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Transitions Out of Unemployment: the Role of Social Networks' Topology and Firms' Recruitment Strategies

Abstract

In this paper we adopt the probabilistic framework of Calvó-Armengol and Jackson (2004) to study the effects of job contact networks on out-of-unemployment transitions. In particular we evaluate the role of different network topologies *vis-a-vis* state-dependent probabilities of receiving information on vacancies, which we relate to different firms' recruitment strategies. We find that 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 the different hypotheses on the firms' hiring process strategy. Furthermore, in scale-free networks the probability of transitions out of unemployment increases in the exponent of the power-law degree distribution, but its value is much lower than what obtainable in Poisson random networks.

Classificazione JEL: D83, J60, J64
Keywords: job contact networks, complex networks, network symmetry, transitions out of unemployment, firms' recruitment strategies.

Contents

I. 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, so that the study of the effects of social ties in labor markets has become a fruitful research area in economics.[2]

An important issue in the studies on social networks in labor markets is network structure, that is, how and to what extent networks' characteristics, such as its topology and the type of connections (e.g. "strong" or "weak" ties, see Granovetter (1973)), play a role in explaining the economic effects of networks. For instance, the effects of network's symmetry and asymmetry in the network topology 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.

In this paper we analyze the effects of social networks' topology on transitions out of unemployment, which represent a specific aspect of mobility in labor markets. In particular we compare, by means of numerical simulations, the effects of different characteristics of network geometries on the probability of transitions out of unemployment. For small networks we focus on symmetric and asymmetric networks, while for large networks we compare scale-free and random networks. Moreover, by considering different options for firms for advertising their vacancies (see below), we also provide a first step in evaluating the role that firms' recruitment strategies can play in such a (socially networked) context.

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

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

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

better than asymmetric ones. In addition, and most interestingly, these results strongly depends on the different hypotheses on the firms' hiring process strategy. In particular, when firms exclusively adopt a referral hiring strategy, by allowing only employed workers to receive information on vacancies, and the network is small, the probability to leave unemployment remarkably drops, 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. On the contrary, when the dimension of the community is sufficiently large, symmetric social networks may preserve a positive probability of leaving unemployment, while asymmetric networks reduce, or even eliminate, mobility. Finally, in scale-free networks the probability of transitions out of unemployment increases in the exponent of the power-law degree distribution, but its value is much lower than what obtainable in Poisson random networks.

The remainder part of the paper is organized as follows: Section II. clarifies the location of the paper in the literature; Section III. presents the theoretical model; Section IV. contains the results of the simulations; Section V. provides further discussion of the main results and provides some concluding remarks and directions for future research.

II. Related Literature

Several studies on occupational and earnings mobility exist in economics (see Atkinson *et al.* (1992) for a survey). In particular many studies, focusing on specific aspects of mobility, such as transitions out of low-pay jobs (e.g., Cappellari (2007)), or transitions out of unemployment (e.g., Lynch (1989)), have empirically investigated the role of different observable individual characteristics (e.g. gender, race, education, work experience), and industrial/labor market structures in explaining differences across individuals in job/employment mobility.

An important finding, common to many of such studies, is that unobservable heterogeneity matters.[3] In this regard, studies on social networks may provide an important contribution 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 than the same types of workers in another location, all other variables held constant"(Calvó-Armengol and Jackson (2004), p. 433).[4]

However, economic studies that explicitly investigate the effects of the presence and the structure of social networks on mobility are rare.[5] Our paper based on the works of Calvó-Armengol (2004), Calvó-Armengol and Jackson (2004) and is closely related to Bramoullé and Saint-Paul (2006). Furthermore, it also partly extends previous work of ours (Lavezzi and Meccheri (2007)).[6]

Calvó-Armengol (2004) and Calvó-Armengol and Jackson (2004) introduce a probabilistic framework in which social networks facilitate the transmission of information on job vacancies among workers, and show that there exists a strictly positive correlation of individual employment outcomes for agents in a same network component, both in the steady state and the transitional dynamics. Moreover, they also study how the geometry of the correlation patterns relates to the geometry of the network. Instead, in Lavezzi and Meccheri (2007) we adopt the Calvó-Armengol and Jackson (2004)'s framework to study the quantitative effects of network symmetry on aggregate output and wage inequality.

However, these studies (including ours) do not explicitly concentrate on the effects of network's geometry on mobility from unem-

[3]With respect to transitions from unemployment, another important result is that there is substantial negative duration dependence (e.g., Lynch (1989)).

[4]From the econometrician's point of view, the 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 to drive the empirical correlation between individual outcomes (e.g., Mansky (1993) and Moffit (2001)).

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

[6] 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 *intra*generational mobility, their focus is on *inter*generational mobility.

ployment to employment.[7] Furthermore, they concentrate on small networks, while here we also consider larger (scale-free and random) networks. Finally, they all assume that job arrival probabilities for each individual do not depend on being employed or unemployed.

In this paper, instead, we consider state-dependent probabilities to access information on jobs. Specifically, we assume that employed individuals have in general a higher probability to obtain information on job vacancies than unemployed individuals. This intends to capture the situation in which firms mainly adopt a recruitment "referral" strategy, by asking first to their employees to refer some applicant linked to them. This is consistent with the case studied in Montgomery (1991) where firms adopt a referral hiring process because they have imperfect information on applicants or, e.g., the case in which employers aim at economize on advertising costs. For instance, in a study of displaced workers in manufacturing, Zippay (2001), p. 103, reports that: "One local 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". Hence, the introduction of this aspect in the model allows to consider the effects of firms' different strategies of advertising vacancies, and to evaluate this channel with respect to other traditional channels such as advertising in magazines, the Internet, etc.

Our paper shares important aspects also with Bramoullé and Saint-Paul (2006). Both papers adopt the probabilistic framework of Calvó-Armengol and Jackson (2004) to study the effects of social connections on mobility in labor markets, and both focus on transitions out of unemployment. However, the mechanisms through which social networks may affect exit rates from unemployment are different. In particular, in Bramoullé and Saint-Paul (2006): (i) unemployed workers may obtain a job only through social connections and, (ii) social networks are random, with ties endogenously

[7] Calvó-Armengol and Jackson (2004) present results on the effects of the structure of social networks on unemployment rates but, in any case, discuss fewer cases than in the present study.

evolving according to the (un)employment status of the agents.[8] In our paper, instead, we consider both the case in which information on vacancies may reach individuals only through "personal" hiring channels, such as social networks, and the case in which other sources of information may be present, e.g. newspapers, agencies, the Internet, etc. In addition, as in Calvó-Armengol and Jackson (2004), we consider exogenous and fixed networks as, differently from Bramoullé and Saint-Paul (2006), we aim to study the effects of different networks' geometries on mobility.[9]

III. Social Networks and the Labor Market

In this section we present a version of the model of Calvó-Armengol and Jackson (2004), in which the probability of receiving information on jobs depends on the agents' employment status.

