

On Job Contact Networks and Labor Market Mobility*

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Abstract

In this paper we adopt the probabilistic framework of Calvó-Armengol and Jackson (2004), in which social networks facilitate the transmission of information on job vacancies among workers, in order to study the effects of social connections on mobility (in terms of transition out of unemployment) in labor markets. Furthermore, we assume that probabilities to access information on job vacancies can change according to individuals' employment status. This also aims at capturing firms' different recruitment strategies. We find that social connections and networks topology can play an important role in explaining labor market mobility. At the same time, we also show that results may strongly depend on different hypotheses concerning individuals' access to information about job opportunities (or firms' recruitment strategies) and on network's dimension.

Keywords: job contact networks, networks' symmetry, mobility, firms' recruitment strategies.

JEL codes: D83, J60, J64

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1 Introduction

Starting from Granovetter (1974), sociologists have highlighted the importance of social networks as sources of information on jobs in labor markets.¹ More recently, economists have devoted considerable attention to this topic,² so that the study of the effects of social relationships in labor markets has become a fruitful research area in economics.

There also exists an extensive literature that has led to conceptual developments in measuring and explaining occupational and earnings mobility (see Atkinson et al. (1992) for a survey), with many studies focusing on specific aspects of mobility, such as transitions out of low-pay jobs (see, e.g., Cappellari (2007)), or transitions out of unemployment (see, e.g., Lynch (1989)). In particular, this literature has empirically investigated the role of different observable individual characteristics (e.g. gender, race, education, work experience), and industrial/labor market structures in affecting the extent of differences across individuals in job/employment mobility. Common to many studies is the finding that unobservable heterogeneity matters and that, with respect to transitions from unemployment, there is substantial negative duration dependence.

As emphasized by Calvó-Armengol and Jackson (2004), studies on social networks may contribute to the analysis of mobility as, for example, networks' characteristics may explain why workers of a particular type in a particular location (assuming networks correlate with location) may experience different employment transitions (including duration dependence) than the same types of workers in another location, all other variables held constant.³

An important issue in the studies on social networks is network structure: that is how and to what extent network characteristics, such as its topology and the type of connections, play a role in explaining the economic effects of networks. For instance, the effects of networks' symmetry have been often discussed qualitatively in the sociological literature (e.g. Granovetter (2005)), but the quantitative effects that this property may produce on individual economic outcomes has so far not received the same attention.⁴

In this paper, we aim at analyzing the effects of social networks and of their geometry on labor market mobility and, in particular, on transitions out of unemployment. To this aim, we will consider differences across employment status in the access to information on jobs, an aspect still not sufficiently analyzed in the literature. Specifically, we will assume that employed individuals have in general a higher probability to obtain information on job vacancies than unemployed individuals. This is consistent with the hypothesis that employers have imperfect information about applicants and, as a consequence, they mainly adopt a recruitment "referral" strategy (see, e.g., Montgomery (1991)), by asking first to their employees to refer some applicant linked to them.⁵

¹Such importance is also confirmed by a number of empirical studies. See, e.g., Montgomery (1991) for further discussion and references.

²See, e.g., Ioannides and Loury (2004) for a survey.

³From the econometric's viewpoint, estimation of social effects is complicated by the possibility that individuals choose to get together, but the determinants of this choice is generally unobserved. This may lead to sorting along relevant unobservables driving the empirical correlation between individual outcomes (e.g., Mansky (1993), Moffit (2001)).

⁴In Lavezzi and Meccheri (2007) we study the quantitative effects of network symmetry on aggregate output and wage inequality.

⁵In a study of displaced workers in manufacturing, Zippay (2001), p. 103, reports that: "One local

As mentioned, although the idea that job contact networks may affect individuals' search outcomes is extensively documented, studies that investigate the effects of the presence and the structure of social networks on mobility are rare. Calvó-Armengol and Jackson (2007) develop a model to study the effects of the social structure on mobility via investment in human capital. However, conversely from our paper in which the analysis is focused on *intragenerational* mobility, their focus is on *intergenerational* mobility.⁶

A notable exception is Bramoullé and Saint-Paul (2006). Their paper, as ours, adopts the probabilistic framework of Calvó-Armengol and Jackson (2004), in which social networks facilitate the transmission of information on job vacancies among workers, in order to study the effects of social connections on mobility in labor markets. However, the mechanisms through which social networks may affect labor market mobility are different. In particular, in Bramoullé and Saint-Paul (2006): (i) social networks are random and social contacts evolve endogenously according to the (un)employment status of the agents;⁷ (ii) unemployed workers may get a job only through social connections.

