%), PACA (16.1%), Languedoc-Roussillon (11.3%), Rhône-Alpes (10.6%) and Alsace (10.5%). 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% of 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, 28.7% in PACA and 25.8% in Ile de France, to 18.6% in Basse Normandie, 19.9% in Auvergne and 20% in Poitou-Charentes.

In our study, the job finding rate is used as an indicator of the economic cycle. Based on the estimations of Hairault et al. (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, *ie* 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.[14] In order to reduce time aggregation biases, we calculate the job finding rate following Shimer (2012) so as to take into account the problem that, while data is available only at discrete dates the underlying environment keeps changing over time. Taking yearly averages, we obtain an average job finding rate per region.[15]

The positive correlation between the economic cycle and the job finding rate is clearly displayed on the left-hand side panel of Figure A.1 in Appendix A. We find that overall the job finding rate follows the evolution of GDP growth. Note though that, whereas decreases in GDP growth, as in 2008–2009, are directly associated with equivalent decreases in the job finding rate, recoveries in GDP growth do not induce equivalent recoveries in the job finding rate. Our cycle indicator displays therefore a smoother progression than GDP growth. Furthermore, as shown by the right-hand side panel of Figure A.1, higher job finding rates during period t translate into decreases in immigrants' unemployment rate in period $t+1$, and vice-versa, reduced job finding rates are associated with unemployment increases.

Fig. 1 displays the progression between 2003 and 2012 of both the job finding rate per year and the share of employed natives and immigrants that declared having found a job through friends, relatives or colleagues. While the left-hand side panel considers all individuals, the right hand side panel focuses on people having at least secondary education. In both cases, the y-axis on the left-hand side represents the

[11] 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). The sampling method consists of a stratification of mainland France into 189 strata (22 French regions x 9 types of urban unit) and a first stage sampling of areas in each stratum (with different probabilities, average sampling rate = 1/600). Areas contain about 20 dwellings and among them only primary residences are surveyed. Access to the LFS data is possible for researchers using the Quetelet Prodego website (http://quetelet.progedo.fr/).

[12] When implementing robustness tests using a cell approach, we will consider the two digit occupation classification (provided by the two first digits of the code associated with each occupation defined at four digit level), in order to ensure a sufficient number of observations for every occupation. This will lead us to consider 24 occupations. For both, the individual data analysis and the cell analysis, we exclude from our sample farmers, civil servants, military and clergymen.

[13] 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 and there is no information on the use of social networks to find a job.

[14] We thank Idriss Fontaine for providing us with all the prepared data to compute the job finding rates. For further details, see Fontaine (2016).

[15] 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.

Table 1
Descriptive statistics of the sample by region.

Region	Network matching rate	Proportion of immigrants	Origin of immigrants			Number of observations
			Europe	Africa	Other	
Ile-de-France	0.258	0.211	0.272	0.532	0.196	44,262
Champagne-Ardenne	0.217	0.065	0.332	0.470	0.198	7471
Picardie	0.231	0.058	0.356	0.496	0.147	8455
Haute-Normandie	0.240	0.045	0.312	0.543	0.145	8741
Centre	0.224	0.067	0.413	0.443	0.144	9036
Basse-Normandie	0.186	0.024	0.287	0.547	0.166	6097
Bourgogne	0.231	0.070	0.495	0.399	0.106	7526
Nord-Pas-de-Calais	0.232	0.046	0.397	0.478	0.125	18,635
Lorraine	0.232	0.080	0.508	0.285	0.207	8543
Alsace	0.238	0.105	0.449	0.307	0.245	8326
Franche-Comt	0.205	0.072	0.333	0.468	0.199	6503
Pays de la Loire	0.227	0.032	0.208	0.548	0.245	13,882
Bretagne	0.209	0.028	0.306	0.472	0.222	8480
Poitou-Charentes	0.201	0.041	0.525	0.387	0.088	6564
Aquitaine	0.241	0.080	0.417	0.449	0.133	8903
Midi-Pyrnes	0.206	0.082	0.320	0.518	0.162	7969
Limousin	0.209	0.057	0.366	0.487	0.147	5000
Rhne-Alpes	0.221	0.106	0.386	0.455	0.159	21,745
Auvergne	0.199	0.058	0.447	0.354	0.198	5182
Languedoc-Roussillon	0.257	0.113	0.276	0.624	0.100	6552
Provence-Alpes Cte dAzur	0.287	0.160	0.259	0.644	0.097	14,414
Corse	0.328	0.216	0.485	0.504	0.011	517
All regions	0.235	0.105	0.323	0.507	0.170	232,803

Source: Data from Labor Force Surveys 2003–2012.

proportion of individuals (natives and immigrants, respectively) claiming to have found a job through social interactions, while the y-axis on the right-hand side represents the job finding rate.

Several conclusions can be drawn from Fig. 1. 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, the network matching rate is lower among high skilled workers. Third, while the network matching rate of natives has followed a smoothly decreasing trend since 2004, for immigrants the decrease in the job finding rates during the period 2007–2009 is associated with an increase in the network matching rate. The share of skilled immigrant workers declaring having found a job through social networks decreases when the job finding rate increases and vice-versa (see right-hand side panel). The diverging behavior of the native and immigrant network matching rate for identical changes in the job finding rate suggests that networks do not operate along the same dimensions for natives and immigrants, underlining the importance of focusing on the immigrant population subgroup.[16]

We consider two different indicators of the network matching rate. First, due to the fact that we are considering survey data and not census data, we cannot exactly estimate equation (2). We employ the French LFS since it is the unique population representative database which precisely asks the individual how she found her job in the firm. Included among possible answers is "through family relations, personal relations or professional relations". The French LFS is a sequence of non-exhaustive quarterly cross-sections that does not allow for rigourously computing hirings per period t, which stands for the denominator in equation (2). For the same reason, we are unable to compute the numerator, since it corresponds to the number of new hirings during period t that took place through social networks. We propose then an indicator of the network matching rate which proxies equation (2) using stock variables, which are available in the LFS.

Instead of considering the share of hirings in period t having found the job through social networks (equation (2)), we consider the share of employed people in period t that has found a job through social networks[17]:

$$\text{Estimated } NetMat = \frac{\text{Nb. employed in period t having found a job through social networks}}{\text{Nb. employed in period t}} \quad (4)$$

We exploit yearly variation in this indicator with respect to yearly variation in the job finding rate in order to estimate the relationship between the share of employed people (immigrants in our case) finding a job through social networks and the economic cycle. According to our theoretical framework, the share of new hirings having found a job through social networks is decreasing in the job offer rate a. Therefore, we also expect the share of employed people having found a job through networks to decrease as a increases, particularly since we will estimate this relationship exploiting yearly variations in both variables. As stated above, in the econometric analysis we also consider as an independent variable the share of employed people in period t that found a job through social networks and has less than 3 years of seniority in that job. This is the best proxy we can have for new hires.[18]

For our second indicator we do not require a direct recommendation from a network member. It measures the proximity between jobs occupied by immigrants and the most popular job among their peers in the region. Our indicator is inspired by 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 her peers in the corresponding federal state. We generalize here this indicator and we consider the whole set of jobs where "established immigrants" from origin o in region g are present. That is, from the total immigrant population, we are going to exclude immigrants with

[16] As shown by Figure A.2 in Appendix A, there is a positive correlation between the immigrants' network matching rate and the immigrants' relative wage with respect to natives. This suggests that the increased use of social networks to find a job may improve immigrants' relative performance in terms of wages with respect to natives.

[17] Both outcomes (ie. share of hirings and share of employed people) are obviously expected to be strongly positively correlated.

[18] When considering less than two years of seniority the number of observations is too low.