III.A. Labor turnover

Time is discrete and indexed by $t = 0, 1, 2, ..., T$. The economy is populated by infinitely-lived agents (workers) with similar observable traits, indexed by $i \in \{1, 2, ..., n\}$.[10] In each period a worker can be either employed or unemployed. 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.[11] Every period (from $t = 0$ onwards) has

[8]Specifically, Bramoullé and Saint-Paul (2006) assume that the probability of tie formation between two employed individuals is greater than between an employed and an unemployed, producing an "inbreeding bias"effect.

[9] Bramoullé and Saint-Paul (2006)'s model is instead a more suitable framework to study the issue of duration dependence.

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

[11]This assumption is irrelevant in many examples we will discuss but, for simplicity, we make it as some of cases will feature zero-employment as an absorbing state.

two phases: at the beginning of the period each worker can receive information on a vacancy with arrival probability $a \in [0, 1)$. Parameter a captures information on vacancies not transmitted through the network, that is information from firms, agencies, newspapers, etc. If unemployed, the worker takes the job, while, if employed, s/he passes the information to a friend/relative/acquaintance who is unemployed, according to a rule, which will be specified below. At the end of the period every employed worker loses the job with breakdown probability $b \in (0, 1)$.

In this paper we consider different assumptions on the probability a. Let us define a_{s_i}, $s_i \in S = (e, u)$, the probabilities of hearing about a job when, respectively, unemployed or 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. In particular, 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 different assumptions (randomness and endogeneity) on the social network. In Cases 2 and 3 employed workers have in each period a higher probability of hearing about vacancies than unemployed workers. As mentioned, with these two cases we aim at capturing a situation in which employers adopt a recruitment "referral" strategy, by asking first to their employees to refer some applicant. This produces an advantage of the employed over the unemployed in accessing information on vacancies. Moreover, it makes (employed) social connections the main, or unique, source of information on job opportunities for unemployed workers.

III.B. 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 $g_{ij} = 0$ 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 hears about a job with probability a_u when unemployed and keeps the job. In the second case, instead, worker i is employed and hears with probability a_e about a job, that s/he passes only to an unemployed worker $j(\neq i)$ among her/his connections (i.e. in her/his *neighborhood*). We assume that i randomly chooses j among all her/his unemployed contacts.[12] Hence, the probability that worker j receives information from 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 hears about a vacancy makes direct use of it if s/he is unemployed. Otherwise, s/he passes the information to someone who is connected to her/him. The choice of the worker to whom pass the information is "selective", in the sense that information is never passed to someone who does not need it (that is, someone who is already employed),[13] but it is random with respect to the subset of the connected workers who are unemployed.

[12] The same results would obtain if, since there is no cost in passing information, we assume that i passes the information to all her/his unemployed contacts and then the firm randomly chooses among them to fill the vacancy.

[13] For the sake of simplicity, we assume that in each period a worker can observe the state of agents in her/his neighborhood at the end of the previous period. In other words, s/he cannot observe if they 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.

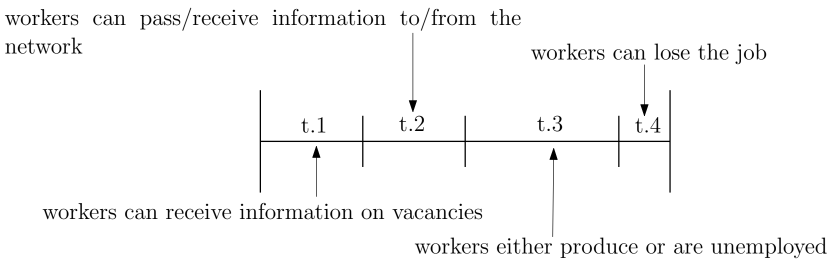

Figure 1: Timing

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).

III.C. Transitions Out of Unemployment

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:

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

where, e.g., $p_{ue,g}^i$ is the probability for agent i 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 the second row of $\mathbf{P}_g^i$ are given, respectively, by b and $(1-b)$. Transition probabilities in the first row, instead, depend on the joint effect of the probabilities of receving information on jobs, both directly and through the social network.[14] The latter depend, in each period, on the number of connections of agent i (i.e. on his/her *degree*), on the degree of agent i's contacts, on the number of unemployed agents in both agent i's neighborhood and in the neighborhoods of agent i's contacts.

[14]The latter are computed analytically in Calvó-Armengol (2004) on the assumption that each agent in the neigborhood of i is employed and has a information on a job to pass.

In what follows, we present estimates of *average* transition probabilities, based on the frequencies of transitions across the states of employed and unemployed over simulated time series for each agent. We will focus on the values of $\hat{p}^i_{ue,g}$, the estimated values of $p^i_{ue,g}$ (exit probability, for short), in different networks. In this simple setting, these values are sufficient to evaluate the overall level of mobility in the labor market.[15]

IV. Simulations

In this section we present the results of various 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 $\overline{P}_g$, whose elements are denoted by $p_{kh,g}$, $(k,h) \in S$.[16]

IV.A. Transitions Out of Unemployment 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 $b = 0.015$,[17] the average transition matrix is given by:

$$\overline{\mathbf{P}}_{G_0} = \begin{bmatrix} 0.9017, & \mathbf{0.0983} \\ 0.0150, & 0.9850 \end{bmatrix}. \tag{2}$$

[15]That is, values of $\hat{p}_{ue,g}$ in different networks capture the same information obtainable from mobility indices based on the entire transition matrix, such as $ML = 1 - |\lambda_2|$, where λ_2 is the second largest eigenvalue of the transition matrix, $MT = \frac{k-tr(P)}{k-1}$, where k is the number of states, or $MD = 1 - |det(P)|^{1/(k-1)}$. See, e.g., Checchi *et al.* (1999), p. 357.

[16]Average transition probabilities are estimated by the frequencies of transitions in the simulated time series of all agents. When this does not cause confusion, we will omit the subscript g.

[17]These 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.

The value of p_{ue} is given by $a(1-b)$, that is by the probability of hearing about a job multiplied by the probability of not being fired at the end of the period.[18]

IV.B. Transitions Out of Unemployment in Symmetric and Asymmetric networks

Now we analyze the transition matrices when agents belong to a social network, in particular we examine different network topologies for different values of a_u and a_e. Consider, as a first example, the networks in Figures 2 and 3, taken from Example 1 in Calvó-Armengol (2004).