In this paper, instead, it is assumed that information on vacancies may reach individuals through “personal” hiring channels such as social networks, and through other sources of information, both public (newspapers, agencies, the Internet, etc.) and private, such as firms' advertising when employed. Therefore, the probability to access information on job can change according to agents' employment status. In addition, in our case as well as in Calvó-Armengol and Jackson (2004), the network is exogenous and fixed. This, on one hand, permits to compare the effects on mobility of different network structures (most notably, symmetric versus asymmetric networks) and, on the other hand, to evaluate firms' strategy of advertising vacancies.⁸

Our main results can be summarized as follows: firstly, social connections produce sizable increases in upward mobility from unemployment and, in general, symmetric network topologies perform better than asymmetric ones. In addition, and most interestingly, these results strongly depends on different hypotheses on the firms' hiring process strategy. In particular, when firms exclusively adopt a referral hiring strategy and the network is small, the degree of mobility drops remarkably, the role of the network in allowing workers to leave the state of unemployment is very limited, and the geometry of the network is almost irrelevant.

The paper is organized as follows: Section 2 presents the theoretical model; Section 3 contains the results of the simulations; Section 4 provides concluding remarks.

plant has formalized and systematized [the] networking process. When job openings occur, the social security numbers of current employees are put into a lottery, and those whose numbers are drawn can refer two acquaintances for the position”.

⁶In the sociological literature see, e.g., Wegener (1991) and Zippay (2001).

⁷Specifically, Bramoullé and Saint-Paul (2006) assume that the probability of social link formation between two employed individuals is greater than between an employed and an unemployed, producing an “inbreeding bias” effect.

⁸ Bramoullé and Saint-Paul (2006)' model is instead a more suitable framework to focus on the issue of duration dependence.

2 A model of social networks and labor market mobility

In this section we present a model which follows Calvó-Armengol and Jackson (2004), except for the hypotheses on the probability of receiving information on jobs which, in our case, depends on the employment status.

2.1 Labor turnover

Time is discrete and indexed by $t = 0, 1, 2, \dots, T$. The economy is populated by homogeneous, infinitely-lived agents (workers) indexed by $i \in \{1, 2, \dots, n\}$.⁹ In each period a worker can be either unemployed or employed. Thus, by indicating with s_i the employment status of worker i in period t , we have two possible agents' states:

$$s_i = \begin{cases} e, & \text{employed} \\ u, & \text{unemployed.} \end{cases}$$

The labor market is subject to the following turnover. Initially, all workers are employed. Every period (from $t = 0$ onwards) has two phases: at the beginning of the period each worker can receive an offer of a job with arrival probability $a \in [0, 1)$. Parameter a captures all the information on vacancies which is not transmitted through the network, that is information from firms, agencies, newspapers, etc. When an employed agent receives an offer she passes the information to a friend/relative/acquaintance who is unemployed. At the end of the period every employed worker loses the job with breakdown probability $b \in (0, 1)$.

In this paper we will consider different assumptions on the probability a . Let us define a_{s_i} , $s_i \in S = (u, e)$, the probabilities of, respectively, hearing about a job when unemployed and hearing about a job when employed. These values can be ordered as $a_e \geq a_u \geq 0$, on the assumption that being employed can offer an advantage of hearing about jobs. We will study the following cases:

1. $a_e = a_u = a > 0$;
2. $a_e > a_u > 0$;
3. $a_e > a_u = 0$.

Case 1 corresponds to that studied by Calvó-Armengol and Jackson (2004), while Case 3 is studied by Bramoullé and Saint-Paul (2006) with additional assumptions on the endogeneity of the social network. Case 2 (and 3, which represents an extreme version of the former) aims at capturing a situation in which employers have imperfect information about applicants and, as a consequence (and according to the empirical evidence in, e.g., Montgomery (1991)), they adopt first a recruitment “referral” strategy, by asking to their employees to refer some applicant linked to them through a social network.

⁹In what follows we omit the time subscript t , whenever this does not generate confusion.