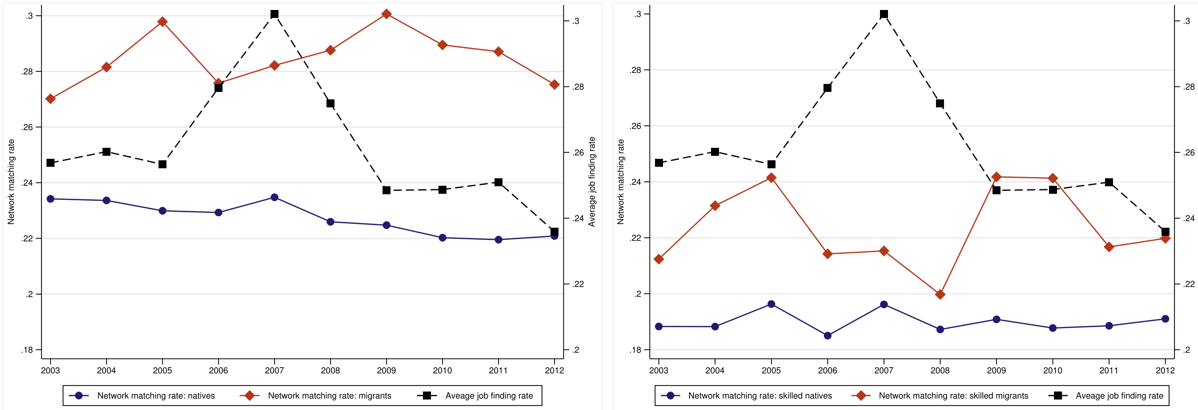

Fig. 1. Relationship between the network matching rate and the job finding rate. Note: the y-axis on the left hand side stands for the share of natives and immigrants (separately) that declares having found a job through social interactions. The y-axis on the right-hand side stands for the job finding rate.
Source: data on the network matching rate comes from French Labor Force Surveys (2003–2012). Data on the job finding rate is provided by Fontaine (2016).

less than 6 years of residence in France.[19] The remaining sample is then uniquely composed by "established immigrants". We use this sample to compute for every origin in every region the set of jobs where these immigrants are present.

For every origin o and in each region g, we rank the jobs where "established immigrants" are present from the most popular one to the least popular one. 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 "established immigrants" from origin o is the most numerous, a rank equal to $M-1$ to the job where the number of "established immigrants" from origin o is the second most numerous, and so on. The last job in the ranking will be the job in the region where the number of "established immigrants" 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 jobs ranked from M for the most popular job to 1 for the least popular job for the considered origin in the region.

We then define for every immigrant i with less than 6 years of residence in the host country and for every immigrant i with less than 3 years of seniority in the current job a variable $Dist_{iogjt}$ capturing the distance between the ranking of the job where the individual is employed in region g and the most popular job among the established peers in region g. The distance is smaller the closer the individual is employed with respect to the most popular job of their established peers in the region. Distance is then defined as:

$$Dist_{iogjt} = RPopular_{ogt} - R_{iogjt} \tag{5}$$

where $RPopular_{ogt}$ stands for the ranking of the most popular job of "established immigrants" from origin o in region g at date t, *ie* if in period t "established immigrants" 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 immigrant i (with less than 6 years of residence or/and less than 3 years of seniority) 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:

$$ExJobI_{iogjt} = 1 - \frac{Dist_{iogjt} - Min\{Dist_{ogjt}\}}{Max\{Dist_{ogjt}\} - Min\{Dist_{ogjt}\}} \tag{6}$$

The closer $ExJobI_{iogjt}$ is to unity, the closer the immigrant with less than 6 years of residence in the host country or/and less than 3 years of seniority in the current job is to the most popular job of the established peers in the region.

Contrary to our first indicator which only considers direct recommendations from social contacts, our second indicator focuses on 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. 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 the chances to obtain the job. In an involuntary way, the individual belongs to a social network associated with the own geographical origin that increases the employment probability in that job (because it facilitates communication, reduces cultural distance, etc). This is the idea behind the largely diffused instrument in migration literature, which uses the historical settlement of immigrants to predict current geographical locations and occupations (see Altonji and Card, 1991; Card, 2001; Card, 2009; Cortes and Tessada, 2011; D'Amuri; Peri, 2014 or Moreno-Galbis; Tritah, 2016).

4. Econometric strategy

We estimate the varying role of the network matching rate along the economic cycle. We work with survey data so that we build our indicators using stock variables rather than flows. We consider three different population subgroups: (*i*) the whole population of immigrants, (*ii*) immigrants having arrived in France less than 6 years ago and (*iii*) immigrants having less than 3 years of seniority in their current job (which corresponds to hirings over the two past years). We test the robustness of our results over the corresponding skilled immigrant population.

We define the network matching rate as the probability P_{iogjt} that the individual i from origin o living in region g and occupied in job j declares having found the job through social interactions (which corresponds to the indicator defined in equation (4)) and estimate the following linear probability model:

$$P_{iogjt} = \gamma_0 + \gamma_1 a_{gt} + \gamma_t + \gamma_o + \gamma_j + \gamma_{ot} + \gamma_{oj} + \gamma_{jt} + \epsilon_{ogjt} \tag{7}$$

where a_{gt} represents the job finding rate in region g at date t. According to the model's prediction, the network matching rate should be decreasing in this job finding rate. As a robust test, we also propose a more flexible specification, including a quadratic profile of the job finding rate, to allow for a non monotonic relation between the network matching

[19] To become eligible for French nationality, France requires foreign born people to have resided in the country for at least 5 years. We thus adopt this legal threshold and consider that after 5 years of residence immigrants are already integrated or well "established" in France.

rate and labor market conditions.

We control for year, origin and job fixed effects (γ_t, γ_o and γ_j, respectively). Year fixed effects allow to control for aggregate shocks. Origin fixed effects capture systematic differences in the importance of the network matching rate across origins. This allows to control for differences in the network size across origins and for systematic discrimination against some of the origins. Job fixed effects allow to control for systematic differences in our network matching rate indicator across jobs.

We also consider fixed effects origin-year, job-year and job-origin (γ_{ot}, γ_{jt} and γ_{oj}, respectively). Origin-year fixed effects allow for differential shocks across origins, which may induce different evolutions in the size of the network across origins or may respond to discriminatory shocks. Job-year fixed effects control for specific shocks that may affect one particular job due to a technological innovation or change in the productive structure. Job-origin fixed effects account for the systematic concentration of some origins in certain types of jobs.

To identify the effect of the economic cycle on the network matching rate, we exploit changes in the individual probability of finding a job through social connections as a function of changes in the job finding rate. By controlling for year fixed effects, we capture the part of the network matching rate variation that is common to all individuals in all regions.[20] The remaining variability in the network matching rate is then specific to the individual and to the socioeconomic environment where the individual lives, which is the region in our case (since we control for origin and job fixed effects). It seems then intuitive to relate this individual and region specific component of the network matching rate to the job finding rate of the region where the individual lives. We exploit heterogeneity across regional job finding rates to estimate the relationship between the network matching rate and the job finding rate. We exclude regional fixed effects as we do not have enough variability to identify individually regional fixed effects and the coefficient of the regional job finding rate.

Because serial correlation within a particular labor market (*ie* region) may be a concern, we implement weighted OLS regressions with robust standard errors clustered at the region-year level. We use weights provided by the LFS.