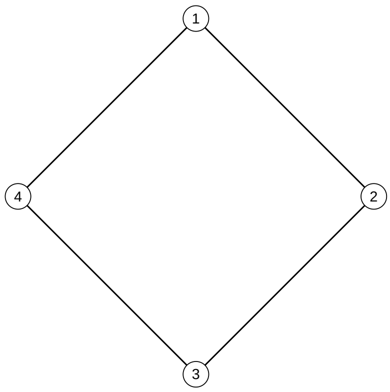

Figure 2: Network G_A

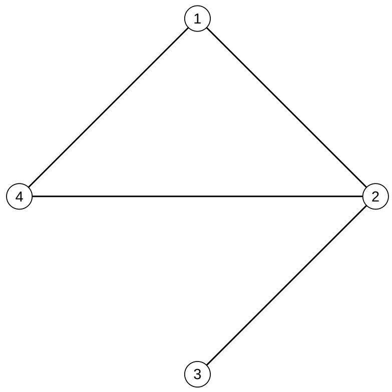

Figure 3: Network G_B

Networks G_A and G_B are characterized by the same number of agents, $n = 4$, and links, $N = 4$, and the same *average degree*, $z = 2$.[19] However, they have a different geometry: network G_A is a symmetric network, since all agents have the same degree, 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 degree 3 and agent 3 has degree 1, while agents 1 and 4 maintain the same degree.

[18] The exact value of $\hat{p}_{ue}$ should be 0.0985. The discrepancy depends on small departures from the law of large numbers.

[19] The average degree of a network is the average of the agents'degrees. The simple formula to obtain z is: $z = 2N/n$.

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 degree of the agents to whom every agent is connected. In network G_A any agent has two links with agents of degree 2. Differently, in network G_B agents 1 and 4 have one link with an agent of degree 2 (respectively agents 4 and 1), and one link with an agent of degree 3, agent 2. Agent 2 has two links with two agents, 1 and 4, having degree 2, and one link with agent 3, who has degree 1.

In this paper we measure the level of symmetry by the *centralization* index, C_g, introduced by Freeman (1979) and discussed, e.g., by Wasserman and Faust (1994), p. 180. This index assumes the value of zero when the network is symmetric (as Network G_A), and the value of one when the network is a star, that is all the existing links connect a central agent to any other agent. In network G_B, $C_g = 0.6667$.

As a first step, 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.[20]

Hence, we expect network G_A to generate a higher value of p_{ue} than network G_B (and, in general, symmetric networks to display higher values of p_{ue} 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 information on the role of firms' hiring

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

strategy.

Case 1: $\mathbf{a_e = a_u > 0}$. In this case, we assume that all individuals receive information on job vacancies independently of their employment status ($a_e = a_u = 0.10$), as in Calvó-Armengol and Jackson (2004).[21] $\overline{\mathbf{P}}_{G_A}$ and $\overline{\mathbf{P}}_{G_B}$ denote the average transition matrices associated, respectively, to networks G_A and G_B.

$$\overline{\mathbf{P}}_{G_A} = \begin{bmatrix} 0.7511, & \mathbf{0.2489} \\ 0.0149, & 0.9851 \end{bmatrix} \tag{3}$$

$$\overline{\mathbf{P}}_{G_B} = \begin{bmatrix} 0.7636, & \mathbf{0.2364} \\ 0.0151, & 0.9849 \end{bmatrix} \tag{4}$$

Note that, obviously, both networks are associated to a higher value of the exit probability than in the case with no links in Eq. (2): the estimated probability $\hat{p}_{ue}$ increases from about 10% to about 25%, indicating that the effect of the network is sizable. As we discuss below, this value is essentially associated to the value of z, and not to the fact that this network is *dense*, in the sense that most of the possible links are present.[22]

In addition, as predicted, even if the two networks are very similar, the symmetric network G_A is associated to a higher probability to exit unemployment than the asymmetric network 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 1 reports the estimated exit probabilities for each individual, $\hat{p}^i_{ue}$, $i = 1, .., 4$.[23]

agent	1	2	3	4
$\hat{p}^i_{ue}$	0.2457	0.3149	0.1780	0.2433

Table 1: Individual exit probabilities in Network G_B. $a_e = a_u = 0.10$

[21] Here and in what follows, we maintain $b = 0.015$ and $T = 500,000$.

[22] The *density* of a network is the ratio of existing links to the maximum possible number of links (see, e.g., Wasserman and Faust (1994), p. 164). The density in G_A and G_B is 0.667.

[23] We do not report results on individual agents in the symmetric network G_A as, clearly, they correspond to the average values in Eq. (3).

In network G_B, $\hat{p}^2_{ue}$ increases, while $\hat{p}^3_{ue}$ decreases, as the degree of agents 2 and 3 is, respectively, increased and decreased. Note also that $\hat{p}^1_{ue}$ and $\hat{p}^4_{ue}$ decreased, although the degree of agents 1 and 4 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.[24] Overall, in a comparison between G_A and G_B , the negative contributions from agents 1, 3 and 4 outweigh the positive contribution from agent 2 on the transtion probability from unemployment.

Case 2: $\mathbf{a_e > a_u > 0}$. Now we consider the case in which employed individuals have a higher probability to hear about a job vacancy, although also unemployed individuals may directly receive some information on vacancies. In particular, we make the following assumptions on 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. (5) and (6).

$$\overline{\mathbf{P}}_{G_A} = \begin{bmatrix} 0.7992, & \mathbf{0.2008} \\ 0.0149, & 0.9851 \end{bmatrix} \tag{5}$$

$$\overline{\mathbf{P}}_{G_B} = \begin{bmatrix} 0.8164, & \mathbf{0.1836} \\ 0.0149, & 0.9851 \end{bmatrix} \tag{6}$$

Note that the exit probability $\hat{p}_{ue}$ drops of approximately 5 percentage points, which reflects the drop in a_u.[25] Table 2 contains the results on individual transition probabilities in network G_B.

agent	1	2	3	4
$\hat{p}^i_{ue}$	0.1955	0.2645	0.1284	0.1918

Table 2: Individual exit probabilities in Network G_B. $a_e = 0.10$, $a_u = 0.05$

[24] See Calvó-Armengol and Jackson (2004).

[25] Obviously, by properly reducing a_u and, simultaneously, increasing a_e, we could obtain a case with $a_e > a_u > 0$ in which the average exit probability increases, instead of decreasing, with respect to Case 1. For example, with $a_u = 0.05$ and $a_e = 0.15$, we obtain $\hat{p}_{ue} \approx 0.28$, for network G_A, and $\hat{p}_{ue} \approx 0.25$, for network G_B. Our choice to only reduce a_u has not, however, relevant *qualitative* effects on the main aspects we aim to investigate, that is comparing individual employment outcomes with different network's structures.

