The impact of network cycles on employment and inequality*

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Abstract

How do short network cycles, the building component of close-knit network neighborhoods, affect diffusion? We show that short network cycles induce stochastic affiliation in diffusion processes channeled by networks. We then explore the micro and macroeconomic consequences of this affiliation in labor markets. Short network cycles generate diffusion inefficiencies in the transmission of job information that in turn affect employment, wages, and inequality within and across networked societies. In particular, they organize employment probabilities in the sense of the first-order stochastic dominance: people in close-knit neighborhoods exhibit worse labor-market outcomes. Moreover, short network cycles reinforce spatial and temporal correlations in employment status, shaping labor-market transition rates and amplifying aggregate employment fluctuations.

Keywords: (stochastic) affiliation, clustering, diffusion, inequality, information transmission, labor markets, network cycles, networks, unemployment, wages.
JEL: A14, D85, J60, J30.

1 Introduction

The key role of social networks in shaping socio-economic phenomena is well documented.[1] One particularly active research area investigates theoretically and empirically how the architecture of interaction patterns shape the diffusion of behaviors, beliefs, information, product adoption, idiosyncratic shocks, and other phenomena in a networked system (see e.g. Ballester et al. (2006), Centola (2010), Galeotti et al. (2010), Acemoglu et al. (2012), Banerjee et al. (2013), Campbell (2013), Elliott et al. (2014), Banerjee et al. (2019), Galeotti et al. (2020), Carvalho et al. (2021)). Although this literature has established the key role of network connectivity, network centrality, and their distributions in diffusion processes, finer details of the network architecture have received little attention.

One of the most prevalent features of real-world social, economic, and financial networks is high transitivity of relationships: friends of friends are typically friends, coauthors of coauthors are coauthors, competitors share clients and providers in supply chain networks, banks trading on the over-the-counter derivative markets

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[1]See Goyal (2007), Vega-Redondo (2007), Jackson (2010), and Jackson et al. (2017).

frequently trade with the same partners etc. (Goyal et al., 2006; Iori et al., 2008; Jackson and Rogers, 2007; Jackson, 2010; Jackson et al., 2012; Acemoglu et al., 2012). In network terminology, empirically observed networks contain a large number of triangles, squares, and other short network cycles. Although these cycles play a central role in fostering cooperation (Granovetter, 2005; Coleman, 1988), risk sharing (Bloch et al., 2008), trust building (Karlan et al., 2009), favor exchange (Jackson et al., 2012), or public good provision (Bramoullé and Kranton, 2007; Ruiz-Palazuelos, 2021), their role in diffusion is poorly understood.[2]

The first objective of this paper therefore is to characterize formally whether and why short network cycles matter in diffusion processes on networks.[3] Although a few studies suggest that local clustering may affect diffusion (Centola, 2010; Campbell, 2013), they do not provide a general formalization.[4] The main reason stems from the difficulty of disentangling the effect of cycles and clustering from that of other network features, which is a stumbling block for any causal claims regarding the effect of short cycles and for a microfoundation of their role in network processes. Here, we provide a general characterization.

As a second goal, since social contacts and the architecture of relationships are widely recognized as a key source of employment information (Ionamides and Datcher, 2005; Beaman, 2016),[5] we explore the role of short network cycles (and thus social cohesion and close-knittedness) in the flow of information about jobs. We particularly address the question of how short cycles affect employment and wages of individuals, groups, and societies in the short and the long run.

To this aim, we build on models developed by Calvó-Armengol (2004) and Calvó-Armengol and Jackson (2004, 2007).[6] People are distributed on a network and employed individuals who hear about vacancies pass the information on to their unemployed network neighbors. Calvó-Armengol (2004) shows that higher degree and lower second-order degree increase the individual probability of employment and detects a non-monotonic effect of shifts of the degree distribution on employment in cycle-free regular networks. Calvó-Armengol and Jackson (2004) show that such a network model generates unemployment correlations across time and path-connected individuals, exhibits duration dependence and persistence, and allows to understand the dynamics of inequalities and drop-out decisions.[7] Last, Calvó-Armengol and Jackson (2007) analyze wages in a similar model. Our contribution to this literature is to model explicitly the role of local network density of links, measured by the presence of short cycles, isolating their effect from that of the first- and second-order degree.

As for the first objective, we show that short network cycles generate *stochastic affiliation* in diffusion processes.[8] More precisely, if two friends of individual i are friends or have another common friend, the information flows from these two friends to i are stochastically affiliated even in a one-period model, whereas these flows are independent if they are connected neither directly nor indirectly in any other way.[9] This implies that the

[2]In a recent survey, Jackson et al. (2017) conclude their discussion of local clustering patterns as follows: "The full understanding of the importance of local network structure is still in its infancy" (p. 76).

[3]Our focus on cycles naturally bridges the concepts of the clustering coefficient, traditionally considered the network measure of social cohesion, and network support, recently proposed by Jackson et al. (2012), as they both rely on the extent of triangles or three-cycles.

[4]Centola (2010) compares experimentally diffusion in two networks that differ in the presence of short cycles but also in other important aspects of the architecture while Campbell (2013) characterizes their role in specific random graphs with triads, preventing the characterization of a general pure effect of clustering.

[5]Granovetter (2018) concludes that people rely primarily on contacts when finding a job, independently of the occupation, skill, location, or socio-economic background (see also Myers and Schultz, 1951; Corcoran, Datcher and Duncan, 1980; Marsden and Campbell, 1990; Montgomery, 1991; Marmaros and Sacerdote, 2002; Munshi, 2003; Franzen and Hangarther, 2006; Pellizari, 2010; and Bentolila et al., 2010, among many others). Cappellari and Tatsiramos (2015) estimate that an additional employed friend increases the probability of finding a job by 3.7%. Some studies directly explore the variation of employment status of some network members on other network integrants (see e.g. Topa, 2001; Bayer et al., 2008; Beaman, 2011; Beaman and Magruder, 2012). Topa (2001) and Conley and Topa (2002) document geographic, ethnic, and race correlations in employment, suggesting a network-based flow of information about jobs.

[6]Calvó-Armengol (2004) and Calvó-Armengol and Jackson (2004, 2007) have in turn been inspired by the early contributions of Boorman (1975) and Diamond (1981). See also Montgomery (1991). Galeotti and Merlino (2014) model endogenous formation of networks.

[7]Unemployed agents obtain more (less) information when their contacts are employed (unemployed), giving rise to robust forms of correlations in wages and employment status of path connected agents.

[8]Stochastic affiliation is a strong form of correlation; see Section 2 for a formal definition.

[9]Some results in Calvó-Armengol (2004) and Calvó-Armengol and Jackson (2004, 2007) rely on the assumption that the inflow of information from two neighbors of i to i is independent. Our contribution is to show that this assumption fails already in the static model if the two neighbors are connected or if they share a friend $j \neq i$. We further explore the consequences.

diffusion does not only depend on the number of first- and second-order connections but also on the geometry created by these links. Thus, two neighborhoods or two networks where the players have the same number of first- and second-order neighbors (i.e. the same *joint* distribution of degree and second-order degree) but differing clustering patterns induce different diffusion dynamics. This result provides a microfoundation for *why* short networks cycles, namely triangles and squares, shape diffusion on networks.

The second set of results concerns the micro and macroeconomic implications of short network cycles in our labor-market application. We prove that, *ceteris paribus*, network cycles organize the employment probabilities in the sense of the first-order stochastic dominance. At the individual level, people in densely-knit neighborhoods have lower employment prospects than individuals with the same connectivity but lower local clustering; at the population level, close-knit networks exhibit higher unemployment rates than more loosely-knit societies with the same joint distributions of first- and second-order degrees. The intuition stems from information affiliation: stochastic affiliation increases the probability of mismatch between vacancies and job candidates, leading to diffusion inefficiencies. That is, network cycles are a source of labor-market frictions when employers rely on referrals. This search frictions in turn have important short- and long-run consequences for employment, wages, and inequality within and across networks. We further illustrate that economically relevant and statistically strong effects are exclusively limited to short cycles in our model. Importantly, none of these results relies on spatial segregation of low- and high-clustering nodes. Although spatial correlations in the employment of path-connected people, characterized in Calvó-Armengol and Jackson (2004, 2007), can weaken the negative impact of short cycles in integrated societies, we show that their detrimental role might persists in the steady state. Hence, policies aiming at the integration of dense and loosely-knit agents would only have a limited effect.

These findings extend for wages. Leaving constant other network features, three- and four- cycles reduce the expected wage of agents involved in these cycles. However, this negative effect is driven by the unemployment probability. Conditional on having a job, the expected wages of individuals involved is short cycles are actually higher. The affiliation of information flows increases the probability of multiple job offers in dense neighborhoods but such multiplicity is no longer redundant if we analyze wages: multiple job offers allow agents to select among offers with different wages if unemployed or accept better-paid jobs if employed. Hence, the effect of short network cycles may be beneficial in this case. This indicates that close-knittedness may be both beneficial and detrimental depending on the variable under consideration and the context.[10]

Short network cycles further affect other key features of the employment dynamics. Most importantly, they increase serial correlations of employment. This has two implications. Firstly, since the variability of the steady-state employment is virtually unaffected by network cycles but serial correlation increases considerably, the fluctuations of employment within denser neighborhoods or in closely-knit societies exhibit larger amplitude. This effect is generated by a combination of factors. First, network diffusion generates employment time correlations, as well as correlations between connected nodes. Employed friends maintain their contacts employed due to the diffusion channel, while unemployed agents make their contacts more vulnerable (Calvó-Armengol and Jackson, 2004). However, the associated affiliation in job-market information flows caused by short network cycles amplifies these effects and extends them from individuals to network neighborhoods: it slows down the transition between different employment states, maintaining employment within cycled groups of employed individuals as well as perpetuating unemployment in unemployed cycled neighborhoods. However, if several members of an employed neighborhood lose their job, they make their circles more vulnerable and drag the whole neighborhood towards unemployment; conversely, if a positive shock hits an unemployed neighborhood the network externality spills over more easily in cycled neighborhoods. That is, the same mechanism generates longer, more persistent employment fluctuations and more pronounced booms and troughs in closely-knit neighborhoods and networks. These mechanisms establish network cycles as an important amplifier of the diffusion of local idiosyncratic shocks throughout the whole economy. Secondly, the combination of higher time persistence of employment, more sluggish labor-market transitions, and lower average unemployment rates causes that, even though the probability of maintaining a job is unaffected as close-knittedness rises, the likelihood of remaining unemployed

[10]There is a long-standing debate in economic sociology regarding whether dense neighborhoods are beneficial or detrimental. Relationships in close-knit networks are typically stronger, enabling trust and cooperation (Granovetter, 1973; Burt, 1992; Coleman, 1988; Bloch et al., 2008; Lippert and Spagnolo, 2011; Jackson et al., 2012). However, close-knit networks inhibit the flow of novel information and individuals in tight neighborhoods may receive redundant information (Granovetter, 1973, 2005; Blau, 1986; Burt, 2001).

steadily increases.

The findings of this paper have several implications. As for labor economics, we deepen our understanding of the micro and macroeconomic consequences of job referrals and social networks in labor markets and the economy as a whole. First, we uncover one possible mechanism behind the strength of weak ties (Granovetter, 1973): since weak connections are less likely to be embedded in short cycles,[11] the strength of weak ties lies not only on the informational content but also on the lack of correlation in the information they provide.[12] Granovetter's (1973) argues that the benefits of weak ties derive from their ability to transmit information to larger audiences and to provide novel information. We show that individuals immersed in loose-knit communities may enjoy information advantages even when they are in contact with the same number of people and when the kind of information they receive is of the same nature as in highly cohesive neighborhoods. Thus, weak ties might be relevant not solely because of their bridging role, but due to their capacity to provide independent information.

Second, taking into account that the empirical evidence consistently corroborates that real-life labor markets heavily rely on employee referrals (Granovetter, 2018), we show that social cohesion is an important determinant of individual and aggregate labor-market performance. Short cycles increase inequality, they are a relevant source of labor-market frictions, and shape labor fluctuations over time and space in our model. Since the detected impact is in line with the fact that search frictions lead to sluggish aggregate employment dynamics and labor market churning (e.g. Pissarides, 1985; Bentolilla and Bertola, 1999; Mortensen and Pissarides, 1999; Burgess et al., 2001), we identify a previously ignored source of labour-market sluggishness: network close-knittedness.

Furthermore, we contribute to the emerging literature showing that network linkages propagate idiosyncratic shocks and amplify aggregate risk (Calvó-Armengol and Jackson, 2004; Acemoglu et al., 2012; Carvalho et al., 2021).[13] In contrast to this literature that focuses on connectivities and centralities, we are the first to uncover that another network feature, short network cycles and network close-knittedness, amplifies the diffusion of idiosyncratic shocks. Since short network cycles are ubiquitous in real-life social, financial, and economic networks, the mechanism characterized in our paper deserves deeper empirical investigation.

Since employment fluctuations and employment transitions are strongly correlated with business cycles and aggregate macroeconomic volatility cannot be explained without consideration of labor-market fluctuations (Kydland, 1995; Mortensen and Pissardies, 1999), our work contributes to further understanding of key stylized facts of macroeconomic dynamics more generally.

As for network theory, we show that network close-knittedness goes beyond triangles and the clustering coefficient as both the number and the organization of cycles of different lengths determine to what extent one benefits from the social capital embedded in social structures.[14] Moreover, since the transmission of information in this paper resembles the network diffusion of many other phenomena, our results have implications beyond the labor market literature. We show formally that clustering matters keeping constant the first- and second-order degree distributions–the two features typically considered in the diffusion literature–by inducing correlations in diffusion. Network cycles and the induced affiliation will likely play a relevant role in the dynamics of other network phenomena and abstracting from them may thus provide an incomplete picture of the mechanisms behind network diffusion.

The paper is organized as follows. Section 2 presents the model. Section 3 analyzes the static version of the model while the dynamic analysis can be found in Section 4. Section 5 introduces wages. Finally, Section 6 concludes.

[11] Granovetter (1973) argues that the strength of a tie between two individuals is intimately related to the "*overlap in their friendship circles*." According to Marsden and Campbell (1984), the overlap of social circles is a particularly good measure of the strength of a tie. Louch (2000) indeed observes that when two contacts of an individual speak to each other frequently or know each other for a long time, i.e. they can be thought of as *strong ties* according to Granovetter (1973) definition, the probability that they are mutually linked increases by 178% and 278%, respectively.

[12] Conversely, this mechanism provides a rationale behind the *structural holes* argument of Burt (2009): one of the advantages of bridging holes is the diversification of information flows from otherwise disconnected parts of the network.

[13] This literature is in turn closely linked to the key role of the distribution of firm sizes and its role in aggregate systematic risk; see e.g. Gabaix (2001) or Carvalho and Gabaix (2013).

[14] Triadic closure, clustering and recently support (i.e. cycles of length three) have received a great deal of attention in the literature across fields (Jackson et al., 2017). However, both concepts ignore the role of longer cycles in shaping socio-economic phenomena.

2 Model

To study the role of short cycles in labor markets, we build on the model of Calvó-Armengol (2004) and Calvó-Armengol and Jackson (2004, 2007). First, we present and analyze the static, one-period version of the model where we introduce and consider the impact of short cycles. See Section 4 for the analysis of the dynamics and long-run consequences.

2.1 The network

People are distributed on an undirected fixed network that is used to disseminate information about job openings. The network $g = (N, E)$ is characterized by a set of nodes $N = \{1, .., n\}$ and a set of edges or links E between them. We write $g_{ij} = 1$ if individuals i and j are directly linked in g and $g_{ij} = 0$ otherwise. Let $A = (g_{ij})_{i,j \in N}$ be the $n \times n$ symmetric adjacency matrix of the network, with $g_{ii} = 0$. To simplify notation, we sometimes denote a link between i and j by ij. G is the set of all feasible networks.

The set of i's direct contacts in g is defined as $N_i(g) = \{j \in N : g_{ij} = 1\}$; let $n_i(g) = |N_i(g)|$ be the (first-order) *degree* of individual i. Analogously, denote the set of i's second-order or indirect neighbors (neighbors of i's neighbors) as $N_i^2(g) = \{k \in N : g_{ij}g_{jk} = 1 \text{ for some } j \in N,\ i \neq k\}$ and $n_i^2(g) = \left|N_i^2(g)\right|$. Observe from the previous definitions that $N_i(g)$ and $N_i^2(g)$ may have a non-empty intersection; that is, some contacts of i may simultaneously be i's indirect contacts. For a pair of nodes i and j, define $N_{ij}(g) = \{k \in N : k \in N_i(g) \cap N_j(g)\}$ as the set of common contacts of both i and j, with $n_{ij}(g) = |N_{ij}(g)|$. The set of contacts of i that are not shared with j is $N_{i-j}(g) = N_i(g) \backslash N_{ij}(g)$, with $n_{i-j}(g) = |N_{i-j}(g)|$. Distance between nodes i and j in network g is the length of the shortest path between them, denoted as $d_{ij}(g)$. Naturally, $d_{ij}(g) = 1$ if $ij \in E$, $d_{ij}(g) = 2$ if there is $k \in N$ such that $ik, kj \in E$ but $ij \notin E$, and so on.

This paper focuses on the effect of cycles on the probability of receiving information about job vacancies through network contacts.

Definition 1 (Cycle) *A $K-$cycle $Z_K(g)$ is a sequence of distinct nodes $i_1, i_2, \ldots, i_{K-1}, i_K$, such that $K>2$, $g_{i_k i_{k+1}} = 1$ for each $k \in (1, \ldots, K-1)$, and $g_{i_1 i_K} = 1$.*

In words, a $K-$cycle in a network g is a sequence of K linked nodes starting and ending in the same node. A cycle may be equivalently defined as the set of edges. For example, a *three-cycle* or a *triangle* is a path passing through three edges: ij, jk, ki. Equivalently, we may refer to a triangle as the sequence $\{i, j, k\}$.[15] Analogously, a *four-cycle* or a *square* is a path through four edges ij, jk, kl, li or a sequence $\{i, j, k, l\}$. We denote $S_S(g)$ the set of all three- and four-cycles and $S_L(g)$ the set of all K-cycles for $K > 4$ in g; $S(g) = S_S(g) \cup S_L(g)$ thus corresponds to the set of all K-cycles in g. Last, $S_S^i(g)$, $S_L^i(g)$, and $S^i(g)$ are the sets of the corresponding cycles, in which i is involved.

The clustering coefficient of individual i is the fraction of i's direct contacts who are neighbors themselves. In the above terminology, the coefficient measures the number of triangles in i's neighborhood divided by the number of all possible triangles among all i's contacts. Formally,[16]

$$C_i(g) = \frac{\sum_{j \neq i; k \neq j; k \neq i} g_{ij} g_{ik} g_{jk}}{\sum_{j \neq i; k \neq j; k \neq i} g_{ik} g_{ij}}.$$

Clustering coefficient reflects the density or close-knittedness within a node's neighborhood; when the coefficient is high, the neighborhood is densely interconnected because most of i's contacts are linked. The average clustering coefficient of network g is simply $C(g) = \frac{1}{n} \sum_{i=1}^{n} C_i(g)$ and measures the overall level of local density within the network.

[15] In graph theory, the term n-cycle is sometimes used as a description of a circle network of n nodes. In Figure 2, g_b and g_c would be examples of three- and four-cycles, respectively, under that terminology. In this paper, cycles may also represent a part of more complex architectures, rather than the whole network.

[16] The coefficient is not defined for $n_i(g) < 2$. In such a case, some authors consider clustering to be equal to zero (e.g. Vega-Redondo, 2007), while others leave it undefined.

Note that the clustering coefficient counts the triangles but abstracts from longer cycles. Lind et al. (2005) propose a coefficient that keeps track of the fraction of four-cycles as follows:

$$C_i^4(g) = \frac{\sum g_{ij} g_{jm} g_{mk} g_{ik}}{\sum g_{ij} g_{ik} g_{jm}},$$

where i, j, k and m are nodes of the network. For node i, the number of squares is given by the number of common neighbors among i's contacts (i.e. that is sequences $\{i, j, k, m\}$ such that $g_{ij} g_{jm} g_{mk} g_{ik} = 1$). Again, $C^4(g) = \frac{1}{n} \sum_{i=1}^{n} C_i^4(g)$.

A distinct but related concept is *support*, proposed by Jackson et al. (2012): A link jk is supported if $\exists\ i \in N : i \in N_{jk}(g)$; the link is unsupported if $N_{jk}(g) = \oslash$. A link jk is supported by i if $i \in N_{jk}(g)$; the link is unsupported by i if $i \notin N_{jk}(g)$. The more links are supported by i, the higher is i's embeddedness. Hence, network support is another measure of close-knittedness, but it differs from the clustering coefficient (see Jackson et al., 2012).

Certain network architectures play a particular role in our analysis. First, a *tree* is a network with no cycles of any length; that is, $S(g) = \emptyset$ and $C_i(g) = C_i^4(g) = 0$ for each $i \in N$. A *cycle network* is the only graph of n nodes and n links containing one n-cycle. In Figure 2, networks $g_b - g_d$ depict a triangle, square, and pentagon, respectively; network g_g represents a hexagon. A *regular network* is a network in which $|n_i(g)|$ is equal for all $i \in N$; a regular network is symmetric in the number of direct and indirect contacts of each individual but not necessarily in other network features.[17] A special case of regular network is a *vertex-transitive network*, where no node can be distinguished from any other based on its neighborhood since they all have a structurally identical neighborhood, second-order neighborhood, and so on. There are several formal definitions of these networks (see e.g. Weisstein, 2016), but an important property of these graphs is that each node occupies a structurally equivalent position in the network.[18] Hence, every vertex-transitive graph is regular, and each node has the same degree, second-order degree, and the clustering coefficient. However, the converse is not true; not all regular networks are vertex-transitive, and not all networks in which all nodes have the same clustering coefficient are vertex-transitive. For instance, every node in a network may have the same number of links but they can still differ in other characteristics, such as the clustering coefficient or global centrality. Examples of vertex-transitive networks include empty and complete networks, circles, cubes, many lattice networks, and Caley graphs.

Figure 1 displays examples of vertex-transitive networks; all nodes in the five networks occupy an identical position. In case of the first three networks, all vertices have four connections and twelve second-order neighbors, but the number of triangles involving a given node increases from zero in case of the leftmost network to two in case of the middle network. The fourth and fifth networks are also vertex-transitive with $n_i(g) = 4$ for all i, but each node is involved in several three- and four-cycles. To see the difference between clustering and support, note that the clustering coefficient of each node increases from zero to one as we move from the left to the right. Nevertheless, the support is already maximal in the third and fourth networks where every single edge is supported, while the clustering is lower than one in these networks because each node has contacts who are not connected.