2.2 Social links and job information transmission

Social networks may be characterized by a graph g representing agents' links, where $g_{ij} = 1$ if i and j know each other, and $g_{ij} = 0$ indicates if they do not. It is assumed that $g_{ij} = g_{ji}$, meaning that the acquaintance relationship is reciprocal. Given the assumptions on arrival probabilities, the probability of the joint event that agent i in period t learns about a job and this job ends up in agent's j hands, is described by π_{ij} :

$$\pi_{ij}(s_i) = \begin{cases} a_u & \text{if } \langle j = i \cup s_i = u \rangle \\ a_e \frac{g_{ij}}{\sum_{k: s_k = u} g_{ik}} & \text{if } \langle s_i = e \cup s_j = u \rangle \\ 0 & \text{otherwise} \end{cases}$$

In the first case, worker i receives with probability a_u an offer for a job when she is unemployed and keeps the offer for herself. In the second case, instead, worker i is employed and receives with probability a_e an offer for a job, that she passes only to an unemployed worker $j (\neq i)$ connected to her by a link. We assume that i chooses j randomly among all her unemployed contacts. Hence, the probability that worker j receives the information by worker i is equal to $\frac{g_{ij}}{\sum_{k: s_k = u} g_{ik}}$. Clearly, $\pi_{ij} = 0$ in all remaining cases.

To sum up, a worker who receives an offer makes direct use of it if she is unemployed. Otherwise, she passes the information to someone who is connected to her. The choice of the worker to whom pass the information is “selective”, in the sense that the information is never passed to someone who does not need it (that is, someone who is already employed),¹⁰ but it is random with respect to the subset of the connected workers who are unemployed.

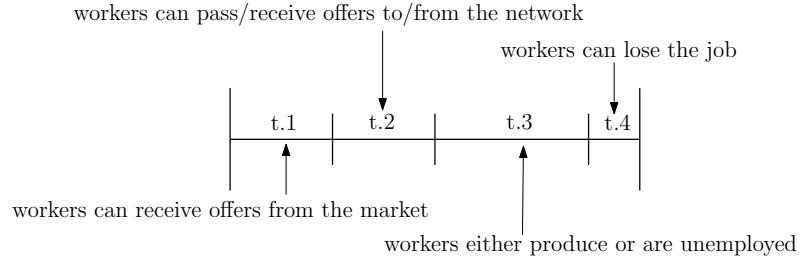


Figure 1: Timing

Figure 1 shows the timing of the events for a generic period t (for convenience, the period has been represented as composed by four different consecutive sub-periods, with sub-periods $t.1$, $t.2$ and $t.4$ having negligible length).

¹⁰For the sake of simplicity, we assume that in each period a worker can observe the state of her connections at the end of the previous period. In other words, she cannot observe if her connections have already received an offer from someone else. If all of the worker's acquaintances do not need the job information, then it is simply lost. It is also lost if it is passed to someone that has received information on other jobs.

2.3 Labor market mobility

The process governing agents' transitions across the states of employed and unemployed can be represented as a Markov chain with two states: $S = (u, e)$. Formally, given the graph g , the transition matrix for agent i in period t has the following form:

$$\mathbf{P}_g^i = \begin{bmatrix} p_{uu,g} & p_{ue,g} \\ p_{eu,g} & p_{ee,g} \end{bmatrix} \quad (1)$$

where, e.g., $p_{ue,g}$ is the probability, for an agent in state u at the end of period t , to be in state e at the end of period $t + 1$ (the other probabilities have analogous interpretation).

The elements of $\mathbf{P}_g^i$ can be easily determined:¹¹

$$\mathbf{P}_g^i = \begin{bmatrix} 1 - [a_u + (1 - a_u)P_i(g)](1 - b) & [a_u + (1 - a_u)P_i(g)](1 - b) \\ b & 1 - b \end{bmatrix} \quad (2)$$

where $P_i(g)$ is defined in Calvó-Armengol (2004) and indicates the probability that agent i obtains a job through her connections.¹² Note that the effect of a_e , not appearing in Eq. (2), is captured by the term $P_i(g)$, through the value of α indicated in Note 12.