By comparing Eqs. (5) and (6) with Eqs. (3) and (4) it is possible to verify that the reduction in the value of a_u (for given a_e) reduces on average the probability to leave unemployment, and that in symmetric networks this probability is, on average, higher than in the asymmetric network G_B. However, agent 2 in G_B enjoys a higher exit probability than the average agent in G_A in Case 1. Hence, for some agents, an increase in degree may counterbalance a reduction in a_u, so that they have a higher exit probability in an asymmetric network than in a symmetric network with a higher value of a_u.[26]

Case 3: $\mathbf{a_e > a_u = 0}$. Now we consider the case in which only employed individuals may hear about a job vacancy ($a_e = 0.10$ and $a_u = 0$). As a consequence, unemployed individuals can find a job only if they receive information on job vacancies from someone an employed member of their neighborhood. 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 remarked, consider an endogenous random network and, consequently, can not compare different networks' topologies.

When $a_u = 0$ the dynamics undergoes a radical qualitative change, as the configuration of the system in which all agents are unemployed becomes absorbing. However, given that we are considering a large number of periods, we are interested in evaluating whether the system is *actually* absorbed whithin 500,000 periods, which may represent a sufficient interval for practical purposes. This is relevant as it allows to highlight another aspect of network topology. That is, given that, for $t \to \infty$, the system is absorbed with probability one, the topology and the size of the network may affect the *speed* at which this absorption occurs. In particular we find that: (i) an increasing size of the network can contribute to increase the capacity of the system to "resist" asborption; (ii) when the network is asymmetric, absorption takes place faster. Some examples will

[26] This 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.

clarify this point.[27]

In networks G_A and G_B we observed absorption in all cases, with no appreciable differences in the length of the periods before absorption. In this case the network is very small, and differences in the topology do not matter. However, given that absorption in the zero-employment state is conditional on having all agents unemployed in the same period, when the number of agents increases, the occurrence of such event becomes less likely. With the same parameters, we find that the first structure in which the event of zero-employment has a low probability features 8 agents.[28] Eq. (7) contains the results obtained with the symmetric network G_C in Figure 4.

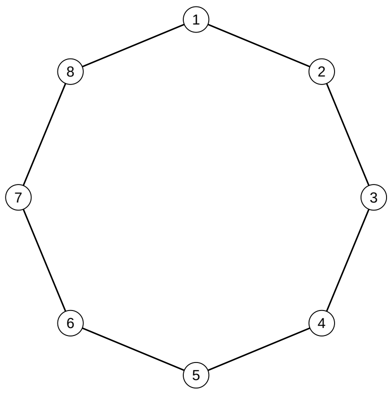

Figure 4: Network G_C

$$\overline{\mathbf{P}}_{G_C} = \begin{bmatrix} 0.8490 & \mathbf{0.1510} \\ 0.0150 & 0.9850 \end{bmatrix} \tag{7}$$

In this case the network alone can generate a positive probability for workers to leave the state of unemployment, with an estimated value of $\hat{p}_{ue} \approx 15\%$, even if unemployed workers do not have direct access to information on jobs.[29]

[27]The following examples are based on series of 5 simulations for various types of networks, with $T = 500,000$, $a_e = 0.10$, $b = 0.015$ and $z = 2$.

[28]With $n = 5, 6$ we observed absorption in all cases, with $n = 7$ we observed absorption in four cases while, with $n = 8$, we observed absorption in one case only (at period $158,968$).

[29]If the agents in network G_C were separated in two groups of four agents connected as in network G_A, the system would preserve symmetry in a sense, but it would be absorbed as it would replicate the results for network G_A. This confirms the importance of the *size* of the

If we introduce a moderate amount of asymmetry in the network, for example by rewiring one link, we can obtain a structure such as G_D in Figure 5. In particular, network G_D has a level of centralization equal to $C_g = 0.19$.[30]

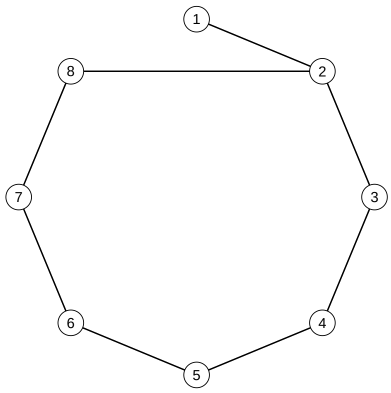

Figure 5: Network G_D

In this case absorption appears as likely as in G_C.[31] The transition matrix, when absorption does not take place, becomes as in Eq. (8), with a predictable decrease in $\hat{p}_{ue}$.

$$\overline{\mathbf{P}}_{G_D} = \begin{bmatrix} 0.8620 & \mathbf{0.1380} \\ 0.0150 & 0.9850 \end{bmatrix} \tag{8}$$

However, when we increase the amount of asymmetry, absorption becomes the most likely event. By rewiring another link in Network G_D, we obtain network Network G_E in Figure 6, in which $C_g = 0.38$. In this case absorption becomes the most likely event.[32]

This result is clearly confirmed in the extreme case of asymmetry given by the star network in Figure 7, for which $C_g = 0.95$.[33]

symmetric network and points to the role of "structural holes" (see Burt (1992)), that is agents connecting otherwise separated groups. We thank Salvatore Modica for suggesting us this case, and refer to Lavezzi and Meccheri (2007) for further discussion.

[30] Clearly, network G_D has the same value of z as G_C. The same holds for networks G_E and G_F that follow.

[31] For network G_D, we observed absorption in one out of five simulations, at period $130, 705$.

[32] For network G_E, we obtained absorption in four out of five simulations. The estimated value of the exit probability when absorption does not take place is $\hat{p}_{ue} = 0.1239$.

[33] In Figure 7 we added one link between agents 2 and 3 with respect to the pure star topology to preserve the value of $z = 2$. This makes C_g different from one.

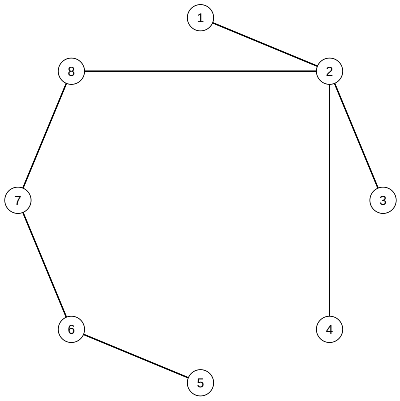

Figure 6: Network G_E

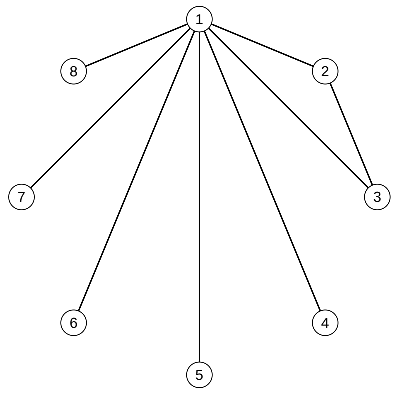

Figure 7: Network G_F

With network G_F we obtained absorption in all simulations. However, if we compare the average number of periods before absorption in G_E and G_F, we have, respectively, $230,292$ and $67,097$. This highligths that, as mentioned, a more asymmetric structure makes absorption faster.