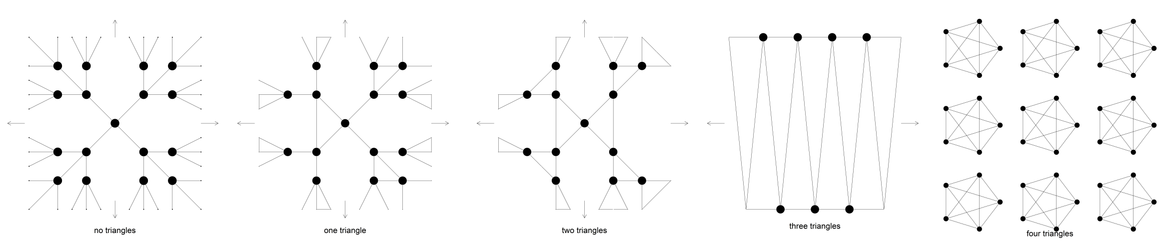


Figure 1: Vertex-transitive networks with degree four but increasing clustering from the left to the right.

[17]Some authors call regular networks symmetric (e.g. Calvó-Armengol, 2004). However, the term symmetric network exists in graph theory and it is more restrictive than regularity.

[18]In fact, vertex-transitive graphs are also called node-symmetric (Chiang and Chen, 1995), a name that reflects better the main feature of these networks.

2.2 Information flows

In our model, initially each worker is employed.[19] Then, every agent looses her job with probability $b \in (0,1)$. Afterwards, each node may hear about a vacancy with probability $a \in (0,1)$, regardless of her employment status. We assume that all jobs are identical.[20] Loosing the job and hearing about a vacancy are independently distributed and independent across individuals.

At this point, each worker can be in one out of four possible situations or status:

Status 1. Each person is employed and has heard about a new job with probability $\alpha = a(1-b)$.

Status 2. She is unemployed and has not heard about any offer with probability $\beta = b(1-a)$.

Status 3. She is unemployed but has heard about an offer with probability $\delta = ab$.

Status 4. She is employed with no offer to pass to contacts with probability $\gamma = (1-a)(1-b)$.

We label these different status as 1 to 4 respectively, and define the random variables $X_1^i(g)$, $X_2^i(g)$, $X_3^i(g)$, $X_4^i(g)$ as the number of i's contacts who are in each status. Particular realizations of these variables are denoted as $x_1^i(g)$, $x_2^i(g)$, $x_3^i(g)$ and $x_4^i(g)$, with $x_1^i(g) + x_2^i(g) + x_3^i(g) + x_4^i(g) = n_i(g)$. Similarly, the variables $X_m^{jk}(g)$ and $X_m^{j-k}(g)$ measure respectively the number of agents in $N_{jk}(g)$ and $N_{j-k}(g)$ who are in status $m \in \{1,2,3,4\}$; $x_m^{jk}(g)$ and $x_m^{j-k}(g)$ denote again their realizations. Define $Y_i^s(g)$ a random variable, such that $y_i^s(g) = 1$ if i is in state $s = \{1,2,3,4\}$; $y_k^s(g) = 0$ otherwise. Unemployed individuals who hear about a job (those in status 3) immediately accept the offer. Workers who are employed and have heard about a vacancy (in status 1) pass the offer to one of their unemployed neighbors (in status 2) uniformly at random. As a result, status 1 and 2 play a key role in our analysis.

The model assumes that all agents at any point in time have perfect information about the labor status of their direct contacts.[21] Observe that only individuals in state 1 can pass an offer to one of their direct contacts in status 2 (i.e. those who lost their job but have not heard about any offer) who immediately accepts the offer. Therefore, an individual's contacts who are in status 1 will be called *potential providers* and her second-order contacts (the contacts of her contacts) who happen to be in status 2 will be named *competitors*. By construction, it is possible that an individual in status 2 simultaneously receives several offers from her different contacts. In such a case, she accepts one of them at random and the others remain unfilled. These redundant offers may generate search frictions in the labor market.

Assume that node i is unemployed. We represent the information flow from $j \in N_i(g)$ to i through a random variable $I_j^i(g)$ taking value 1 when i receives information from j and 0 otherwise. $I_j^i(g)$ is a function of the state of j and j's network position. First, it depends on whether j is in state 1 (a provider), an event with probability α. If so, she passes an offer to one of her unemployed neighbors with equal probability. Thus, i receives an offer from j with probability $\frac{1}{X_2^{j\setminus i}(g)+1}$, where $X_2^{j\setminus i}(g)$ denotes the number of j's contacts other than i who are in state 2. Then,

$$I_j^i(g) = \begin{cases} 1 & \text{with probability} \quad \left(\frac{\alpha}{X_2^{j\setminus i}(g)+1}\right) \\ 0 & \text{with probability} \quad \left(1 - \frac{\alpha}{X_2^{j\setminus i}(g)+1}\right) \end{cases} \tag{1}$$

[19] This assumption is inconsequential. All the results hold if all people start with the same probability of being employed.

[20] In Section 5, we relax this assumption and allow for wages to differ across jobs.

[21] In Calvó-Armengol (2004), employed individuals with a job offer pass the vacancy to one of their contacts who lost their job. Unemployed individuals may have later received an offer but this is not observed by other agents. Though this is not explicitly stated, it can be seen in the proof of his Proposition 1, where the decision to pass information depends on b instead of β. We change slightly this assumption and assume that the decision depends on β. If we maintained the assumption of Calvó-Armengol (2004), our results would in fact be reinforced.

2.3 The probability of receiving an offer through the network and the unemployment rate

Denote $P^i(g)$ the probability that node i receives a job offer from at least one neighbor in network g when she is is status 2 (i.e. unemployed). With this notation, we can write the employment probability of node i as $E_i(g) = (1-b)+ba+b(1-a)P^i(g)$, which can be interpreted as the individual employment prospect in network g. The employment rate of the network is $E(g) = \frac{1}{n}\sum_{i \in N} E_i(g)$; the unemployment rate is thus $U(g) = 1 - E(g)$.

Since a and b are exogenously given and the same for all individuals, the only difference in (un)employment rates across nodes and networks arises from $P^i(g)$ so we analyze how this probability depends on network cycles.

$P^i(g)$ depends on the employment status of i's direct and indirect (second-order) contacts. The status of i's direct neighbors determines the number of i's potential providers, $X_1^i(g)$, while the status of the contacts of the potential providers determines the number of competitors ($X_2^{j\setminus i}(g)$) and thus the probability with which any potential provider j passes an offer to i (see (1)). As we show below, both three- and four-cycles affect the probability with which i receives at least one offer through her contacts.

Assume that $y_i^2(g) = 1$ and $y_j^1(g) = 1$, $j \in N_i(g)$. Since each node $k \in N_j(g) \setminus i$ may be unemployed (that is, in status 2) with probability β, the probability that i does not receive any offer from j is[22]

$$q_j(n_j(g)) = \sum_{h=0}^{n_j(g)-1} \binom{n_j(g)-1}{h} \beta^h (1-\beta)^{n_j(g)-1-h} \frac{h}{h+1}. \tag{2}$$

In a similar vein, the probability that i does not receive any offer from j, conditional on knowing the status of $k \in N_j(g) \setminus i$, is

$$q_j(n_j(g) \mid y_k^2(g) = x) = \sum_{h=0}^{n_j(g)-2} \binom{n_j(g)-2}{h} \beta^h (1-\beta)^{n_j(g)-2-h} \ \frac{h+x}{h+x+1}. \tag{3}$$

Expressions (2) and (3) directly lead to the following claim:

Claim 1 (Individual probability) *Assume that $y_i^2(g) = 1$ (unemployed) and let $y_j^1(g) = 1$ for a node $j \in N_i(g)$ (potential provider of i). Then, $q_j(n_j(g))$ is increasing in $n_j(g)$ and independent of network cycles, and $q_j(n_j(g) \mid y_k^2(g) = 1) > q_j(n_j(g) \mid y_k^2(g) = 0) = q_j(n_j(g) - 1)$.*

Claim 1 illustrates first that the probability with which i does not receive any offer from a particular provider j (or, conversely, the probability that she does, i.e. $1 - q_j(n_j(g))$) only depends on the number of (potential) competitors in j's neighborhood and this probability is not affected by the presence of cycles within i's or j's neighborhoods. Hence, network cycles do not affect the *individual* decision to pass information about jobs. However, Example 1 below illustrates that cycles do affect the probability of getting an offer from *at least one* contact, altering one's employment prospects. Second, Claim 1 shows how knowing the status of a neighbor of a neighbor affects this probability and that knowing that one neighbor does not need a job is equivalent to having one competitor less. These latter results play a key role if a neighbor of a neighbor can simultaneously be a direct neighbor.

Example 1 (Effect of short cycles) *Consider networks g_b, g_c, g_e, and g_f in Figure 2 and assume that $y_i^2(g) = 1$ in each network. The probability that node 1 receives a job offer from at least one neighbor in network g, $P^1(g)$, satisfies the following:*[23]

$$P^1(g_e) > P^1(g_c) > P^1(g_b). \tag{4}$$

Note that node 1's degree is the same in the three networks, while her second-order degree is the same in networks g_b and g_e but lower in g_c. However, individual 1 is more likely to be employed in the tree network g_e, followed

[22] Since $q_j(n_j(g))$ is identical for any $k \in N_j(g)$ including i, we do not index this probability by i throughout the paper to simplify the notation.

[23] Detailed calculations may be found in Appendix A.2.

by the square network g_c, as compared to the triangle network g_b even though the number of competitors is the same in the first two networks and even though node 1 has one competitor less in g_c than in g_e. Similarly, $P^1(g_f)$ may be larger or lower than $P^1(g_b)$, depending on the parameters. If, say, $\alpha = 0.9$ and $\beta = 0.01$, $P^1(g_f) = 0.9886 > P^1(g_b) = 0.9810$, despite the fact that the number of 1's potential competitors is greater in g_f than in g_b. □

Claim 1 and Example 1 jointly deliver several messages. First, the geometry of network neighborhoods affects the probability of receiving a job offer, beyond the number of first- and second-order neighbors. We particularly point to the role of short cycles. Since Claim 1 shows that their presence does not affect the probability of receiving an offer from one particular individual, their role in Example 1 stems from the lack of independence of information flows coming from different contacts j and k if they belong to a cycle with i (operationalized by a multivariate random variable $(I^i_j(g),\, I^i_k(g))$). The example particularly suggests that network cycles affect individuals negatively and their length may matter. Last but not least, the impact of cycles is economically relevant: their effect in Example 1 rivals with that of two-link-away connections. We formalize these observations in the next section.

3 Results

3.1 Cycles and affiliation of information flows

In cycle-free networks (e.g. trees), $N_i(g) \cap N^2_i(g) = \emptyset$ and $N_{jk}(g) = \{i\}$ if $j, k \in N_i(g)$, implying that information flows from neighbors j and k to i are independent. The probability that neighbor j passes an offer to i depends on j's status and on $X^{j\setminus i}_2$, but it depends neither on the status of any other $k \in N_i(g)$ nor on the status of any second-order contact $s \in N_k(g) \setminus i$, $k \neq j$.

In contrast, if $j, k \in N_i(g)$ and $jk \in E$ (i.e. j and k form a three-cycle with i), the information flow from j to i depends on both j's and k's status and, similarly, that from k depends on k's and j's status. More precisely, the probability that j transmits information about a job opening to i depends on whether j is employed and possesses such information and on whether k also needs a job. If k does, k will provide no information to i and this is independent of cycles. However, since j and k are friends, k now competes with i for information from j, decreasing i's probability of receiving information from j. Such *indirect* effect of the status of k on $P^i_j(g)$–and thus on $P^i(g)$–is a direct consequence of the cycle $\{i, j, k\}$. This indirect effect is missing when j and k do not belong to any short cycle with i.

Similar dependence appears when j and k belong to a four-cycle together with i. If a four-cycle $\{i, j, s, k\}$ is present, the lack of independence in information flows from j and k to i comes from the fact that the probabilities of receiving a job offer from each of them depend on a common variable, the status of individual s.

We formalize these statements using the concept of stochastic affiliation:[24,25]

Proposition 1 (Affiliation) *Assume $y^2_i(g) = 1$ and consider $j, k \in N_i(g)$.*
(a) $I^i_j(g)$ and $I^i_k(g)$ are strictly affiliated if either $S^i_S(g) = \{i, j, k\}$ or $S^i_S(g) = \{i, j, s, k\}$ for one $s \neq i, j, k$.
(b) Conditional on the status of j's and k's neighbors who form three or four-cycles with i, $I^i_j(g)$ and $I^i_k(g)$ are conditionally independent.

Strict affiliation in information flows from node i's potential providers implies that, conditional on receiving an offer from a provider j with high probability, the probability that i receives another offer from a provider k increases if the two providers are connected directly or through another node $s \neq i$.

[24] This concept was introduced to economics by Milgrom and Weber (1982). Two random variables are affiliated if, conditional on observing a low (high) value of one variable, the probability of observing a low (high) value of the other variable increases. Formally, two random variables X and Y are affiliated if for all $x < x'$ and for all $y < y'$:

$$f(x', y) * f(x.y') \leq f(x', y') * f(x, y)$$

where *f(x,y)* is the joint density function of variables X and Y. Since two independent random variables are affiliated according to the above expression, we say that two variables are *strictly* affiliated if the condition holds with strict inequality.

[25] All proofs are relegated to Appendix A.1.

We illustrate the intuition behind the proof using an example. Consider a triangle network g_b in Figure 2 composed of individuals i, j, and k and assume that node i is unemployed. Denote $f(I_j^i(g_b),I_k^i(g_b))$ the joint density function of $I_j^i(g_b)$ and $I_k^i(g_b)$. First, consider that $j \in N_i(g)$ is employed and hears about an open position; this happens with probability α. Only j will pass information to i, but not k, when k is employed but does not have information about other jobs, an event that has probability $1-\alpha-\beta$. Node j transmits a job offer to i with probability 1 in such a case. In contrast, i only receives a job offer from j with probability $\frac{1}{2}$ if k needs a job and thus competes with i for j's information, an event that has probability β. As a result and due to the network symmetry,

$$f(1,0) = f(0,1) = \alpha\beta\frac{1}{2} + \alpha(1-\alpha-\beta).$$

Second, i receives no offer from any of her neighbors if either none of them has any information to pass or one of them does but passes it along to a competitor, leading to

$$f(0,0) = (1-\alpha)^2 + 2\alpha\beta\frac{1}{2}$$

Last, a node does not lose the job and hears about a vacancy with probability α. Therefore, i might receive two offers from both j and k with probability $f(1,1) = \alpha^2$.

Note that

$$f(1,1) * f(0,0) = \alpha^2\Big((1-\alpha)^2 + \alpha\beta\Big) > \alpha^2\Big((1-\alpha-\beta) + \beta\frac{1}{2}\Big)^2 = f(0,1) * f(1,0)$$
$$(1-\alpha)^2 + \beta\alpha > (1-\alpha)^2 - \beta(1-\alpha-\frac{1}{4}\beta),$$

which implies that $I_j^i(g_b)$ and $I_k^i(g_b)$ are strictly affiliated.

To illustrate the case of a four-cycle, consider the four-node network g_c in Figure 2 and take the perspective of a node i with $N_i(g_c) = \{j,k\}$ and $N_i^2(g_c) = \{s\}$. In this example, it cannot happen that i receives an offer with probability 1 from j and with probability $\frac{1}{2}$ from k, or viceversa. If $y_s^2(g_c) = 0$ (i.e. s does not need a job), both potential providers j and k can only pass a job along to i with probability 1. Conversely, if $y_s^2(g_c) = 1$, both potential providers j and k will pass information to i with a lower probability $\frac{1}{2}$. Hence, the probabilities that each of the two neighbors of i pass information to her are not independent.

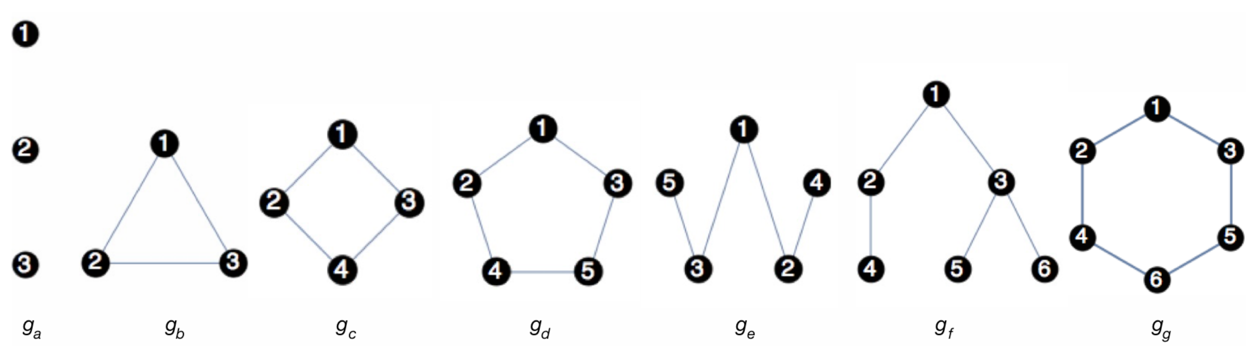


Figure 2: Networks with different local connectivity and clustering patterns: empty network with $n = 3$, triangle, square, pentagon, two trees, and a hexagon.

Part (b) of Proposition 1 shows that the affiliation in the information flows is the only reason for such dependence. Once we condition on the status in the corresponding neighborhoods, the information flows become independent.

3.2 Effects of cycles on employment

Proposition 1 shows that network cycles generate affiliation in information flows but provides no prediction concerning the direction of the effect. Calvó-Armengol (2004) shows that, within cycle-free networks, direct contacts are beneficial whereas second-order contacts are detrimental for the individual probability of employment. However, example 1 indicates that this does not necessarily hold in networks that contain short cycles. Let us denote $\left(n_i(g); \{n_j(g)\}_{\forall j \in N_i(g)}\right)$ as the *joint degree distribution* of i. The following proposition characterizes the effects of short cycles, keeping constant the joint degree distribution (i.e. the number of direct contacts and the number of contacts of her contacts for each i):[26]

Proposition 2 (Effect of cycles) *Let* $g = (N, E)$ *and* $g^x = (N^x, E^x)$*,* $x \in \{t, s\}$*, be three networks, such that* $N \subseteq N^x$*,* $\left(n_i(g); \{n_j(g)\}_{\forall j \in N_i(g)}\right) = \left(n_i(g^x); \{n_j(g^x)\}_{\forall j \in N_i(g^x)}\right)$ *for* $\forall i \in N$ *and* $x \in \{t, s\}$*,* $S_S(g^t) = S_S(g) \cup \{i, j, k\}$ *and* $S_S(g^s) = S_S(g) \cup \{i, j, z, k\}$ *for some* $i, j, k, z \in N$*. Then,*

(i) $P^h(g) > P^h(g^t)$ *for* $h \in \{i, j, k\}$ *and* $P^f(g) = P^f(g^t)$ *for all* $f \in N \setminus \{i, j, k\}$*.*

(ii) $P^h(g) > P^h(g^s)$ *for* $h \in \{i, j, k, z\}$ *and* $P^f(g) = P^f(g^s)$ *for all* $f \in N \setminus \{i, j, k, z\}$*.*

(iii) $P^h(g^s) > P^h(g^t)$ *for* $h \in \{i, j, k\}$ *and* $P^h(g^s) = P^h(g^t)$ *for* $f \in N \setminus \{i, j, k, z\}$*.*

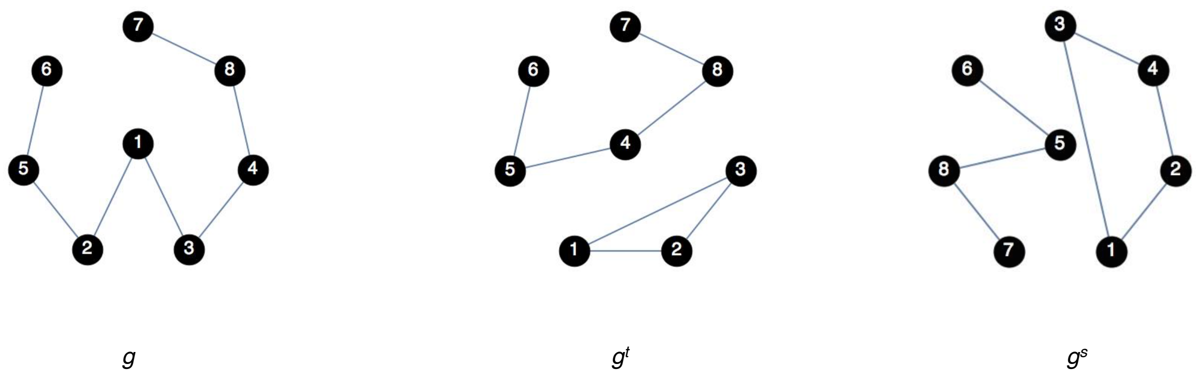


Figure 3: Example of g, g^t and g^s from Proposition 2.

Figure 3 provides an example of the networks in Proposition 2. Networks g, g^t and g^s have the same *joint* distribution of degree and second-order degree and the set of cycles is the same with one exception: g^t (g^s) has one additional triangle (square) compared to g.[27]

Part (i) indicates that if an individual has the same degree and her neighbors also have the same degrees in both networks but she is involved in one triangle more in g^t than in g (e.g. the case of nodes 1, 2, and 3 in Figure 3), she is less likely to get a job offer through her network contacts in g^t. In contrast, the remaining nodes (i.e. nodes $4-7$ in Figure 3) are unaffected by the difference between g and g^t. Part (ii) shows that the same holds for a square but, as Part (iii) indicates, the impact of a triangle is larger that that of a square.

A direct consequence of Proposition 2 for labor-market outcomes is that under the conditions of the proposition, the rate of employment of i is lower if i belongs to a triangle or square in g^t or g^s, respectively: $E_i(g) > E_i(g^s) > E_i(g^t)$. That is, i is more likely to be unemployed in $g^x, x \in \{s, t\}$ than in g and more so if the additional cycle is a triangle rather than a square, while $E_i(g) = E_i(g^s) = E_i(g^t)$ for the nodes that are not involved in any of the additional cycles.

To illustrate the intuition behind the proposition, let us compare a tree network g, in which $S_S(g) = \emptyset$, with a network g^t such that $S_S(g^t) = \{i, j, k\}$. Let $N_i(g) = N_i(g^t) = \{j, k, v, \ldots, z\}$. Assume $ik, ij \in E \cap E^t$, and

[26] Observe that keeping constant the joint degree distribution imposes the same assortativity in both networks.

[27] Note that keeping the second order degree constant implies that the number of neighbors of i's contacts is constant; thus, whenever the distribution of degree and second order degree is the same in the different networks, the conditions of Proposition 2 hold.

$jk \in E^t$ but $jk \notin E$. If $i \in N$ is in status 2 (i.e. i needs a job), the probability that she does not receive any offer from $j \in N_i(g)$ is $R^i_j(g) = \alpha q_j(n_j) + (1-\alpha)$. In the following illustration, to simplify notation we omit the superscript i and the dependence on g to write R_j.

Since $S_S(g) = \emptyset$, the probability that i does not receive any offer from any neighbor in g is simply the product of the individual probabilities over all i's neighbors. Therefore, the probability that i receives at least one offer from her contacts is (see Proposition 1 in Calvó-Armengol, 2004):

$$P^i(g) = 1 - R_j R_k R_v ... R_z = 1 - \prod_{h \in N_i(g)} R_h. \tag{5}$$

Since the only difference between g and g^t relevant for i is that $jk \in E$, Proposition 1 shows $I^i_j(g^t)$ and $I^i_k(g^t)$ are affiliated. As a result, $R_{jk} \neq R_j R_k$, where R_{jk} is the probability that i does not receive any offer neither from j nor from k. Consequently,

$$P^i(g^t) = 1 - R_{jk} R_v ... R_n = 1 - R_{jk} \prod_{h \in N_i(g) \setminus \{j,k\}} R_h. \tag{6}$$

Note from (5) and (6) that $P^i(g) > P^i(g^t)$ if $R_{jk} > R_j R_k$.