For our second indicator we estimate a similar equation:

$$ExJobI_{iogjt} = \gamma_0 + \gamma_1 a_{gt} + \gamma_t + \gamma_j + \gamma_o + \gamma_{ot} + \gamma_{oj} + \gamma_{jt} + \epsilon_{ogjt} \tag{8}$$

where the closer $ExJobI_{iogjt}$ is to unity, the closer the immigrant is to the most popular job of the established peers in the region; 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. 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}. Again, we use weights provided by the LFS and adjust robust standard errors for the clustering of observations at the region-year level.

5. Results

In the first step, we use the traditional definition of the network matching rate based on direct recommendations. We estimate the relationship between the probability that the immigrant has found the job through direct recommendation from a social connection and the job finding rate. We introduce as control variables the age, age squared, sex, educational level and marital status of the individual. Panel A of Table 2 considers all individuals while Panel B considers only individuals having at least secondary education (*ie* skilled individuals). Moreover, within each panel, we implement separate regressions over the whole population of immigrants, recently arrived immigrants with less than 6 years of residence and immigrants with less than 3 years seniority in their job. Columns (1)–(3) and columns (7)–(9) in Table 2 present linear probability estimation results from equation (7). Columns (4)–(6) and (10)–(12) allow for a quadratic profile in job finding rate.

Columns (1)–(3) from Panel A reveal a negative and significant correlation between the network matching rate and the job finding rate when considering all immigrants or those with less than 3 years seniority in the job. For immigrants with less than 6 years of residence in France, the coefficient is not significant. An increase from the first to the third quartile of the job finding rate distribution (which corresponds to an increase by 34.7% in the job finding rate) is associated with a decrease in the probability of finding a job through a direct recommendation by 15.35% when considering all immigrants and by 15.24% when considering immigrants with less than 3 years of seniority.

In columns (4)–(6) from Panel A, we allow for a quadratic relationship between the probability of finding a job through a social network and the job finding rate. In this case, we find a decreasing and convex relationship between the probability of finding a job through social networks and the job finding rate when considering the whole immigrant population. The relationship becomes linearly decreasing when considering immigrants with less than 3 years seniority in their job.

These findings remain robust when focusing exclusively on skilled immigrants (Panel B). Furthermore, when considering skilled immigrants with less than 6 years of residence in France, a significant and decreasing relationship also arises.[21] For skilled immigrants, an increase from the first to the third quartile of the job finding rate distribution is associated with a decrease by 12.44% in the probability of finding a job through a direct recommendation for all skilled immigrants, by 33.66% when considering recently arrived skilled immigrants and by 24.47% for skilled immigrants with less than 3 years of seniority in the job. These negative values are on average larger (in absolute terms) than when considering the whole population of immigrants, suggesting that the network matching rate of skilled workers relates more negatively to the job finding rate than the network matching rate of unskilled immigrants.

Figs. 2 and 3 show the estimated marginal effects (along with confidence intervals at the 95 percent interval) along the distribution of the job finding rate. Fig. 2 reveals that, for the whole population of immigrants and for immigrants with less than 3 years of seniority, there is a negative and convex relationship between the probability of finding a job through a social connection and the job finding rate. In line with the model's predictions, the relationship remains negative even if it seems to reach an inflexion point at the top of the job finding rate distribution when considering immigrants with less than 3 years of seniority in the job. In contrast, for immigrants with less than 6 years of residence in France the estimated marginal effects are not significantly different from zero all along the job finding rate distribution, confirming findings from Table 2.

Fig. 3 displays the marginal effects for skilled immigrants. When considering all skilled immigrants and skilled immigrants with less than 3 years of seniority in the job, we still find a decreasing relationship which reaches an inflexion point at the top of the job finding rate distribution. For skilled immigrants with less than 6 years of residence in France the relationship between the probability of finding a job through social networks and the job finding rate still remains not significantly different from zero.

Combining results from Table 2 with Figs. 2 and 3, we conclude that, consistent with the predictions of our theoretical setup, a decreasing

[20] The common component could actually be driven by policy measures adopted by the central government or institutional reforms. As shown later in the paper, estimation results do not essentially differ when including or not including year fixed effects and their interactions.

[21] Results remain robust if we do not include year fixed effects and their interactions. See Table B.1 in Appendix B.

Table 2
Estimates of the network matching rate based on direct ties. Individual data approach.

	Dependent variable: network matching rate											
	Panel A: Probability that the individual has found the job through direct ties						Panel B: Probability that the skilled individual has found the job through direct ties					
	Benchmark estimation			Quadratic profile			Benchmark estimation			Quadratic profile		
	All	Recent Immigrants	Immigrants seniority < 3	All	Recent Immigrants	Immigrants seniority < 3	All	Recent Immigrants	Immigrants seniority < 3	All	Recent Immigrants	Immigrants seniority < 3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Job finding rate	−0.676***	−0.440	−0.702***	−1.970***	−2.912	−2.652*	−0.442***	−1.064*	−0.922***	−2.337**	−0.313	−3.862
	(0.095)	(0.313)	(0.188)	(0.682)	(2.357)	(1.378)	(0.134)	(0.628)	(0.337)	(1.115)	(5.182)	(2.705)
Job finding rate^2				2.384*	4.487	3.595				3.479*	−1.333	5.406
				(1.232)	(4.239)	(2.445)				(2.023)	(9.202)	(4.891)
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
Individual Controls (age, age2, married, female, education)	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	24,480	2305	5929	24,480	2305	5929	9542	1177	2686	9542	1177	2686
R-squared	0.237	0.605	0.450	0.237	0.606	0.450	0.379	0.807	0.653	0.379	0.807	0.653

Note: estimates from linear regression models, with robust standard errors clustered at the region-year level. Weights equal standard individual weights provided by the French Labor Force Survey. Individual characteristics include age, age^2, marriage, gender and education level. Origin fixed effects correspond to North Africans, Africans, Turkish, South-East-Asians, South-Europeans, North Europeans, East Europeans, South-Americans and North-Americans. Significance levels are ***($p < 0.01$), **($p < 0.05$) and *($p < 0.1$).
Source: authors' calculations, data from Labor Force surveys 2003–2012.

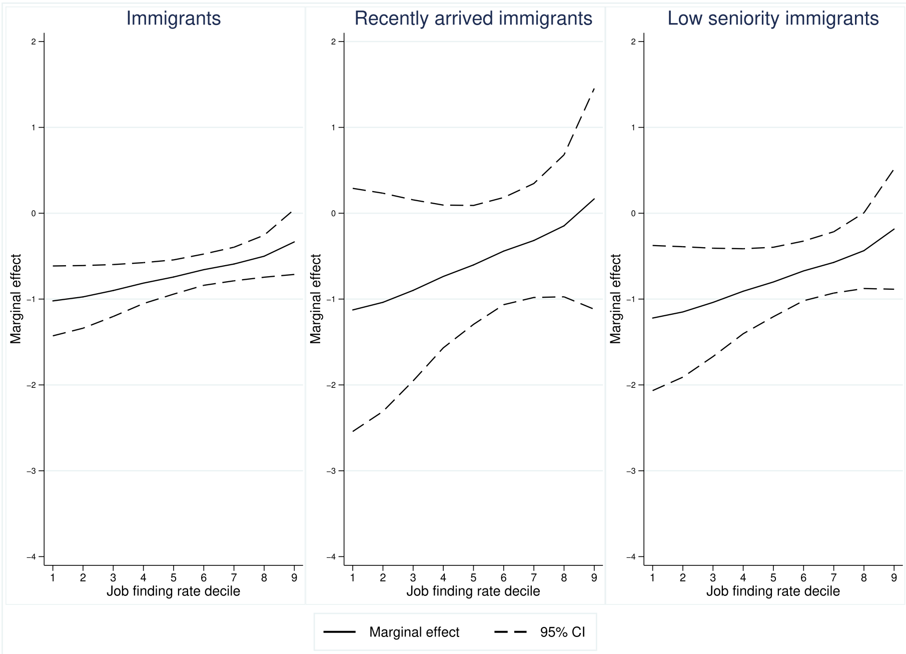

Fig. 2. Individual data: predicted marginal effect of the job finding rate on the network matching rate along the job finding rate distribution.
Source: authors' calculations, data from Labor Force surveys, 2003–2012. Predicted marginal effects correspond to the estimated values of the derivative of equation (7) with confidence intervals at the 95 percent level: $\frac{\partial P_{iogt}}{\partial a_{gt}} = \widehat{\gamma 1} + 2\widehat{\gamma 1} a_{gt}$, where a_{gt} stands for the job finding rate in region g at year t. Estimated values change along the job finding rate distribution since the derivative depends on a_{gt}.