These results provide first insights on the role of networks' topology and size in affecting transitions out of unemployment.[34] However, to what extent are they generalizable? For example, since we have analyzed networks characterized by the same average degree, it is not clear at once the role played in this context by the density of links of the network. While these aspects are considered in greater detail in the next section on complex (larger) networks, the following simple examples may provide, in this regard, other indications.

[34]Note that, if we consider the state $s_i = u$ as "employed in a low-pay job", and the state $s_i = e$ as "employed in a high-pay job", our results could also be interpreted in terms of low-pay/high-pay transitions. Indeed, we have examined a more general case with three states (unemployed, employed in a low-pay job and employed in a high-pay job). This requires the introduction of several parameters, such as different values of a across states and across jobs but, in relation to the main topic of our study (i.e. the role of networks' structure), does not provide significantly different insights from those obtainable with two states. In other words, the changes of the transition probabilities in different networks mimic those presented here. This depends on the very simple structure of the labor market assumed here. We defer the reader to the concluding section for further discussion on this point.

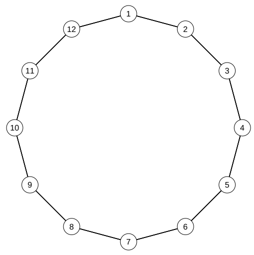

Figure 8: Net. G_G

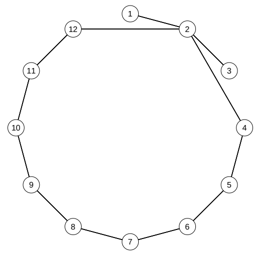

Figure 9: Net. G_H

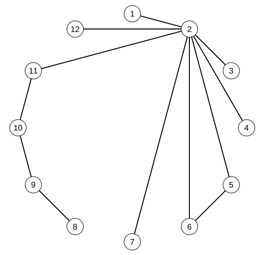

Figure 10: Net. G_I

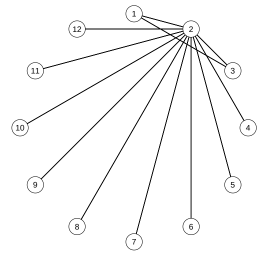

Figure 11: Net. G_L

Figures $8 - 11$ represent four different network's geometries for $n = 12$ and $z = 2$ with increasing values of C_g.[35] For each of those networks, Table 3 reports, respectively, the centralization index, the exit rate from unemployment (for the representative simulation) and the average number of periods before absorption (the number of absorptions out of five simulations is reported in pharentesis).

network	C_g	$\hat{p}_{ue}$	periods before abs.
G_G	0	0.1506	NA (0)
G_H	0.22	0.1325	NA (0)
G_I	0.65	0.0718	422,813 (2)
G_L	0.98	0	83,421 (5)

Table 3: Results with Networks $G_G - G_L$ ($a_e = 0.10$, $a_u = 0$).

Results from networks $G_G - G_L$ confirm previous insights. Specifically, making network's topology more asymmetric reduces, on the one hand, the exit rate from unemployment and, on the other hand, increases the probability of absorption and, when the system is likely to be absorbed, reduces the (average) number of periods before absorption. Moreover, comparing results of network G_G against those of network G_C (with eight agents), gives us further evidence on the role of network's dimension (i.e. number of agents in the network), which aligns with previous claims. Although networks G_C and G_G are both perfectly symmetric (with a centralization index equal to zero), we never obtained absorption for G_G, while, even if with small

[35]We have also simulated other networks with (a)symmetry degrees falling in between those presented here. Results are in line with those here described.

probability (one case out of five simulations), absorption is resulted a possible event for network G_C.[36]

We have seen that, for $a_e > a_u = 0$, $T = 500,000$, and for given values of z, an increase in n can allow the system to avoid absoprtion. In addition, increasing values of C_g, for given n and z, can make absorption more probable. Next we analyze the consequences of increasing z, for fixed n and comparable values of C_g, which would amount to increasing the density of the network. Consider network G_M in Figure 12.

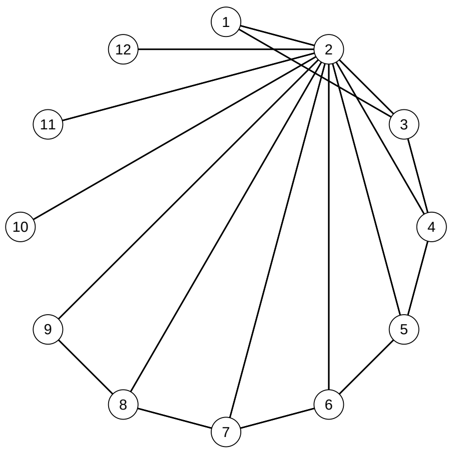

Figure 12: Network G_M

Its topology is comparable with networks G_I and G_L. Indeed, in network G_M, $C_g = 0.87$, a value close to $C_{G_I} = 0.65$ and $C_{G_I} = 0.98$: all three networks are characterized by a relatively high "amount" of asymmetry. However, while $z = 2$ in G_I and G_L, in G_M $z = 3$. This difference plays a crucial role. While, as we have seen above, absorption in the zero-employment state is a likely with G_I and very likely with G_L, we never obtained absorption with network G_M. Figure 13 summarizes the results of various simulations.[37]

[36]Notice also that, both networks generate approximately the same value of $\hat{p}_{ue} \approx 15\%$, when not absorbed.

[37]We present results of five simulations with increasing values of C_g for different values of z. The procedure to increase C_g is the same discussed in the presentation of Figures 4-7. For this reason, we did not obtain closely matching values of C_g across simulations for different z.

