The impact of information networks on spatial diffusion of technological knowledge and regional economic growth: An agent-based modeling approach

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1 Introduction

Spatial diffusion of technological progress is a one of the key factors explaining different regional economic growth. Empirical work clearly underlines that innovation diffusion between regions is far from being instantaneous as predicted by the neoclassical theory, but specific regions appear as innovation leaders, while others realize technological progress mainly via spill-over of technological knowledge from innovation leaders. Accordingly, regional growth patterns are determined in part by regional difference in technological progress. Classical approaches explaining technology transfer between regions basically argue that the speed of technology transfer from a more advanced to less advance regions is proportional to the technology gap between these regions. This implies a convergence of technological progress in the long run, i.e. lacking behind regions are catching-up with the technology leader. However, empirical studies hardly support neoclassical catching-up hypothesis especially at the regional level. Moreover, classical catching-up models are criticized for not explicitly modeling the complex process of technological knowledge diffusion among regions.

As a critique of simple neoclassical models evolutionary models of innovation diffusion and technological progress have been developed (Dawid, 2006). In contrast to neoclassic, evolutionary economics focus on a explicit procedural way of representing of decision-making rather than relying on abstract optimizing calculus (Dopfer, 2001; Dosi and Winter, 2002; Fagerberg and Verspagen, 2002; Nelson, 1995; Nelson and Winter, 2002). Focusing on decision-making procedures makes agent-based modeling a natural choice. Accordingly, pioneering work in evolutionary economics in this field apply agent-based models, e.g. Nelson and Winter (1982). Inspired by the work of Nelson and Winter (1982) a large body of literature applying agent based computational economics (ACE) modeling approaches to explain innovation and technological change have been developed, which commonly understand innovation and technological progress as a result of a dynamic process among interacting heterogenous agents. Moreover, this literature highlights in particular the special nature of knowledge as the most important factor for the production of innovation (Dawid, 2006). ACE models contributed significantly to the understanding of the complex process of innovation and technological progress. For example, ACE approaches could provide satisfying explanation for a number of empirically established stylized facts, which have not been predicted by standard equilibrium models. However, although ACE approaches focus on interaction among heterogenous agents existing approaches to innovation and technological progress do not explicitly analyze the impact of specific interaction patterns, that is network relations among firms, on innovation.

The impact of networks on economic behavior is an innovative and emerging field in economics that also profited tremendously from ACE-modeling Wilhite (2006); Jackson (2005). However, economic research on networks is still in its infancy and studies on the impact of network's typology on innovation diffusion and technological progress rather exists yet.

In this context the paper offers an agent based modeling approach that focuses on the impact of network's typology on regional information diffusion and regional technological progress.

Technically, we derive a rather simple model that particulary focus on the role of information networks in the accumulation of knowledge by regional firms. New technological knowledge is exogenously generated in a leader region and randomly transmitted to regional firms. Within a region transmission of technological know-how occurs in information networks. Further, following central findings of existing ACE literature on innovation (Dawid, 2006) we assume that firms can only transmit information that they were able to process, where firms' capacity to process new technological knowledge depends on accumulated technological know-how. Therefore, given an exogenous rate of generation of new technological information in the technological leader regions, the speed of information accumulation within a region crucially depends on the speed of information transfer within the regional firm network, where the latter depends on network structures.

Applying our simple agent based model we simulate the impact of different network typologies on spatial diffusion of knowledge and regional technological. In particular, we simulate two different network types, i.e. small-world and free-scale networks, varying global network structures, which are clustering and centralization. Main results of our simulation studies are the following:

(i) Information network structures have a significant impact on both spatial information diffusion and regional technological progress. (ii) Information diffusion in networks is only imperfect, i.e. accumulated knowledge in regional networks correspond only to a constant fraction of technological knowledge generated in leader regions. (iii) In particular, this fraction is c.p. higher for scale-free networks when compared to small-world networks. Moreover, this fraction increased for scale-free networks with the preferential attachment parameter and for small world networks with the α-parameter. (iv) In contrast to classical catch-up models our network approach to spatial diffusion of technological knowledge implies that except for extreme centralized or dense networks catching-up does not occur. In contrast, depending on the concrete typology of regional information networks a constant productivity gap to the technological leader is stabilized or regions characterized by extremely clustered information networks are even increasingly falling behind.

