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Network Industry*

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Knowledge Dynamics in a Network Industry[*]

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Abstract

In this paper, we model the impact of networks on knowledge growth in an innovating industry. Specifically, we compare two mediums of knowledge exchange; random interaction, and the case in which interaction occurs on a fixed architecture. In a simulation study, we investigate how the medium of knowledge exchange contributes to knowledge growth under different scenarios related to the industry's innovative potential. We measure innovative potential by considering the extent to which knowledge can be codified, and the available technological opportunities. Our results tend to support the conjecture that spatial clustering generates higher long run knowledge growth rates in industries characterized by highly tacit knowledge, while the opposite is true when the degree of codification is important.

Key Words: Network, Network Industry, Clustering, Innovation, Knowledge.

1   Introduction

In recent years, work on technical change has emphasized the importance of information flows and transfers. At the same time, research on the economics of knowledge has changed our view from that of the early 1960s. We no longer think of knowledge as a public good, easily reproduced and diffused; knowledge is now considered at best a quasi-public good, and reproduction and diffusion are non-trivial activities. Thus there has been concern with mechanisms and structures that impinge on knowledge transmission. These concerns have prompted two important ideas about how to promote knowledge production and circulation,

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namely clustering or agglomeration of inventive activities; and the localization of technical change. In a sense both of these approaches are driven by the same concerns regarding critical masses of researchers, epistemic communities who can share knowledge easily, and the importance of absorptive capacity for knowledge acquisition.

Knowledge spillovers, the existence of local factor endowments, specialized financial and legal facilities all favour the localization of knowledge diffusion. Numerous studies on clustering find that geographical proximity tends to facilitate innovation, and one of the most important factors is knowledge spillovers [1]. Jaffe et al. [2], Baptista [3] and Baptista and Swann [4] all show empirically that diffusion of knowledge is faster within geographical clusters.[1] But the value of clustering is also a function of the characteristics of the knowledge base. The propensity to cluster tends to be higher in industries where knowledge is more tacit, since in these situations the transmission of knowledge requires repeated, face-to-face contacts [6]. This observation is connected with industry life cycles, since it is generally accepted that in the early phases of the industry life cycle, knowledge is less codified, so face-to-face interaction tends to facilitate its transmission [7]. Empirical research also suggests that the propensity to cluster in the early stages of the life cycle can be higher [8]. The key in both ideas has to do with the ability of an agent to learn and integrate knowledge that is available. This "absorptive capacity" depends on factors like the level of prior knowledge, the degree of codification, and the extent to which the sender and receiver share tacit knowledge. (On these issues see for example Refs [9-11]).

The value of absorbing knowledge is two-fold. It increases an agent's knowledge stock directly, and it provides the agent with new knowledge that can be combined with his/her existing knowledge.[2] This fits with recent descriptions of the innovative process as recombination of a firm's existing knowledge.[3] But if recombination of a firm's existing knowledge can spur innovation, so much the more can the combination of new knowledge with existing knowledge (on this, see Antonelli [18]). If innovation is driven by recombination, spurred

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[1] For a survey on these issues, see Feldman [5].

[2] See Kogut and Zander [12] on what they refer to as "combinative capability".

[3] A concrete manifestation of this process is the architectural innovation as defined by Henderson and Clark [13]. As we use it here, however, the innovation process is more general in the sense that it encompasses generation of new knowledge, products or processes whereas architectural innovation is defined by "reconfiguration of an established system to link together existing components in a new way".(See for example, Refs [13-17])

by the diffusion of knowledge, it is clear why concern about improving knowledge flows among innovating agents has increased in recent years, and has prompted interest in both clustering and networking.

Positive externalities from agglomeration provide incentives for clustering, but negative externalities, such as increased congestion, can also exist [19]. In addition, the rapid developments in information and communication technologies are clearly carrying knowledge diffusion to a more global scale. The more codified is the knowledge base of the industry, the weaker is the need for geographical proximity to ensure efficient diffusion of knowledge and thus the efficient recombination in innovation. Thus localization of innovative activity may not, in all cases, be the most effective way to guarantee efficient knowledge transmission and in turn the innovative potential of agents.