The transition probabilities in the first row can be computed analytically under the assumption that all contacts of agent i have a job to pass, which implies that they are employed and have received information on a vacancy.¹³ This provides us with a theoretical value of these probabilities, in particular of $p_{ue,g}$ which represents the exit rate from unemployment. This value can be considered as the upper limit of the exit rate, being constructed under the most favorable hypothesis from agent i 's perspective.

However, not all of agent i 's contacts are employed and have a job to pass in every period and therefore, the actual exit rates in every period can be different. This makes the Markov chain nonstationary. In what follows we will consider both the theoretical value of $p_{ue,g}$ and the actual value, estimated from simulations.

The representation of the process in Eq. (2) provides a convenient way to disentangle the different effects on mobility of the probability of hearing about a job, a_{s_i} , $s_i \in S$, and of obtaining information from members of the network. For example, when we consider the case $a_e > a_u = 0$, that is when we assume that unemployed workers can obtain a job only through the network, the transition matrix becomes:

$$\mathbf{P}_g^i = \begin{bmatrix} 1 - P_i(g)(1 - b) & P_i(g)(1 - b) \\ b & 1 - b \end{bmatrix}, \quad (3)$$

¹¹See also Calvó-Armengol (2004), p. 195.

¹²Specifically, $P_i(g) = 1 - \prod_{j \in N_i(g)} q(n_j(g))$ where $q(n_j(g)) = 1 - \alpha \frac{1 - (1 - b)^{n_j(g)}}{bn_j(g)}$ is the probability that i does not receive a job from agent $j \in N_i(g)$, where $N_i(g)$ is the set of agent i 's contacts, $\alpha = a_e(1 - b)$, and $n_j(g)$ is the size of $N_j(g)$. Probabilities $P_i(g)$ are computed in Calvó-Armengol (2004) on the assumption that a worker can lose the job with probability b at the beginning of a period, while in our case this may occur at the end of the period, as assumed in Calvó-Armengol and Jackson (2004). However, the hypothesis we explain in Note 10 allows us to utilize the formulas for $P_i(g)$.

¹³This is the hypothesis under which the values of $P_i(g)$ are analytically computed in Calvó-Armengol (2004).

while, if $a_u > 0$ and agent i has no contacts in network g , her transition matrix is:

$$\mathbf{P}_g^i = \begin{bmatrix} 1 - a_u(1 - b) & a_u(1 - b) \\ b & 1 - b \end{bmatrix}. \quad (4)$$

In Section 3 we present the results of the simulations in which we explore different assumptions on the parameters on job market characteristics (a_e and a_u), and on the geometry of social networks. We also compare, for different situations, the exit rate from unemployment $p_{ue,g}$ obtained from simulations with that computed on the basis of Eq. (2).

3 Simulations

In this section we present the results of the simulations of the model. For a given network g , and a given set of parameters' values, we estimate the transition matrices for individual agents and the average matrix for the entire population, denoted by $\bar{\mathbf{P}}_g$.¹⁴

3.1 Mobility without social networks

Consider a population of $n = 4$ agents, with no social interactions (we call the empty network G_0). In the simplest case in which $a_u = a_e = a$, for given values of $a = 0.10$ and $b = 0.015$,¹⁵ the average transition matrix is given by:

$$\bar{\mathbf{P}}_{G_0} = \begin{bmatrix} 0.9009, & 0.0991 \\ 0.0150, & 0.9850 \end{bmatrix}.^{16} \quad (5)$$

The level of mobility in this case can be quantified in: $ML = 0.114$.¹⁷

3.2 Mobility in symmetric and asymmetric networks

Now we analyze transition matrices in presence of social networks, in particular we examine different network topologies. Consider in particular the two networks in Figure 2, which are taken from Example 1 in Calvó-Armengol (2004).

¹⁴Individual transition probabilities are estimated by the frequencies of transitions in the realization of each agent's stochastic process. Average transition probabilities are estimated by the frequencies recorded in the simulated time series of all agents.

¹⁵These values are taken from Calvó-Armengol and Jackson (2004), p. 430. In their words: "If we think about these numbers from the perspective of a time period being a week, then an agent loses a job roughly on average once in every 67 weeks, and hears (directly) about a job on average once in every ten weeks". We simulate the model for a large number of periods, setting $T = 500,000$. All simulations are programmed in R (<http://www.r-project.org/>), codes are available upon request from the authors.