2 Evolutionary Economics and Innovation: A brief literature review

Although innovation and technological has always been considered as one of the driving forces of economic growth (Maddison, 1991; Freeman, 1994) this aspect of economic activity has for a long time been largely neglected in mainstream economics. However, today not only a large empirical literature on this issue has been established, but also a wide range of different modeling approaches have been used to gain theory-based insights about the origins of technological progress. These approaches include dynamic equilibrium models, static and dynamic game theory, theory of complex systems and evolutionary economics. For an overview on this literature see for example Dawid (2006); Dosi (1988); Grossman (1994); Nelson and Winter (2002).

Technological change is a highly decentralized dynamic search process under strong substantive and procedural uncertainty, where numerous heterogenous agents search in parallel for new products or production processes, but are interlinked through market and non-market interactions. In more specific terms Dawid (2006) summarized the following characteristic properties of innovation process: (i) the dynamic structure of the process, (ii) the the special nature of knowledge as the most important input of for the production of innovation, (iii) the fundamental uncertainty involved and (iv) the heterogeneity between agents. Due to the genuine and complex properties of innovation process standard equilibrium models do not provide satisfying explanations for a several of empirically established stylized facts. Therefore, in nowadays especially ACE-models turn out to be fruitful approach contributing significantly to the literature (Dawid, 2006). In contrast to standard equilibrium models evolutionary approaches, i.e. ACE-models, represent decision-making of economic agents in an explicit procedural way rather than applying abstract optimization calculus. Moreover, the former explicitly takes interactions between heterogenous agents into account instead of using representative agents.

The pioneering work applying an evolutionary economic approach to analyze innovation processes goes back to Nelson and Winter (1982). Nelson and Winter (1982) considered individual firms applying a simply linear production technology, where two input factors, labor and physical capital are transformed into one output. Firms technology is characterized by input coefficients for both factors and firms can improve the value of their input coefficient by local search and imitation. Firms can invest into innovation or imitation, where Nelson and Winter (1982) assume an initial heterogeneity among firms regarding applied innovation strategies, i.e. it is assumed that the industry is a mix of imitators and innovators. The model focus on simulation of long term development of industry and Nelson and Winter (1982) were able to reproduce dynamic patterns of key variables for Solow's data. Following Nelson and Winter (1982) the focus on reproduction of stylized facts using micro-founded dynamic models has been a main theme of subsequent evolutionary research on industrial dynamics and growth (see literature overview provided in Dawid (2006)).

Later ACE approaches focus also on the other specific characteristics of innovation process, i.e. the fundamental uncertainty (Dawid, 1999; Cooper, 2000; Natter et al., 2001; Dawid and Reimann, 2005) and heterogeneity (Chiaromonte and Dosi, 1993; Dawid and Reimann, 2005; Ballot and Taymaz, 1997; Llerena and Oltra, 2002).

A special emphasis is put on the role of knowledge accumulation in innovation processes. The success of innovative activities of a firm does not only depend on its current investment, but also to a large extent on the size and structure of the knowledge base a firm has accumulated (Dawid, 2006). A large body of empirical evidence has demonstrated that the knowledge base needed for successful innovation has to be gradually accumulated over time (Dosi, 1988). Accumulation of knowledge is a rather complex process and quite different from accumulation of physical capital. It involves several mechanisms, e.g. in-house R&D, informal transfer of knowledge between companies (spillovers), or learning by doing. In particular, knowledge can only to a certain extent been traded on a market, a contrary it often flows through specific local and global communication network channels established between firms (Cohen and Levinthal, 1989; Rosenberg, 1990). Moreover, Cantner and Pyka (1998) demonstrate that knowledge spillovers between firms not only demand for established informal information network relations to transfer technical information, but beyond pure transmission of technical information, knowledge accumulation requires that firms are able to process received information, where the latter again crucially depends on firm's current knowledge. This point is often neglected in models of technical spillover, but as we will show has crucial implications for the accumulation of knowledge.