Regardless of the scope of the diffusion, whether local or global, knowledge networks are the main means through which diffusion is realised. Diffusion occurs through interaction, and thus the structure of the network over which agents interact obviously influences the extent of diffusion, and thus the innovative potential of the economy. If the system is characterized as a network or a graph, communication structures that exhibit cliques of agents can be interpreted to represent high clustering, whereas geographically random networks connote diffusion on a more global scale. Empirical studies have found that networks of innovators exist and have successfully characterized the structures of these networks (Refs [20-22]). Further, simulation studies have shown that network structures can have a significant impact on how rapidly knowledge grows in an economy [23]. Obviously these features of networks interact with industry-specific factors, which should be taken into account for developing regional policies.

In this paper we try to address all these aspects of the innovation process. We model agents as located on a network and any agent receives knowledge from other agents with whom he/she has direct links (that is, agents in his/her neighbourhood). Firstly, the extent to which the receiver can increase his/her knowledge is a function of the relative knowledge levels between him/her and the sender. We assume that the recipient of a knowledge broadcast uses the new knowledge to increase his/her own knowledge stock. However, if the recipient is too weak vis-á-vis the sender he/she has difficulties absorbing that knowledge. By contrast, if his/her knowledge level is close to that of the sender,

absorption is not an issue, but he/she receives little new which he/she can combine with his/her existing knowledge. The functional form that we employ controls this concave, non-monotone relationship between knowledge acquisition and relative knowledge levels between the sender and the receiver. Secondly, how effective agents are in knowledge acquisition is also a function of the features of the industry. In an industry, knowledge can be weakly or strongly codified, which will affect average abilities to innovate. Similarly, industries can be differentiated by their general level of technological opportunities, which also affects average abilities to innovate. One parameter controls the extent of absorption as a function of these industry features.

We look at the mean knowledge growth under different network architectures on which agents transmit knowledge. At one extreme of the family of architectures that we consider we have an entirely local network with high cliquishness (and thus clustering). At the other we consider a network with no spatial structure, in which diffusion is global. We analyse knowledge growth in the family of networks that lie between these two extremes. In this framework we observe that the network architecture that performs best depends on the properties of the knowledge base and the innovation process. The simulation results indicate that clustering is only efficient when knowledge is difficult to absorb and technological opportunities are higher, which we suggest is typical of industries in the early stages of their life cycle.

2 The Model

We begin with a schematic description of the model, before giving the technical details of the parameterization of the network architecture and the dynamics of knowledge creation, distribution and acquisition. The issue of the agent rationality of broadcasting knowledge is left aside: rather, observing that it exists, we are interested in the effects of the structures over which it takes place (see [24] for a model in which knowledge sharing is an equilibrium behaviour).

4

2.1 A schematic description of the model

A large population of individuals is located on a graph, each agent having direct connections with a small number of other agents. Each agent has a scalar knowledge endowment. At random times, an agent is selected; he/she innovates, after which he/she broadcasts his/her updated knowledge to his/her direct neighbours. Knowledge is received and (partially) assimilated by agents in the broadcaster's neighbourhood. Below we explain the two aspects of the model; knowledge interaction and network structure.

2.1.1 Knowledge interaction

Consider n agents existing on an undirected, connected graph $G\left(S,\Gamma\right)$, where $S=\{1,\dots,n\}$ is the set of agents (vertices) and $\Gamma=\{\Gamma_i,\forall i\in S\}$ the list of connections (the vertices to which each vertex is connected). Specifically, $\Gamma_i=\{j\in S-\{i\}\mid d\left(i,j\right)=1\}$, where $d\left(i,j\right)$ is the length of the shortest path (geodesic) from vertex i to vertex j on the graph. Only agents separated by one edge can interact: when i broadcasts only those agents in Γ_i are potential recipients. In expected value the network is of uniform degree: $E[\#\Gamma_i]=s$. The algorithm for constructing it is given in Section 2.1.3.

Each individual $i\in S$ is characterized by a knowledge endowment which evolves over time as the agent innovates and receives information broadcast by other agents. Formally, let $v_{i,t}$ denote agent i's time t knowledge endowment. Though we employ the word knowledge, $v_{i,t}$ should rather be seen as a form of human capital or competence, whose accumulation results from individuals performing learning and innovative activities. To clarify matters, the interpretation of having, for two agents i and j, the inequality $v_{i,t}>v_{j,t}$ is that i knows everything that j knows, and has some knowledge in addition.