¹⁶These values, and others in the results presented below, slightly differ from those computable from Eq. (4) for small deviations from the law of large numbers.

¹⁷This index is given by $ML = 1 - |\lambda_2|$, where λ_2 is the second largest eigenvalue of the transition matrix. With 2X2 matrices this mobility index equals other indices such as: $MT = \frac{k - \text{tr}(P)}{k-1}$, where k is the number of states, or $MD = 1 - |\det(P)|^{1/(k-1)}$. See, e.g., Checchi *et al.* (1999), p. 357.

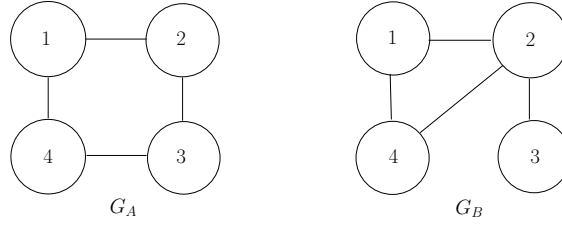


Figure 2: Networks G_A and G_B

Both networks G_A and G_B have the same number of agents, $n = 4$, and links, $N = 4$, and the same average number of links for each agent, that is $\mu = 2$.¹⁸ However, they have a different geometry: network G_A is a symmetric network, since all agents have the same number of links, while network G_B is an asymmetric network. In particular, network G_B is obtained from G_A by simply rewiring one link. This introduces an asymmetry, as in network G_B agent 2 has three links and agent 3 has only one link, while agents 1 and 4 maintain the same number of links. In other words, agents 1, 2 and 4 form a cluster of interconnected agents, from which agent 3 is partially excluded. In addition, there exists a difference in the number of links of the agents to whom every agent is connected. In network G_A any agent has two links with agents who have two links. Differently, in network G_B agents 1 and 4 have one link with an agent with two links (respectively agents 4 and 1), and one link with an agent with three links, agent 2. Agent 2 has two links with two agents, 1 and 4, who have two links, and one link with agent 3, who has one link.

In what follows we examine the consequences of modifying the values of job arrival probabilities in networks G_A and G_B . Our aim is to evaluate changes in such probabilities *vis-a-vis* changes in network topology. Previous studies already provide us with some insights: in particular, Calvó-Armengol (2004) shows that Network G_A produces better results in terms of (average) unemployment and welfare, while Lavezzi and Meccheri (2007) show that, as an implication of Calvó-Armengol (2004)'s results, network G_A is associated to higher average output and less inequality.¹⁹

Hence, we expect network G_A to be associated to higher mobility than network G_B (and, in general, symmetric networks to display more mobility than asymmetric networks), as job opportunities are more evenly spread in a symmetric than in an asymmetric network. However, we are also interested in evaluating the *size* of this effect, with respect to changes in a , as this may provide some guidance on the contribution of social networks on unobserved heterogeneity across agents and some information on the role of firms' hiring strategy.

Case 1: $\mathbf{a_e} = \mathbf{a_u} > \mathbf{0}$. In this case, we assume that all individuals receive information on job vacancies independently on their employment status, as in Calvó-Armengol and Jackson (2004). $\bar{\mathbf{P}}_{G_A}$ and $\bar{\mathbf{P}}_{G_B}$ denote the average transition matrices associated, respectively, to networks G_A and G_B .

¹⁸The simple formula to obtain μ , the average number of links per agent, is $\mu = 2N/n$.

¹⁹In Lavezzi and Meccheri (2007) we also discuss the relevance for these results of the hypothesis that agents are homogeneous.

$$\overline{\mathbf{P}}_{G_A} = \begin{bmatrix} 0.7497, & 0.2503 \\ 0.0151, & 0.9849 \end{bmatrix} \quad (6)$$

$$\overline{\mathbf{P}}_{G_B} = \begin{bmatrix} 0.7640, & 0.2360 \\ 0.0150, & 0.9850 \end{bmatrix} \quad (7)$$

Note that, obviously, both networks are associated to higher upward mobility than in the case with no links in Eq. (5): the exit rate p_{ue} increases from about 10% to about 25%, indicating that the effect of the network is sizable. This occurs as the network is dense, in the sense that most of the possible links are present²⁰ (but see also the case in Eq. (12 below).