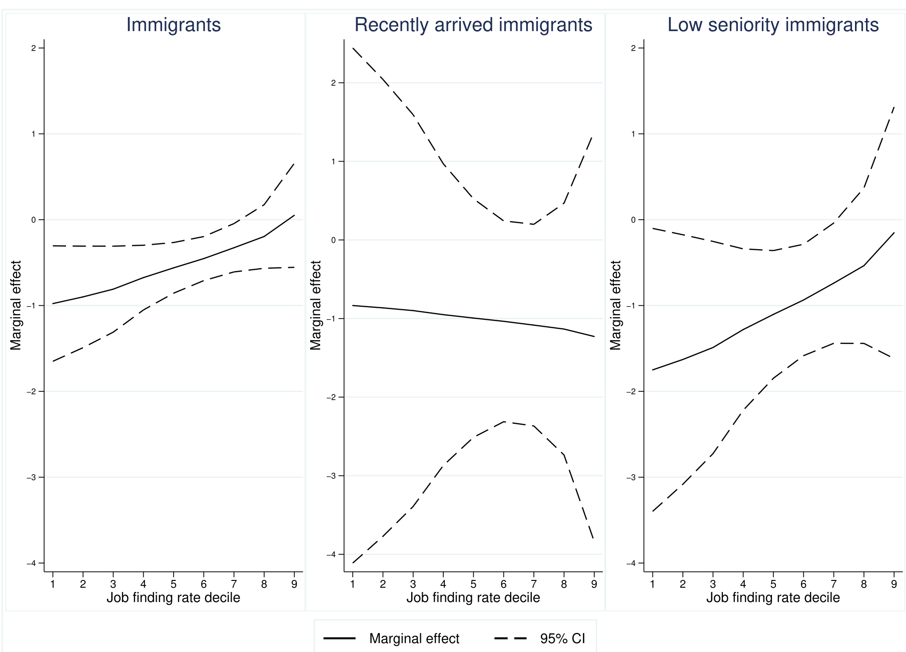

Fig. 3. Individual data: predicted marginal effect of the job finding rate on the network matching rate of skilled employed along the job finding rate distribution.
Source: authors' calculations, data from Labor Force surveys 2003–2012. Predicted marginal effects correspond to the estimated values of the derivative of equation (7) with confidence intervals at the 95 percent level: $\frac{\partial P_{iogt}}{\partial a_{gt}} = \widehat{\gamma 1} + 2\widehat{\gamma 1} a_{gt}$, where a_{gt} stands for the job finding rate in region g at year t. Estimated values change along the job finding rate distribution since the derivative depends on a_{gt}.

relationship between the network matching rate and the job finding rate arises when we consider the whole population of immigrants or those who have been hired over the past two years. The probability that an immigrant finds a job through a social connection decreases as the job finding rate starts increasing.

We conduct in Appendix B several additional tests in order to assess the robustness of our results. We first propose an aggregated data approach based on cells defined at the region-origin-year level. Consistent with the indicator defined in equation (4), we consider as a dependent variable the ratio between the number of individuals from origin o having found their job through social interactions in region g and the total number of employed people in the cell. We control by year and origin fixed effects as well as by their interaction.

Estimation results from the cell approach are summarized in Table B.3. Again Panel A considers all individuals while Panel B considers only individuals having at least secondary education (*ie* skilled individuals). Moreover, within each panel, we distinguish between the whole population of immigrants, recently arrived immigrants with less than 6 years of residence and immigrants with less than 3 years seniority in their job. Panel A in Table B.3 clearly suggests a negative correlation between the network matching rate and the job finding rate. Panel B also displays a decreasing relationship between the network matching rate and the job finding rate not only for the whole skilled immigrant population, but also for skilled immigrants with less than 3 years seniority at their job.

Marginal effects of the job finding rate on the network matching rate are represented in Figures B.1 and B.2 in Appendix B. Figure B.1 reveals that when considering the whole population of immigrants and immigrants with less than 3 years of seniority, the marginal effects are negative and approach zero as we move up in the job finding rate distribution. For recently arrived immigrants, the estimated marginal effects are negative but are not significantly different from zero along the job finding rate distribution.

Conclusions remain robust when we exclusively focus on the skilled population. As revealed by Figure B.2 for all skilled immigrants and for those with less than 3 years of seniority, the values of the marginal effects are significantly negative but increasing towards zero along the job finding rate distribution. For recently arrived immigrants, the marginal effect of the job finding rate is again negative but not significantly different from zero. Findings from Figures B.1 and B.2 are consistent with results obtained when exploiting individual data (see Table 2).

Due to the large number of origins we consider (9 different origins), when we use the region-origin-year cell approach the proportion of region-origin-year cells adopting the zero value is around 30%. To deal with this issue, we propose two alternative approaches. First, in Table B.4 in Appendix B we aggregate immigrants into 3 large origins: African immigrants, European immigrants and Other origins. By reducing the number of origins we are artificially increasing the number of observations per origin, and thus per cell, decreasing in this way the proportion of region-origin-year cells adopting the zero value. Estimation results in Table B.4 are 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 immigrant population and immigrants with less than 3 years of seniority in the job. Similar conclusions are drawn when focusing on skilled immigrants.

An alternative approach to deal with region-origin-year cells adopting the zero value consists of focusing only on regions having a proportion of immigrants above the average.[22] Table B.5 in Appendix B displays the results when considering uniquely immigrant-abundant regions. Again, consistent with estimations in Table 2 we find that, when considering all immigrants and immigrants with less than 3 years seniority, the relationship between the network matching rate and the job finding rate follows a decreasing profile. When considering skilled immigrants, the relationship remains decreasing.

All in all, combining the whole set of estimation results in Table 2, in Figs. 2 and 3 and various robustness tests, we can conclude that consistent with predictions from our theoretical setup, the probability that immigrants find a job through direct recommendation decreases during economic expansions, as the job finding rate rises. The relationship is decreasing for both all immigrants and immigrants who have recently found a job (less than 3 years seniority), independent from skill. This relationship does not hold, though, for recently arrived immigrants. This may be explained by the nature of this population subgroup. Among recently arrived immigrants we include those with 5 or less years of residence in the host country. Within this group, we may find individuals that have already been working in the same firm for 4 or 5 years as well as individuals with less than 1 or 2 years seniority. This heterogeneous composition together with the reduced number of observations may cancel the potential relation between the economic cycle and the network matching rate.

Our second indicator of the network matching rate is inspired by the one proposed in Patel and Vella (2013), but in our paper we take into account the fact that different origins may be more or less concentrated among jobs across regions. The intuition behind our indicator is that a large share of immigrants from origin *o* in a job should improve the matching efficiency of individuals from origin *o* in that job due to cultural proximity. We are not able to anticipate, however, the relationship between proximity to the most popular job of the individual's peers in the region and the job finding rate. On the one hand, during expansion periods (for high job finding rates) the matching probability of individuals from origin *o* may increase relatively more in jobs where there is a large share of their peers. On the other hand, during expansion periods immigrants may find more easily jobs outside the traditional jobs occupied by their peers, because there are more employment opportunities available in the market.