Finally, it should be mentioned that there also exists equilibrium models in the so-called new growth theory (NGT) that explicitly take knowledge spillovers into account (Eeckhout and Jovanovics, 2002). However, these approaches model spillover effects via an one-dimensional stock variable representing an aggregate of physical and human captial and do not explicitly model the interaction that finally lead to transmission of knowledge among firms. Moreover, Dawid (2006) pointed out that in contrast to evolutionary growth models also the advanced approaches of NGT are often silent or generate implausible predictions e.g. regarding fluctuations of growth rates, co-existence of several technologies employed in the same industry as well as the endogenous generation of persistent cross-regional differences in growth rates.

However, although existing ACE-literature clearly contributed to literature on innovation processes, there are still some issues that have not been fully addressed. For example, although ACE-approaches clearly recognized the importance of established informal and formal interfirm network structures for knowledge accumulation and its role in innovation process, there hardly exists studies analyzing the impact of different network typologies on knowledge accumulation and technological progress.

This gap is addressed in this paper, where we derive a simple ACE-model on knowledge accumulation including explicitly the structure of network channels in which knowledge flows between firms. The model is derived in the next section.

3 The model

3.1 Firm's production technology

We consider a set of business firms located in a specific region F, with $i = 1, ..., n$ denoting an individual firm. Each firm produces the same output X applying a firm specific production technology, G_i:

$$X_{it} = G_i(K_{it}, L_{it}, C_{it}) = A_i(K_{it}) \quad g_i(L_{it}, C_{it}) \tag{1}$$

where t denotes the time period t=1,...,T. X_{it} is the output of firm i in period t, L_{it} and C_{it} denote firm's inputs of the standard production factors labor and capital in period t, respectively, while K_{it} denotes the "accumulated" technological knowledge of firm i in period t. We assume a two-stage production technology, which is separable in technological knowledge and standard production factors, labor and capital. Accordingly, $g_i()$ denotes firm's production function at the lower stage transforming labor and capital into an aggregated standard input g(), which given firms level of technological knowledge is then transformed into the final output. The function $A_i()$ determines how firm's technological knowledge translates into final output. In each period firm's technological knowledge is considered as a quasi-fix production factor, hence firms production function is well-behaved in standard inputs as long as we assume that the function g() is well-behaved, i.e. quasi-concave in labor and capital. However, regarding firm's knowledge it is common to assume economy of scales (Bröcker, 2002). However, for the moment we only assume that A() is monoton increasing in accumulated knowledge.

Since the focus of our analysis is on firm's accumulation of knowledge and its implication for firm's realization of technological progress we assume for simplicity that firms inputs of labor and capital are exogenously fixed, i.e. firms output growth solely results from accumulation of technological knowledge. In the next subsection we derive a simple ACE-model of firm's accumulation of knowledge.

3.2 Modeling information diffusion in networks and the accumulation of knowledge

As we already stated above in the literature on innovation the success of innovative activities of a firm does not only depend on its current investment, but also to a large extent on the size and structure of the knowledge base a firm has accumulated (Dawid, 2006). Moreover, accumulation of knowledge involves several mechanisms, e.g. in-house R&D, informal transfer of knowledge between companies (spillovers), or learning by doing. In this paper we focus on the diffusion of knowledge between firms in a peripherial region and neglect other mechanism of knowledge accumulation [1] Accordingly, we assume that new technological knowledge is constantly generated in a leading regions and then is randomly transmitted to a firm in the peripherial region, and finally diffuses between regional firms.

Modeling diffusion of new knowledge we incorporate two fundamental results of previous

[1] However, the model of knowledge accumulation derived here also applies if we assume new knowledge is generated via learning by doing in the regional network instead of assuming new knowledge is exogenously generated in the leading region and randomly transmitted to a firm of the regional network.

studies on technological spillover. First, diffusion of knowledge between firms is not trivial, i.e. requires the existence of an established information network channel between firms (Cohen and Levinthal, 1989; Rosenberg, 1990). Transmission of new technological knowledge between firms can only occur if staff members of two firms communicate with each other. Obviously, communication between firms requires specific opportunities to interact, e.g. doing business or meeting within a business organization or even meeting on a social event like dinner parties, playing golf, etc. Of course, depending on specific business, organizational and social relations opportunities of interactions significantly vary across firms. Accordingly, the frequency of information transmission varies significantly across pairs of firms. As will be shown in detail below, firm's opportunities to communicate can be captured via defining firm specific information network ties, where the structure of information networks has a crucially impact on knowledge accumulation.