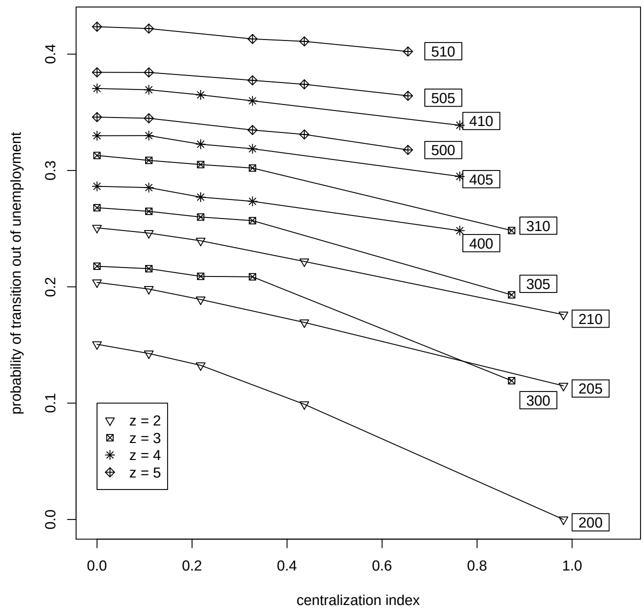

Figure 13: Relation between $\hat{p}_{ue}$ and C_g for different levels of z and a_u. Labels indicate z and the value of a_u (ex. "510" means: $z = 5$ & $a_u = 0.10$, etc.) $n = 12$, $a_e = 0.10$.

Figure 13 shows that:

1. when z increases, density increases, and $\hat{p}_{ue}$ on average increases;

2. for given z, there exists a negative relationship between $\hat{p}_{ue}$ and C_g;

3. the higher z, the less likely is the system to be absorbed when $a_u = 0$;

4. there is some evidenence that, as z increases the difference in the values of $\hat{p}_{ue}$ at high values of C_g is less sensitive to a_u being 0.05 or 0;

5. when $z = 2$, $a_e = a_u = 0.10$, and $C_g = 0$, the value of $\hat{p}_{ue}$ is about 25% (see the first observation of the line labelled "210"). This is the same value found with the same parameter values but with $n = 4$ (i.e. with Network G_A in Figure 2.) Results not

presented here show that the same value of $\hat{p}_{ue}$ is also found with $n = 5, 6, 7, 8$. This shows that, when the system does not feature an absorbing state, the nature of interactions in social networks is actually *local* as, from the point of view of the individual agent, what matters is her/his *degree* and not the *size* of the network.[38]

These results may also provide some insights on the issue of short-term vs. long-term unemployment. Specifically, the possibility to become a long-term unemployed becomes particularly serious the more likely the conditions for absorption in the zero-employment state apply.[39] Hence, when considering the effects that may generate or reduce long-term unemployment, we highlight which networks' characteristics can be crucial in this respect.

In this regard, we have also examined an alternative scenario, in which the probability a_u decreases with the length of the unemployment spell. This may happen because spending time as unemployed progressively prevent workers from receiving information on jobs.[40] In particular, denoting the length of the unemployment spell by t_s, we studied the case in which $a_u(t_s) = a_u/t_s$, which is one of many possible functional forms in which $da_u/dt_s < 0$. Results related to a comparison between such a case and that in which a_u is positive and fixed ($a_u = 0.10$) are presented in Figure 14.[41]

[38]See also the remarks in footnote 36.

[39]Studies on transitions from unemployment have found "duration dependence", that is the dependence on the probability of leaving unemployment from the length of the unemployment spells. Bramoullé and Saint-Paul (2006) treat this issue by assuming that the probability to form links is higher between two employed workers than between an employed and an unemployed worker. Calvó-Armengol and Jackson (2004), p. 433, show that, with fixed networks, there is duration dependence in the sense that a long spell of unemployment for a worker signals that most agents in her/his neighborhood are likely to be unemployed. Hence, the longer the spell, the higher the probability that her/his connections will keep possible information on jobs for themselves.

[40]Theories on human capital, for instance, point out that workers' human capital depreciate over time when they are unemployed, and this reduces firms' propensity of making job offers to those workers.

[41]Figure 14 refers to a comparison between different (four) network structures (different centralization index), with $n = 6$ and $z = 2$. Each value (for each network) is the average exit rate of unemployment out of a total of three simulations. Due to computational constraints, we set $T = 100,000$.

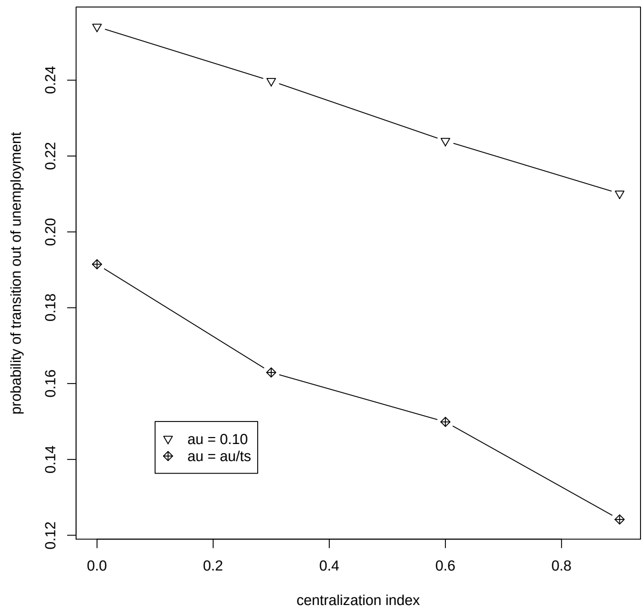

Figure 14: Comparison among different networks' structures with $a_u = 0.10$ and a_u varying with workers' unemployment spell. $n = 6$, $z = 2$.

As expected, when arrival probabilities for unemployed workers decrease according to unemployment spell, (average) exit rates from unemployment remarkably reduce (e.g. because long-term unemployment becomes a relevant possibility for some worker in the network). However, this is much more evident the higher is the network's asymmetry (i.e. the higher is the network's centralization index). More in detail, a comparison of the extreme values of C_g shows that the decrease of $\hat{p}_{ue}$ is more than proportional when arrival probabilities for unemployed workers are decreasing in t_s.

In conclusion, these results provide us with different indications concerning the role of networks' topology, dimension and density of agents' connections in affecting out-of-unemployment transitions. The next section analyzes complex networks, which have a much larger size than those analyzed so far.

IV.C. Transitions Out of Unemployment in Complex Networks

In this section we focus on complex networks. The definition of complex networks applies to *large* networks with different characteristics from regular structures like lattices, characteristics typically identified as statistical properties (see, e.g., the survey of Newman (2003)).

In particular, we compare two archetypical network structures: random networks and scale-free networks. A random network, originally introduced by Erdös and Rényi (1959), is obtained by considering a set of n nodes and a random number of links, each link existing with probability q.[42] These networks, for large n, are characterized by a Poisson degree distribution of the form: $p_k = \frac{z^k e^{-z}}{k!}$, where p_k is the fraction of agents having degree k, and z is the average degree. Scale-free networks are instead characterized by a power-law degree distribution. That is, the degree distribution can be represented as $p_k = k^{-\alpha}$, where α is a positive number. These networks are defined scale-free because, by rescaling the independent variable, k in this case, the form of the function p_k remains unchanged.