Table 1 presents the probabilities R_{jk} conditional on the status of j and k for networks g and g^t under the conditions of Proposition 2.[28] The first column of the table lists the four possible combinations of the status of j and k: both j and k are in status 1 and thus they are potential providers of i (row 1), two cases in which one of them is a provider while the other one is not (rows 2 and 3), and the fourth situation where none of them is a provider of i (row 4). The second and third columns, denoted respectively as g and g^t, contain the probabilities that i does not receive any offer neither from j nor k under each scenario in any of the two networks. The probabilities R_{jk} are obtained by simply adding up the four expressions in the corresponding columns.[29]

R_{jk}/status	g^t	g	$g^t - g$
j,k providers	$\alpha^2 q_j(n_j-1) q_k(n_k-1)$	$\alpha^2 q_j(n_j) q_k(n_k)$	$\alpha^2 \left[q_j(n_j-1) q_k(n_k-1) - q_j(n_j) q_k(n_k) \right]$
j is provider, k not	$\alpha q_j(n_j) - \alpha^2 q_j(n_j-1)$	$\alpha(1-\alpha) q_j(n_j)$	$\alpha^2 \left[q_j(n_j) - q_j(n_j-1) \right]$
k provider, j not	$\alpha q_k(n_k) - \alpha^2 q_k(n_k-1)$	$\alpha(1-\alpha) q_k(n_k)$	$\alpha^2 \left[q_k(n_k) - q_k(n_k-1) \right]$
j,k not providers	$(1-\alpha)^2$	$(1-\alpha)^2$	0

Table 1: Probability that i does not receive any offer from $j,k \in N_i(g)$ in g^t and g.

The last column (labeled $g^t - g$) in Table 1 is the difference between these probabilities (R_{jk} across the two networks. If we add up the four rows of this last column, we obtain

$$R_{jk} - R_j R_k = \alpha^2 \Big[\Big(q_j(n_j) - q_j(n_j-1) \Big) \Big(1 - q_k(n_k-1) \Big) + \Big(q_k(n_k) - q_k(n_k-1) \Big) \Big(1 - q_j(n_j) \Big) \Big] > 0. \tag{7}$$

by Claim 1. Therefore, $P^i(g) > P^i(g^t)$.

Table 1 further illustrates how the affiliation affects the information flows from j and k to i. In g^t, the affiliation increases the likelihood that i receives two offers from both j and k or none, while decreasing the probability of receiving just one offer. When j and k are providers (row 1 in Table 1), $R_{jk} - R_j R_k < 0$ by Claim 1. In contrast, two events in Table 1 (one neighbor can pass information to i while the other cannot, corresponding to cases in rows 2 and 3) yield a lower probability of not getting at least one offer in g^t than in g, $R_{jk} - R_j R_k > 0$. Expression (7) shows that the opposing effects are non-neutral and the aggregate effect on i is negative (higher probability of not getting at least one offer). In g^t, i receives two offers simultaneously from j and k more often but she can accept only one of the jobs while the other one remains unfilled. Therefore,

[28]Appendix A.2 contains the detailed computation of the probabilities in Table 1.

[29]Note that $R_{jk}(g) = R_j(g) R_k(g)$ but $R_{jk}(g^t) \neq R_j(g^t) R_k(g^t)$.

short network cycles, by inducing affiliation, increase the likelihood of mismatch between candidates and jobs; affiliation decreases the employment prospects of people in closely-knit neighborhoods. In economic terms, transitivity in relationships and overlapping in the neighborhoods of different individuals, through the effect of affiliation of information flows, prevent an efficient diffusion and generate labor market frictions.[30]

The above argument extends naturally when the starting network g is not a tree, and to cycles of length four. Regarding the former, $P^i(g)$ and $P^i(g^t)$ would be more complex than a product of R_h's if $S(g) \neq \emptyset$, but the comparison between the corresponding expressions (5) and (6) would again reduce to the comparison of the probabilities $R_{jk}(g)$ and $R_j(g)R_k(g)$. As for four-cycles, the argument is the same, except that the affiliation, and the fact that $R_{jk}(g^s) \neq R_j(g^s)R_k(g^s)$, stems from the status of contacts of neighbors such as $s \in N_{jk}(g^s)$. If s is employed, her status makes it more likely that *both* j and k share a job information with i and when s is unemployed it is more likely that i does not receive any offer from any of them.

Proposition 2 has several implications and raises a few issues that are worth stressing here. First, note that the above comparison holds both within and across networks. That is, it does not matter whether we compare two individuals across two networks as in Proposition 2 or two individuals within the same network. The reason is that, in the static, one-period version of the model, only the local neighborhood matters. More precisely, the employment probability of an individual is determined only by the status of agents in her first- and second-order neighborhood and by the geometry of these local neighborhoods. Therefore, any two nodes with the same degree, second-order degree, and, say, the same numbers of squares but different number of triangles could also be compared. The following two remarks clarify this point:

Remark 1 *In the one-period model, m-cycles do not affect employment prospects for any $m > 4$.*

Remark 2 *In the one-period model, $I_g^i(g)$ is unaffected by cycles that do not contain i.*

It is important to note that none of the above two remarks would hold in a dynamic model (see Section 4, where we analyze the dynamics).

Second, what can we say about the unemployment at the network level? Proposition 2 can be interpreted as an individual as well as a network-level result. Since the employment prospects of agents only differ in the probability $P^i(g)$, the next statement directly follows from Proposition 2:

Corollary 1 (Network level) *Consider networks g, g^t, and g^s from Proposition 2 with $N = N^t = N^s$. Then, the unemployment rate in each network is such that:*

$$U(g^t) > U(g^s) > U(g). \tag{8}$$

In words, our results allow us to compare two networked societies in terms of unemployment as long as the assumptions in Proposition 2 hold: when two networks have the same *joint degree distribution* and they only differ in one short cycle, the network that contain the cycle has higher unemployment rate and the effect is stronger for a triangle than for a square.

The above discussion raises a natural question: can we compare two societies if we relax some of the assumptions of Proposition 2? The answer is no. The following example shows that having the same *joint degree distribution*, $\left(n_i(g); \{n_j(g)\}_{\forall j \in N_i(g)}\right)$, in both networks is a necessary condition. If we relax this assumption, for example by only maintaining constant the degree distribution, Proposition 2 may fail to hold.

Example 2 (Equal joint degree distribution as a necessary condition) *Consider networks g and g' in Figure 4. Both networks have the same degree distribution, but the joint distribution differs across them. At the individual level, being involved in more cycles does not necessarily translate in lower unemployment if the*

[30] Note that this effect is stronger that a simple diversification argument. A higher probability of receiving two offers or none, and a lower probability of having just one offer could be equivalent if the individual could benefit more from receiving two offers than from receiving just one. However, two offers are equivalent to just one offer because the individual can only have one job. Thus, the negative effect is stronger, because people cannot fully enjoy the advantage of receiving multiple job offers. In other words, even a slightly risk loving individual would, *ceteris paribus*, prefer not to be involved in cycles.

Figure 4: Networks in Example 2.

number of direct and indirect contacts is not held constant. For instance, node 1 belongs to the cycle {1,2,3} in network g' while she is not involved in any cycle in network g. Nevertheless, $P^1(g') = 0.1334 > P^1(g) = 0.1285$ *for* $a = 0.1$ *and* $b = 0.2$.[31] *The reason is that node 1 competes with a smaller number of agents in* g' *than in* g *for information and this benefits her more than the harm that comes from the affiliation induced by the triangle. From the perspective of the entire network, although* $S(g') \setminus S(g) = \{1,2,3\}$, $E(g') = 0.84013 > E(g) = 0.84012$ *for* $a = 0.1$ *and* $b = 0.2$. *Hence, having less cycles does not guarantee lower unemployment if the joint distribution of the direct and two-links-away friends is not held fixed.* □

Example 2 illustrates that, if two networks have the same distributions of degrees and neighbors' degrees but a distinct joint distribution of both variables, the (un)employment rates cannot be generally ranked according to Corollary 1. This is an important observation: Example 2 shows that Proposition 2 and Corollary 1 cannot be generalized by relaxing the assumption of holding fixed the joint distribution of connectivity and second-order connectivity.

Next we compare specific networks with different clustering coefficient.

Corollary 2 (Vertex-transitive networks) *Consider two vertex-transitive networks* g *and* g', *with* $\left(n_i(g); \{n_j(g)\}_{\forall j \in N_i(g)}\right) = \left(n_i(g'); \{n_j(g')\}_{\forall j \in N_i(g')}\right)$ *for* $\forall i \in N$. *If* $C_i(g') \geq C_i(g)$, $C_i^4(g') \geq C_i^4(g)$ *for all* i, *and at least one of them is satisfied with strict inequality, then* $U(g') > U(g)$.

The corollary is a direct consequence of Proposition 2 and the definition of vertex-transitive networks (see Section 2.1). Remember that a network is vertex-transitive if all the nodes occupy identical positions. Hence, they have the same degree, second-order degree, clustering coefficient, global centrality etc. As a consequence, if we compare two such networks that have the same number of neighbors and number of neighbors' contacts, we can compare their unemployment rates in line with both Proposition 2 and Corollary 1. To provide an illustration, Corollary 2 predicts that unemployment increases as we move from the first to the third network in Figure 1.

According to Proposition 2 what matters for labor prospects is the number of short cycles, while we refer to the clustering coefficients in Corollary 2. Due to the popularity of the clustering coefficient, one may ask why we do not link unemployment directly to the coefficient in Proposition 2? The main reason is that the relationship between the number of cycles and the clustering coefficients is not one-to-one. As an illustration, consider node i in networks g_a - g_c in Figure 5. Although $C_i(g_a) = C_i(g_b) = \frac{1}{3}$, $P^i(g_a) \neq P^i(g_b)$ because the two triangles in g_b additionally form a four-cycle that affects i's the information flows and thus the employment prospects of those involved in the four-cycle. Similarly, $C_i^4(g_b) = C_i^4(g_c)$ but $P^i(g_b) \neq P^i(g_c)$. In vertex-transitive networks to which we refer in Corollary 2, differences in the number of cycles in which agents are involved are controlled for, since all agents occupy identical positions. The short cycles in their neighborhoods are then distributed equally. However, more complex architectures contain more complex interactions between the two clustering coefficients

[31] See Section A.2 for the derivation of all the probabilities.

and cycles of different lengths, depending on who is involved in which cycle. Therefore, we express our main results in terms of additional network cycles to illustrate their *ceteris paribus* effect. A result a là Proposition 2 that would link employment to the clustering coefficient should account for both the number of cycles and their distribution across agents.

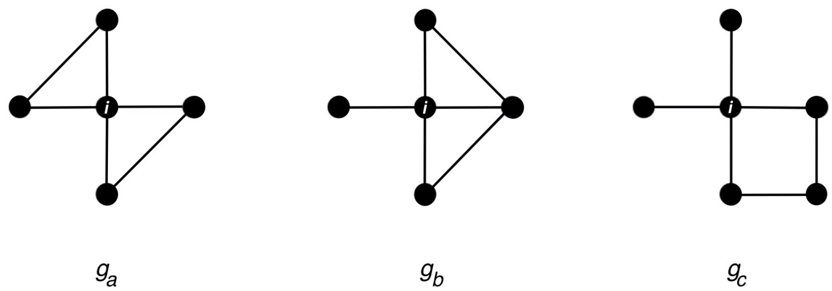


Figure 5: Relation between short cycles and the clustering coefficients

4 Dynamic analysis

In this section, we examine the long-run consequences of network cycles in labor markets. Calvó-Armengol and Jackson (2004) showed in a similar model that the unemployment rate is positively correlated across time periods and path-connected agents, and that there is duration dependence. They further provide numerous examples illustrating that the network topology shapes the long-run labor-market performance. In this section, we separate the impact of short cycles on long-run employment and inequality patterns from that of other network features.

In our dynamic setup time evolves in discrete steps denoted by t. At the beginning of each period t, a worker may be employed or unemployed, depending on her employment status in period $t-1$. If she starts employed, she has a probability $b \in (0,1)$ of losing the job. Afterwards, all workers (employed and unemployed) hear about a vacancy with probability $a \in (0,1)$. As in the static model, losing a job and hearing about a vacancy are independently distributed and independent across individuals and periods. Afterwards, unemployed individuals who have heard about a job accept it immediately, while those employed pass it along to one of their unemployed connections at random.

We assume that at $t = 1$, all nodes start being employed.[32] The only difference between the first and the subsequent periods is the initial employment status; in subsequent periods, not necessarily all individuals are employed at the beginning of the period, but they may bring unemployment from the previous period.

Let the *state* at the beginning of period t be the vector $s_t = (E_{1t}, \ldots, E_{nt})$, where $E_{it} = 0$ if node i is unemployed when period t starts and $E_{it} = 1$ if i is employed. Each state s_t has an associated employment rate $E_t = \frac{\sum E_{it}}{n}$ and unemployment rate $U_t = 1 - \frac{\sum E_{it}}{n}$. From $t = 2$ on, the state s_t will be determined by the parameters a and b, the network architecture g that channels the flow of information about job openings and the employment state of the previous period s_{t-1}; the rest of the history is irrelevant. This constitutes a Markov chain.

Since the state space is finite, we can represent the transition distribution probability through the transition matrix P with element (i,j) given by $p_{ij} = \Pr(S_{t+1} = j \mid S_t = i)$. Each row of P contains the probabilities of each possible state s_{t+1}, i.e. all possible combinations of employment and unemployment for all nodes given that they started the period in state s_t.

In this framework, the Markov chain is time-homogeneous, so that the transition matrix P is the same in each period, and the t-period transition probability can be computed as the t-th power of the transition matrix, P^t. As a result, the dynamics can be modeled as a finite-state irreducible and aperiodic Markov chain and the

[32]The model converges to a unique steady-state distribution, independently of the initial state of the system. The initial employment state is thus irrelevant after convergence.

process converges to a unique limit distribution (Young, 1993). Note that the initial state becomes irrelevant after a certain number of periods and the limit probabilities over states only depend on the parameters of the model, a and b, as well as on the network architecture g. We are interested in the steady-state probability distribution over all possible employment states: $lim_{t\to\infty} P^t = \Pi$, where Π is a matrix in which each row is the limit distribution of the process and yields the probability of each possible state s. From this limit probability distribution over states, we first check whether the effects of short cycles identified in Section 3 persist in the long run. In addition, we study other moments of the distribution, the space correlations and the persistence of unemployment, focusing on how they change as we systematically manipulate the close-knittedness of network neighborhoods.

We start by computing the exact limit distribution of the proposed Markov chain for a few simple networks and all values of $a, b \in (0, 1)$ (subsection 4.1). However, the relevant statistics do not have a general closed-form solutions, even in the case of very simple networks, and characterizing the limit distributions for larger and more complex network structures is not feasible. As a consequence, the rest of the section relies on Monte Carlo methods to study how network cycles shape the steady state (un)employment patterns, in a set of selected networks and for given values of a and b. We present the results of the simulations for $a = b = 0.1$. The conclusions are qualitatively robust to alternative parameter constellations.[33]

To facilitate the comparison of the long-run dynamics across networks, we build networked *economies* with different architectures but the same number of nodes. For each network architecture we simulate 100 economies for 10,000 periods for each parameter constellation and, to analyze the steady state distribution, we report the unemployment patterns of the last 1,000 periods.[34]

We present our results in three subsections. Subsection 4.1 analyzes whether the length of network cycles matters for long-run employment. Subsection 4.2 studies how network cycles shape long-run inequality within networks, and Subsection 4.3 makes comparisons across homogeneous networks.

4.1 Long-run unemployment in cycle networks

In this subsection, we characterize the steady state distributions of the Markov chain for a few cycle networks (see Section 2 for a definition). Consider the networks g_a through g_d in Figure 2 (an empty network with $n = 3$, a triangle, a square, and a pentagon, respectively). The one-period analysis shows that three- and four-cycles matter and the former have a larger impact on employment than the latter. Here, we show that this result persists in the long run. The dynamic model further allows us to test whether the influence of cycles extends to cycles of longer lengths and whether the effect vanishes as we increase the cycle length.

Networks g_a to g_d are simple and the positions of all nodes symmetric in each of them, which allow us to compute the transition matrices, the limit state distributions as a function of a and b, and the associated average steady-state employment rates for each node and network.[35] Figure 6 plots the differences in employment rates between a few pairs of networks as a function of the parameters (a, b). The figure reveals that the steady-state employment rate in networks g_a to g_d can be ranked as $E[g_a] < E[g_b] < E[g_c] < E[g_d]$ for any $a, b \in (0, 1)$. That is, the steady state employment rates scale up with the length of the cycle (from three to five) in each network. This points to the persistence in the long run of the negative role of short cycles that we identified in the static model. In the following subsections we corroborate this negative effect using alternative manipulations of network close-knittedness. Moreover, the above ranking of the average employment rate shows that the impact extends to five-cycles and is decreasing with the cycle length.

Although we are able to obtain explicitly the limit distributions as a function of a and b for the networks in Figure 2, the expressions for the relevant statistics are unmanageable and the complexity of the limit distributions increases dramatically with the network size. Thus, in the following we provide numerical experiments for $a = b = 0.1$ in cycle networks. To that aim, we complement the networks g_a to g_d, analyzed above, with the hexagon network g_g in Figure 2. Table 2 reports the long-run labor-market outcomes from the simulation

[33] The analysis for different values is available from the authors upon request.

[34] We performed robustness checks to see how fast the model converges and it actually converges to the steady state relatively fast. We are thus confident that running the model for 10,000 periods and selecting the last 1,000 provides a good approximation of the steady-state distributions.

[35] We include the empty network for comparison purposes.

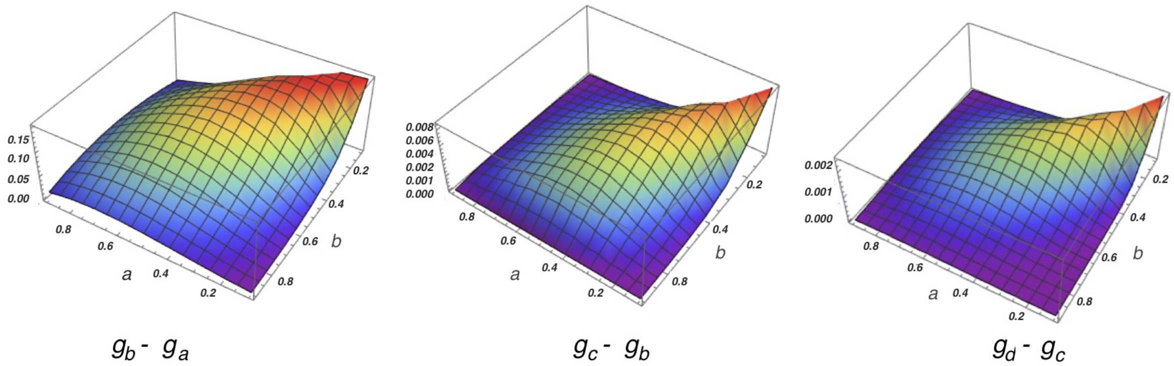


Figure 6: Differences in steady-state employment rates in networks g_a, g_b, g_c, and g_d from Figure 2.

exercise. Each cell reports the average steady-state outcome in the last 1,000 periods (out of the simulated 10,000) from 100 economies composed of 60 individuals each.

We report four types of outcomes in Table 2 (as well as in Tables 3, A10, and A11):

A. *Employment statistics* report the number of nodes in each economy, the number of economies, the total number of cycles,[36] the average employment rate, its standard deviation and the coefficient of variation.

B. *Time and spatial correlations* report the serial correlations in average employment and the simple-matching coefficients (SMC) in employment of connected and two-links-away nodes.[37]

C. *Transition rates* provide information about the changes and persistence of the labor-market status of agents.[38]

D. *Kolmogorov-Smirnov, Wilcoxon, and Fligner-Killeen tests* report the statistics (and p-values) of non-parametric tests of equality of distributions, means and variances of employment, respectively, across all pairs of networks after convergence.

Table 2 corroborates our previous result for the static case: $E[g_a] < E[g_b] < E[g_c] < E[g_d]$. The tests for equality of distribution and mean show that the labor market outcomes of g_a, g_b, g_c and g_d are all statistically different from each other and therefore the type of cycle prevalent in the economy is relevant ($p < 0.00001$; Kolmogorov-Smirnov and Wilcoxon rank-sum tests); the variances of the average employment do not differ systematically though.[39] The differences in the employment rates are relatively small between the triangle, square, and pentagon economies. While the employment rate in the triangle network is 29.14% higher than in the empty network, the increase is 30.65% in the square network, and 31.22% for the pentagon. Quantitatively speaking, in an economy composed of 1,000,000 workers, for the selected parameters values ($a = b = 0.1$), there would be around 8,000 and 11,000 unemployed individuals more in the triangle economy in the long-run, as compared to the square and pentagon economies, respectively.

Figure 7 reveals that the different economies can be ranked in the sense of the first-order stochastic dominance: the limit distribution of employment in the pentagon economy first-order stochastically dominates (FOSD, hereafter) the square economy, which FOSD the triangle economy.[40]

[36] Each economy contains many cycles; for example, with 60 nodes an economy contains 20 triangles or 15 squares or 12 pentagons or 10 hexagons.

[37] The simple-matching coefficient reports the fraction of network links in which the two nodes involved share the employment status. For instance, a value of 0.6 means that 60% of connected members in all simulated economies in the last 1,000 periods were either both employed or both unemployed.

[38] We label EE the fraction of people who keep being employed from one period to the next, UU is the fraction of those who remain unemployed, EU is the fraction of the population that were employed in one period but unemployed in the next, while UE is the reverse case. For example, $EE = 0.80$ means that that 80% of people across all the simulated economies, in the last 1,000 periods, kept their jobs from one period to the next. The other cases are interpreted accordingly.

[39] The non-parametric Fligner-Killeen tests of equality of variances only allow to reject the equality at 5% in two cases, but the ranking is not systematic.

[40] To focus on cycles, the empty network is omitted in Figure 7 but the ranking in the sense of the first-order stochastic dominance extends to the empty network.