To analyze the role of networks in the process of knowledge accumulation, we first define an information network T as a graph of F^2, e.g. the information network is a subset of pairs $(i, j) \in F^2$, where $i, j \in F$ are usually called vertices and a pair (i, j) is called an edge. Let $t_ij = 1$ indicate a tie between firm i and j implying that firm i and firm j have an information relation, then the information network T can be defined as follows:

$$T = \left\{ (i, j) \in F^2 \middle| \, t_{ij} = 1 \right\} \tag{2}$$

In detail, networks can have different structures and different graphs have different topologies. Quantitative network theory developed a set of local and global network indicators to described specific network structures and typologies (Wasserman and Faust, 1994).

Second, following Cantner and Pyka (1998) we assume that beyond pure transmission of technical information, knowledge accumulation requires that firms are able to process received information, where the latter again crucially depends on firm's current knowledge. As will be elaborated below we formally incorporate the impact of firm's current knowledge on knowledge accumulation, via assuming that new technological knowledge can only be processed if firm's current knowledge is already above a specific threshold.

Overall, we assume the following simple three stage procedure of knowledge accumulation in a regional economy, F:

1. Generation and transmission of new knowledge to peripherial region:
   New knowledge is constantly generated in the leading region and randomly transmitted to a firm $i \in F$ in the peripherial region. In particular, we denote k_t the new knowledge signal generated in period t and $K_T = \sum_{t=1}^{T} k_t$ the maximal accumulated knowledge available in the leading region. In each time period a firm $i \in F$ is randomly selected and the accumulated knowledge of the leading region, K_t, is transmitted. Formally, let j=0 denote the index of the leading region and let d_{i0t} denote a dummy variable, where $d_{i0t} = 1$ indicates that a firm has received the accumulated knowledge of the leading region in period t. Then random selection implies that for a firm i d_{i0t} equals 1 with probability $1/|F|$.

2. Diffusion of knowledge between regional firms:
   In each time period regional firms communicate their accumulated knowledge to other

regional firms within information network channels. Formally, let π denote the common conditional probability that a firm i transmit its accumulated knowledge, K_{it}, to another firm j, if both firms have an established information tie, $t_{ij} = 1$. Then we can for each firm i define the set of received information in period t: $M_t^I = \{K_{jt}|\, d_{ijt}t_{ij} = 1\}$, where d_{ijt} is a random variable which is 1 with probability π and zero with probability $1 - \pi$.

3. Processing of received information:
   Depending on the technological information received from other regional firms via information diffusion or from the leading region via direct knowledge injection, each firm accumulates its new knowledge. However, knowledge accumulation is restricted by firm's current knowledge. Formally, the following accumulation rules is defined:

$$K_{it+1} = K_{it} + k_{iT(i,t)+1}$$
$$k_{iT(i,t)+1} = \begin{cases} k_{t=T(i,t)+1} & ,if MaxK_{ijt} > K_{it} \\ 0 & otherwise \end{cases}$$

   ,where $T(i)_t$ denotes the number of technological information signals a firm i has accumulated up to time period t, while $MaxK_{ijt}$ is the maximal accumulated knowledge a firm received in time period t, i.e.:

$$MaxK_{ijt} = Max\,\{K_{jt}|\, d_{ijt}t_{ij} = 1, j \in F \text{ } or \text{ } d_{i0t} = 1\}$$

4 Simulation of network typology and knowledge accumulation

In the following simulation analyzes we are going to analyze the impact of different information network structures on knowledge accumulation. To this end we will define network indicators and based on these indicators we define network types, i.e. random, small-world and scale-free networks, that have become popular in the field of Economics and Networks (Jackson, 2005). Furthermore, we will define a specific algorithms that allow the generation of hybrid networks that exhibit a specific typology and characteristic network structures. Although both global and local network indicators as well as network generation algorithm have already been developed in the literature, we will describe these in more detail in the following since these are not standard in the growth literature.