The scale-free property has been detected by various types of networks, including social networks (see, e.g., Newman (2003), p. 177). For the present discussion, it is important to remark that networks with scale-free degree distributions are network which display a high level of inequality in the distribution of links. In particular, when the distribution is scale-free, the tail of the distribution is "fat", indicating that a non-negligible number of agents have a disproportionately high number of links. Moreover, being the distibution scale-invariant, the same level of inequality found at low levels of k is also found at high k. These characteristics put the scale-free networks in sharp contrast to random networks as the latter, in

[42] Another type of random network is obtained by considering a fixed number of nodes and a fixed number of edges which are randomly attached to the existing links. See, e.g., Newman (2003), p. 187.

particular, do not display fat tails in the degree distributions.[43]

It is well-known that actual social networks have statistical properties that make them very different from random networks. However, it is still useful to utilize random networks as a benchmark because they represent a structure which abstracts from any particular behavior of the agents in the construction of their social networks. For example, the scale-free property may emerge when agents' behavior displays "preferential attachment", that is when links are preferentially formed with individuals already having a relatively high number of connections.[44]

In our analysis we considered the average degree of a random network as it well represents the characteristics of the network (while this does not hold for scale-free networks), and the value of the coefficient α for scale-free networks. In particular, we evaluated the relationship between p_{ue} and the average degree z in random networks, and between p_{ue} and the exponent α of the power-law degree distribution in scale-free networks. Figures 15 and 16 display the results.[45]

[43]When plotting the cumulative degree distribution of a random network on a log-linear scale, this appears as a straight line. Differently, to obtain a straight line in the cumulative degree distribution of a scale-free networks, this has to be plotted on a log-log scale.

[44]But see Jackson and Rogers (2007) for a hybrid model that combines features of random and scale-free networks.

[45]Both figures contain the results for 40 networks. All networks have been generated with the package `igraph`, and have been simulated with the parameters: $n = 2000$, $T = 5000$. For scale-free networks, the coefficient of the power-law has been estimated from the realized network structure. To keep a minimal level of comparability between the networks in the two figures, we imposed to each random network represented in Figure 15 the same average degree of one of the networks of Figure 16. Note that, as predictable, we never observed absorption with 2000 agents.

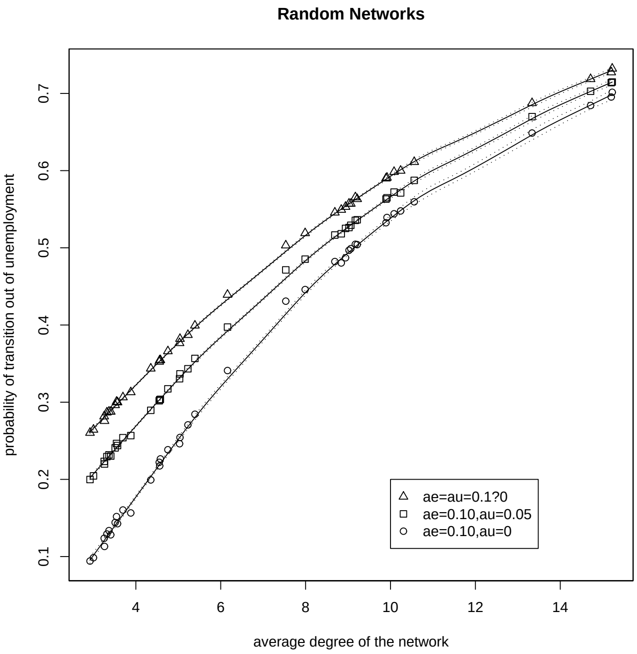

Figure 15: Relation between p_{ue} and z

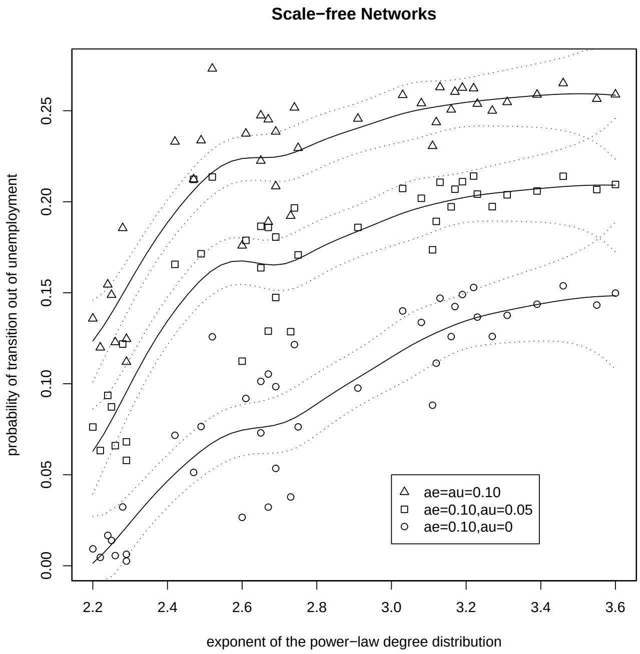

Figure 16: Relation between p_{ue} and α

Figures 15 and 16 highlight various results:

1. there exists a clear positive relation between $\hat{p}_{ue}$ and z, indicating that an increase in the (average) number of links, and then of the density, has positive effects on transitions out of unemployment.

2. There exists a positive relation between $\hat{p}_{ue}$ and α, which appers more irregular than the former.[46] A higher level of α indicates that the dimension of the fat tail is lower and, therefore, scale-free networks with higher exponents can be considered in this sense less "asymmetric". Indeed, albeit quite irregular, there exists a negative relationship between the level of α and the centralization index. Figure 17 reports the estimate of this

[46] Figures 15 and 16 contain nonparametric estimates of the relationship, respectively, between $\hat{p}_{ue}$ and α and between $\hat{p}_{ue}$ and z, for different values of the parameters a_e and a_u. The estimates are accompanied by the variability bands, which differ from the confidence bands, but provide a good indication the precision of the estimates. See Bowman and Azzalini (1997), pp. 75-76, for details.

relationship, highligthting that the largest drops in centralization approximately take place for $2.2 \leqslant \alpha \leqslant 2.6$, which are the values for which, in Figure 16, we observe the largest increases in $\hat{p}_{ue}$.