Estimation results of equation (8) are summarized in Table 3. When considering immigrants with less than 6 years of residence in France, a significant linearly decreasing relationship arises. For recently hired immigrants (less than 3 years seniority) the relationship is also decreasing. These results remain robust when focusing on skilled immigrants (Panel B). An increase from the first quartile to the third quartile of the job finding rate distribution is associated with a decrease in the proximity to the most popular job by 20.71% for recently arrived immigrants and by 20.06% for recently hired immigrants. When considering skilled people the decrease equals 49.79% and 36.10%, respectively. In line with estimations from Table 2, the network matching rate indicator based on proximity to the most popular job of the peers in the region also shows that the network matching rate of skilled workers relates more negatively with the job finding rate than the network matching rate of all workers.

The important loss of observations when considering only recently arrived and recently hired immigrants may lead to a loss in precision in our estimations. To deal with this issue we propose the two approaches already applied in Appendix B to the cell analysis. First we aggregate into 3 origins our immigrant population. The main drawback of this approach is that we are mixing people from very different origins and this may cancel origin-individual effects. The second approach consists of focusing only on regions that have a share of immigrants above the average. This should lead to an improvement in the quality of our estimations since we eliminate regions where the number of individuals is very low.

Columns (1)–(4) in Table 4 estimate the relationship between proximity to the most popular job of peers in the region and the job finding rate when considering only 3 aggregate origins (African, European, Others). Columns (5)–(8) consider instead regions having a proportion of immigrants above the average. Estimates in Columns (1)–(2) reveal a decreasing relationship between proximity to the most popular job of peers in the region and the job finding rate. This result holds whether we consider recently arrived or recently hired immigrants. Similar conclusions apply when focusing on the skilled population (columns (3)–(4)).[23] These results are coherent with conclusions drawn from Table 2 and the precision of our estimations is improved (*ie* standard errors are reduced) with respect to Table 3.

Columns (5)–(8) in Table 4 consider instead regions having a proportion of immigrants above the average (*ie* immigrant-abundant regions). In line with findings in Table 2 and with findings in columns (1)–(4) the relationship between proximity to the most popular job of peers in the region and the job finding rate is decreasing whether we focus on immigrants with less than 3 years of seniority or on recently arrived immigrants. Nothing changes when considering skilled immigrants.

[22] Corse, Ile de France, PACA, Languedoc-Roussillon, Rhône-Alpes and Alsace.

[23] Again, results remain robust if we do not include year fixed effects. See Table B.2 in Appendix B.

Table 3
Proximity of the individual from origin *o* to the most popular job among the peers in the region.

	Dependent variable: Proximity between the job of the immigrant and the most popular job among the peers in the region			
	Panel A: all immigrants		Panel B: skilled immigrants	
	Recent Immigrants (1)	Immigrants seniority < 3 (2)	Recent Immigrants (3)	Immigrants seniority < 3 (4)
Job finding rate	−2.036***	−2.163***	−4.740*	−3.676***
	(0.616)	(0.378)	(2.431)	(0.631)
Job finding rate^2				
Fixed Effects				
Origin	YES	YES	YES	YES
Year	YES	YES	YES	YES
Job	YES	YES	YES	YES
Origin∗Year	YES	YES	YES	YES
Origin∗Job	YES	YES	YES	YES
Job∗Year	YES	YES	YES	YES
Individual Controls (age, age2, married, female, education)	YES	YES	YES	YES
Observations	1153	4307	593	1890
R-squared	0.865	0.678	0.963	0.808

Note: estimates from linear regression models, with robust standard errors clustered at the region-year level. Weights equal standard individual weights provided by the French Labor Force Survey. Individual characteristics include age, age^2, marriage, gender and education level. Origin fixed effects correspond to North Africans, Africans, Turkish, South-East-Asians, South-Europeans, North Europeans, East Europeans, South-Americans and North-Americans. Significance levels are ***($p < 0.01$), **($p < 0.05$) and *($p < 0.1$).
Source: authors' calculations, data from Labor Force surveys 2003–2012.

Results presented in Tables 3 and 4, with the indicator of the network matching rate based on indirect ties, tend to confirm the main findings of Table 2 and Figs. 2 and 3 obtained with the standard network matching rate indicator. For both recently hired immigrants with less than 3 years of seniority in the job and for recently arrived immigrants, we find that the relationship between the network matching rate, *ie* proximity to the most popular job of the peers in the region, and the job finding rate is decreasing. Results hold when considering 3 aggregate origins or immigrant-abundant regions with a proportion of immigrants above the average.

6. Discussion and concluding remarks

Referrals play a major and increasing role in recruiting policies of big companies. The efficiency of the network matching rate is 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 analyze the correlation between the network matching rate and the job finding rate, which stands for our indicator of market conditions.

The first network matching indicator presented in this paper exclusively focuses on matches taking place through direct recommendations coming from network members. The second indicator exploits a positive externality dimension related to indirect ties. While the two indicators of the network matching rate capture different dimensions of the network effect, they both provide consistent results. For the observed values of the job finding rate, the relationship between the network matching rate and the job finding rate is decreasing when considering the whole population of immigrants and for recently hired immigrants. These findings are consistent with our theoretical setup.[24]

The set of our estimations, however, must be interpreted with caution for several reasons that have been already underlined by the literature (see Goel and Lang, 2017). First of all, our measure of use of network remains imperfect. In the LFS individuals are asked if they found the job through friends, relatives or former colleagues. When the individual provides a positive answer we assume that the individual has benefited from a direct recommendation from the tie. This may not be the case. As remarked by Goel and Lang (2017) if a friend, relative or former colleague tells the individual about a job opening and the individual then applies for and gets the job, the individual is likely to report that the job was obtained through a friend, relative or former colleague, while there has not been a direct recommendation.

Second, in our empirical estimations, we cannot tease out whether employers rely more on referrals during certain economic conditions or whether job applicants are more likely to seek out referrals during those times. As in most of the literature on this subject, our data only contains information on the employees' side (no employers' data). Moreover, the only useful information we have on networks is whether the individual has found the job through friends, relatives or former colleagues. It is thus not possible to disentangle if the progression of the network matching rate along the economic cycle is driven by the employer side or the employee side.

Third, social norms associated with some geographical origins may dictate that new immigrants (or those recently entering the labor market) may work for a close friend or relative. In this case it could be possible that our estimated coefficient on the job finding rate may be partially capturing this social norm, rather than an economic cycle effect. Note though, that our estimations include origin fixed effects that are going to capture systematic differences in the network matching rate across origins. These systematic differences could come from different social norms across origins, differences in the network size implying differences in access to job offers across origins or different discrimination attitudes towards different origins by natives.

Fourth, related with the previous point and as remarked by Goel and Lang (2017), individuals coming from origins with large social networks in France may endogenously reduce their search effort through formal channels, increasing their probability of finding a job through social networks. We do not consider this point as problematic, since we precisely seek to identify the use of these networks along the economic cycle. Moreover, origin fixed effects allow control for systematic

[24] These findings are in line with papers considering endogenous intensity of the information flow (see Galeotti; Merlino, 2014 or Schmutte, 2016). Our results also match conclusions from Mourao et al. (2017) analyzing migration decisions along the electoral cycle.

Table 4
Proximity of the individual from origin o to the most popular job among the peers in the region. 3 aggregate origins (African, European, Others) and regions having a proportion of immigrants above the average.