We now consider four "axiomatic" assumptions that distinguish knowledge from other sorts of human capital. In modelling increases in an agent's knowledge as a result of receipt of new information:

($A1$) the resultant knowledge level is continuous in the initial level of the recipient;

($A2$) if the recipient knows more than the broadcaster the knowledge level of the recipient does not change (which also justifies the assumption regarding the knowledge overlap above);

5

($A3$) when the recipient's knowledge level is small relative to that of the broadcaster, the increment to his/her knowledge decreases as he/she falls further behind;

($A4$) it is in general possible for a recipient to leapfrog the broadcaster, achieving a higher knowledge level than the broadcaster after the episode.

The first assumption needs little explanation. The second one seems reasonable in that if what I tell you is already completely familiar to you, it is unlikely to provoke any innovative activity on your part. The third assumption arises from the following idea. As your knowledge outstrips mine more and more, it becomes increasingly difficult for me to understand what you are telling me. Thus as the recipient's knowledge level decreases (relative to that of the broadcaster) his/her absorptive capacity, and thus his/her ability to use what he/she hears effectively in innovation falls. The fourth hypothesis seems intuitively obvious — a great part of the motivation for firms to innovate is to become the industry leader, and this must be possible in a model of innovation.

These axioms are formalized in the following way. If agent i makes an exogenous innovation in period t, his/her knowledge increases according to

$$v_{i,t+1} = v_{i,t} \left(1 + \beta_i\right), \tag{1}$$

where the β_is are i.i.d. over some small interval $(0, \beta]$.[4] Differences in individual innovative abilities capture inter firm heterogeneity. Having innovated (increasing his/her knowledge level from $v_i(t)$ to $v_i(t+1)$), agent i then broadcasts to any agent $j \in \Gamma_i$. When i broadcasts, the knowledge endowment of j increases as

$$v_{j,t+1} = v_{j,t} \left[1 + g\left(v_{j,t}, v_{i,t+1}\right)\right], \tag{2}$$

where $g\left(\cdot, \cdot\right)$ satisfies the 4 axioms of absorption and innovation. In the numerical analysis below, we define $g\left(\cdot, \cdot\right)$ as

$$g\left(v_{j,t}, v_{i,t+1}\right) = \max\left\{0; r_{i,j}^{\gamma}\left(1 - r_{i,j}^{\gamma}\right)\right\}$$

with

$$r_{i,j} = \frac{v_{j,t}}{v_{i,t+1}} \tag{3}$$

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[4]In the simulations, increasing β did not influence the results, thus it is set equal to 0.0005.

the ratio of the recipient's to broadcaster's knowledge level. Given the knowledge level of the broadcaster, $g(\cdot, \cdot)$ is continuous in the level of the recipient $(A1)$. The max operator ensures that if the recipient already knows what is being broadcast, there is no benefit from receiving it $(A2)$. Given $v_{i,t+1}$, $g(\cdot, v_{i,t+1})$ is decreasing in its first argument $v_{j,t}$ for small $v_{j,t}$ $(A3)$ and approaches zero as $v_{j,t} \to 0$. Finally for $\gamma > 1$, $v_{j,t+1} > v_{i,t+1}$ for some values of $v_{j,t}$ $(A4)$.

2.1.2 Innovative potential and knowledge flows

Figure 1 represents the ratio of the recipient's new — in the sense of posterior to the broadcast — knowledge level relative to that of the broadcaster, as a function of this ratio before the transmission.
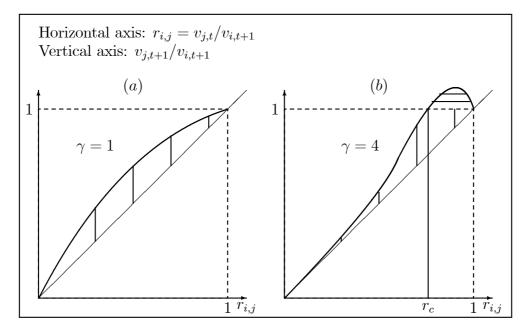

Figure 1: Absorption and innovation as functions of $r_{i,j}$, the ratio of the recipient to the broadcaster's knowledge endowment; two polar cases are presented: on panel $(a), \gamma = 1$ corresponds to pure absorption, whereas on panel $(b), \gamma = 4$ displays both absorption (vertical lines) and innovation (horizontal lines).