	Networks				
	Empty ($n=3$)	Triangle	Square	Pentagon	Hexagon
A. Employment statistics					
Nodes in each economy:	60	60	60	60	60
Number of economies:	100	100	100	100	100
Total number of cycles:	-	2000	1500	1200	1000
Employment rate (E):	0.5275	0.6812	0.6892	0.6922	0.6917
St. Dev. of E:	0.0648	0.0696	0.0698	0.0694	0.0695
Coef. Variation of E:	0.1229	0.1022	0.1013	0.1003	0.1005
B. Time and spatial correlations					
Correlation(E_{t-1}, E_t):	0.8119	0.8039	0.8043	0.7993	0.8001
Correlation(E_{t-2}, E_t):	0.6596	0.6496	0.6493	0.6424	0.6433
Average SMC (1st neighbors):	NA	0.6380	0.6263	0.6232	0.6229
Average SMC (2nd neighbors):	NA	NA	0.6130	0.5965	0.5965
C. Transition rates					
Fraction continue employed EE:	0.4801	0.6267	0.6340	0.6367	0.6362
Fraction continue unemployed UU:	0.4251	0.2644	0.2557	0.2522	0.2527
Fraction lost job EU:	0.0474	0.0544	0.0552	0.0556	0.0556
Fraction found job UE:	0.0474	0.0545	0.0552	0.0555	0.0556
Conditional: EE/(EU+EE)	0.9101	0.9200	0.9199	0.9198	0.9197
Conditional: UU/(UE+UU)	0.8997	0.8292	0.8225	0.8195	0.8198
D. Kolmogorov-Smirnov, Wilcoxon, and Fligner-Killeen tests					
(equality of distribution; mean; variance)		D (p)	W (p)	χ^2 (p)	
Empty vs. triangle		0.7460 (0.0000)	549147871 (0.0000)	52.8604 (0.0440)	
Empty vs. square		0.7674 (0.0000)	467889490 (0.0000)	37.8294 (0.3414)	
Empty vs. pentagon		0.7782 (0.0000)	432566331 (0.0000)	33.9011 (0.4725)	
Empty vs. hexagon		0.7779 (0.0000)	440002393 (0.0000)	38.5586 (0.3118)	
Triangle vs. square		0.0477 (0.0000)	4676213322 (0.0000)	47.9243 (0.0715)	
Triangle vs. pentagon		0.0638 (0.0000)	4553235062 (0.0000)	43.5134 (0.1271)	
Triangle vs. hexagon		0.0596 (0.0000)	4570659747 (0.0000)	42.7190 (0.1734)	
Square vs. pentagon		0.0166 (0.0000)	4877763199 (0.0000)	33.3234 (0.5006)	
Square vs. hexagon		0.0159 (0.0000)	4895893172 (0.0000)	54.7886 (0.0178)	
Pentagon vs. hexagon		0.0042 (0.3354)	5018302682 (0.1552)	32.3255 (0.5979)	

Table 2: Long-run labor market statistics in cycle networks.

Although the long-run employment distributions of the pentagon and hexagon economies FOSD all the remaining ones, these two economies generate very similar employment distributions. In fact, we cannot reject the equality of the distributions or their moments. This suggests that the economically relevant and statistically strong long-run impact of network cycles is limited to relatively short network cycles.

The simulated limit distributions enable us to analyze other long-run effects of network cycles that go beyond the average employment rates of the cycle economies. For instance, one important macroeconomic question concerns employment fluctuations. We thus check how network cycles affect the volatility and structure of employment. As mentioned above, we find no systematic effects of network cycles on employment volatility across our comparison networks. Even though we confirm there are time and network correlations in employment and that the correlations decrease with time and network distance, we detect virtually no systematic impact of network-cycle length on the values of all these correlations.

In sum, the numerical experiment performed in this section confirms and complements our previous theoretical results. Network cycles decrease employment prospects even in the long run and their impact diminishes with the length of the cycle. Furthermore, although relatively longer cycles could theoretically induce associations in information flows once the model is repeated, we find that statistically strong and economically relevant long-run effects of network cycles are limited to short cycles, such as triangles and squares and to a lesser extent five-cycles. The effects do not seem to go beyond five-cycles after convergence.[41] In the following sections, we limit our attention to the role of triangles.[42]

[41] This conclusion only holds generally in qualitative terms. For other values of a and b, the exact cycles lengths for which differences vanish may change.

[42] The effects of squares and pentagons in the reported simulation exercises are again qualitatively similar but quantitatively

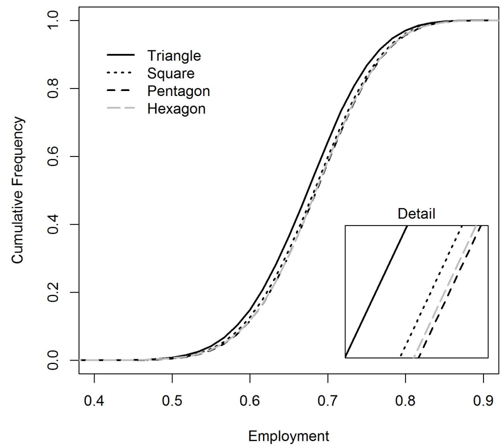


Figure 7: Cumulative density function of the employment rate in cycle networks.

4.2 Network cycles and long-run inequality

In the previous subsection, all nodes occupy symmetric positions, which precludes within-network comparisons. However, an important question is whether network cycles can be a source of long-run inequality. In this section, we present the results of two experiments. First, we investigate whether triangles affect inequality persistently even if the nodes with low and high clustering are not segregated in the network. Then, we analyze the impact of the clustering coefficient in an economy simulated on a real-life friendship network.

Different clustering in an integrated network. We explore a network that integrates individuals with two different levels of clustering. Specifically, we analyze the long-run effects of short cycles in the network depicted in Figure 8. The network is composed of 28 individuals with equally sized first- and second-order neighborhoods ($n_i(g) = 3$ and $n_i^2(g) = 6$ for all i) but differing clustering patterns. In particular, 7 nodes have clustering equal to zero, whereas 21 agents belong to one three-cycle (i.e. have clustering equal to 1/3).

More importantly for our purpose, the low- and high-clustering individuals are not segregated in the network: each low-clustering individual is only connected with high-clustering individuals and each high-clustering node is connected to one low-clustering and two high-clustering agents. Hence, this network enables us to study whether short network cycles have any implications on long-run inequality even if people are not segregated by the density of their neighborhoods. Such "no-segregation" condition is important because of the steady-state spatial correlations in employment status across directly and indirectly connected individuals, shown in Calvó-Armengol and Jackson (2004). Such long-run employment correlations across network paths reduce the inequality across nodes in the same component and may thus potentially eliminate the negative effect of short cycles if high- and low-clustering individuals are close to each other in the network. We therefore test whether differing clustering patterns can still generate inequality even when nodes are not segregated by clustering.

Table 3 summarizes the long-run labor-market outcomes for the whole network (column *All*) as well as disaggregated for the low- and high-clustering individuals. The structure of the table is the same as in Table 2. To ensure the comparability of all statistics across the two node types, we report the results of 100 independent realizations for each type. Due to the differing number of the two types of nodes in the network, we simulated 300 economies/networks and report the results of 100 randomly chosen economies for the high-clustering individuals and of all the 300 economies for the low-clustering agents. This way, we compare a total of 2,100 low- vs. 2,100 high-clustering individuals in the last 1,000 periods of the simulated Markov chain.

From Table 3, we observe some differences between the two types in their long-run employment prospects. Low-clustering individuals are more likely to be employed (Wilcoxon signed rank test, $p = 0.0001$). However, the

weaker than those of triangles.

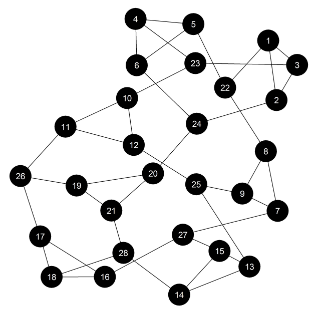


Figure 8: Regular network with $n_i(g) = 3$ and $n_i^2(g) = 6$ for all i, and two types of nodes regarding their close-knittedness, high- and low-clustering agents, integrated.

difference in employment volatility is small and statistically non-significant (Fligner-Killeen test, $p = 0.2587$). Although significant, the small size of the differences observed in mean employment between low and high clustering nodes is partly driven by the spatial correlation and the fact that there is no spatial segregation between the two types. We reject the equality of the two distributions at any reasonable significance level, using the Kolmogorov-Smirnov test of equality of distributions ($p < 0.00001$). Figure 9(a) illustrates the comparison. We observe that the steady-state employment distribution of the low-clustering individuals second-order stochastically dominates the employment distribution of the positive-clustering nodes.

The two types of nodes further differ in the persistence of the employment status. Note that short cycles increase the serial correlations of employment (see the reported 95% confidence intervals of $\mathrm{Cor}(E_t, E_{t-1})$). That is, the correlation of employment between two consecutive periods is higher if the node is embedded in a more dense neighborhood. As a result, the employment cycles exhibit a different structure for each type. Figure 9(b) provides an example of employment cycles of low and high clustering nodes in one of the simulated economies. It illustrates that high clustering maintains the employment state more stable across consecutive periods but, once we escape a state, the troughs and peaks of employment cycles may be lower and higher, respectively, in close-knit network environments. These features result from a combination of different network effects. Since short network cycles increase spatial correlation, connected individuals are more likely to be in the same state across periods and network links, and the effect "drags" the employment of most members of a clustered community up or down, toward a new common employment status.

The higher employment persistence among high-clustering individuals also affects labor-market transitions. High-clustering individuals are less likely to preserve their employment, and also more likely to remain unemployed across periods.

Summarizing, network integration of low and high clustering nodes quantitatively and qualitatively attenuates but does not eliminate the detrimental impact of short cycles. As a consequence, a policy aiming at the integration of communities with differing clustering patterns does not necessarily eliminate all labor-market disadvantages generated by network close-knittedness.

Clustering in a real-world network. In contrast to the network depicted in Figure 8, typical social networks may show a certain degree of segregation of clustering patterns and perhaps some correlation between clustering and connectivity, among other features. For that reason, we now turn to a real-life friendship network to simulate our model and study the long-run effects of clustering. We use the network elicited in Brañas et al. (2010). First, this particular network is not too large and thus computationally it is not too demanding. And, second, it exhibits typical features of real-life social networks, including a large variability in the joint distribution of degrees, second-order degrees and clustering, positive assortativity, and negative clustering-degree correlation (see Brañas et al. (2010) for details). We use the giant component of their network with $n = 76$, depicted in Figure A1 in Appendix A.3, and again simulate 100 independent networked economies over 10,000 periods. The average steady-state employment rate is 72.37% ($E = 0.7237$; $sd(E) = 0.06$) and it exhibits large serial and

	All	Type of node Low clust.	High clust.
A. Employment Statistics			
Num. nodes:	28	7	21
Num. economies/networks:	300	300	100
Employment rate (E):	0.7314	0.7341	0.7314
St. deviation of E:	0.1023	0.0979	0.1119
Coef. variation of E:	0.1399	0.1334	0.1530
B. Time and spatial correlations			
Cor(E_{t-1}, E_t):	0.7951	0.7180	0.7763
95% confidence intervals of Cor(E_{t-1}, E_t):		[0.7150; 0.7210]	[0.7738; 0.7787]
Cor(E_{t-2}, E_t):	0.6343	0.5197	0.6059
Simple-Matching Coef. (1st neighb.):	0.6446		
Simple-Matching Coef. (2nd neighb.):	0.6205		
C. Transition rates			
EE:	0.6750	0.6773	0.6743
UU:	0.2123	0.2091	0.2133
EU:	0.0563	0.0568	0.0562
UE:	0.0563	0.0568	0.0562
Conditional: EE/(EU+EE)	0.9230	0.9226	0.9231
Conditional: UU/(UU+UE)	0.0563	0.7864	0.7915
D. Kolmogorov-Smirnov, Wilcoxon signed rank, and Fligner-Killeen tests			
(equality of distribution; mean; variance)	D (p)	W (p)	χ^2 (p)
Low vs. high clustering	0.03461 (0.0000)	1928266058 (0.0001)	20.309 (0.2587)

Table 3: Steady-state labor-market statistics in the network from Figure 8 (last 1,000 periods).

spatial correlations.

Our main interest is to determine how these patterns at the individual level correlate with market outcomes. Table 4 reports three regressions, one for each relevant labor market outcome: individual employment (E_i), its standard deviation (sd(E_i)) and time correlation ($Cor(E_{it}, E_{it-1})$). We consider the three dependent variables for each network member in the last 1,000 periods. The independent variables are the individual's first- and second-order degrees and clustering coefficient. In columns (2) and (3), we further control for the average individual employment in the steady state. To provide a clean effect of the clustering coefficient, the regressions only include individuals with $n_i(g) \geq 2$ so that they have a well defined clustering. Standard errors are clustered at the network level (the smallest independent unit in the simulated data).

The results corroborate the theoretical hypotheses. The average employment, its volatility, and the serial correlations all change systematically with individual degree, second-order degree, and the clustering coefficient. The estimates are statistically strong ($p < 0.00001$). Most importantly, holding the first- and second-order degree constant, the clustering coefficient decreases individual employment and increases simultaneously its volatility and autocorrelation.[43]

4.3 Vertex-transitive networks

In this section, we analyze the effect of clustering in a special type of homogeneous networks. To that aim, we start from a series of vertex-transitive networks (see Figure 1), in which all nodes occupy identical positions. Then, we hold the first- and second-order degree distributions constant across the networks to the extent possible and vary systematically the number of triangles each node is embedded in. We perform this exercise for degree-three and degree-four networks. Figures A2 and A3 in Appendix A.3 illustrate the networks under comparison; Tables A10 and A11 present the steady-state labor-market statistics.

Figure 10 summarizes the main findings of this subsection. Independently of whether we focus on $n_i(g) = 3$ or $n_i(g) = 4$, for each node the steady-state probability distribution of employment in a network with less triangles dominates the distribution with more triangles. In all cases, the distributions and the means are significantly

[43] Tables A7 - A9 in Appendix A.3 illustrate the importance of our *ceteris paribus* condition. The estimated effects of the regressors may switch sign depending on their combination in the model. Moreover, the tables show that the results are robust to controlling for global centrality of each node.

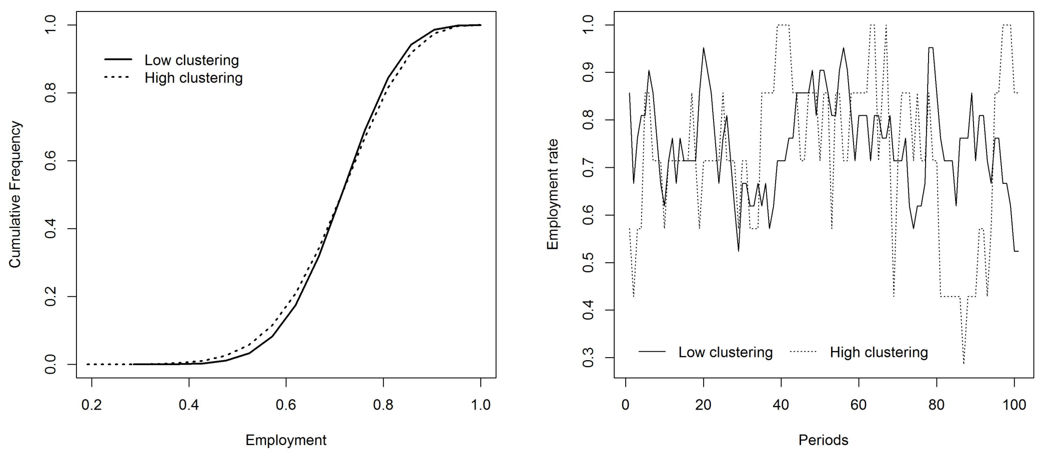


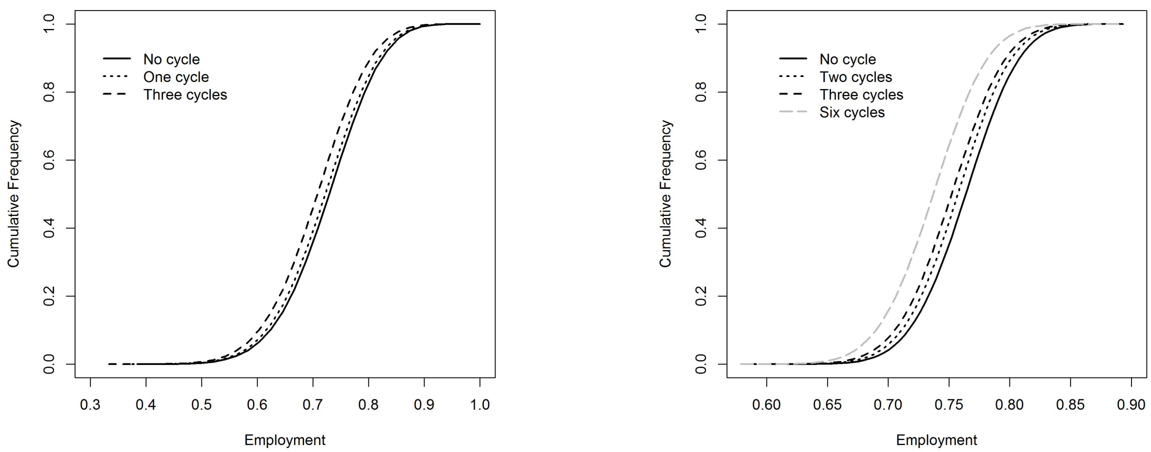
Figure 9: Cumulative density function of employment and employment fluctuations with two types of nodes (Figure 8).

	Dependent variable:		
	E_i	sd(E_i)	Cor(E_{it}, E_{it-1})
	(1)	(2)	(3)
Degree	0.029***	−0.001***	−0.011***
	(0.0003)	(0.0001)	(0.0004)
Second-order degree	−0.008***	0.001***	0.004***
	(0.0004)	(0.0001)	(0.0004)
Clustering coef.	−0.006***	0.001***	0.012***
	(0.001)	(0.0003)	(0.001)
Average E_{it}		−0.535***	−0.383***
		(0.002)	(0.010)
Constant	0.662***	0.830***	1.005***
	(0.002)	(0.002)	(0.007)
Observations	6,300	6,300	6,300
R^2	0.648	0.964	0.653
Adjusted R^2	0.648	0.964	0.653
Residual Std. Error	0.035 (df = 6296)	0.006 (df = 6295)	0.028 (df = 6295)
F Statistic	3,866.398*** (df = 3; 6296)	41,584.200*** (df = 4; 6295)	2,962.656*** (df = 4; 6295)

Note: robust st. errors clustered at network level in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 4: Real-world network: OLS. People with $n_i(g) \geq 2$ who have well defined clustering coefficient.

different ($p < 0.00001$), while the variances do not differ systematically. In quantitative terms, the steady-state employment rate decreases from 73.62% to 72.95% under $n_i(g) = 3$ as we move from a cycle-free network to the case when each node is involved in exactly one triangle. This would correspond to over 6,660 unemployed in a one-million-people economy. The employment rate further decreases to 71.57% in a network with $C(g) = 1$, corresponding to 20,525 more unemployed with respect to the zero-clustering network. The average employment is naturally higher in networks where $n_i(g) = 4$ for each node, but the ranking with respect to triangles is preserved: the employment rates are 76.5%, 75.88%, 75.36%, and 73.8% as we move from the zero-clustering network to a fully clustered architecture in our four networks under study. We thus conclude that, *ceteris* *paribus*, uniform increases of the clustering coefficient organize the distribution of employment in the sense of the first-order stochastic dominance.



(a) $n_i(g) = 3$ for each $i \in N$

(b) $n_i(g) = 4$ for each $i \in N$

Figure 10: Cumulative distributions of employment in vertex-transitive networks.

In line with the results of the previous sections, in the case of homogeneous networks short cycles induce larger serial correlations in the steady-state employment status. As a consequence, since the variance is similar across the networks but the time correlations increase steadily with the number of triangles, the peaks and troughs of the employment cycles are somehow higher and lower as we increase the clustering of the networks under study. This, jointly with the lower employment prospects in more close-knit networks, affects labor-market transitions: the likelihood of keeping a job is virtually unaffected across the networks as we increase their close-knittedness. In contrast, the probability of remaining unemployed between two consecutive periods increases steadily. Correlations in employment of linked people increase in the limit distributions but they decrease between two-links-away individuals. All these observations corroborate the conclusions from the previous subsections.

5 Wages

In this section, we briefly analyze the impact of three-cycles on wages. To that purpose, we analyze an extension of the static model from Section 2 in which job offers may come with different wages.

5.1 Information transmission with wages

Let $W_i(g)$ be a random variable denoting the wage of the position occupied by individual i in network g. For simplicity, we assume that there are two wage levels in the economy: low-paying positions with wage w_0 and high-paying positions with wage $w_1 > w_0$. Initially, all people are employed in a high-paying job.[44] Again, each worker may lose her job with probability $b \in (0,1)$. Then, each individual hears about a low- or a high-paying job with probabilities a_0 and a_1, respectively, with $a_0 + a_1 = a \in (0,1)$. At this stage, each worker can find herself in one out of six situations (status):

Status 1: with probability $\alpha_0 = a_0(1-b)$, she is employed in a high-paying job and possesses information about a low-paying job,

[44] Once again, this assumption is inconsequential. All the results are qualitatively robust as long as all people occupy a high-paying job with the same probability.

Status 2: with probability $\alpha_1 = a_1(1-b)$, she is employed in a high-paying job and has received information about a high-paying job,

Status 3: with probability $\beta = b(1-a_0-a_1)$, she is unemployed and has no information about any vacancy,

Status 4: with probability $\delta_0 = a_0 b$, she is unemployed but has heard about a low-paying job,

Status 5: with probability $\delta_1 = a_1 b$, she is unemployed but has heard about a high-paying job,

Status 6: with probability $\gamma = (1-b)(1-a_0-a_1)$, she is employed with no offer to pass to her contacts.

where α=α_0+α_1. Let us write $\bar{y}_i^s(g) = 1$ if agent i is in status s.[45] At this stage, unemployed workers who learn about a vacancy (agents in status 4 or 5) immediately accept the offer, regardless of whether the job is high- or low-paying. Employed workers who learn about a low-paying job (status 1) or a high-paying job (status 2) pass the offer uniformly at random onto one of their unemployed contacts (in status 3), who accepts the offer.

Individuals in status 1 and 2 are potential providers; we call them *low providers* and *high providers*, respectively. Second-order neighbors in status 3 will be called *competitors*. As in Section 2, it is possible that an unemployed individual receives multiple offers simultaneously. In such a case, she accepts the job with the highest wage, while the other positions remain unfilled.

5.2 The incidence of triangles on wages

We first show that adding a triangle to a network as in Proposition 2 reduces the expected wage of the nodes involved in the triangle:

Proposition 3 (Wage) *Consider networks g and g^t defined in Proposition 2. Then, $E[W_h(g)] > E[W_h(g^t)]$ for $h \in \{i,j,k\}$ and $E[W_z(g)] = E[W_z(g^t)]$ for all $z \neq i,j,k$.*

Proposition 3 complements Proposition 2 by showing that lower employment prospects of clustered individuals and networks translate into lower expected wages. However, this result raises a question: Is this finding driven by the unemployment channel or does higher clustering affect wages through additional mechanisms? To answer this question, the following proposition focuses on the expected wage conditional on ending up employed and asks whether close-knit neighborhoods are associated to higher or lower wages:

Proposition 4 (Conditional wage) *Consider networks g and g^t defined in Proposition 2. Then, $E[W_h(g^t) \mid E_h(g^t) = 1] > E[W_h(g) \mid E_h(g) = 1]$ for $h \in \{i,j,k\}$ and $E[W_z(g^t) \mid E_h(g^t) = 1] = E[W_z(g) \mid E_h(g) = 1]$ for all $z \notin \{i,j,k\}$.*

We know from Proposition 2 that forming part of short network cycles decreases the individual employment probability. Therefore, it is not surprising that it decreases the expected wage. Nevertheless, Proposition 4 shows that the negative effect is driven by the unemployment channel. If we compare the wages of two *employed* individuals whose local positioning only differs in the cohesion of their networks, we find that the presence of triangles is beneficial. The intuition behind this finding is closely related to that of Proposition 2. The lack of independence of information flows from different neighbors persists, leading to higher probability of receiving multiple offers. However, while multiple offers do not increase one's employment likelihood because each agent can only accept one job, they do increase the probability of hearing about at least one high-paying job. As a result, receiving multiple offers is not redundant any longer and the expected wage conditional on being employed is higher in clustered neighborhoods.