In addition, as predicted, the symmetric network G_A is associated to higher mobility than the asymmetric network G_B . Table 1 contains the values of ML for the two matrices.

	G_A	G_B
ML	0.265	0.251

Table 1: Mobility indices in G_A and G_B

The introduction of social connections, therefore, improves individual perspectives on average. With an asymmetric network, however, the average improvement conceals differences at individual level. Table 2 reports the relevant values to assess the individual levels of mobility in Network G_B , the theoretical and estimated exit rates, p_{ue} and $\hat{p}_{ue}$ respectively, and the individual mobility indices ML^i .²¹

agent	1	2	3	4
p_{ue}	0.2628	0.3344	0.1845	0.2628
$\hat{p}_{ue}$	0.2469	0.3106	0.1772	0.2452
ML^i	0.262	0.326	0.192	0.260

Table 2: Individual exit rates and mobility indices in Network G_B . $a_e = a_u = 0.10$

In network G_B mobility of agent 2 increases while mobility for agent 3 decreases, as the number of their links is, respectively, increased and decreased. Note also that the mobility of agents 1 and 4 is decreased although the number of their links is unchanged. This depends on the fact that, in network G_B , they face more competition in the possibility of receiving information on jobs from agent 2.²² Overall, in a comparison between G_A and G_B , the negative contributions to mobility from agents 1, 3 and 4 outweigh the positive contribution from agent 2.

Finally, as expected, comparing theoretical and estimated exit rates we have that the latter are lower than the former (this also holds for network G_A for which theoretical individual exit rates, which are the same for all individuals, are 0.2634 against 0.2503 of Eq. (6)), and the differences amount on average to 1.5 percentage points. This reflects

²⁰See, e.g., Watts (1999), p. 15.

²¹We do not report results on individual agents in the symmetric network G_A as, clearly, they correspond to the average values in Eq. (6).

²²See Calvó-Armengol and Jackson (2004).

what asserted in Section 2.3, that is, theoretical values can be considered as upper limits of exit rates, being constructed under the most favorable hypothesis from each agent's perspective.

Case 2: $\mathbf{a_e} > \mathbf{a_u} > \mathbf{0}$. Now we consider the case in which employed individuals have a higher probability to hear about a job vacancy, although also unemployed individuals may receive some information about vacancies. In particular, we make the following assumptions about job arrivals probabilities: $a_e = 0.10$ and $a_u = 0.05$. The new values of $\overline{\mathbf{P}}_{G_A}$ and $\overline{\mathbf{P}}_{G_B}$ are reported in Eqs. 8 and 9.

$$\overline{\mathbf{P}}_{G_A} = \begin{bmatrix} 0.7978, & 0.2022 \\ 0.0150, & 0.9850 \end{bmatrix} \quad (8)$$

$$\overline{\mathbf{P}}_{G_B} = \begin{bmatrix} 0.8157, & 0.1843 \\ 0.0151, & 0.9849 \end{bmatrix} \quad (9)$$

Note that the exit rate p_{ue} drops of approximately 5 percentage points.²³ Table 3 contains the results on mobility for G_A and G_B , while Table 4 contains the results on individual mobility in network G_B .

	G_A	G_B
ML	0.217	0.199

Table 3: Mobility indices in G_A and G_B

agent	1	2	3	4
p_{ue}	0.2226	0.2983	0.1400	0.2226
$\hat{p}_{ue}$	0.1969	0.2630	0.1283	0.1957
ML^i	0.212	0.278	0.144	0.211

Table 4: Individual exit rates and mobility indices in Network G_B . $a_e = 0.10$, $a_u = 0.05$

By comparing Eqs. (8) and (9) with Eqs. (6) and (7) it is possible to verify that the reduction in the value of a_u reduces on average mobility, and that in symmetric networks there is, on average, more mobility than in the asymmetric network G_B . However, agent 3 in G_B enjoys more mobility than the average agent in G_A in Case 1. Hence, for some agents, an increase in the number of links may counterbalance a reduction in a_u , so that their mobility is higher in an asymmetric network than in a symmetric network with a higher value of a_u .²⁴

Finally, the difference among the theoretical and actual values increases to an average of 2.5 percentage points. The explanation is the following. With a lower a_u the average length of unemployment spells increases. In particular, when a_u decreases from 0.10 to 0.05 the average unemployment spell increases from about 4 to 5 periods. From the point

²³By construction, the reduction in p_{ue} is of the same order of magnitude of the reduction in a_u . See Eq. (4).