The $45°$ line on the right side of $r_{i,j} = 1$ indicates that it is only possible to learn from more advanced people; if the recipient has more knowledge than the sender, $r_{i,j} > 1$ and the knowledge of the receiver does not change. For $r_{i,j} \leq r_c$, there is only imitation: the recipient does not leapfrog the broadcaster. In this region, "total" knowledge creation can be seen as the vertically shaded area on the left of r_c. By contrast, for $1 > r_{i,j} \geq r_c$ there is

explicitly innovation and leapfrogging of the sender by the receiver. In this region, "total" knowledge creation is the horizontally shaded area plus the vertically shaded area to the right of r_c. How these areas respond to changes in γ is depicted in Figure 2.
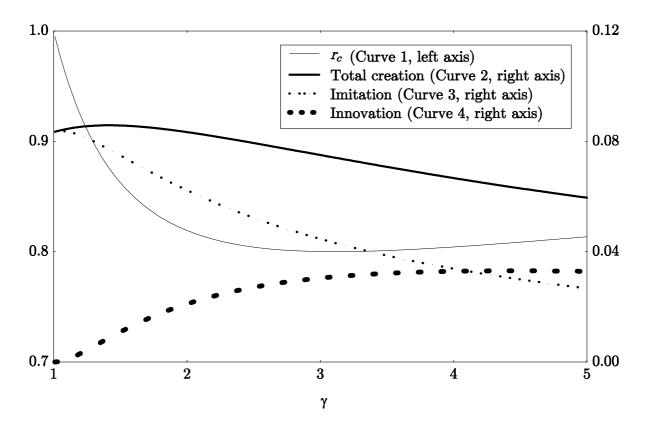

Figure 2: The various contributions to knowledge creation as functions of γ.

In Figure 2, consider first the behaviour of r_c, the implicit solution to

$$r_c \left[1 + r_c^\gamma \left(1 - r_c^\gamma\right)\right] = 1$$

which is in the interval $[0, 1]$. The critical r_c (curve 1) first falls with γ, before slowly rising again. As a consequence the total amount of knowledge creation from imitation (curve 3) first increases weakly, before decreasing. Finally, total knowledge creation is given by

$$\int_0^1 r \left[1 + r^\gamma \left(1 - r^\gamma\right)\right] - r \; dr = \frac{1}{\gamma + 2} - \frac{1}{2\left(\gamma + 1\right)},$$

and is depicted as curve 2 in Figure 2. As can be seen, it peaks at $\gamma = \sqrt{2}$. Finally, Curve

8

4 shows the contribution of innovation. It is an increasing function of γ.[5]

Thus, γ captures two effects that work in opposite directions.

First, the amount of knowledge accumulation attributable to imitation (curve 3 in figure 2) falls as γ increases. The second effect is that the amount of knowledge accumulation due to imitation (in which the receiver leapfrogs the sender) increases with γ (curve 4). As γ increases knowledge growth becomes concentrated on those agents with high $r_{i,j}$ values. In a certain sense this creates selectivity in knowledge accumulation.

The precision in the argument above is based on an implicit assumption on the distribution of knowledge among agents: for any broadcast, the $r_{i,j}$ values of the recipients are uniformly distributed between 0 and 1. While in practice this will almost never be the case, the two effects we discussed are real, and we expect the behaviour of the system to be driven by their interplay.

One way of thinking about γ is that it captures the innovative potential of industries, the extent of knowledge tacitness, technological opportunities, and relatedly the phase of the industry life cycle. It is generally accepted that in the earliest phases of the industry life cycles, technological opportunities are higher but knowledge is less codified (which decreases the extent of absorption). The functional form that we employ in knowledge creation permits us to model this aspect. We assume that highly tacit knowledge renders the prior knowledge level of the recipient important, i.e. *who* gets the knowledge matters more for innovation. This is why higher γ implies that knowledge flows are more selective, in the sense that the agents in the high end of the knowledge spectrum benefit more from the technological opportunities. Low levels of γ has the opposite effect. This could be interpreted to mean that knowledge is more codified, yet technological opportunities are lower. Thus, a wider range of agents can benefit from a broadcast (knowledge flow is less selective), but the extent to which they can leapfrog the sender is limited.