This result provides an additional channel for how network cycles contribute to the persistence and widening of income inequalities across communities and over time periods.

[45] Bear in mind that there are four status in Sections 2 - 4, while there are six of them in this extended version of the model.

6 Conclusions

This paper analyzes systematically the role of short network cycles in labor market outcomes. We show formally that densely-knit neighborhoods lead to the affiliation in information diffusion with important micro- and macroeconomic consequences on expected unemployment rates, wages, inequality, and employment fluctuations. In particular, network cycles lead to lower expected employment rates both at the individual and the population level and both in the short and long run. Moreover, clustering leads to employment fluctuations with higher volatility and more persistence (higher time correlation). Clustering results also in lower expected wages. This effect is, however, driven by the lower probability of employment; for employed workers, expected wages are higher if they belong to short cycles. The reason is that the detected affiliation may be beneficial as it increases the probability of receiving multiple offers and being able to select better-paying jobs. Our results provide clear empirical predictions of the effects of close-knit networks on labor market outcomes, which deserves further research.

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A Appendix

A.1 Proofs

A.1.1 Proof of Proposition 1.

Part (a). *Three cycle.* Consider a node $i \in N$ such that $y_i^2(g) = 1$. Assume that $S_S^i(g) = \{i, j, k\}$. Then, there is no $s \neq i, j, k$ such that $\{i, j, s, k\} \in S_S(g)$. The probabilities of i receiving different combination of job offers from j and k, $f(I_j(g), I_k(g))$, thus are:

$$
\begin{aligned}
f(1,0) &= \alpha(1-\alpha-\beta)\big[1 - q_j(n_j - 1 \mid 0)\big] + \alpha\beta\big[1 - q_j(n_j - 1 \mid 1)\big] + \alpha^2\big[1 - q_j(n_j - 1 \mid 0)\big]q_k(n_k - 1 \mid 0)\\
f(0,1) &= \alpha(1-\alpha-\beta)\big[1 - q_k(n_k - 1 \mid 0)\big] + \alpha\beta\big[1 - q_k(n_k - 1 \mid 1)\big] + \alpha^2\big[1 - q_k(n_k - 1 \mid 0)\big]q_j(n_j - 1 \mid 0)\\
f(0,0) &= (1-\alpha^2) + \alpha(1-\alpha-\beta)q_j(n_j - 1 \mid 0) + \alpha(1-\alpha-\beta)q_k(n_k - 1 \mid 0) + \alpha\beta q_j(n_j - 1 \mid 1)\\
&\quad + \alpha\beta q_k(n_k - 1 \mid 1) + \alpha^2 q_j(n_j - 1 \mid 0)q_k(n_k - 1 \mid 0)\\
f(1,1) &= \alpha^2\big[1 - q_j(n_j - 1 \mid 0)\big]\big[1 - q_k(n_k - 1 \mid 0)\big]
\end{aligned}
$$

Then,

$$
\begin{aligned}
&[f(1,0) * f(0,1)] - [f(1,1) * f(0,0)] = \\
&\alpha^2\beta\Bigg[\Big(q_j(n_j - 1 \mid 0) - q_j(n_j - 1 \mid 1)\Big)\Big[\Big(1 - q_k(n_k - 1 \mid 0)\Big) - \beta\Big(q_k(n_k - 1 \mid 1) - q_k(n_k - 1 \mid 0)\Big)\Big]\\
&+\Big(q_k(n_k - 1 \mid 0) - q_k(n_k - 1 \mid 1)\Big)\Big[\Big(1 - q_j(n_j - 1 \mid 0)\Big) - \beta\Big(q_j(n_j - 1 \mid 1) - q_j(n_j - 1 \mid 0)\Big)\Big]\Bigg] < 0,
\end{aligned}
$$

since by assumption $\alpha, \beta > 0$, and by Claim 1 $q_m(n_m - 1 \mid 0) - q_m(n_m - 1 \mid 1)\Big) < 0$ and

$$
\Big[\Big(1 - q_m(n_m - 1 \mid 0)\Big) - \beta\Big(q_m(n_m - 1 \mid 1) - q_m(n_m - 1 \mid 0)\Big)\Big] > 0 \text{ for } m \in \{j, k\}.
$$

Therefore, $I_j^i(g)$ and $I_k^i(g)$ are strictly affiliated.

Four cycle. If rather $S_S^i(g) = \{i, j, z, k\}$, $X_2^j(g)$ and $X_2^k(g)$ both depend on the status of z and $I_j^i(g)$ and $I_k^i(g)$ are not independent. More precisely, $f(I_j^i(g), I_k^i(g))$ are as follows:

$$
\begin{aligned}
f(1,0) &= \alpha(1-\alpha)\Big[\beta(1 - q_j(n_j - 1 \mid 1)) + (1-\beta)(1 - q_j(n_j - 1 \mid 0))\Big]\\
&+\alpha^2\Big[\beta(1 - q_j(n_j - 1 \mid 1))q_k(n_k - 1 \mid 1) + (1-\beta)(1 - q_j(n_j - 1 \mid 0))q_k(n_k - 1 \mid 0)\Big]
\end{aligned}
$$

$$
\begin{aligned}
f(0,1) &= \alpha(1-\alpha)\Big[\beta(1 - q_k(n_k - 1 \mid 1)) + (1-\beta)(1 - q_k(n_k - 1 \mid 0))\Big]\\
&+\alpha^2\Big[\beta(1 - q_k(n_k - 1 \mid 1))q_j(n_j - 1 \mid 1) + (1-\beta)(1 - q_k(n_k - 1 \mid 0))q_j(n_j - 1 \mid 0)\Big]
\end{aligned}
$$

$$f(0,0) = (1-\alpha)^2 + \alpha(1-\alpha)\Big[\beta q_k(n_k - 1 \mid 1) + (1-\beta) q_k(n_k - 1 \mid 0)\Big]$$
$$+\alpha(1-\alpha)\Big[\beta q_j(n_j - 1 \mid 1) + (1-\beta) q_j(n_j - 1 \mid 0)\Big]$$
$$+\alpha^2\Big[\beta q_k(n_k - 1 \mid 1) q_j(n_j - 1 \mid 1) + (1-\beta) q_j(n_j - 1 \mid 0) q_k(n_k - 1 \mid 0)\Big]$$

$$f(1,1) = \alpha^2\Big[\beta\Big(1 - q_k(n_k - 1 \mid 1)\Big)\Big(1 - q_j(n_j - 1 \mid 1)\Big) + (1-\beta)\Big(1 - q_k(n_k - 1 \mid 0\Big)\Big(1 - q_j(n_j - 1 \mid 0)\Big)\Big]$$

Then,

$$[f(1,0) * f(0,1)] - [f(1,1) * f(0,0)] =$$
$$\alpha^2\beta\Big(q_k(n_k - 1 \mid 0) - q_k(n_k - 1 \mid 1)\Big)\Big(q_j(n_j - 1 \mid 1) - q_j(n_j - 1 \mid 0)\Big)(1-\beta) < 0$$

by Claim 1. As a result, $I_j(g)$ and $I_k(g)$ are strictly affiliated.

Part (b). Let $X_2^{j-k\setminus k}$ be the random variable of the agents in $N_{j-k}(g) \setminus \{k\}$ who are in state 2. If $jk \in E$

$$p[I_j^i(g) = 1 \mid x_2^{jk}(g), y_k^2(g)] = \frac{\alpha}{X_2^{j-k\setminus k} + x_2^{jk}(g) + y_k^2(g)} \tag{1}$$

and $p[I_j^i(g) = 0 \mid x_2^{jk}(g), y_k^2(g)] = 1 - p[I_j^i(g) = 1 \mid x_2^{jk}(g), y_k^2(g)]$. If rather $jk \notin E$,

$$p[I_j^i(g) = 1 \mid x_2^{jk}(g)] = \frac{\alpha}{X_2^{j-k\setminus k}(g) + x_2^{jk}(g)} = \frac{\alpha}{X_2^{j-k}(g) + x_2^{jk}(g)}. \tag{2}$$

Note from (1) and (2) that, when conditioned on the status of neighbors of j and k who belong to three- or four-cycles with i, $I_j^i(g)$ and by symmetry $I_k^i(g)$ depend on $X_2^{j-k\setminus k}$ and $X_2^{k-j\setminus j}$, two events that are independent of each other. As a result, $I_j^i(g)$ and $I_k^i(g)$ are independent conditional on the status of agents who form three- and/or four-cycles with i. ■

A.1.2 Proof of Proposition 2

The proof of Proposition 2 relies on Lemmas 1 and 2.

Lemma 1 *Let $g = (N, E)$ and $g^t = (N^t, E^t)$ be two networks such that $i \in N \cap N^t$, $j, k \in N_i(g) \cap N_i(g^t)$, and $n_h(g) = n_h(g^t)$ for $h \in \{j, k\}$. If $S_S^i(g^t) = S_S^i(g) \cup \{i, j, k\}$, then $P_{jk}^i(g) > P_{jk}^i(g^t)$.*

Proof of Lemma 1. Let $y_i^2(g) = y_i^2(g^t) = 1$. Denote $\eta = n_{jk}(g) = n_{jk}(g^t)$ the number of four-cycles, in which i, j and k are involved in both g and g^t.
Case (a) With probability α^2, $y_j^1(g) = y_k^1(g) = 1$ and, in such a case, the probability with which i receives an offer neither from j nor from k in g is

$$R_{jk}^i\big(g | y_j^1(g) = 1, y_k^1(g) = 1\big) = \sum_{h=0}^{\eta} \binom{\eta}{h} \beta^h (1-\beta)^{\eta-h} q_j(n_j - \eta \mid h)\, q_k(n_k - \eta \mid h) \tag{3}$$

where

$$q_j(n_j - \eta \mid x_2^{jk}) = \sum_{h=0}^{n_j-\eta} \binom{n_j - \eta}{h} \beta^h (1-\beta)^{n_j-\eta-h} \left(\frac{h + x_2^{jk} - 1}{h + x_2^{jk}}\right)$$

is the probability that j does not transmit any offer to i, conditional on $X_2^{jk} = x_2^{jk}$, and analogously for $q_k(n_k - \eta \mid x_2^{jk})$.

For g^t,

$$R^i_{jk}\big(g^t|y^1_j(g^t)=1, y^1_k(g^t)=1\big) = \sum_{h=0}^{\eta}\binom{\eta}{h}\beta^h(1-\beta)^{\eta-h}\Big[q_j(n_j-\eta-1\mid h)\,q_k(n_k-\eta-1\mid h)\Big] \tag{4}$$

Subtracting expressions (4) and (3) and multiplying by their corresponding probabilities lead to

$$\begin{aligned}\alpha^2\Big[R^i_{jk}\big(g^t|y^1_j(g^t)=1, y^1_k(g^t)=1\big) - R^i_{jk}\big(g|y^1_j(g)=1, y^1_k(g)=1\big)\Big]=\\ = \alpha^2\sum_{h=0}^{\eta}\beta^h(1-\beta)^{\eta-h}\Big[q_j(n_j-\eta-1\mid h)\,q_k(n_k-\eta-1\mid h) - q_j(n_j-\eta\mid h)\,q_k(n_k-\eta\mid h)\Big]\end{aligned} \tag{5}$$

Case (b) If $y^1_j(g)=1$ but $y^1_k(g)=0$, the probability that k does not transmit any offer to i is equal to 1 while the probability with which j does not transmit information to i in g, conditional on k not being a provider, is

$$R^i_{jk}\big(g|y^1_j(g)=1, y^1_k(g)=0\big) = q_j(n_j) = \sum_{h=0}^{\eta}\binom{\eta}{h}\beta^h(1-\beta)^{\eta-h}q_j(n_j-\eta\mid h) \tag{6}$$

Observe that it does not matter in g whether k needs a job or not. Then, the probability that i does not receive information neither from j nor from k is

$$\begin{aligned}\alpha(1-\alpha)R^i_{jk}\big(g|y^1_j(g)=1, y^1_k(g)=0\big) = \alpha(1-\alpha)q_j(n_j) \;=\; \alpha(1-\alpha)\sum_{h=0}^{\eta}\binom{\eta}{h}\beta^h(1-\beta)^{\eta-h}q_j(n_j-\eta\mid h)\\ = \alpha\sum_{h=0}^{\eta}\binom{\eta}{h}\beta^h(1-\beta)^{\eta-h}\Big[q_j(n_j-\eta\mid h) - \alpha q_j(n_j-\eta\mid h)\Big]\end{aligned} \tag{7}$$

In network g^t, on the contrary, it matters whether $y^2_k(g^t)=0$ or $y^2_k(g^t)=1$ because $k\in N_j(g^t)$ and k can thus compete with i for job information from j. Then,

$$\begin{aligned}\alpha(1-\alpha)R^i_{jk}\big(g^t|y^1_j(g^t)=1, y^1_k(g^t)=0\big)\\ = \alpha\beta R^i_{jk}\big(g^t|y^1_j(g^t)=1, y^1_k(g^t)=0, y^2_k(g^t)=1\big) + \alpha\big(1-\alpha-\beta\big)R^i_{jk}\big(g^t|y^1_j(g^t)=1, y^1_k(g^t)=0, y^2_k(g^t)=0\big)\\ = \alpha\beta q_j(n_j-1\mid y^2_k(g^t)=1) + \alpha(1-\alpha-\beta)q_j(n_j-1\mid y^2_k(g^t)=0)\end{aligned} \tag{8}$$

being the first term the probability that j does not transmit information to i when $y^2_k(g^t)=1$ (k competes with i) whereas the second term corresponds to the probability that provider j does not transmit information to i when either $y^3_k(g^t)=1$ or $y^4_k(g^t)=1$. Since $q_j(n_j) = \beta q_j(n_j-1\mid y^2_k(g^t)=1) + (1-\beta)q_j(n_j-1\mid y^2_k(g^t)=0)$, (8) is equal to:

$$\begin{aligned}&\alpha\beta q_j(n_j-1\mid y^2_k(g^t)=1) + \alpha(1-\alpha-\beta)q_j(n_j-1\mid y^2_k(g^t)=0) =\\ &\alpha\beta q_j(n_j-1\mid y^2_k(g^t)=1) + \alpha(1-\beta)q_j(n_j-1\mid y^2_k(g^t)=0) - \alpha^2 q_j(n_j-1\mid y^2_k(g^t)=0) =\\ &\quad\alpha q_j(n_j) - \alpha^2 q_j(n_j-1) = \alpha\sum_{h=0}^{\eta}\binom{\eta}{h}\beta^h(1-\beta)^{\eta-h}\Big[q_j(n_j-\eta\mid h) - \alpha q_j(n_j-\eta-1\mid h)\Big]\end{aligned} \tag{9}$$

The difference between expressions (9) and (7) leads to:

$$\alpha(1-\alpha)\Big[R^i_{jk}\big(g^t|y^1_j(g^t)=1, y^1_k(g^t)=0\big) - R^i_{jk}\big(g|y^1_j(g)=1, y^1_k(g)=0\big)\Big]$$

$$= \alpha^2 \sum_{h=0}^{\eta} \binom{\eta}{h} \beta^h (1-\beta)^{\eta-h} \Big[q_j(n_j - \eta \mid h) - q_j(n_j - \eta - 1 \mid h) \Big] \tag{10}$$

Case (c) If $y_j^1(g) = 0$ but $y_k^1(g) = 1$, the equivalent of (10) has by symmetry the following form:

$$\alpha(1-\alpha)\Big[R_{jk}^i\big(g^t | y_j^1(g^t) = 0, y_k^1(g^t) = 1\big) - R_{jk}^i\big(g | y_j^1(g) = 0, y_k^1(g) = 1\big) \Big]$$

$$\alpha^2 \sum_{h=0}^{\eta} \binom{\eta}{h} \beta^h (1-\beta)^{\eta-h} \Big[q_k(n_k - \eta \mid h) - q_k(n_k - \eta - 1 \mid h) \Big]. \tag{11}$$

Case (d) If $y_j^1(g) = y_k^1(g) = 0$, $R_{jk}^i(g^t | y_j^1(g^t) = 0, y_k^1(g^t) = 0) - R_{jk}^i(g | y_j^1(g) = 0, y_k^1(g) = 0) = 0$.

The sum of expressions (5), (10), and (11) reflects the difference in the probabilities, with which i does not receive any offer from either j or k in networks g^t and g. Formally,

$$\begin{aligned} R_{jk}(g^t) - R_{jk}(g) = \alpha^2 \sum_{h=0}^{\eta} \binom{\eta}{h} \beta^h (1-\beta)^{\eta-h} \Bigg[& \Big(q_j(n_j - \eta \mid h) - q_j(n_j - \eta - 1 \mid h) \Big) \Big(1 - q_k(n_k - \eta - 1 \mid h) \Big) \\ & + \Big(q_k(n_k - \eta \mid h) - q_k(n_k - \eta - 1 \mid h) \Big) \Big(1 - q_j(n_j - \eta \mid h) \Big) \Bigg] > 0 \end{aligned} \tag{12}$$

by Claim 1. Consequently, $P_{jk}^i(g) > P_{jk}^i(g^t)$. ■

Lemma 2 *Let $g = (N, E)$ and $g^s = (N^s, E^s)$ be two networks such that $i \in N \cap N^s$, $j, k \in N_i(g) \cap N_i(g^s)$, and $n_h(g) = n_h(g^s)$ for $h \in \{j, k\}$. If $S_S(g^s) = S_S(g) \cup \{i, j, z, k\}$, $P_{jk}^i(g) > P_{jk}^i(g^s)$.*

Proof of Lemma 2. Let $y_i^2(g) = y_i^2(g^s) = 1$. The probability with which i receives no offer from j or k if $j(k)$ is a provider but $k(j)$ is not is independent of the four-cycles that i shares with j and k. As a result, $R_{jk}^i(g | y_j^1(g) \neq y_k^1(g)) = R_{jk}^i(g^s | y_j^1(g^s) \neq y_k^1(g^s))$. Similarly, $R_{jk}^i(g | y_j^1(g) = y_k^1(g) = 0) = R_{jk}^i(g^s | y_j^1(g^s) = y_k^1(g^s) = 0) = 1$. Hence, the only difference between g and g^s arises when $y_j^1(g) = y_k^1(g) = y_j^1(g^s) = y_k^1(g^s) = 1$. We focus on this case below.

In network g^s, node i forms $n_{jk}(g^s) = \eta$ four-cycles with j and k. Denote z the node such that $\{z\} \in N_{jk}(g^s) \setminus N_{jk}(g)$. Define $X_2^{jk\setminus z}(g^s)$ as the random variable of the agents in $N_{jk}(g^s) \setminus \{z\}$ who are in state 2, and $x_2^{jk\setminus z}(g^s)$ as a realization of this variable. The expected probability that i does not receive any offer from providers j and k can be expressed considering whether $z \in N_{jk}(g^s)$ is in status 2 (with probability β) or not:

$$R_{jk}^i\big(g^s | y_j^1(g^s) = y_k^1(g^s) = 1\big) =$$

$$\sum_{h=0}^{\eta-1} \binom{\eta-1}{h} \beta^h (1-\beta)^{\eta-1-h} \Big[\beta q_j(n_j - \eta - 1 \mid h+1) q_k(n_k - \eta - 1 \mid h+1) + (1-\beta) q_j(n_j - \eta - 1 \mid h) q_k(n_k - \eta - 1 \mid h) \Big] \tag{13}$$

where

$$q_j\big(n_j - \eta - 1 \mid x_2^{jk\setminus z}(g^s) + y_z^2(g^s)\big) = \sum_{h=0}^{n_j-\eta-1} \binom{n_j - \eta - 1}{h} \beta^h (1-\beta)^{n_j-\eta-1-h} \left(\frac{h + x_2^{jk\setminus z}(g^s) + y_z^2(g^s) - 1}{h + x_2^{jk\setminus z}(g^s) + y_z^2(g^s)} \right)$$

is the probability that j does not transmit any offer to i, conditional on $x_2^{jk}(g^s) = x_2^{jk\setminus z}(g^s) + y_z^2(g^s)$, and analogously for $q_k\big(n_k - \eta - 1 \mid x_2^{jk\setminus z}(g^s) + y_z^2(g^s)\big)$. Note that (13) depends on the number of agents in $N_{jk}(g^s) \setminus \{z\}$ in status 2 (captured by the terms multiplying the expression in brackets) as well as on the status of z.

In network g, node i forms $\eta - 1$ four-cycles with j and k. Since $S_S(g^s) = S_S(g) \cup \{i, j, k, z\}$ and $n_m(g^s) = n_m(g)$ for all $m \in N \cap N^s$, there exist two nodes that we label s, l such that $N_j(g) \setminus N_j(g^s) = \{l\}$ and $N_k(g) \setminus N_k(g^s) = \{s\}$, $l \neq s$.[1] Then, the probability that i does not receive any offer from providers j and k in g can be expressed in function of whether $y_s^2(g) = 1$ and $y_l^2(g) = 1$ as follows:

$$R^i_{jk}\big(g|y_j^1(g) = y_k^1(g) = 1\big) = \sum_{h=0}^{\eta-1} \binom{\eta-1}{h} \beta^h (1-\beta)^{\eta-1-h}$$

$$= \Bigg[\beta^2 q_j(n_j - \eta - 1 \mid h+1) q_k(n_k - \eta - 1 \mid h+1) + \beta(1-\beta) q_j(n_j - \eta - 1 \mid h+1) q_k(n_k - \eta - 1 \mid h) \tag{14}$$

$$+\beta(1-\beta) q_j(n_j - \eta - 1 \mid h) q_k(n_k - \eta - 1 \mid h+1) + (1-\beta)^2 q_j(n_j - \eta - 1 \mid h) q_k(n_k - \eta - 1 \mid h)\Bigg].$$

The difference between expressions (14) and (13) is

$$R_{jk}\big(g|y_j^1(g) = y_k^1(g) = 1\big) - R_{jk}\big(g^s|y_j^1(g^s) = y_k^1(g^s) = 1\big)$$

$$= \sum_{h=0}^{\eta-1} \binom{\eta-1}{h} \beta^h (1-\beta)^{\eta-1-h}$$

$$\beta(1-\beta) * \Bigg[q_k(n_k - \eta - 1 \mid h+1) - q_k(n_k - \eta - 1 \mid h)\Bigg] * \Bigg[q_j(n_j - \eta - 1 \mid h) - q_j(n_j - \eta - 1 \mid h+1)\Bigg] < 0.$$

Thereby, $R_{jk}\big(g^s|y_j^1(g^s) = y_k^1(g^s) = 1\big) > R_{jk}\big(g|y_j^1(g) = y_k^1(g) = 1\big)$. Since $P[y_j^1(g^s) = y_k^1(g^s) = 1] > 0$ by model assumptions, $P^i_{jk}(g) > P^i_{jk}(g^s)$. ■

Proof of Proposition 2. Since the only difference across networks g, g^t, and g^s arises from network transmission toward the agents involved in the additional triangle in g^t and square in g^s, we can focus on the probabilties of receving information from neighbors, $P^i(g)$, when $y_i^2(g) = y_i^2(g^t) = y_i^2(g^s) = 1$.