²⁴This result ceases to hold, for example, when we set $a_e = 0.10$ and $a_u = 0.025$. We omit the presentation of the whole set of results for this case.

of view of an unemployed agent with an unemployed contact in period t , this implies that the latter has a lower probability of becoming employed in period $t + 1$. This worsens the perspective of the former of receiving in a short time information on a job from the contact. This increases the distance between the theoretical and the estimated values of p_{ue} .²⁵

Case 3: $a_e > a_u = 0$. Here we consider the case in which only employed individuals may hear about a job vacancy. As a consequence, unemployed individuals can get a job only if they receive information on job vacancies from someone who is employed and belongs to the same social network. This case represents an extreme version of the one analyzed in Case 2, and corresponds to the situation studied by Bramoullé and Saint-Paul (2006) who, as already remarked, also consider an endogenous random network.

When $a_u = 0$, the dynamics undergoes a radical qualitative change, as the state in which all agents are unemployed becomes an absorbing state for the whole system. Hence, the probability of occurrence of such event becomes crucial.²⁶ One fundamental determinant of the event is the number of agents: the higher the number, the lower the probability that, in the same period, all agents are unemployed.

For example, maintaining $a_e = 0.10$ with $n = 4$ returns the values of $\bar{\mathbf{P}}_{G_A}$ and $\bar{\mathbf{P}}_{G_B}$ in Eqs. 10 and 11.

$$\bar{\mathbf{P}}_{G_A} = \begin{bmatrix} 0.9997 & 0.0003 \\ 0.0123 & 0.9877 \end{bmatrix} \quad (10)$$

$$\bar{\mathbf{P}}_{G_B} = \begin{bmatrix} 0.9999 & 0.0001 \\ 0.0125 & 0.9875 \end{bmatrix} \quad (11)$$

Table 5 contains the results on mobility, while Table 6 contains the values of p_{ue} , $\hat{p}_{ue}$ and ML in G_B .

	G_A	G_B
ML	0.015	0.015

Table 5: Mobility indices in G_A and G_B

agent	1	2	3	4
p_{ue}	0.1825	0.2622	0.0956	0.1825
$\hat{p}_{ue}$	0.0001	0.0001	0.0001	0.0001
ML^i	0.013	0.016	0.014	0.018

Table 6: Individual exit rates and mobility indices in Network G_B . $a_e = 0.10$, $a_u = 0$

These values are generated from the fact that, after a certain number of periods, all agents become unemployed in the same period, and this situation is perpetuated until the end of the simulation. Therefore, the degree of mobility drops remarkably. Note also that

²⁵With decreasing values of a_u , i.e. $a_u = 0.025$ and $a_u = 0.0125$, we find a confirmation of this result.

²⁶In the limit, the system is absorbed with probability one.

the geometry of the network is almost irrelevant. Clearly, there is a significant difference between the estimated values $\hat{p}_{ue}$ and those computable analytically p_{ue} , which amount to approximately 0.18 in network G_A and lie between a range of 0.09 – 0.26 in G_B .

When we increase the number of agents, the occurrence of the event of zero-employment becomes less likely. In our simulations, we find that the minimum number of agents to avoid absorption is $n = 8$. Eq. (12) contains the results obtained with the symmetric network G_C in Figure 3.

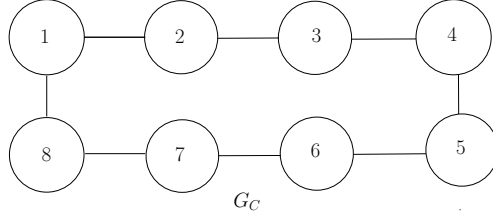


Figure 3: Network G_C

$$\overline{\mathbf{P}}_{G_C} = \begin{bmatrix} 0.8492 & 0.1508 \\ 0.0150 & 0.9850 \end{bmatrix} \quad (12)$$

Hence, in this case the network alone is able to allow workers to leave the state of unemployment, with an estimated value of $\hat{p}_{ue} \approx 15\%$, even if unemployed workers do not have access to information on jobs.²⁷