Having specified a schematic description of knowledge interaction, the following section analyses the network dynamics.

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[5]To link Figures 1 and 2: for $\gamma = 4$ for example, the value of the imitation is equal to the vertically shaded area in figure 1 panel (b); the value of innovation in Figure 2 is equal to the vertically shaded area in Figure 1 panel (b). Consequently the value of total knowledge created is the total shaded area, which is curve 2 in Figure 2, and which is the sum of curves 3 and 4.

2.1.3 Interaction patterns

We aim to compare, in terms of aggregate knowledge levels, two different cases. In the first case, holding the architecture of the network fixed throughout a single simulation, we run simulations for different architectures, and investigate whether the network architecture matters. In the second case, each time the randomly selected agent broadcasts, he/she does so to a different set of agents (we call this case homogeneous mixing), so that there is no network within a single simulation. We investigate how diffusion over a network compares to the homogeneous mixing case. Below each of the two cases is explained in detail.

Network In the case of fixed networks, the network structure on which agents interact is held fixed in a single simulation, i.e. every time a particular agent broadcasts, the same set of agents — his/her neighbours — receive information. In different simulations, however, we vary the structure of this network by the following re-wiring procedure. The agents are located at fixed, regular, intervals around a circle. At one extreme of the space of network structures, we have a regular structure: each agent is connected to his/her s nearest neighbours, $s/2$ on each side. [6]At the other extreme each agent is connected to, on average, s agents located at random on the circle. To interpolate, we use the following algorithm. Create the regular structure. With probability p rewire each edge of the graph. That is, sequentially examine each edge of the graph; with probability p disconnect one of its vertices, and connect it to a vertex chosen uniformly at random. By this algorithm, we tune the degree of randomness in the graph with parameter $p \in [0,1]$.[7]

The structural properties of these graphs can be captured by the concepts of average path length and average cliquishness. To illustrate, in friendship networks, the path length is the number of friendships in the shortest chain connecting two agents, whereas cliquishness reflects the extent to which friends of one agent are also friends of each other. Formally, defining $d(i,j)$ as the length of the shortest path between i and j, the average path length

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[6]While this algorithm does not produce a scale-free network [25] it is a standard way to explore this family of networks.

[7]See Watts and Strogatz [26] in the context of small worlds, and Cowan and Jonard [23] for an application.

$L(p)$ is

$$L(p) = \frac{1}{N} \sum_{i \in S} \sum_{j \neq i} \frac{d(i,j)}{N-1}$$

and average cliquishness $C(p)$ is given by

$$C(p) = \frac{1}{N} \sum_{i \in S} \sum_{j,l \in \Gamma_i} \frac{X(j,l)}{\#\Gamma_i(\#\Gamma_i - 1)/2},$$

where $X(j,l) = 1$ if $j \in \Gamma_l$ and $X(j,l) = 0$ otherwise.

Homogeneous mixing   In the homogeneous mixing case, there is no network on which interaction is mediated. Agents interact in a totally random manner, and broadcast each time to different set of s agents. For all $i \in S$ who is called to broadcast, Γ_i is randomly constructed each period by drawing s vertices in the population S without replacement.

3   Results

We consider an economy with $n = 500$ agents, each agent being connected to, on average, $s = 10$ other agents. Each agent is endowed with a knowledge scalar, initialized randomly at the outset from a uniform distribution $U[0,1]$. Two separate families of histories are run.

First, network structure is fixed. In this case, within a single simulation run, composed of $\tau = 30,000$ periods, we hold the value of p fixed, and compute the resulting knowledge levels. In each period, one randomly selected agent innovating according to (1) and then broadcasting his/her knowledge. The receivers are those who are directly connected to him/her, specified at the beginning of the run, and their knowledge levels are updated according to (2). Each agent is therefore selected 60 times on average to broadcast his/her knowledge. A simulation run consists in setting a p value, creating the network, setting the value of γ and so creating the innovation function, and then iterating the process for τ periods. For each p, γ pair we preform 100 replications. We vary p from $p = 0$ (a perfectly regular structure) to $p = 1$ (a purely random graph), and use 15 values of γ ranging from 1 to 5.