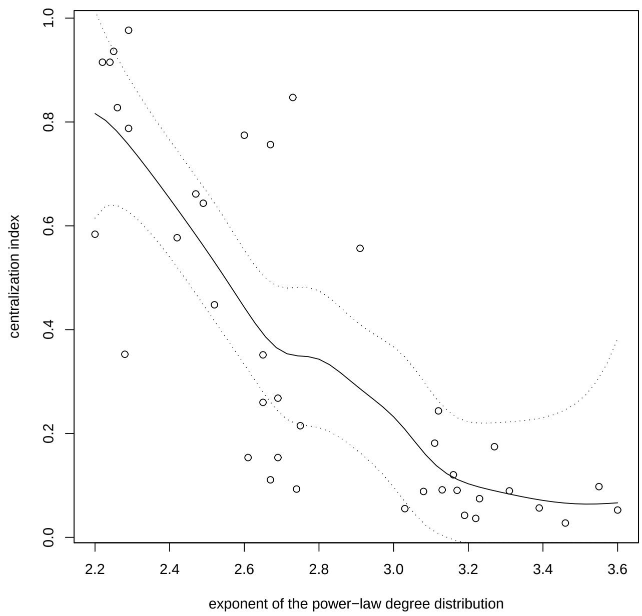

Figure 17: Relation between C_g and α

3. The relation between $\hat{p}_{ue}$ and z appears concave. In addition, as z increases, the difference between the values of $\hat{p}_{ue}$ corresponding to Cases 1, 2 and 3 tends to vanish. This indicates that: i) an increase in the average number of links has higher marginal effects on p_{ue} for lower levels of z; ii) for sufficiently *dense* random networks, the difference between employed and unemployed in accessing information on jobs has little effect on the probability of leaving unemployment. The latter result may depend on the fact that, for low levels of z and for the given level of n, the random network may be *disconnected*, that is some agents may have degree zero.[47]

[47] In random networks, there exists a threshold probability level depending on n, below which the network is disconnected, given by $q^C(n) = \frac{logn}{n}$ (see, e.g. Vega-Redondo (2007), p. 38).

4. Also the relation between $\hat{p}_{ue}$ and α appears concave, but the degree of concavity seems lower when $a_e > a_u = 0$. In addition, the differences in the values of a_e and a_u seem to matter more in scale-free networks.

5. The levels of $\hat{p}_{ue}$ attainable with scale-free networks reach a maximum value of approximately 25%, and are remarkably lower than those obtainable in random networks. The latter, with moderately values of z of about 14 may even raise the value of $\hat{p}_{ue}$ to approximately 70%.

The next section summarizes the results, provides further discussion and concludes.

V. Discussion and Concluding Remarks

In this paper we have provided a first attempt to investigate the effects of social networks on a specific aspect of occupational mobility, that is transitions out of unemployment. In particular, in the theoretical framework originally proposed by Calvó-Armengol and Jackson (2004), we have explored various aspects of network topology in a context where firms may adopt recruitment strategies that favor the employed over the unemployed in the access to information on vacancies.

Our study confirms that social networks can play an important role in facilitating workers to leave unemployment. However, it also provides a number of qualifications to this general, well-known result. Let us summarize our main findings:

1. for a given average degree of the network, the average probability of leaving unemployment is increasing in the level of symmetry of the network (although some workers in asymmetric networks may find themselves in more advantageous positions);

In our case, with $n = 2000$, $q^C(n) = 0.038$. Since $z = q(n-1)$, the threshold level of z is approximately equal to 7.6.

2. for a given dimension of the network, an increase in z and therefore of the density increases the probability of transition out of unemployment;

3. the adoption of hiring stategies which favor employed workers in accessing information on jobs reduces on average the probability of leaving unemployment;

4. when the probability for unemployed workers to directly receive information on jobs is zero, than the system can be absorbed in the zero-employment state. In this case:

   (a) an increase in the size of the network can hinder absorption for realistically long periods of time;

   (b) for a given size of the network, an increase in asymmetry reduces the capacity of the system to avoid absorption and, given the certainty of absorption, it increases the speed at which it takes place;

5. in scale-free networks the probability of leaving unemployment is incresing in the exponent of the power-law degree distribution, but its value is much lower than what obtainable in comparable random networks.

In particular, the scale-free property emerges, as noted, when a "preferential attachment" mechanism of link generation is at work. This requires that links are preferentially formed with agents having a higher number of existing links. From a social perspective, this may occur if individuals actually choose to preferentially link to "well-connected" agents, or simlpy because "well-connected" agents are easier to reach because they have many links. In any case, as long as this aspect is relevant in actual societies and as long as job contact networks are important, this characteristic of social interactions provides a *negative* contribution to occupational mobility, by reducing in our case the probability of leaving unemployment with respect to the "pure" form of random networks.

In general, such results confirm 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 exit probabilities from unemployment). 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.

Finally, our results may also provide some insights on related issues, such as long-term unemployment and "duration dependence". In particular, as analyzed at the end of Section IV.B., networks' topology and firms' recruitment strategies can play a crucial role in this respect. Namely, the possibility to become a long-term unemployed is higher, the more asymmetric is the structure of network to which the worker belongs and the more likely firms adopt a referral recruitment strategy (or the more the probability of receiving information about jobs decreases according to workers' unemployment spell).

As this paper represents a first step toward the analysis of networks' topology, firms' recruitment strategies and labor market mobility, it is relevant to briefly discuss some potential ways of extending this paper, which represent the directions of our current research. First, although, as explained above, the assumption that firms mainly adopt a referral recruitment strategy can be consistent with actual firms' behaviors, it could be interesting to analyze also the opposite case, in which unemployed agents receive information on vacancies more often than the employed ones (because, for instance, the former put more effort in finding these openings), and compare results with those of this paper.

More generally, there are other aspects of firms' hiring strategy that our model does not capture. For instance, firms often make job offers to workers already employed in other firms. Clearly, introducing this aspect into the analysis, on the one hand, would make the framework more complicated, since issues concerning employment contracts termination and renegotiation should be taken into consideration but, on the other end, would produce more general results.

Secondly, while in this paper the analysis of the role of networks' topology has only focused on symmetric vs. asymmetric networks, the effects of other well known networks' topology characteristics, particularly relevant in social networks, (e.g., the "small world" property, or the presence of "structural holes") are worth considering.

Third, it would be interesting to explore in more details the implications of workers and/or jobs heterogeneity, since this may contribute to analyze the role of social networks in explaining phenomena such as wage mobility and mobility out of low-pay jobs that, as discussed above, have given rise to a substantial literature. It is important to stress, however, that, in order to obtain more exhaustive results about those issues, major changes (that are largely outside the scope of this paper) are needed. For example, aspects related to workers/jobs matching or to internal labor markets procedures must be necessarily included into the analyses. By contrast, as emphasized in footnote 34, simply introducing job heterogeneity in this framework does not produce significant modifications to our results.

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