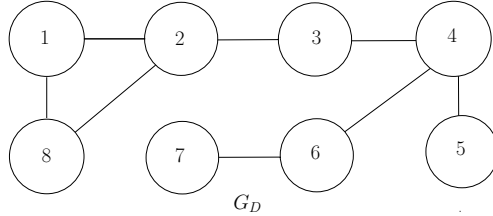


Figure 4: Network G_D

However, when we introduce some asymmetry, as in network G_D in Figure 4, the capacity of the network to be able to allow escape from unemployment is severely reduced. The most likely event in our simulations is that, after a certain number of periods, the system is absorbed in the zero-employment state.²⁸ This is reflected in results such as those in Eq. (13) and Table (7).

$$\overline{\mathbf{P}}_{G_D} = \begin{bmatrix} 0.9746 & 0.0254 \\ 0.0151 & 0.9849 \end{bmatrix} \quad (13)$$

²⁷The value of $\hat{p}_{ue}$ in (12) is lower than its theoretical value which is equal to 0.1832.

²⁸We tried 5 simulations for both networks G_C and G_D . In no cases we obtained absorption with network G_C , while we obtained absorption in network G_D in four cases. Given the very high number of periods for every simulation, we consider these differences significant and conclude that the most likely event with network G_D is absorption.

agent	1	2	3	4	5	6	7	8
p_{ue}	0.1825	0.2616	0.1819	0.2622	0.0956	0.1832	0.0963	0.1825
$\hat{p}_{ue}$	0.0264	0.0286	0.0266	0.0285	0.0213	0.0260	0.0209	0.0262
ML^i	0.042	0.044	0.042	0.043	0.036	0.041	0.036	0.042

Table 7: Individual exit rates and mobility indices in Network G_D . $a_e = 0.10$, $a_u = 0$

These results suggest that networks' topology and its dimension (i.e. the number of individuals that belong to the network) interact and may affect mobility results. In particular, when individuals may receive information on vacancies only through social connections, the role of network's topology (and of the presence of the network itself) vanishes if the number of individuals (or "community dimension") is relatively small. This is because there is a very high probability that, sooner or later, all individuals become unemployed and, as a consequence, the circulation of information on job vacancies through social contacts becomes impossible.²⁹ However, when we increase the dimension of the population, we find that the probability of absorption in the zero-employed state is much higher with asymmetric networks' geometries.

This confirms, once again, that network's symmetry can enhance the circulation of information in job contact networks and produce better employment outcomes (in this case, measured in terms of mobility or exit rates from unemployment). In our examples this is reflected by the fact that in G_C , differently from in G_D , individuals are never all unemployed in the same period, even if very long time intervals are considered. By implication, this also suggests that the role of hiring channels such as newspapers, agencies, the Internet, firms' advertising, etc., as opposed to job contact networks, becomes more relevant for smaller communities (or groups of agents with same observable characteristics), in particular when they are also characterized by a larger dispersion of social connections across community's members.

4 Concluding Remarks

In this paper we have proposed an extension of the model originally proposed by Calvo-Armengol and Jackson (2004). In particular, we assumed that employed workers have, in a given time period, a higher probability to receive information on vacancies than unemployed. This can be justified by firms' recruitment strategies to avoid adverse selection problems. Then, we explored the role of some aspects of network's topologies in this framework with respect to job mobility and transitions out of unemployment.

We showed that social networks may indeed play an important role in facilitating the average workers to leave the state of unemployment, especially when the network is symmetric (although some workers in asymmetric networks may find themselves in more advantageous positions).

However, in the extreme case in which unemployed workers have no access to information on jobs, small networks are not sufficient to avoid the case in which all workers

²⁹Clearly, this is a limit case and one should expect that firms, when all workers are unemployed, would start advertising their vacancies among the unemployed too. This opens up the possibility of exploring in more details the choice of firms' recruiting strategy in relation to the state of the agents in the network, an extension which goes beyond the scope of the present paper.

become unemployed and the network topology becomes irrelevant. Larger networks, especially when they are symmetric, do instead provide a positive probability of leaving unemployment.

This suggests that, the role of public sources of information on vacancies becomes more important the smaller is the community and the more asymmetric is the topology of the social network, providing in this way a guidance on possible policies to favor the abandonment of the state of unemployed.

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