Second we perform simulations under homogeneous mixing. As in the previous case, 100 replications are recorded. Every period an agent is selected randomly to broadcast, he/she

innovates according to (1), and broadcasts his/her knowledge to a randomly selected set of agents. The receivers' knowledge levels are updated according to (2).

We measure the aggregate performance of the system by the long run growth rates of the mean knowledge levels. The average knowledge in the economy, for a particular value of p, at time t is

$$\mu_t(p) = \frac{1}{n} \sum_{i \in S} v_{i,t} \tag{4}$$

The one-period growth rate at time t is measured by

$$\rho_t(p) = \frac{\mu_t(p)}{\mu_{t-1}(p)} - 1,$$

and will be evaluated close to the end of the simulation horizon. Obviously, there is no p value for the homogeneous mixing case, denoted H. To understand the effect of having a fixed network structure, we also examine normalized growth rates, that is, we compute

$$\rho_t^*(p) = \frac{\rho_t(p)}{\rho_t(H)} \tag{5}$$

We are interested in the influence of two parameters. The first is $p \in [0,1]$, which determines the network structure. The second is $\gamma \in [1,5]$ which measures the selectivity and leapfrogging effects, as explained above.

3.1 Homogeneous mixing

The results for the case of homogeneous mixing are given in Figure 3, which provides a box-plot representation of growth rates as a function of γ.

Knowledge growth is lowest when $\gamma = 1$. This is no surprise as the complete absence of leapfrogging implies (see Figure 1, panel 1) absorption until nothing remains to absorb, and knowledge levels remain constant thereafter. From Figure 3, it is clear that there is a critical level of γ that yields maximum growth, and after which growth falls. Considering the discussion above, this fall can be explained very simply: randomness reinforces the effect of selectivity. Consider cliquishness. Cliquishness generates similarity in knowledge levels, so in a non-cliquish world, knowledge levels are dispersed. This implies that in a non-cliquish world, the range of people who can leapfrog is relatively small and so is the growth of knowledge attributable to leapfrogging. Obviously there is no world having lower
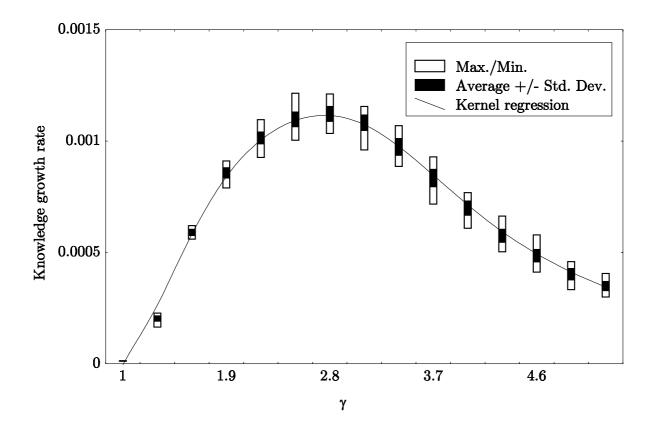
Figure 3: The distribution of growth rates under homogeneous mixing.

cliquishness than a world of homogeneous mixing. Hence knowledge generation is weak in the presence of high selectivity effects (large γ), even though those who leapfrog make very large gains.

This is also directly visible from Figure 2, in which we see that the relative importance of selectivity and leapfrogging vary with γ, and the best overall growth is achieved for $\gamma \approx 3$. Just like the expected amount of knowledge creation, the simulated growth rate also has an interior peak.

3.2 Knowledge dynamics in the network

Figure 4 shows the relationship between network architecture, characterised by the disorder in the network (the parameter p), and knowledge growth for different values of γ. We present both the original data points and, for each p-value, the corresponding nonparametric kernel estimate. This convention applies to all the following figures.