	Dependent variable Proximity between the job of the immigrant and the most popular job among the peers in the region							
	Panel A: 3 aggregate origins (African, European, Others)				Panel B: immigrant-abundant regions			
	All immigrants		Skilled immigrants		All immigrants		Skilled immigrants	
	Recent Immigrants (1)	Immigrants seniority $<$ 3 (2)	Recent Immigrants (3)	Immigrants seniority $<$ 3 (4)	Recent Immigrants (5)	Immigrants seniority $<$ 3 (6)	Recent Immigrants (7)	Immigrants seniority $<$ 3 (8)
Job finding rate	-1.486^{***}	-2.073^{***}	-2.415^{***}	-2.847^{***}	-1.771^{*}	-2.053^{***}	-8.612^{***}	-3.701^{***}
	(0.408)	(0.293)	(0.703)	(0.420)	(0.875)	(0.624)	(1.836)	(0.754)
Fixed Effects								
Origin	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES
Job	YES	YES	YES	YES	YES	YES	YES	YES
Origin∗Year	YES	YES	YES	YES	YES	YES	NO	NO
Origin∗Job	YES	YES	YES	YES	YES	YES	NO	NO
Job∗Year	YES	YES	YES	YES	YES	YES	YES	YES
Individual Controls (age, age2, married, female, education)	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1382	5234	692	2325	844	2883	452	1349
R-squared	0.765	0.627	0.909	0.743	0.920	0.783	0.916	0.749

Note: estimates from linear regression models, with robust standard errors clustered at the region-year level. Weights equal standard individual weights provided by the French Labor Force Survey. Individual characteristics include age, age^2, marriage, gender and education level. For columns (1)–(4) origin fixed effects correspond to Africans, Europeans and Others. For columns (5)–(8) origin fixed effects correspond to North Africans, Africans, Turkish, South-East-Asians, South-Europeans, North Europeans, East Europeans, South-Americans and North-Americans. In columns (7)–(8), we do not have enough variability to identify individually interacted origin-year and origin-job fixed effects due to the reduced sample size. Significance levels are $^{***}(p < 0.01)$, $^{**}(p < 0.05)$ and $^{*}(p < 0.1)$.
Source: authors' calculations, data from Labor Force surveys 2003–2012.

differences in the use of social networks across origins.

Finally, a major limitation of our second indicator is that, due to data limitations, it is defined at the regional level to ensure a sufficient number of observations per origin. Because regions are quite large there may be strong heterogeneities from one place to another among immigrants from the same origin living in the same region. As they stand, our main result, according to which the matching efficiency of job contact networks is countercyclical among immigrants, has to be interpreted with perspective and must take into account the above limitations. More detailed data would be needed to further investigate the robustness of our estimation result, in particular concerning the geographic dimension.

Finally, we remark that applying quantitative methods for studying the structure and dynamics of complex networked systems, *ie* “complex network analysis”, remains above the scope of this paper.

Our findings have two main policy implications. The first one is that migration policies should better account for the relationships that migrants can have within the destination country. While applications for work permits usually focus on migrants’ individual characteristics, we argue that successful migrations will heavily depend on the ability to mobilize social networks when searching for a job, particularly during low-growth periods. The second implication concerns the contribution of migrants to growth. As discussed in Schmutte (2016), social networks influence the efficiency of the labor markets. Social networks are helpful for employers to find better workers and for workers to find better jobs. When economic conditions are poor, the role of social networks is more influential. As a consequence, better matches can be expected between workers and firms and this is expected to enhance economic growth. Furthermore, from an individual perspective, immigrants would end up with better wages and lower probability of unemployment.

For future research, we plan to investigate the medium and long-term consequences of the role of social networks on both duration in current job, job quality and wages. Longitudinal data tracking immigrants over time along with information on how they have found their job will be necessary. Moreover, while in this paper we have not applied quantitative methods for studying the structure and dynamics of complex networks, *ie* “complex network analysis”, it may be interesting in the future to study how differential changes in the structure of social networks of immigrants from different origins may have affected their labor market outcomes.

Compliance with ethical standards

The authors declare that they have no conflict of interest.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

A. Descriptive statistics

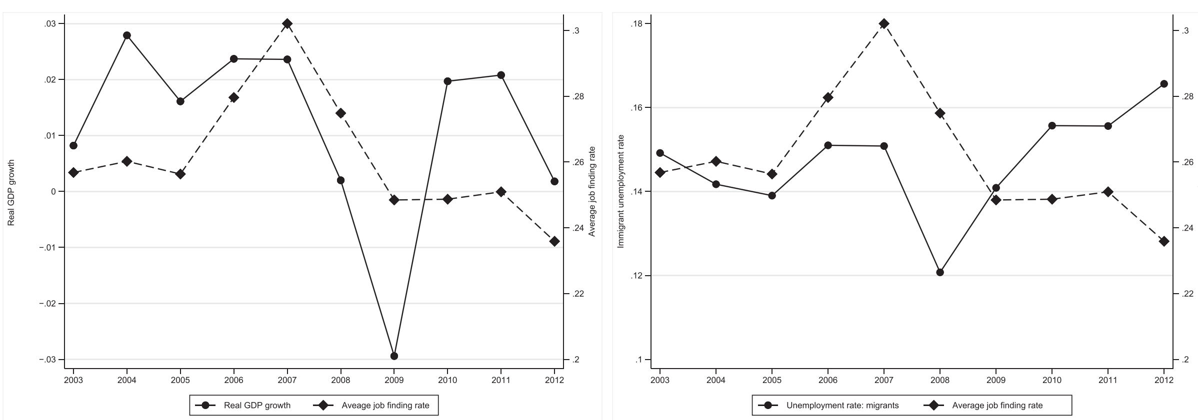

Fig. A.1 Relationship between real GDP growth and job finding rates.

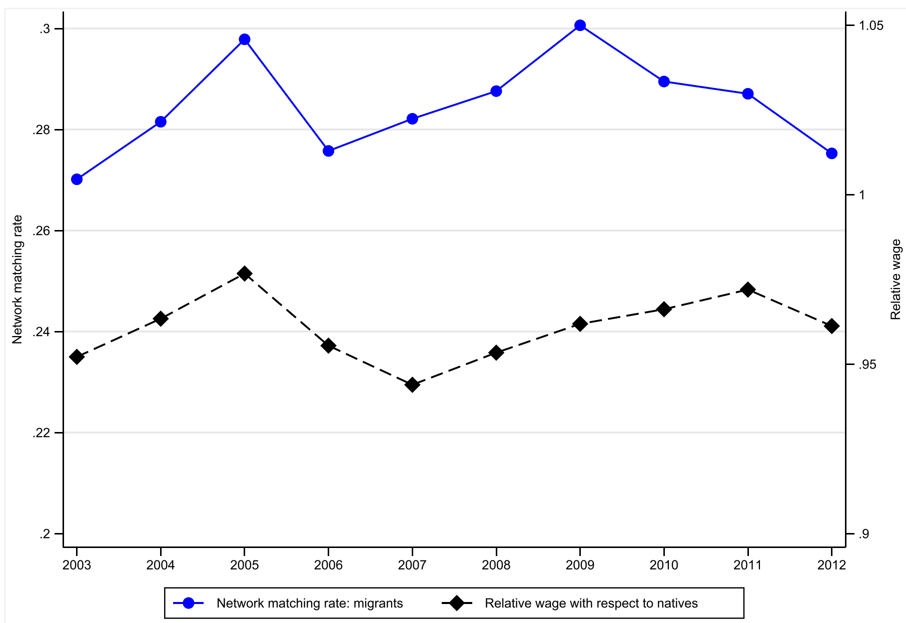

Fig. A.2 Relationship between the immigrants' network matching rate and the immigrants' relative wage with respect to natives.