`Part (i).` By Lemma 1, $P^i_{jk}(g) > P^i_{jk}(g^t)$ and $P^i_m(g) = P^i_m(g^t)$ for any $m \notin \{j, k\}$. As a result, $P^i(g) > P^i(g^t)$. Analogously, $P^j(g) > P^j(g^t)$ and $P^k(g) > P^k(g^t)$. Since the remaining nodes have the same positioning in terms of degree, second-order degree, and short cycles in g and g^t, $P^s(g) = P^s(g^t)$ for any $s \neq i, j, k$.

`Part (ii).` By Lemma 2, $P^i_{jk}(g) > P^i_{jk}(g^s)$ and $P^i_m(g) = P^i_m(g^s)$ for any $m \notin \{j, k\}$, implying that $P^l(g) > P^l(g^s)$ for $l \in \{i, j, k, z\}$, while $P^t(g) = P^t(g^s)$ for $t \neq i, j, k, z$.

`Part (iii).` Denote $\eta = n_{jk}(g) = n_{jk}(g^t)$ the number of four-cycles, in which i, j and k are involved in both g and g^t. Since $S_S(g^s) = S_S(g) \cup \{i, j, k, z\}$, $\eta' = \eta + 1$ is the number of four-cycles that i, j and k form in g^s. In what follows, we relate the probabilities of (not) receiving information in g^t and g^s conditional on the status of j and k case by case:
Case (a) If $y_j^1(g^t) = y_j^1(g^s) = 1$ and $y_k^1(g^t) = y_k^1(g^s) = 1$, the probability that i does not receive any offer from j and k in g^s is

$$\alpha^2 R_{jk}\big(g^s|y_j^1(g^s) = 1, y_k^1(g^s) = 1\big) = \alpha^2 \sum_{h=0}^{\eta'} \binom{\eta'}{h} \beta^h (1-\beta)^{\eta'-h} \Big[q_j(n_j - \eta' \mid h)\, q_k(n_k - \eta' \mid h)\Big], \tag{15}$$

where

$$q_j(n_j - \eta' \mid x_2^{jk}) = \sum_{h=0}^{n_j - \eta'} \binom{n_j - \eta'}{h} \beta^h (1-\beta)^{n_j - \eta' - h} \left(\frac{h + x_2^{jk} - 1}{h + x_2^{jk}}\right) \tag{16}$$

[1]Note that it is possible that $s = z$ or $l = z$.

reflects the probability that j does not transmit any offer to i, conditional on $X_2^{jk} = x_2^{jk} \geq 1$, and analogously for $q_k(n_k - \eta \mid x_2^{jk})$. Since $\eta' = \eta + 1$, (15) can be rewritten as

$$\alpha^2 R_{jk}\big(g^s|y_j^1(g^s) = 1, y_k^1(g^s) = 1\big) = \alpha^2 \sum_{h=0}^{\eta+1} \binom{\eta+1}{h} \beta^h (1-\beta)^{\eta+1-h} \Big[q_j(n_j - \eta - 1 \mid h)\, q_k(n_k - \eta - 1 \mid h)\Big]$$
$$= \alpha^2 \sum_{h=0}^{\eta} \binom{\eta}{h} \beta^h (1-\beta)^{\eta-h} \Big[\beta q_j(n_j - \eta - 1 \mid h+1) q_k(n_k - \eta - 1 \mid h+1) + (1-\beta) q_j(n_j - \eta - 1 \mid h) q(n_k - \eta - 1 \mid h)\Big] \tag{17}$$

In g^t, $jk \in E^t$. Hence, $y_j^1(g^t) = y_k^1(g^t) = 1$ implies that one neighbor of j (i.e. agent k) does not compete with i for information and viceversa for k. Therefore, the probability that i receives an offer from neither j nor k in g^t is

$$\alpha^2 R_{jk}(g^t|y_j^1(g^t) = 1, y_k^1(g^t) = 1) = \alpha^2 \sum_{h=0}^{\eta} \binom{\eta}{h} \beta^h (1-\beta)^{\eta-h} \Big[q_j(n_j - \eta - 1 \mid h)\, q_k(n_k - \eta - 1 \mid h)\Big]$$
$$= \alpha^2 \sum_{h=0}^{\eta} \binom{\eta}{h} \beta^h (1-\beta)^{\eta-h} \Big[\beta q_j(n_j - \eta - 1 \mid h)\, q_k(n_k - \eta - 1 \mid h) + (1-\beta) q_j(n_j - \eta - 1 \mid h)\, q_k(n_k - \eta - 1 \mid h)\Big] \tag{18}$$

Then (18)-(17),

$$\alpha^2 \Big[R_{jk}\big(g^t|y_j^1(g^t) = 1, y_k^1(g^t) = 1\big) - R_{jk}\big(g^s|y_j^1(g^s) = 1, y_k^1(g^s) = 1\big)\Big]$$
$$= \alpha^2 \sum_{h=0}^{\eta} \binom{\eta}{h} \beta^h (1-\beta)^{\eta-h} \Big[q_j(n_j - \eta - 1 \mid h) q_k(n_k - \eta - 1 \mid h) - q_j(n_j - \eta - 1 \mid h+1) q(n_k - \eta - 1 \mid h+1)\Big] \tag{19}$$

Case (b) Let $y_j^1(g^s) = y_j^1(g^t) = 1$ and $y_k^1(g^s) = y_k^1(g^t) = 0$. Since j is a provider but k is not, the probability that i does not receive any offer from k is one and independent of the number of common neighbors of j and k in status 2. In such a case, the number of four-cycles that i forms with j and k is irrelevant and information flows from j and k are equal in g^s and in g^t. Then, the difference in the probability that i gets an offer in g^t with respect to g^s neither from j nor from k when j is a provider and k is not is given by expression (10) (see the proof of Lemma 1). That is,

$$\begin{aligned} &\alpha(1-\alpha)\Big[R_{jk}\big(g^t|y_j^1(g^t) = 1, y_k^1(g^t) = 0\big) - R_{jk}\big(g^s|y_j^1(g^s) = 1, y_k^1(g^s) = 0\big)\Big] \\ &\quad = \alpha^2 \sum_{h=0}^{\eta} \binom{\eta}{h} \beta^h (1-\beta)^{\eta-h} \Big[q_j(n_j - \eta \mid h) - q_j(n_j - \eta - 1 \mid h)\Big] \end{aligned} \tag{20}$$

Case (c) When rather $y_j^1(g^s) = y_j^1(g^t) = 0$ while $y_k^1(g^s) = y_k^1(g^t) = 1$, by analogy with Case (b):

$$\begin{aligned} &\alpha(1-\alpha)\Big[R_{jk}\big(g^t|y_j^1(g^t) = 0, y_k^1(g^t) = 1\big) - R_{jk}\big(g^s|y_j^1(g^s) = 0, y_k^1(g^s) = 1\big)\Big] \\ &\quad = \alpha^2 \sum_{h=0}^{\eta} \binom{\eta}{h} \beta^h (1-\beta)^{\eta-h} \Big[q_k(n_k - \eta \mid h) - q_k(n_k - \eta - 1 \mid h)\Big]. \end{aligned} \tag{21}$$

Case (d) If $y_j^1(g^t) = 0$ and $y_k^1(g^t) = 0$, the probabilities are identical in g^t and g^s.

Adding up the relevant expressions (19), (20), and (21) weighted by their corresponding probabilities, we get the difference in the probability that i does not receive any offer neither from j nor from k in the two networks as follows:

$$R_{jk}(g^t) - R_{jk}(g^s) =$$

$$\alpha^2 \sum_{h=0}^{\eta} \binom{\eta}{h} \beta^h (1-\beta)^{\eta-h} \Big[-\beta q_k(n_k - \eta - 1 \mid h+1) \Big(q_j(n_j - \eta - 1 \mid h+1) - q_j(n_j - \eta - 1 \mid h) \Big)$$
$$- \beta q_j(n_j - \eta - 1 \mid h) \Big(q_k(n_k - \eta - 1 \mid h+1) - q_k(n_k - \eta - 1 \mid h) \Big)$$
$$+ \Big(q_j(n_j - \eta \mid h) - q_j(n_j - \eta - 1 \mid h) \Big) + \Big(q_k(n_k - \eta \mid h) - q_k(n_k - \eta - 1 \mid h) \Big)$$

Given that $q_j(n_j - \eta \mid x_2^{jk}) = \beta q_j(n_j - \eta - 1 \mid x_2^{jk} + 1) + (1-\beta) q_j(n_j - \eta - 1 \mid x_2^{jk})$,

$$R_{jk}(g^t) - R_{jk}(g^s) =$$
$$\alpha^2 \sum_{h=0}^{\eta} \binom{\eta}{h} \beta^h (1-\beta)^{\eta-h} \Big[\Big(q_j(n_j - \eta \mid h) - q_j(n_j - \eta - 1 \mid h) \Big) \Big(1 - q_k(n_k - \eta - 1 \mid h+1) \Big)$$
$$+ \Big(q_k(n_k - \eta - 1 \mid h+1) - q_k(n_k - \eta - 1 \mid h) \Big) \Big(1 - q_j(n_j - \eta - 1 \mid h) \Big) \Big] > 0.$$

As each case occurs with positive probability, $P^i_{jk}(g^s) > P^i_{jk}(g^t)$. Since $P^i_m(g^s) = P^i_m(g^t)$ for $m \neq \{j,k\}$, $P^i(g^s) > P^i(g^t)$. By symmetry and Part (ii), $P^h(g^s) > P^h(g^t)$ for $h \in \{j,k,z\}$. ■

A.1.3 Proof of Proposition 3

Since the difference in i's expected wage between g and g^t only arises from network transmission by j and k while the expected wage conditional on receiving it from any $s \in N_i(g) \setminus \{j,k\}$ is the same in both networks, we can focus on the expected wage of an employed agent i who has received her job from either j or k.

Denote $\eta \in \{0\} \cup \mathbb{N}$ the number of four-cycles, in which the three i, j and k are involved. In what follows, we analyze the expected wage conditional on whether i has received a job from any $s \in N_i(g) \setminus \{j,k\}$:
Case (a) Assume first that i has received no offer from any $s \in N_i(g) \setminus \{j,k\}$. In such a case, i's expected wage depends exclusively on information flows from j and k in both networks. The rows of Table A1 list all the situations that can arise depending on the status of j and k. The second column (denoted $g^t - g$) contains the difference in the expected wage of i between g^t and g, multiplied by the probability of the occurrence of each case. As a result, the sum of all the elements in the second column of Table A1 is the difference in i's expected wage between g and g^t. After some simplification, we get

$$E[W_i(g^t)] - E[W_i(g)] = \sum_{h=0}^{\eta} \binom{\eta}{h} \beta^h (1-\beta)^{\eta-h}$$
$$-(\alpha_0^2 w_0 + \alpha_1^2 w_1) \Big[\Big(q_k(n_k \mid h) - q_k(n_k - 1 \mid h) \Big) * \Big(1 - q_j(n_j \mid h) \Big) + \Big(q_j(n_j \mid h) - q_j(n_j - 1 \mid h) \Big) * \Big(1 - q_k(n_k - 1 \mid h) \Big) \Big]$$
$$-\alpha_0 \alpha_1 * w_0 \Big[\Big(q_j(n_j \mid h) - q_j(n_j - 1 \mid h) \Big) * \Big(2 - q_k(n_k \mid h) - q_k(n_k - 1 \mid h) \Big)$$
$$+ \Big(q_k(n_k \mid h) - q_k(n_k - 1 \mid h) \Big) * \Big(2 - q_j(n_j \mid h) - q_j(n_j - 1 \mid h) \Big) \Big]. \tag{22}$$

Using that $q_j(n_j) = \sum_{h=0}^{\eta} \binom{\eta}{h} \beta^{\eta} (1-\beta)^{\eta-h} q_j(n_j - \eta \mid h)$, we get after some algebra that $E[W_i(g)] > E[W_i(g^t)]$ if i receives no information from any $s \in N_i(g) \setminus \{j,k\}$.
Case (b) Assume that i receives at least one offer of a low-paying but no high-paying job from agents $s \in N_i(g) \setminus \{j,k\}$. Then, $E[W_i(g)] > E[W_i(g^t)]$ if the probability of receiving a high-paying job from either j or k or both is greater in g than in g^t. Agent i receives information about a high-paying job from j and k only if

at least one of them is a high provider, corresponding to cases (2 - 4) and (7 - 8) in Table A1. Operating, the difference in these probabilities between g and g^t is

$$\sum_{h=0}^{\eta}\binom{\eta}{h}\beta^h(1-\beta)^{\eta-h}$$

$$\alpha_0^2\Big[\Big(q_k(n_k \mid h) - q_k(n_k - 1 \mid h)\Big)\Big(1 - q_j(n_j - 1 \mid \ h)\Big) + \Big(q_j(n_j \mid h) - q_j(n_j - 1 \mid h)\Big)\Big(1 - q_k(n_k - 1 \mid \ h)\Big)\Big] > 0$$

by Lemma 1. Hence, $E[W_i(g)] > E[W_i(g^t)]$ conditional on receiving at least one low offer from an $s \in N_i(g) \setminus \{j, k\}$.

Case (c) If i receives at least one high-payoff offer from $\{s \in N | s \in N_i(g) \setminus \{j, k\}\}$, her expected wage is w_1 in both networks, independently on the information flows from j and k.

Since all cases occur with positive probability, $E[W_i(g)] > E[W_i(g^t)]$. ■

Table A1: Expected wage of agent $i's$ in function of the offers she receives from j, k if i, j, and k are involved in η four-cycles.

Cases	$g^t - g$
(1) $\bar{y}_j^1 = 1, \bar{y}_k^1 = 1$	$\sum_\eta \alpha_0^2 w_0 \Big[q_j(n_j - \eta \mid h) q_k(n_k - \eta \mid h) - q_j(n_j - 1 - \eta \mid h) q_k(n_k - 1 - \eta \mid h) \Big) \Big]$
(2) $\bar{y}_j^2 = 1, \bar{y}_k^2 = 1$	$\sum_\eta \alpha_1^2 w_1 \Big[q_j(n_j - \eta \mid h) q_k(n_k - \eta \mid h) - q_j(n_j - 1 - \eta \mid h) q_k(n_k - 1 - \eta \mid h) \Big) \Big]$
(3) $\bar{y}_j^2 = 1, \bar{y}_k^1 = 1$	$\sum_\eta \alpha_0 \alpha_1 \Big[q_j(n_j - 1 - \eta \mid h) \Big[\Big(1 - q_k(n_k - 1 - \eta \mid h)) \Big) w_0 - w_1 \Big] - q_j(n_j - \eta \mid h)) \Big[\Big(1 - q_k(n_k - \eta \mid h) \Big) w_0 - w_1 \Big] \Big] \Big]$
(4) $\bar{y}_j^1 = 1, \bar{y}_k^2 = 1$	$\sum_\eta \alpha_0 \alpha_1 \Big[q_k(n_k - 1 - \eta \mid h) \Big[\Big(1 - q_j(n_j - 1 - \eta \mid h)) \Big) w_0 - w_1 \Big] - q_k(n_k - \eta \mid h)) \Big[\Big(1 - q_j(n_j - \eta \mid h) \Big) w_0 - w_1 \Big] \Big] \Big]$
(5) $\bar{y}_j^1 + \bar{y}_j^2 = 0, \bar{y}_k^1 = 1$	$-\alpha_0 w_0 \alpha \Big[q_k(n_k) - q_k(n_k - 1) \Big]$
(6) $\bar{y}_j^1 = 1, \bar{y}_k^1 + \bar{y}_k^2 = 0$	$-\alpha_0 w_0 \alpha \Big[q_j(n_j) - q_j(n_j - 1) \Big]$
(7) $\bar{y}_j^1 + y_j^2 = 0, \bar{y}_k^2 = 1$	$-\alpha_1 w_1 \alpha \Big[q_k(n_k) - q_k(n_k - 1) \Big]$
(8) $\bar{y}_j^2 = 1, \bar{y}_k^1 + \bar{y}_k^2 = 0$	$-\alpha_1 w_1 \alpha \Big[q_j(n_j) - q_j(n_j - 1) \Big]$
(9) $\bar{y}_j^1 + \bar{y}_j^2 + \bar{y}_k^1 + \bar{y}_k^2 = 0$	0

Note: $\sum_\eta = \sum_{h=0}^{\eta} \binom{\eta}{h} \beta^h (1-\beta)^{\eta-h}$ is an abbreviated form of an expression that conditions on the status of the common neighbors of providers j and k.

A.1.4 Proof of Proposition 4

Since the expected wage before the network transmission is independent of the network and i's expected wage conditional on receiving it from a neighbor $s \in N_i(g) \setminus \{j,k\}$ is equal in both networks, the only difference between the two networks for a node i can arise when i receives her job either through i or j. We thus focus on the expected wage of an individual i who found her job through either j or k, conditional on being employed through i or j. There are eight possible cases in function of the status of j and k listed in Table A2. Overall, such conditional expected wage in of i in a network g is

$$
\begin{gathered}
E\big[W_i(g) \mid \ I^i_j(g) + I^i_k(g) \geq 1\big] = \\
\alpha_0^2 E\big[W_i(g) \mid \ I^i_j(g) + I^i_k(g) \geq 1, \bar{y}^1_j(g) = 1, \bar{y}^1_k(g) = 1\big] + \alpha_1^2 E\big[W_i(g) \mid \ I^i_j(g) + I^i_k(g) \geq 1, \bar{y}^2_j(g) = 1, \bar{y}^2_k(g) = 1\big] \\
+\alpha_1\alpha_0 E\big[W_i(g) \mid \ I^i_j(g) + I^i_k(g) \geq 1, \bar{y}^2_j(g) = 1, \bar{y}^1_k(g) = 1\big] + \alpha_1\alpha_0 E\big[W_i(g) \mid \ I^i_j(g) + I^i_k(g) \geq 1, \bar{y}^1_j(g) = 1, \bar{y}^2_k(g) = 1\big] \\
+\alpha_0(1-\alpha) E\big[W_i(g) \mid \ I^i_j(g) + I^i_k(g) \geq 1, \bar{y}^1_j(g) + \bar{y}^2_k(g) = 0, \bar{y}^1_k(g) = 1\big] \\
+\alpha_0(1-\alpha) E\big[W_i(g) \mid \ I^i_j(g) + I^i_k(g) \geq 1, \bar{y}^1_j(g) = 1, \bar{y}^1_j(g) + \bar{y}^2_k(g) = 0\big] \\
+\alpha_1(1-\alpha) E\big[W_i(g) \mid \ I^i_j(g) + I^i_k(g) \geq 1, \bar{y}^1_j(g) + \bar{y}^2_k(g) = 0, \bar{y}^2_k(g) = 1\big] \\
+\alpha_1(1-\alpha) E\big[W_i(g) \mid \ I^i_j(g) + I^i_k(g) \geq 1, \bar{y}^2_j(g) = 1, \bar{y}^1_j(g) + \bar{y}^2_k(g) = 0\big].
\end{gathered}
$$

Table A2 contains the expected wages $E\big[W_i(g) \mid \ I^i_j(g) + I^i_k(g) \geq 1, \bar{y}^s_j, \bar{y}^s_k\big]$ conditional on each possible state combination of j and k in networks g and g^t. For example, the expected wage of an employed individual i if she received the job either from her neighbor j or k who both possess information about a high paying job satisfies the following:

$$
E\big[W_i(g) \mid \ I^i_j(g^t) + I^i_k(g^t) \geq 1, \bar{y}^1_j(g^t) = 1, \bar{y}^1_k(g^t) = 1\big] = \frac{\sum_\eta \Big(1 - q_j(n_j - \eta - 1 \mid h) q_k(n_k - \eta - 1 \mid h)\Big) w_0}{\sum_\eta \Big(1 - q_j(n_j - \eta - 1 \mid h) q_k(n_k - \eta - 1 \mid h)\Big)}
$$

$$
= E\big[W_i(g) \mid \ I^i_j(g) + I^i_k(g) \geq 1, \bar{y}^1_j(g) = 1, \bar{y}^1_k(g) = 1\big] = \frac{\sum_\eta \Big(1 - q_j(n_j - \eta \mid h) q_k(n_k - \eta \mid h)\Big) w_0}{\sum_\eta \Big(1 - q_j(n_j - \eta \mid h) q_k(n_k - \eta \mid h)\Big)} = w_0,
$$

where $\eta = n_{jk}(g) = n_{jk}(g^t)$ is the number of four-cycles in which i, j and k are involved in both g and g^t, and $\sum_\eta = \sum_{h=0}^{\eta} \binom{\eta}{h} \beta^h (1-\beta)^{\eta-h}$ is an abbreviated form of an expression that conditions on the status of the common neighbors of j and k.

Note that the only difference between g and g^t arises in cases (3) and (4). To compare these cases, note first that the probability that i receives at least one offer either from j of from k in g satisfies:

$$
\begin{gathered}
P^i_{jk}(g) = P^i_j(g) + \Big(1 - P^i_j(g)\Big) P^i_k(g) = \sum_\eta \Big[1 - q_j(n_j - \eta \mid h) q_k(n_k - \eta \mid h)\Big] = \\
\sum_\eta \Big[\Big(1 - q_j(n_j - \eta \mid h)\Big) + q_j(n_j - \eta \mid h)\Big(1 - q_k(n_k - \eta \mid h)\Big)\Big]
\end{gathered} \tag{23}
$$

where $P^i_j(g) = \sum_\eta 1 - q_j(n_j - \eta \mid h)$ is the probability that i receives information from j.