Broadly speaking, at any p-value, the relationship between γ and knowledge growth is

only weakly increasing: knowledge growth increases and then flattens out. For p close to 1, we get slightly more: a pattern similar to the one reported in the previous paragraph in the case of homogenous mixing, with an increase followed by a decrease, the peak being around $\gamma = 3$. More interesting, however, is that for low values of γ knowledge growth rates increase with p, whereas for high γ values, knowledge growth rates decrease with p. In other words, when relative contribution of imitation to total knowledge creation is high (low γ), a random world (high p) dominates other structures. At the other extreme, when innovation is relatively important (high γ) a cliquish world (low p) performs best.
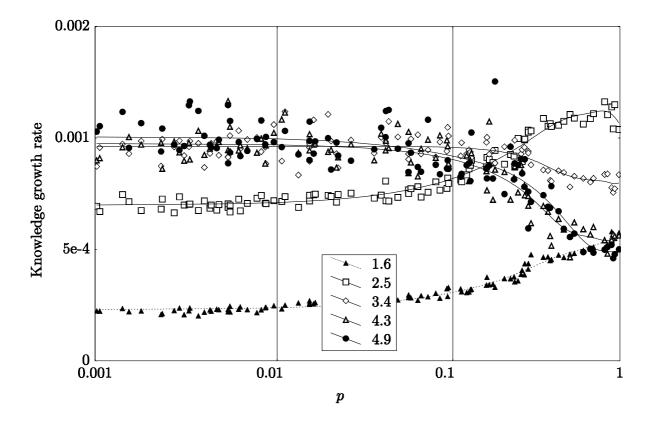

Figure 4: Growth rate of knowledge as a function of p, for a set of γ-values.

When γ is low, r_c approaches 1. Leapfrogging disappears as an important part of knowledge growth, since there are few agents able to leapfrog, and the extent to which they overtake the broadcaster is very small. Thus imitation becomes the driver of knowledge accumulation, and short paths will contribute to rapid growth. At the same time, since leapfrogging is not important, and agents far beneath the broadcaster can still absorb significant amounts of knowledge, similarity becomes unimportant and the value of

14

cliquishness, which creates similarity among neighbours' knowledge levels (see Figure 5), disappears.[8] When short paths are valuable, and cliquishness is not, a random graph, which has small diameter, will be most efficient in producing knowledge.

On the other hand, when γ is high, leapfrogging becomes important, and agents who leapfrog make big advances. Thus, a weak agent (one whose knowledge level puts him/her below r_c), is unable to leapfrog, and further learns little by imitating (the $g(\cdot, \cdot)$ function lies close to the 45 degree line for low $r < r_c$). Such agents will rapidly be "left behind". What connects this observation to the result above is that in a cliquish world, agents tend to have knowledge levels similar to their neighbours. This is shown in Figure 5. In a cliquish world, when an agent broadcasts, most of his/her neighbours will be above the r_c threshold, and thus can leapfrog him/her, making big advances. Thus relatively few agents get "left behind" and aggregate knowledge levels grow rapidly. When γ is high, cliquish structures produce rapid knowledge growth.
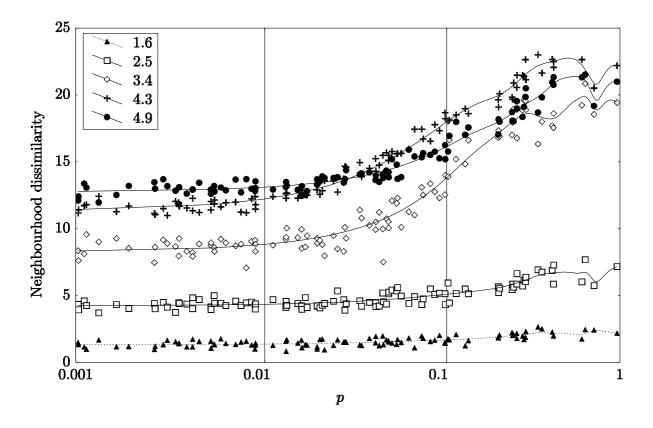

Figure 5: Neighbourhood dissimilarity as a function of network architecture.

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[8] If γ falls below 1, the bulk of knowledge accumulation shifts to those agents far below the broadcaster.