B. Additional econometric results

Table B.1
Estimates of the network matching rate based on direct ties. Individual data approach. No year fixed effects.

	Dependent variable: network matching rate											
	Panel A: Probability that the individual has found the job through direct ties						Panel B: Probability that the skilled individual has found the job through direct ties					
	Benchmark estimation			Quadratic profile			Benchmark estimation			Quadratic profile		
	All	Recent Immigrants	Immigrants seniority < 3	All	Recent Immigrants	Immigrants seniority < 3	All	Recent Immigrants	Immigrants seniority < 3	All	Recent Immigrants	Immigrants seniority < 3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Job finding rate	−0.594***	−0.558**	−0.657***	−1.789***	−1.914	−2.123*	−0.467***	−0.820***	−0.625***	−2.218**	2.570	−2.874*
	(0.082)	(0.225)	(0.156)	(0.659)	(1.877)	(1.116)	(0.125)	(0.296)	(0.211)	(1.058)	(2.543)	(1.584)
Job finding rate^2				2.207*	2.457	2.716				3.221*	−6.096	4.157
				(1.229)	(3.377)	(1.978)				(1.930)	(4.432)	(2.874)
Fixed Effects												
Origin	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Job	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Origin*Year	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Origin*Job	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Job*Year	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Individual Controls (age, age^2, married, female, educ)	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	24,480	2305	5929	24,480	2305	5929	9542	1177	2686	9542	1177	2686
R-squared	0.163	0.408	0.292	0.163	0.408	0.292	0.247	0.536	0.429	0.248	0.537	0.429

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

Note: estimates from linear regression models, with robust standard errors clustered at the region-year level. Weights equal standard individual weights provided by the French Labor Force Survey. Individual characteristics include age, age^2, marriage, gender and education level. Origin fixed effects correspond to North Africans, Africans, Turkish, South-East-Asians, South-Europeans, North Europeans, East Europeans, South-Americans and North-Americans. Significance levels are ***($p < 0.01$), **($p < 0.05$) and *($p < 0.1$).

Table B.2
Proximity of the individual from origin *o* to the most popular job among the peers in the region. No year fixed effects.

	Dependent variable: Proximity between the job of the immigrant and the most popular job among the peers in the region			
	Panel A: all immigrants		Panel B: skilled immigrants	
	Recent Immigrants (1)	Immigrants seniority < 3 (2)	Recent Immigrants (3)	Immigrants seniority < 3 (4)
Job finding rate	-1.023^{**}	-1.934^{***}	-2.953^{***}	-2.646^{***}
	(0.485)	(0.277)	(0.738)	(0.405)
Job finding rate^2				
Fixed Effects				
Origin	YES	YES	YES	YES
Year	NO	NO	NO	NO
Job	YES	YES	YES	YES
Origin∗Year	NO	NO	NO	NO
Origin∗Job	YES	YES	YES	YES
Job∗Year	NO	NO	NO	NO
Individual Controls (age, age2, married, female, educ)	YES	YES	YES	YES
Observations	1153	4307	593	1890
R-squared	0.696	0.536	0.783	0.600

Source: authors' calculations, data from Labor Force surveys 2003–2012.
Note: estimates from linear regression models, with robust standard errors clustered at the region-year level. Weights equal standard individual weights provided by the French Labor Force Survey. Individual characteristics include age, age^2, marriage, gender and education level. Origin fixed effects correspond to North Africans, Africans, Turkish, South-East-Asians, South-Europeans, North Europeans, East Europeans, South-Americans and North-Americans. Significance levels are $***(p < 0.01)$, $**(p < 0.05)$ and $*(p < 0.1)$.

Table B.3

Estimates of the network matching rate based on direct ties. Region-origin cell approach.

	Dependent variable: network matching rate											
	Panel A: Share of individuals having found their job through direct ties (cell-approach)						Panel B: Share of skilled individuals having found their job through direct ties (cell-approach)					
	Benchmark estimation			Quadratic profile			Benchmark estimation			Quadratic profile		
	All (1)	Recent Immigrants (2)	Immigrants seniority $<$ 3 (3)	All (4)	Recent Immigrants (5)	Immigrants seniority $<$ 3 (6)	All (7)	Recent Immigrants (8)	Immigrants seniority $<$ 3 (9)	All (10)	Recent Immigrants (11)	Immigrants seniority $<$ 3 (12)
Job finding rate	-0.773^{***}	-0.444^{**}	-0.629^{***}	-2.664^{***}	-1.982	-2.067^{*}	-0.110	-0.364^{*}	-0.678^{***}	-3.268^{***}	-0.433	-4.530^{***}
	(0.098)	(0.195)	(0.136)	(0.672)	(1.873)	(1.171)	(0.187)	(0.214)	(0.166)	(0.784)	(2.011)	(1.336)
Job finding rate^2				3.478^{***}	2.828	2.642				4.931^{***}	0.126	7.036^{***}
				(1.236)	(3.349)	(2.046)				(1.404)	(3.500)	(2.348)
Fixed Effects												
Origin	YES	YES	YES	YES	YES	YES	NO	NO	NO	NO	NO	NO
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Job	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Origin$*$Year	YES	YES	YES	YES	YES	YES	NO	NO	NO	NO	NO	NO
Origin$*$Job	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Job$*$Year	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Individual Controls (age, age2, married, female, education)	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Observations	1583	769	1167	1583	769	1167	220	180	206	220	180	206
R-squared	0.263	0.337	0.222	0.270	0.338	0.223	0.029	0.100	0.095	0.221	0.100	0.127

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

Note: OLS estimates from linear regression models, with robust standard errors clustered at the region level. Weights equal total population of the corresponding region-origin-year cell. 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. Significance levels are $***(p < 0.01)$, $**(p < 0.05)$ and $*(p < 0.1)$.

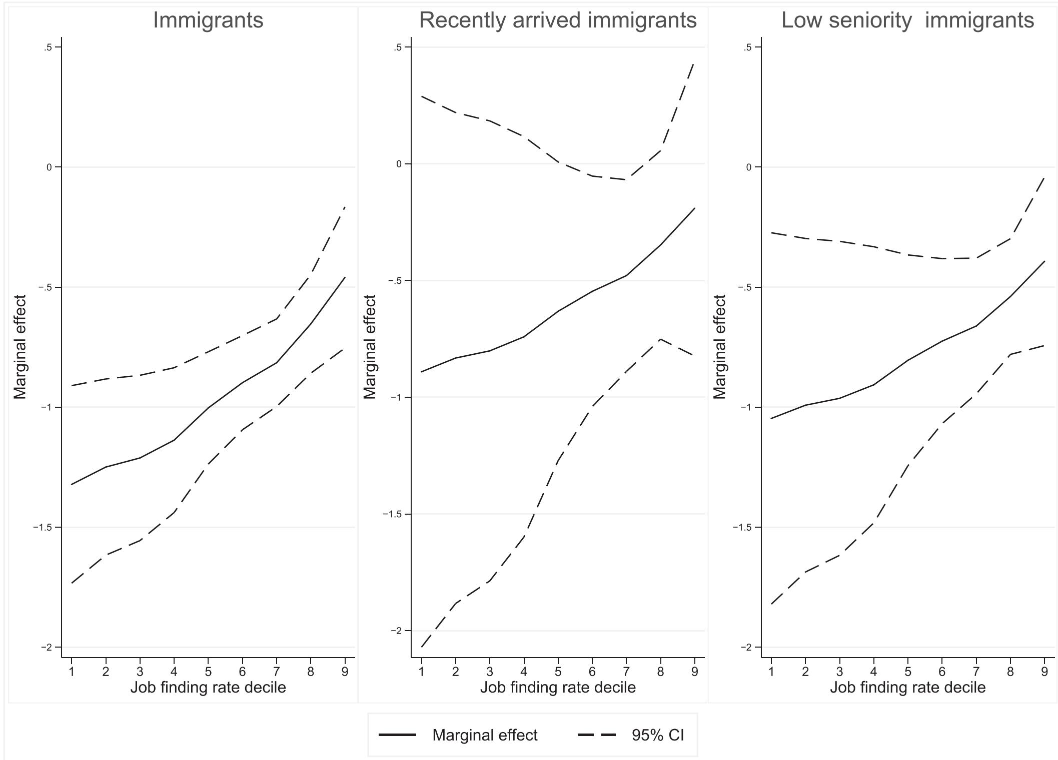

Fig. B.1 Predicted marginal effect of the job finding rate on the regional network matching rate along the job finding rate distribution.