Using the expression (23), we can express i 's expected wage in case (3) in g as follows:

$$
\begin{gathered}
E\big[W_i(g) \mid \ I^i_j(g) + I^i_k(g) \geq 1, \bar{y}^2_j(g) = 1, \bar{y}^1_k(g) = 1\big] = \\
w_0 + \sum_\eta \frac{1 - q_j(n_j - \eta \mid h)}{1 - q_j(n_j - \eta \mid h) q_k(n_k - \eta \mid h)} (w_1 - w_0)
\end{gathered} \tag{24}
$$

and that in case (4) as follows:

$$E\big[W_i(g) \mid \; I^i_j(g) + I^i_k(g) \geq 1, \bar{y}^2_k(g) = 1, \bar{y}^1_j(g) = 1\big] = w_0 + \sum_\eta \frac{1 - q_k(n_k - \eta \mid h)}{1 - q_j(n_j - \eta \mid h) q_k(n_k - \eta \mid h)}(w_1 - w_0). \quad (25)$$

Since both cases occur with the same probabilty, we can add (24) and (25) up to obtain:

$$\begin{aligned} E\big[W_i(g) \mid \; I^i_j(g) + I^i_k(g) \geq 1, \bar{y}^2_j(g) = 1, \bar{y}^1_k(g) = 1\big] + E\big[W_i(g) \mid \; I^i_j(g) + I^i_k(g) \geq 1, \bar{y}^2_k(g) = 1, \bar{y}^1_j(g) = 1\big] \\ = 2w_0 + \sum_\eta \frac{2 - q_j(n_j - \eta \mid h) - q_k(n_k - \eta \mid h)}{1 - q_j(n_j - \eta \mid h) q_k(n_k - \eta \mid h)}(w_1 - w_0) \end{aligned} \quad (26)$$

Analogously, the corresponding expression to (26) in network g^t is

$$\begin{aligned} E\big[W_i(g^t) \mid \; I^i_j(g^t) + I^i_k(g^t) \geq 1, \bar{y}^2_j(g^t) = 1, \bar{y}^1_k(g^t) \geq 1\big] + E\big[W_i(g^t) \mid \; I^i_j(g^t) + I^i_k(g^t) \geq 1, \bar{y}^2_k(g^t) = 1, \bar{y}^1_j(g^t) = 1\big] \\ = 2w_0 + \sum_\eta \frac{2 - q_j(n_j - \eta - 1 \mid h) - q_k(n_k - \eta - 1 \mid h)}{1 - q_j(n_j - \eta - 1 \mid h) q_k(n_k - \eta - 1 \mid h)}(w_1 - w_0). \end{aligned} \quad (27)$$

Note that (27) is greater than (26) if:

$$\begin{aligned} \sum_\eta \Big[2 - q_j(n_j - \eta \mid h) - q_k(n_k - \eta \mid h)\Big] * \Big[1 - q_j(n_j - \eta - 1 \mid h) q_k(n_k - \eta - 1 \mid h)\Big] \\ - \Big[2 - q_j(n_j - \eta - 1 \mid h) - q_k(n_k - \eta - 1 \mid h)\Big] * \Big[1 - q_j(n_j - \eta \mid h) q_k(n_k - \eta \mid h)\Big] \leq 0 \end{aligned} \quad (28)$$

Operating in (28):

$$\begin{aligned} \sum_\eta \Bigg[q_j(n_j - \eta - 1 \mid h) - q_j(n_j - \eta \mid h)\Bigg] * \Bigg[1 - q_k(n_k - \eta - 1 \mid h)\Big(2 - q_k(n_k - \eta \mid h\Big)\Bigg] \\ + \Bigg[q_k(n_k - \eta - 1 \mid h) - q_k(n_k - \eta \mid h)\Bigg] * \Bigg[1 - q_j(n_j - \eta \mid h)\Big(2 - q_j(n_j - \eta - 1 \mid h\Big)\Bigg] \leq 0 \end{aligned} \quad (29)$$

since $q_j(n_j - \eta - 1 \mid h) \leq q_j(n_j - \eta \mid h) \forall j \in N$ by Claim 1, $\Big[1 - q_k(n_k - \eta - 1 \mid h)\Big(2 - q_k(n_k - \eta \mid h\Big)\Big] \geq 0$ and $\Bigg[1 - q_j(n_j - \eta \mid h)\Big(2 - q_j(n_j - \eta - 1 \mid h\Big)\Bigg] \geq 0$. Consequently, (27) is greater than (26), and $E\big[W_i(g^t) \mid I^i_j(g^t) + I^i_k(g^t) \geq 1] \geq E\big[W_i(g) \mid \; I^i_j(g) + I^i_k(g) \geq 1]$. ■

Table A2: Expected wage of i in function of the status of her neighbors j and k, conditional on $E_i(g) = E_i(g^t) = 1$.

Cases	g^t	g
(1) $\bar{y}_j^1 = 1, \bar{y}_k^1 = 1$	w_0	w_0
(2) $\bar{y}_j^2 = 1, \bar{y}_k^2 = 1$	w_1	w_1
(3) $\bar{y}_j^2 = 1, \bar{y}_k^1 = 1$	$\sum_\eta \frac{\left(1-q_j(n_j-\eta-1\|h)\right)w_1+q_j(n_j-\eta-1\|h)\left(1-q_k(n_k-\eta-1\|h)\right)w_0}{\left[1-q_j(n_j-\eta-1\|h)q_k(n_k-\eta-1\|h)\right]}$	$\sum_\eta \frac{[\left(1-q_j(n_j-\eta\|h)\right)w_1+q_j(n_j-\eta\|h)\left(1-q_k(n_k-\eta\|h)\right)w_0]}{\left[1-q_j(n_j-\eta\|h)q_k(n_k-\eta\|h)\right]}$
(4) $\bar{y}_j^1 = 1, \bar{y}_k^2 = 1$	$\sum_\eta \frac{\left[\left(1-q_k(n_k-\eta-1\|h)\right)w_1+q_k(n_k-\eta-1\|h)\left(1-q_j(n_j-\eta-1\|h)\right)w_0\right]}{\left[1-q_j(n_j-\eta-1\|h)q_k(n_k-\eta-1\|h)\right]}$	$\sum_\eta \frac{\left[\left(1-q_k(n_k-\eta\|h)\right)w_1+q_k(n_k-\eta\|h)*\left(1-q_j(n_j-\eta\|h)\right)w_0\right]}{\left[1-q_j(n_j-\eta\|h)q_k(n_k-\eta\|h)\right]}$
(5) $\bar{y}_j^1 + \bar{y}_j^2 = 0, \bar{y}_k^1 = 1$	w_o	w_o
(6) $\bar{y}_j^1 = 1, \bar{y}_k^1 + \bar{y}_k^2 = 0$	w_o	w_o
(7) $\bar{y}_j^1 + \bar{y}_j^2 = 0, \bar{y}_k^2 = 1$	w_1	w_1
(8) $\bar{y}_j^2 = 1, \bar{y}_k^1 + \bar{y}_k^2 = 0$	w_1	w_1

Note: $\sum_\eta = \sum_{h=0}^{\eta} \binom{\eta}{h} \beta^h (1-\beta)^{\eta-h}$ is an abbreviated form of an expression that conditions on the status of the common neighbors of providers j and k.

A.2 Examples

A.2.1 The role of the initial state

In this subsection, we provide an example showing that the results from the main text are robust to relaxing the assumption of initial full employment. We focus on an initial situation, in which each node is unemployed with probability one half.

To this aim, Table A3 lists the employment probabilities of node 1 for each initial combination of employment status of all the network members in networks g_b and g_c in Figure 2. Assuming that each node is (un)employed with probabilty one half and all the initial states thus have the same probability (i.e., $\frac{1}{8}$ for network g_b and $\frac{1}{16}$ for network g_c), the expected employment probability of node 1 is, in g_b:

$$E_i(g_b) = 4 - 4b + a(1+b)\Big[7 - 3a(-1+b)^2 - (4-b)b - 2a^2(1-b)b\Big],$$

while in network g_c :

$$E_i(g_c) = \frac{1}{2} - \frac{1}{2}b + \frac{1}{16}a\Big[14 - a\Big(\frac{21}{4} + (\frac{3}{2} - \frac{3}{4}a)a\Big) + \Big(6 + (6-4a)a\Big)b \\ -\Big(6 - a(\frac{9}{2} + (3 - \frac{3}{2}a)a)\Big)b^2 + \Big(2 - a(6-4a)\Big)b^3 + \frac{3}{4}(1-a)^2ab^4\Big].$$

It is easy to show that $E_i(g_b) < E_i(g_c)$ for any $a, b \in (0,1)$. Moreover, since all nodes occupy an identical position in both networks, $E(g_b) < E(g_c)$ for any $a, b \in (0,1)$.

Table A3: Employment probability of node 1 for each initial state (s_1, s_2, s_3) in networks g_b and g_c in Figure 2.

Triangle (g_b)		Square (g_c)	
Initial state	Employment probability	Initial state	Employment probability
(1,1,1)	$(1-\beta) + \alpha\beta(2-\alpha-\beta)$	(1,1,1,1)	$(1-\beta) + \alpha\beta\Big(2-\alpha-\beta(1-\frac{3}{4}\alpha)\Big)$
		(1,1,1,0)	$(1-\beta) + \alpha\beta\Big(2-\alpha-(1-a)(1-\frac{3}{4}\alpha)\Big)$
(1,1,0)	$(1-\beta) + \alpha\beta\frac{1}{2}(1+a)$	(1,1,0,1)	$(1-\beta) + \alpha\beta\Big(1-\frac{1}{2}\beta\Big)$
		(1,1,0,0)	$(1-\beta) + \alpha\beta\frac{1}{2}\Big(1+a\Big)$
(1,0,1)	$(1-\beta) + \alpha\beta\frac{1}{2}(1+a)$	(1,0,1,1)	$(1-\beta) + \alpha\beta\Big(1-\frac{1}{2}\beta\Big)$
		(1,0,1,0)	$(1-\beta) + \alpha\beta\frac{1}{2}\Big(1+a\Big)$
(0,1,1)	$a + \alpha(1-a)(2-\alpha-\beta)$	(0,1,1,1)	$a + \alpha(1-a)\Big(2-\alpha-\beta(1-\frac{3}{4}\alpha)\Big)$
		(0,1,1,0)	$a + \alpha(1-a)\Big(2-\alpha-(1-a)(1-\frac{3}{4}\alpha)\Big)$
(1,0,0)	$(1-\beta)$	(1,0,0,1)	$(1-\beta)$
		(1,0,0,0)	$(1-\beta)$
(0,1,0)	$a + \alpha(1-a)\frac{1}{2}(1+a)$	(0,1,0,1)	$a + \alpha(1-a)\Big(1-\frac{1}{2}\beta\Big)$
		(0,1,0,0)	$a + \alpha(1-a)\frac{1}{2}\Big(1+a\Big)$
(0,0,1)	$a + \alpha(1-a)\frac{1}{2}(1+a)$	(0,0,1,1)	$a + \alpha(1-a)\Big(1-\frac{1}{2}\beta\Big)$
		(0,0,1,0)	$a + \alpha(1-a)\frac{1}{2}\Big(1+a\Big)$
(0,0,0)	a	(0,0,0,1)	a
		(0,0,0,0)	a

A.2.2 Example 1

Consider agent 1 in networks g_b, g_c, g_e, and g_f depicted in Figure 2. Focus first on networks g_b and g_e; in both networks, $n_1(g_b) = n_1(g_e) = 2$ and $n_1^2(g_b) = n_1^2(g_e) = 2$. Hence, 1's neighborhood and second-order neighborhoods are equally sized. However, the link 23 generates a three-cycle in g_b, which has important consequences for the flow of information from nodes 2 and 3 to agent 1. More precisely, the probability that node 1 receives an offer from one particular neighbor can be expressed as the dot product of two vectors: (i) a vector of the probabilities of the different status combinations of 1's neighbors 2 and 3, and (ii) a vector of the probabilities that 1 receives an offer for each combination. Let

$$\Phi = [\alpha^2,\, \alpha\beta,\, \beta\alpha,\, \alpha(1-\alpha-\beta),\, (1-\alpha-\beta)\alpha,\, (1-\alpha-\beta)^2,\, \beta^2,\, \beta(1-\alpha-\beta),\; (1-\alpha-\beta)\beta]$$

denote the first vector. For example, α^2 is the probability that both neighbors are i's potential providers.

Then, the expected probability of receiving information about a vacancy from, say, *neighbor 2* in networks g_b and g_e is

$$P_2^1(g_b) = P_2^1(g_e) = \Phi * [1, \frac{1}{2}, 0, 1, 0, 0, 0, 0, 0]' = \alpha^2 + \frac{1}{2}\alpha\beta + \alpha(1-\alpha-\beta) = \alpha(1-\frac{\beta}{2}),$$

where Φ are the probabilities of the combined states of nodes 2 and 3 in g_b and 2 and 4 in g_e. Analogously, the probability of getting an offer *from neighbor 3* is:

$$P_3^1(g_b) = P_3^1(g_e) = \Phi * [1, \frac{1}{2}, 0, 1, 0, 0, 0, 0, 0]' = \alpha(1-\frac{\beta}{2}),$$

where Φ are the probabilities of the combined states of 3 and 2 in g_b and 3 and 5 in g_e. The probabilities P_2^1 and P_3^1 are the identical in networks g_b and g_e. However, when we compute the expected probability that agent 1 receives *at least one offer* from her contacts 2 and 3, $P^1(g_b) \neq P^1(g_e)$. First,

$$P^1(g_b) = \Phi * [1, \frac{1}{2}, \frac{1}{2}, 1, 1, 0, 0, 0, 0]' = \alpha^2 + \alpha\beta + 2\alpha(1-\alpha-\beta) = \alpha(2-\alpha-\beta)$$

where Φ are the probabilities of the combined states of 2 and 3 in g_b.

Note that $P_3^1(g_b)(1-P_2^1(g_b)) + P_2^1(g_b)(1-P_3^1(g_b)) + P_2^1(g_b)P_3^1(g_b) = P^1(g_b) + \alpha^2(\beta - \frac{\beta^2}{4}) > P^1(g_b)$. That is, we cannot compute $P^1(g_b)$ directly from $P_2^1(g_b)$ and $P_3^1(g_b)$ because information flows from 2 and 3 to 1 are not independent in g_b.

In contrast, in network g_e,

$$P^1(g_e) = \alpha^2\Phi * [1, 1, 1, 1, 1, 1, \frac{3}{4}, 1, 1]' + \alpha(1-\alpha)\Phi * [1, 1, \frac{1}{2}, 1, 1, 1, \frac{1}{2}, \frac{1}{2}, 1]' +$$
$$+ (1-\alpha)\alpha\Phi * [1, \frac{1}{2}, 1, 1, 1, 1, \frac{1}{2}, 1, \frac{1}{2}]' = \alpha(1-\frac{\beta}{2})[2-\alpha(1-\frac{\beta}{2})],$$

where Φ are the probabilities of the combined states of nodes 4 and 5 in g_e. In such a case, the information flows are independent as $P_3^1(g_e)(1-P_2^1(g_e)) + P_2^1(g_e)(1-P_3^1(g_e)) + P_2^1(g_e)P_3^1(g_e) = P^1(g_e) = 2\alpha(1-\frac{\beta}{2}) - \alpha^2(1-\frac{\beta}{2})^2$.

Most importantly, note that $P^1(g_e) - P^1(g_b) = \alpha^2(\beta - \frac{\beta^2}{4}) > 0$. That is, g_b provides a lower expected probability of receiving a job offer through the network than g_e as a consequence of the lack of independence in information flows.

Consider network g_f, in which node 1 has one competitor mode in this network, node 6, than in g_e. Formally, $P_2^1(g_f) = P_2^1(g_b) = P_2^1(g_e) = \alpha(1-\frac{\beta}{2})$, but

$$P_3^1(g_f) = \alpha\Phi * [1, \frac{1}{2}, \frac{1}{2}, 1, 1, 1, \frac{1}{3}, \frac{1}{2}, \frac{1}{2}]' = \alpha[1-\beta(1-\frac{\beta}{3})],$$

where Φ are the probabilities of the combined states of nodes 5 and 6 in g_f. Consequently, $P_3^1(g_f) < P_3^1(g_b) = P_3^1(g_e) = \alpha(1-\frac{\beta}{2})$. Moreover, since the information flows from nodes 2 and 3 to agent 1 are independent,

$$P^1(g_f) = \alpha(1-\frac{\beta}{2}) + [\alpha - \alpha^2(1-\frac{\beta}{2})][1-\beta(1-\frac{\beta}{3})],$$

implying that $P^1(g_f) < P^1(g_e)$.

Table A4: Employment prospects for parameter values $\beta = 0.01$, $\alpha = 0.9$ (panel A on the left) and $\beta = 0.1$, $\alpha = 0.8$ (panel B on the right)

A	g_b	g_f	g_c	g_e	B	g_b	g_f	g_c	g_e
P_2^1	0.8955	0.8955	0.8955	0.8955	P_2^1	0.7600	0.7600	0.7600	0.7600
P_3^1	0.8955	0.8909	0.8955	0.8955	P_3^1	0.7600	0.7109	0.7600	0.7600
P^1	0.9810	0.9886	0.9871	0.9891	P^1	0.8800	0.9306	0.9280	0.9424

In general, $P^1(g_f)$ may be higher or lower than $P^1(g_b)$. Table A4 illustrates the probabilities, with which node 1 receives job offers from her neighbors in the four networks for different parameter values; note that, as a consequence of the triangle in g_b, node 1 may have better employment prospects in g_f than in g_b even though node 1 has more competitors in g_f.

Finally, let us compare networks g_c and g_e. Again, $n_1(g_c) = n_1(g_e) = 2$ but $n_1^2(g_c) = 1 < n_1^2(g_e) = 2$, which in principle should yield better employment prospects for node 1in g_c than in g_e due to the lower number of potential competitors. The probability of getting information about a job offer *from neighbor 2* in g_c is

$$P_2^1(g_c) = \Phi * [1, \frac{1}{2}, 0, 1, 0, 0, 0, 0, 0]' = \alpha(1 - \frac{\beta}{2}),$$

where Φ are the probabilities of the combined states of nodes 2 and 4 in g_c. Thus, $P_2^1(g_f) = P_2^1(g_b) = P_2^1(g_e) = P_2^1(g_c)$. Similarly, $P_3^1(g_b) = P_3^1(g_e) = P_3^1(g_c) = \alpha(1 - \frac{\beta}{2})$. Therefore,

$$P^1(g_c) = \beta\Phi * [\frac{3}{4}, \frac{1}{2}, \frac{1}{2}, \frac{1}{2}, \frac{1}{2}, 0, 0, 0, 0] + (1-\beta)\Phi * [1, 1, 1, 1, 1, 0, 0, 0, 0] = \alpha(2 - \alpha - \beta + \frac{3}{4}\alpha\beta),$$

being Φ the vector of the probabilities of the combined states of nodes 2 and 3 in g_c.

Thus, $P_1(g_c) < P_1(g_e)$, i.e. in contrast to the results in Calvó-Armengol (2004), node 1 is more likely to receive a job offer through the network in g_e despite the lower number of indirect contacts in g_c. Table A5 shows the probabilities of receiving two, one or no offers.

A.2.3 Example 2

Consider networks g and g' in Figure 4. Both networks have the same degree distribution and the distribution of second-order degree, but the joint first- and second-order distribution differ. For example, $n_1(g) = n_1(g') = 2$ but $n_1^2(g) = 4$ but $n_1^2(g') = 3$. Moreover, $S(g') = \{1, 2, 3\}$ but $S(g) = \emptyset$. That is, $S(g') = S(g) \cup \{1, 2, 3\}$ as in Proposition 2.

(i) Network g**.** Since $R_3^1(g) = R_4^1(g) = \alpha q_3(n_3) + (1-\alpha) = 1 - \alpha + \alpha\left[(1-\beta)\beta + \frac{2\beta^2}{3})\right]$, the probability with which 1 receives at least one offer from her neighbors in network g is:

$$P^1(g) = 1 - \left[1 - \alpha + \alpha\left[(1-\beta)\beta + \frac{2\beta^2}{3}\right]\right]^2$$

The probability that node 2 does not receive information from her neighbor $8 \in N_2(g)$ is $R_8^2(g) = (1-\alpha)$, while the probability she does not receive information from $4 \in N_2(g)$ is $R_4^2(g) = R_3^1(g)$. As a result,

$$P^2(g) = 1 - R_8^2(g)R_4^2(g) = 1 - (1-\alpha)\left[1 - \alpha + \alpha\left[(1-\beta)\beta + \frac{2\beta^2}{3}\right]\right].$$

Consider agent 3. The probability that she does not receive information from her neighbor 1 is $R_1^3(g) = \alpha q_1(n_1) + (1-\alpha) = 1 - \alpha\left[(1 - \frac{1}{2}\beta)\right]$, while $R_5^3(g) = R_6^3(g) = (1-\alpha)$. Then, agent 3 receives information from

Table A5: The probabilities of job offers from 1's neighbors to node 1 in the different networks from Example 1

Example 1	pr. 2 offers in network		
Φ	g_b	g_e	g_c
α^2	1	(1-$\frac{\beta}{2})^2$	$(1-\beta)+\frac{\beta}{4}$
$\alpha\beta$	0	0	0
$\beta\alpha$	0	0	0
$\alpha(1-\alpha-\beta)$	0	0	0
(1-$\alpha-\beta)\alpha$	0	0	0
(1-$\alpha)^2$	0	0	0

Example 1	pr. 1 offer in network		
Φ	g_b	g_e	g_c
α^2	0	β(1-$\frac{\beta}{2}$)	$\frac{\beta}{2}$
$\alpha\beta$	$\frac{1}{2}$	(1-$\frac{\beta}{2}$)	(1-$\frac{\beta}{2}$)
$\beta\alpha$	$\frac{1}{2}$	(1-$\frac{\beta}{2}$)	(1-$\frac{\beta}{2}$)
$\alpha(1-\alpha-\beta)$	1	(1-$\frac{\beta}{2}$)	(1-$\frac{\beta}{2}$)
(1-$\alpha-\beta)\alpha$	1	(1-$\frac{\beta}{2}$)	(1-$\frac{\beta}{2}$)
(1-$\alpha)^2$	0	0	0

Example 1	pr. 0 offers in network		
Φ	g_b	g_e	g_c
α^2	0	$\frac{\beta^2}{4}$	$\frac{\beta}{4}$
$\alpha\beta$	$\frac{1}{2}$	$\frac{\beta}{2}$	$\frac{\beta}{2}$
$\beta\alpha$	$\frac{1}{2}$	$\frac{\beta}{2}$	$\frac{\beta}{2}$
$\alpha(1-\alpha-\beta)$	0	$\frac{\beta}{2}$	$\frac{\beta}{2}$
(1-$\alpha-\beta)\alpha$	0	$\frac{\beta}{2}$	$\frac{\beta}{2}$
(1-$\alpha)^2$	1	1	1

her contacts with probability:

$$P^3(g) = 1 - R^3_1(g)R^3_5(g)R^3_6(g) = 1 - (1-\alpha)^2\left[1 - \alpha + \frac{\alpha\beta}{2}\right]$$

Agent 4 does not receives information from $7 \in N_4(g)$ with probability $R^4_7(g)$ =$(1-\alpha)$, while $R^4_1(g)$=$R^4_2(g) = R^3_1(g)$. Thereby,

$$P^4(g) = 1 - R^4_1(g)R^4_2(g)R^4_7(g) = 1 - (1-\alpha)\left[1 - \alpha + \frac{\alpha\beta}{2}\right]^2.$$

The probability that node 5 does not receive information from her only neighbor $3 \in N_5(g)$ is $1 - R^5_3(g)$, with $R^5_3(g)$=$R^1_3(g)$. Henceforth, $P^5(g) = \alpha - \alpha\left[(1-\beta)\beta + \frac{2\beta^2}{3}\right]$ and $P^5(g)$=$P^6(g)$=$P^7(g)$. Similarly, since $R^8_2(g) = R^4_2(g) = R^3_1(g)$, $P^8(g) = 1 - R^8_2(g) = \alpha - \frac{\alpha\beta}{2}$ and $P^8(g)$=$P^{11}(g)$=$P^{12}(g)$=$P^{13}(g)$=$P^{14}(g)$. Last, $P^9(g)$=$P^{10}(g)$=$1-(1-\alpha)^2$.