3.3 Comparison of random mixing and network cases

Figure 6 shows the re-scaled growth rates, ρ_t^*, using the growth rates in the homogeneous mixing model as the norm. The pattern is essentially the same as for the non-normalized growth rates in Figure 4. There is, though, observable value from a networked structure when γ is high, while there is observable cost from networks when γ is low. The value of a network, however, changes with the structure of the network. We observe in Figure 6 that as p approaches 1, the value (positive or negative) of a network disappears ($\rho \to 1$). This clearly implies that in this model the random network most closely approximates a homogeneous mixing model. At the other extreme, we observed above that for low γ cliquishness has a strong negative impact on growth. A homogeneous mixing model is in a sense the least cliquish situation possibl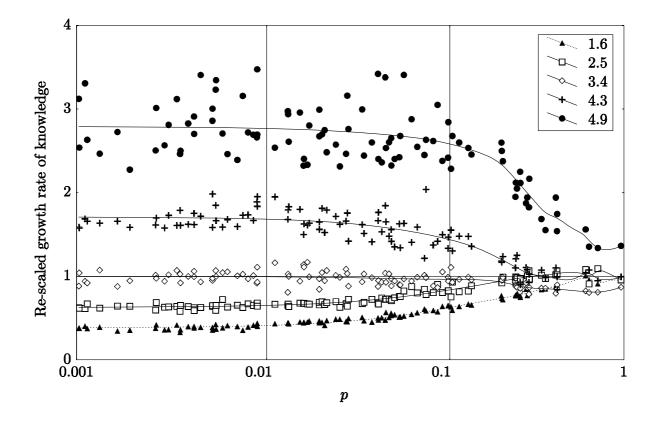e, and so we see (Figure 6) that $\rho(0) < \rho(H)$. Conversely for large γ the opposite is true, and thus $\rho(0) > \rho(H)$.

Figure 6: Normalized growth rates.

What this suggests is that in industries wherein imitation is important a policy favouring

16

networking and perhaps clustering may be misplaced. Important in interpreting this remark is the condition implied by Figure 1, namely that all agents, regardless of their prevailing knowledge stocks, can learn significant amounts from a broadcaster. This could be the case, for example, in a relatively mature industry in which knowledge tends to be highly codified. On the other hand, when a recipient must be highly knowledgeable to use the information he/she receives in an effective way, we see that networks, and in particular cliquish networks or industrial clusters are structures to foster.

4   Conclusion

In this paper, we have focused on the knowledge sharing and creation within a population of agents and how the medium of interaction contributes to the long run knowledge growth rates. We distinguished between two mediums of interaction; the first in which there is no network structure; agents interact and share knowledge randomly, and the second in which interaction is facilitated by a certain fixed network. We also considered different network architectures, at one extreme we took the case of completely regular network in which there is high cliquishness and average path lengths are high. At the other extreme we took a completely random network structure, characterized by low path length and low cliquishness. We considered the cases that fall between these two extremes.

In the process of new knowledge creation, we modelled ongoing innovation in a community of actors, based on the idea that innovation is largely a result of knowledge sharing among a small group of agents. In doing so, we distinguished between industries according to the extent of innovative potential. We took into account the tacitness of knowledge and technological opportunities in assessing innovative potential. Especially in the early stages of the industry life cycle, the industries are characterized by high technological opportunities, yet knowledge is tacit, which decreases the extent of absorption. The functional form that we employ in knowledge creation permits us to model this aspect, with the parameter γ, which measures both the creation of knowledge and the distribution of it. We assumed that highly tacit knowledge renders the prior knowledge level of the recipient important, i.e. who gets the knowledge matters more for innovation. In this sense, high γ implies that knowledge flow is more selective, i.e.; the agents in the high end of the knowledge spectrum

17

benefit more in terms of leapfrogging the sender and thus make better use of the available technological opportunities. Low levels of γ has the opposite effect. Here, knowledge could be seen as more codified, yet technological opportunities are lower. Thus, a wider range of agents can benefit from a broadcast (knowledge flow is less selective), but the extent to which they can leapfrog the sender is limited.

Our results reveal that the existence of network structure can significantly increase the long run knowledge growth rates. But this result depends on the innovative potential of the industry. Increased regularity in the network increases long run growth rates for high values of γ. This implies that regularity and cliquishness is better in industries characterized by more tacit knowledge, and higher technological opportunities. On the other hand, the case with no network structure proved to be better for low γ values; i.e. when the knowledge is more codified, but there are fewer opportunities to leapfrog the sender. The difference between the no-network and network cases diminishes as the network architecture becomes more random. Our results tend to support the hypothesis that spatial clustering is better in industries where knowledge is highly tacit, and there are large amounts of technological opportunities to explore.

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