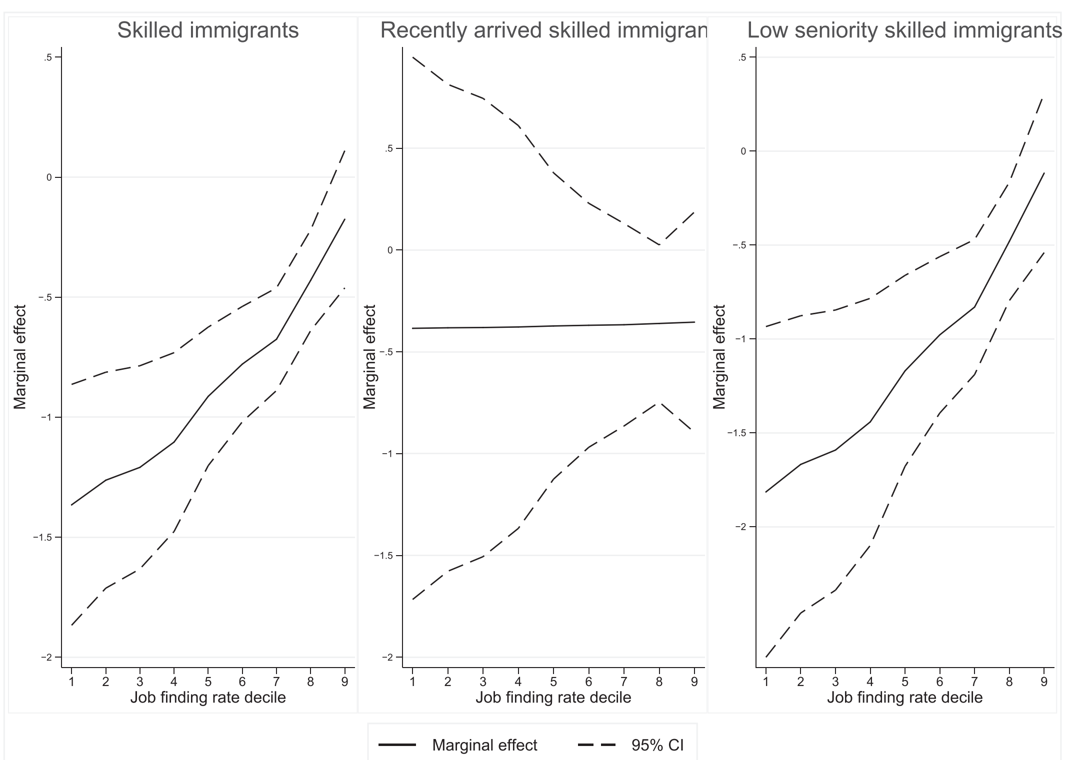

Fig. B.2 Predicted marginal effect of the job finding rate on the regional network matching rate of skilled employed along the job finding rate distribution.

Table B.4
Estimates of the network matching rate based on direct ties. Region-origin cell approach with 3 aggregate origins (African, European and Other).

	Dependent variable: network matching rate											
	Panel A: Share of individuals having found their job through direct ties (cell-approach)						Panel B: Share of skilled individuals having found their job through direct ties (cell-approach)					
	Benchmark estimation			Quadratic profile			Benchmark estimation			Quadratic profile		
	All	Recent Immigrants	Immigrants seniority $<$ 3	All	Recent Immigrants	Immigrants seniority $<$ 3	All	Recent Immigrants	Immigrants seniority $<$ 3	All	Recent Immigrants	Immigrants seniority $<$ 3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Job finding rate	-0.776^{***}	-0.385^{**}	-0.709^{***}	-2.713^{***}	-0.132	-2.868^{***}	-0.580^{***}	-0.180	-0.468^{**}	-3.218^{***}	1.206	-5.418^{***}
	(0.102)	(0.177)	(0.126)	(0.684)	(1.804)	(1.085)	(0.106)	(0.248)	(0.219)	(0.783)	(2.405)	(1.718)
Job finding rate^2				3.564^{***}	-0.464	3.963^{**}				4.830^{***}	-2.538	9.027^{***}
				(1.254)	(3.225)	(1.906)				(1.402)	(4.308)	(3.173)
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	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Origin∗Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Origin∗Job	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Job∗Year	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Observations	649	488	605	649	488	605	627	356	482	627	356	482
R-squared	0.242	0.123	0.156	0.257	0.123	0.162	0.122	0.150	0.102	0.139	0.151	0.122

Source: authors' calculations, data from Labor Force surveys 2003–2012.
Note: OLS estimates from linear regression models, with robust standard errors clustered at the region level. Weights equal total population of the corresponding region-origin cell. Origin fixed effects correspond to Africans, Europeans, Others. Significance levels are $***(p < 0.01)$, $**(p < 0.05)$ and $*(p < 0.1)$.

Table B.5
Estimates of the network matching rate based on direct ties: regions having a proportion of immigrants above the average.

	Dependent variable: network matching rate											
	Panel A: Share of individuals having found their job through direct ties						Panel B: Share of skilled individuals having found their job through direct ties					
	Benchmark estimation			Quadratic profile			Benchmark estimation			Quadratic profile		
	All	Recent Immigrants	Immigrants seniority < 3	All	Recent Immigrants	Immigrants seniority < 3	All	Recent Immigrants	Immigrants seniority < 3	All	Recent Immigrants	Immigrants seniority < 3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Job finding rate	−0.929***	−0.429	−0.593***	−2.947***	−1.402	−0.303	−0.663***	−0.200	−0.715***	−3.039**	−0.945	−2.666
	(0.097)	(0.280)	(0.100)	(0.979)	(3.779)	(2.561)	(0.138)	(0.287)	(0.186)	(1.474)	(3.177)	(2.252)
Job finding rate^2				3.675**	1.771	−0.527				4.359	1.365	3.578
				(1.796)	(6.703)	(4.447)				(2.696)	(5.640)	(3.936)
Fixed Effects												
Origin	YES	YES	YES	YES	YES	YES	NO	NO	NO	NO	NO	NO
Year	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Job	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Origin*Year	YES	YES	YES	YES	YES	YES	NO	NO	NO	NO	NO	NO
Origin*Job	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Job*Year	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Observations	420	283	364	420	283	364	382	371	382	382	371	382
R-squared	0.527	0.463	0.413	0.534	0.464	0.413	0.493	0.300	0.329	0.533	0.301	0.340

Source: authors' calculations, data from Labor Force surveys 2003–2012.
Note: OLS estimates from linear regression models, with robust standard errors clustered at the region level. Weights equal total population of the corresponding region-origin-year cell. 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. Significance levels are ***($p < 0.01$), **($p < 0.05$) and *($p < 0.1$).

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