(ii) Network g'. Information flows from nodes 2 and 3 to 1 are affiliated, since $\{1,2,3\} \in S(g')$. The probability that provider 2 does not transmit information to 1 is $\frac{1}{2}$ when $y^2_3(g') = 1$ (3 is i's competitor) and 0 when $y^2_3(g') = 0$. Conditional on $y^2_2(g') = 1$ (2 is a competitor), the probability that node 3 does not transmits information to 1 is $q_3(n_3 - 1 \mid y^2_2(g') = 1) = \frac{2}{3}\beta + (1-\beta)\frac{1}{2}$=$\frac{1}{2}$+$\frac{\beta}{6}$. Analogously, $q_3(n_3 - 1 \mid y^2_2(g') = 0) = \frac{1}{2}\beta$ is the probability that provider 3 does not transmit information to 1, conditional on $y^2_2(g') = 0$.

Let $\Phi = [\alpha^2, \alpha\beta, \beta\alpha, \alpha(1-\alpha-\beta), (1-\alpha-\beta)\alpha, (1-\alpha-\beta)^2, \beta^2, \beta(1-\alpha-\beta), (1-\alpha-\beta)\beta]$ be the vector of probabilities of all relevant combined states of 2 and 3. Then, the probability that 1 does not receive any offer from 2 or 3 can be expressed as the dot product of Φ and the vector of the probabilities that 1 does not receive any offer in each joint state:

$$R^1_{23}(g') = \Phi * [0, \frac{1}{2}, q_3(n_3 - 1 \mid 1), 0, q_3(n_3 - 1 \mid 0), 1, 1, 1, 1]' = 1 + \alpha^2\left(1 - \frac{\beta}{2}\right) - \alpha\left(2 - \frac{3}{2}\beta + \frac{1}{3}\beta^2\right).$$

Therefore, the probability that 1 receives at least one offer in g' is:

$$P^1(g') = 1 - R^1_{23}(g') = \alpha\left(2 - \frac{3}{2}\beta + \frac{1}{3}\beta^2\right) - \alpha^2\left(1 - \frac{\beta}{2}\right) = P^2(g')$$

by symmetry of 1's and 2's positions.

Consider agent 3. The probability that provider 1(2) does not pass information to 3 when 2(1) is in state 2 is $\frac{1}{2}$ and 0 when 2(1) is not in such a state. Then,

$$R^3_{12}(g') = \Phi * [0, \frac{1}{2}, \frac{1}{2}, 0, 0, 1, 1, 1, 1]' = \alpha\beta + (1-\alpha)^2.$$

Since $R^3_4(g')$=$R^1_3(g)$,

$$P^3(g') = 1 - R^3_{12}(g')R^3_4(g') = 1 - \left[(1-\alpha)^2 + \alpha\beta\right]\left[1 - \alpha + \alpha\left((1-\beta)\beta + \frac{2\beta^2}{3}\right)\right].$$

Observe that $R^4_3(g')$=$R^1_3(g)$, and $R^4_5(g')$=$R^6_5(g')$=$(1-\alpha)$. Hence,

$$P^4(g') = 1 - R^4_3(g')R^4_5(g')R^4_6(g') = 1 - (1-\alpha)^2\left[(1-\alpha) + \alpha\left((1-\beta)\beta + \frac{2\beta^2}{3}\right)\right].$$

As for agent 9, the likelihood that she does not receive information from $10 \in N_9(g')$ is $R^9_{10}(g')$=$R^3_1(g)$, while the probability that she does not receive information from $11 \in N_9(g')$ is $R^{11}_9(g)$=$(1-\alpha)$. This implies that

$$P^9(g') = 1 - R^9_{10}(g)R^9_{11}(g') = 1 - (1-\alpha)\left[1 - \alpha\left(1 - \frac{\beta}{2}\right)\right]$$

Table A6: Employment probability for $a = 0.1, b = 0.2$ in Example 2

Node	$P^i(g)$	$E^i(g)$	$P^i(g')$	$E^i(g')$
1	0.128511	0.843132	0.133440	0.844019
2	0.141147	0.845406	0.133440	0.844019
3	0.215218	0.858739	0.196412	0.855354
4	0.209076	0.857634	0.209855	0.857773
5	0.066464	0.831964	0.066464	0.831964
6	0.066464	0.831964	0.066464	0.831964
7	0.066464	0.831964	0.080000	0.834400
8	0.072800	0.833104	0.080000	0.834400
9	0.153600	0.847648	0.146968	0.846454
10	0.153600	0.847648	0.146968	0.846454
11	0.072800	0.833104	0.072800	0.833104
12	0.072800	0.833104	0.072800	0.833104
13	0.072800	0.833104	0.080000	0.834400
14	0.072800	0.833104	0.080000	0.834400
Aver.	1.564544	0.840116	1.565610	0.840129

and $P^9(g')=P^{10}(g')$ by symmetry. Finally, note that $P^5(g')=P^6(g')=P^5(g)=P^6(g)$, $P^7(g')=P^8(g')=P^{13}(g')=P^{14}(g')=\alpha$, and $P^{11}(g')=P^{12}(g')=P^{11}(g)=P^{12}(g)$.

Table A6 summarizes the employment probabilities of each node for $a = 0.1$ and $b = 0.2$, the values in Example 2. The employment probability of node i is computed as $E^i(g) = (1-\beta) + \beta P^i(g)$, while $E(g) = \frac{1}{n}\sum_{i\in N} E_i(g)$.

A.2.4 Computation of probabilities for Table 1

First, note that since $S_S(g) = \emptyset$, $R_{jk}(g) = R_j(g)R_k(g)$. Formally,

$$R_{jk}(g) = \alpha^2 q_j(n_j)q_k(n_k) + \alpha(1-\alpha)q_j(n_j) + \alpha(1-\alpha)q_k(n_k) + (1-\alpha)^2,$$

considering the four possible cases (both j and k are providers, only j is a provider, only k is a provider and none of them is a provider) and their corresponding probabilities.

If $S_S(g) = \{i, j, k\}$ as in g^t, the probability that i does not receive any offer from provider j conditional on y_k^2 is

$$q_j(n_j - 1 \mid y_k^2) = \sum_{h=0}^{n_j-2} \binom{n_j-2}{h} \beta^h (1-\beta)^{n_j-2} \left(\frac{h + y_k^2}{h + y_k^2 + 1}\right).$$

With this expression in and, we compute $R_{jk}(g^t)$. The probability that i does not receive an offer from j when j is a provider but k is not, depends on whether k is a competitor or not, and the same holds for he probability that i does not receive an offer from k when k is a provider but j is not. There are six cases to consider: (1) both j and k are providers; (2) j is a provider and k a competitor, (3) k is a provider and j a competitor; cases (4) abd (5) in which one is a provider and the other neither a provider nor a competitor (i.e. in state 3 or 4, event that occurs with probability $\delta + \gamma = 1 - \alpha - \beta$); and (6) neither j nor k are providers:

$$\begin{aligned} R_{jk}(g^t) = {} & \alpha^2 q_j(n_j - 1 \mid y_k^2 = 0) q_k(n_k - 1 \mid y_j^2 = 0) + \alpha\beta q_j(n_j - 1 \mid y_k^2 = 1) + \alpha(1-\alpha-\beta) q_j(n_j - 1 \mid y_k^2 = 0) \\ & + \alpha\beta q_k(n_k - 1 \mid y_j^2 = 1) + \alpha(1-\alpha-\beta) q_k(n_k - 1 \mid y_j^2 = 0) + (1-\alpha)^2 = \end{aligned}$$

$$\begin{aligned} & = \alpha^2 q_j(n_j - 1 \mid y_k^2 = 0) q_k(n_k - 1 \mid y_j^2 = 0) \\ & + \alpha\beta q_j(n_j - 1 \mid y_k^2 = 1) + \alpha(1-\beta) q_j(n_j - 1 \mid y_k^2 = 0) - \alpha^2 q_j(n_j - 1 \mid y_k^2 = 0) + \\ & + \alpha\beta q_k(n_k - 1 \mid y_j^2 = 1) + \alpha(1-\beta) q_k(n_k - 1 \mid y_j^2 = 0) - \alpha^2 q_k(n_k - 1 \mid y_j^2 = 0) + (1-\alpha)^2. \end{aligned}$$

Given that $\beta q_j(n_j - 1 \mid y_k^2 = 1) + (1-\beta) q_j(n_j - 1 \mid y_k^2 = 0) = q(n_j)$ and $q_j(n_j - 1 \mid y_k^2 = 0) = q_j(n_j - 1)$, the above probability simplifies to

$$R_{jk}(g^t) = [\alpha^2 q_j(n_j - 1) q_k(n_k - 1)] + [\alpha q_j(n_j) - \alpha^2 q_j(n_j - 1)] + [\alpha q_k(n_k) - \alpha^2 q_k(n_k - 1)] + [(1-\alpha)^2],$$

where each term in brackets corresponds to the probability that i does not receive any offer in each of the four cases in column labeled as g^t in Table 1.

Adding up all the rows of the last column in Table 1, we obtain that

$$R_{jk}(g^t) - R_j(g) R_k(g) = \alpha^2 \Big[\Big(q_j(n_j) - q_j(n_j - 1) \Big) \Big(1 - q_k(n_k - 1) \Big) + \Big(q_k(n_k) - q_k(n_k - 1) \Big) \Big(1 - q_j(n_j) \Big) \Big] > 0$$

because both $q_j(n_j)$ and $q_k(n_k)$ increase in their arguments by Lemma 1. Therefore, $P^i(g) > P^i(g^t)$.

A.3 Additional Material for the Dynamic Analysis

A.3.1 Real-life network

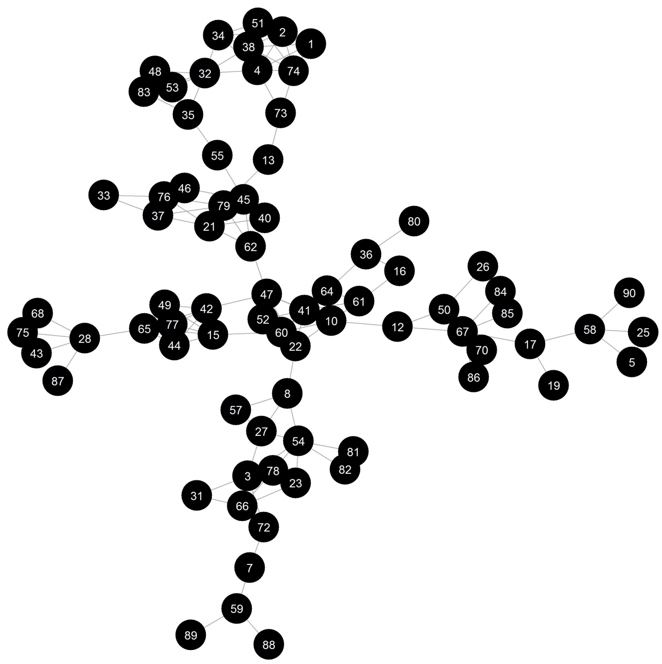


Figure A1: Giant component of the friendship network from Brañas et al. (2010).

Table A7: Average unemployment in the last 1000 periods. Real-world network: OLS. People with well defined clustering.

	Dependent variable:					
	average.e					
	(1)	(2)	(3)	(4)	(5)	(6)
degree		0.027***		0.029***	0.028***	0.029***
		(0.0003)		(0.0003)	(0.0003)	(0.0003)
second_degree			0.006***	−0.008***	−0.008***	−0.007***
			(0.001)	(0.0004)	(0.0004)	(0.0004)
clustering	−0.032***	−0.018***	−0.041***	−0.006***	−0.004*	−0.005***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Betweenness					0.00000**	
					(0.00000)	
eigenvector						−0.010***
						(0.002)
Constant	0.767***	0.639***	0.744***	0.662***	0.662***	0.658***
	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Observations	6,300	6,300	6,300	6,300	6,300	6,300
R^2	0.033	0.629	0.045	0.648	0.648	0.650
Adjusted R^2	0.033	0.629	0.045	0.648	0.648	0.650
Note:				*p<0.1; **p<0.05; ***p<0.01		

Table A8: Standard deviation of (un)employment in the last 1000 periods. Real-world network: OLS. People with well defined clustering.

	Dependent variable:					
	st.dev.E					
	(1)	(2)	(3)	(4)	(5)	(6)
degree		−0.001***		−0.001***	−0.001***	−0.001***
		(0.0001)		(0.0001)	(0.0001)	(0.0001)
second_degree			0.0004***	0.001***	0.001***	0.001***
			(0.0001)	(0.0001)	(0.0001)	(0.0001)
clustering	0.003***	0.003***	0.002***	0.001***	0.0005+	0.001***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
betweenness					−0.00000***	
					(0.00000)	
eigenvector						−0.00003
						(0.0003)
average.e	−0.561***	−0.541***	−0.562***	−0.535***	−0.535***	−0.535***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Constant	0.847***	0.836***	0.847***	0.830***	0.830***	0.830***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Observations	6,300	6,300	6,300	6,300	6,300	6,300
R^2	0.962	0.963	0.962	0.964	0.964	0.964
Adjusted R^2	0.962	0.963	0.962	0.964	0.964	0.964

Note: robust standard errors clustered at realizations; *p<0.1; **p<0.05; ***p<0.01; $^+p = 0.1139$

Table A9: Serial correlation in the last 1000 periods. Real-world network: OLS. People with well defined clustering.

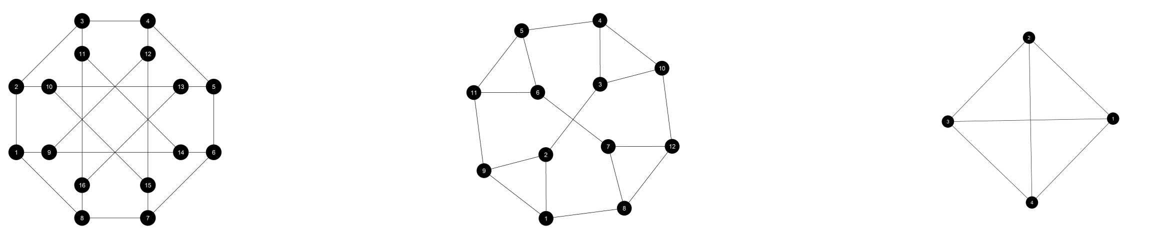
	Dependent variable:					
	time.corr					
	(1)	(2)	(3)	(4)	(5)	(6)
degree		−0.009***		−0.011***	−0.011***	−0.011***
		(0.0003)		(0.0004)	(0.0004)	(0.0004)
second_degree			−0.0002	0.004***	0.004***	0.003***
			(0.0004)	(0.0004)	(0.0004)	(0.0004)
clustering	0.015***	0.017***	0.015***	0.012***	0.009***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
betweenness					−0.00000***	
					(0.00000)	
eigenvector						0.005***
						(0.002)
average.e	−0.620***	−0.405***	−0.620***	−0.383***	−0.382***	−0.381***
	(0.007)	(0.010)	(0.007)	(0.010)	(0.010)	(0.010)
Constant	1.150***	1.030***	1.151***	1.005***	1.005***	1.005***
	(0.005)	(0.007)	(0.005)	(0.007)	(0.007)	(0.007)
Observations	6,300	6,300	6,300	6,300	6,300	6,300
R^2	0.607	0.648	0.607	0.653	0.654	0.654
Adjusted R^2	0.607	0.648	0.607	0.653	0.653	0.653
Note:						*p<0.1; **p<0.05; ***p<0.01

A.3.2 Steady state results for vertex-transitive networks

Here, we present more details regarding the analysis of Section 4.3. First of all, Figure A2 presents the three network under study if $n_i(g) = 3$ and Figure A3 those for $n_i(g) = 4$.

In Figure A2, each node has three links. In (a) and (b), each node has six neighbors of neighbors while $n_i^2(g_{(c)}) = 3$. As for cycles, there is neither any triangle or square in (a), each node is involved in one triangle but no square in (b), whereas $C_i(g_{(c)}) = 1$ for each i and everybody belongs to one four-cycle. Network (c) presents the only feasible degree-three vertex-transitive network with more than one triangle per person. Hence, any differences between (a) and (b) can be attributed to short cycles, but the comparison of (a) and (b) with (c) is more complex. People belong to more short cycles, but they have three competitors less. Table A10 reports the results of the simulations using these networks.

In Figure A3, each node has degree four and, in networks (a), (b), and (c), second-order degree equal to eight while $n_i^2(g_{(c)}) = 8$. Network (c) is not vertex-transitive. All members have identical local position, but the nodes in the interior of the circle are slightly more globally central than those in the periphery in the figure. We constructed a corresponding vertex-transitive network satisfying the above conditions, but the network (c) resembles more the networks (a) and (b) in the presence of cycles of longer length. We thus opted for network (c) in our comparison. There is neither any triangle or square in (a), each node is involved in two or three triangles but no square in (b) and (c),[2] whereas $C_i(g_{(d)}) = 1$ (six triangles) for each i and everybody belongs to three four-cycles and one five-cycle. Network (d) presents the only feasible network with $n_i(g) = 4$ and $C(g) = 1$. Hence, networks (a), (b), and (c) enable a clean comparison with respect to short network cycles, whereas the comparison of these networks with (d) is more complex. Table A11 reports the results of the simulations using these networks.



(a) No triangle

(b) One triangle

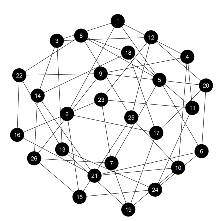
(c) Three triangles; $n = 4$

Figure A2: Vertex-transitive networks with $n_i(g) = 3$ for each i but varying clustering.

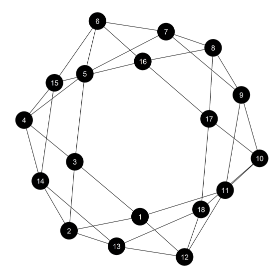
[2]We did not achieve to construct a finite vertex-transitive network with $n_i(g) = 4$ and one triangle for each node.

	Networks		
	No cycle	One cycle	Three cycles
A. Employment statistics			
Net. nodes:	48	48	48
Num. economies:	100	100	100
Num. networks:	100	100	100
Employment rate:	0.7362	0.7296	0.7157
St.Dev.	0.0783	0.0786	0.0784
Coef.variation.	0.1064	0.1077	0.1096
B. Time and spatial correlations			
Correlation(t-1,t):	0.7953	0.7979	0.8015
Correlation(t-2,t):	0.6326	0.6391	0.6469
Simple-Matching coef. (1st neighb.):	0.6455	0.6471	0.6580
Simple-matching coef. (2nd neighb.):	0.6294	0.6215	-
C. Transition rates in the last 1000 periods (out of 10000):			
Fraction keeping employed:	0.6797	0.6734	0.6607
Fraction keeping unemployed:	0.2072	0.2143	0.2293
Fraction lost job:	0.0565	0.0562	0.0550
Fraction found job:	0.0566	0.0562	0.0550
Conditional: EE/(EU+EE)	0.9232	0.9230	0.9232
Conditional: UU/(UE+UU)	0.7856	0.7924	0.8067
D. Kolmogorov-Smirnov, Wilcoxon and, Fligner-Killeen tests			
	D (p)	W (p)	χ^2 (p)
No vs. one cycle	0.0359 (0.0000)	5244320870 (0.0000)	35.6311 (0.2204)
No vs. three cycles	0.1098 (0.0000)	5744366450 (0.0000)	41.5442 (0.0978)
One vs. three cycles	0.0739 (0.0000)	5501532003 (0.0000)	25.5408 (0.7430)

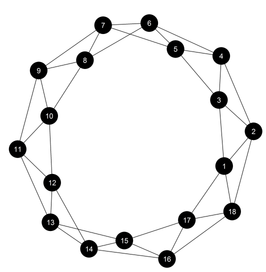
Table A10: Labor-market statistics in vertex-transitive networks with $n_i(g) = 3$ and varying clustering.



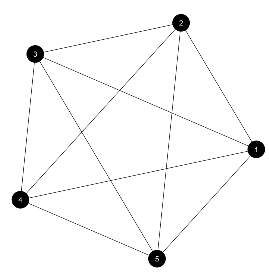
(a) No triangle



(b) Two triangles



(c) Three triangles



(d) Six triangles

Figure A3: Vertex-transitive networks with $n_i(g) = 4$ for each i but varying clustering.

	Networks			
	No cycle	Two cycle	Three cycles	All cycles
A. Employment statistics				
Net. size:	234	234	234	235
Num. economies:	100	100	100	100
Employment rate:	0.7650	0.7588	0.7536	0.7384
St.Dev.	0.0356	0.0354	0.03573	0.03593
Coef.variation.	0.0465	0.0466	0.0474	0.0487
B. Time and spatial correlations				
Correlation(t-1,t):	0.7898	0.7924	0.7947	0.8038
Correlation(t-2,t):	0.6259	0.6278	0.6335	0.6492
Correlation(t-3,t):	0.4965	0.4976	0.5049	0.5265
Correlation(t-4,t):	0.3966	0.3950	0.4048	0.4280
Correlation(t-5,t):	0.3157	0.3161	0.3241	0.3494
Correlation(t-6,t):	0.2501	0.2535	0.2592	0.2851
Correlation(t-7,t):	0.1988	0.2039	0.2069	0.2317
Correlation(t-8,t):	0.1581	0.1639	0.1647	0.1893
Correlation(t-9,t):	0.1269	0.1325	0.1310	0.1538
Correlation(t-10,t):	0.1009	0.1096	0.1058	0.1267
Average SM (1st neighbors):	0.6624	0.6414	0.6664	0.6702
Average SM (2nd neighbors):	0.6496	0.6434	0.6431	-
C. Transition rates:				
Fraction keeping employed:	0.7082	0.7025	0.6977	0.6837
Fraction keeping unemployed:	0.1781	0.1850	0.1904	0.2068
Fraction lost job:	0.0568	0.0562	0.0559	0.0548
Fraction found job:	0.0568	0.05621	0.0559	0.0548
Conditional: EE/(EU+EE)	0.9257	0.9259	0.9258	0.9258
Conditional: UU/(UE+UU)	0.7581	0.7670	0.7729	0.7906
D. Kolmogorov-Smirnov, Wilcoxon, and Fligner-Killeen tests				
	D (p)	W (p)	χ^2 (p)	
No vs. two cycles	0.0731 (0.0000)	5501702434 (0.0000)	70.2851 (0.3682)	
No vs. three cycles	0.1293 (0.0000)	5895907351 (0.0000)	61.7178 (0.7494)	
No vs. all cycles	0.3019 (0.0000)	6932782427 (0.0000)	79.6833 (0.2247)	
Two vs. three cycles	0.0581 (0.0000)	5404198927 (0.0000)	69.7969 (0.4844)	
Two vs. all cycles	0.2363 (0.0000)	6488505634 (0.0000)	95.0611 (0.0299)	
Three vs. all cycles	0.1800 (0.0000)	6102184061 (0.0000)	72.3739 (0.4323)	

Table A11: Labor-market statistics in vertex-transitive networks with $n_i(g) = 4$ but varying clustering.