4.1 Network indicators

Network analysis provides a large set of global and local network indicators and thus a selection of relevant indicators needs to be done. Given the fact that we are mainly interested in the impact of social network structures on information and innovation diffusion, the following global and local indicators are of interest:

Network density

Network density is defined as the number of realized ties divided by the number of theoretically possible ties. If we denote the number of ties an individual firm i forms by t_i, then network density, ϕ is defined as:

$$\phi = \frac{\sum\limits_{i \in F} t_i}{N^2} = \frac{\bar{t}}{N} \tag{3}$$

To simulate density we keep total network size N constant and simulate an average number of network ties, $\bar{t}$.

Global centralization

Global centralization of a network measures the difference in individual network ties (degrees). Accordingly, the larger the variance of individual degrees of actors the larger is c.p. the centralization. Let σ_t denote the variance of degrees in a network, then it holds:

$$\sigma_t = \sum_{i \in F} (t_i - \bar{t})^2 \tag{4}$$

Thus, by definition centralization is simulated by the variance of network degrees, σ_t.

Clustering/transitivity

Network clustering or transitivity is defined as the average density of the actor's neighbourhood network. A neighbourhood network T_i of an actor $i \in F$ is defined as the subset of actors $j \in F$ which have a tie to i:

$$T_i = \{j \in F \,|t_{ij} = 1\} \tag{5}$$

Now, given t_i neighbours of an actor i the density of the neighbourhood network T_i is defined as:

$$\gamma_i = \frac{\sum\limits_{k \in T_i} \sum\limits_{j \in T_i} t_{kj}}{t_i(t_i - 1)} \tag{6}$$

Finally, the global clustering is defined as the average density of all neighbourhood networks:

$$\gamma = \frac{1}{N} \sum_{i \in F} \gamma_i \tag{7}$$

Characteristic path length

We define g_{ij} as the minimum path length connecting an actor i with an actor j. To define g_{ij} formally we define T_{ij}^k as the ij-component of the matrix T^k, with $T = [T_{ij}]$. Then g_{ij} is defined as follows:

$$g_{ij} = \underset{k}{Min} \left\{ k | \, T_{ij}^k > 0 \right\} \tag{8}$$

Further, we define g_i as the mean of all g_{ij}. Then, the characteristic path length (L) is defined as the median of all means g_i. A problem arises if a network is not a strong component, i.e. some actors are isolated. The path length to isolated actors becomes infinity. In this case the characteristic path length can not be calculated. A solution to this problem would be to calculate the characteristic path length only for the strong component of the network, i.e. the subset of actors that are connected with each other via a finite path.

4.2 Random, small-world and scale-free networks

In the emerging literature on "Networks and Economics" different types of networks characterized by specific network indicators have become very popular, i.e. random networks, small-world networks and scale-free networks (Jackson, 2005). Therefore we will briefly define these specific network types based on characteristic values for global network indicators. Hence it is helpful to identify the range of network types and their implications for measuring performance by network indicators.

Random graphs: A random graph is a graph where the edges between the vertices are generated randomly. $T(n,p)$ with a natural number $n \geq 1$ and a probability p denotes the class of all graphs where for every tuple (i,j) of vertices the probability p determines if they are connected, i.e. $t_{ij} = 1$ with probability p for all $i, j \in F$. This takes place independently of the other edges. In particular, random models of network formation include Bernoulli random Graphs (Erdös and Renyi, 1959; Bollobás, 2001) and Markov Graphs or p* networks (Frank and Strauss, 1986; Wasserman and Pattison, 1996).

Small-world graphs: A algorithm for building links that differs from pure Bernoulli random graph has been suggested by Watts and Strogatz (1998); Watts (1999b). In particular, Watts and Strogatz (1998) wanted to generate a network that exhibit both relatively low diameter and nondegenerate clustering. Watts and Strogatz called this specific network structure they generated small-world networks. Small world graphs have become very popular since the path breaking work of Watts (1999a). In particular, small world networks combine two characteristic properties: a relatively high clustering and a relatively low average characteristic path length. In contrast to small-world networks random networks exhibit a relatively low characteristic path length, but clustering is also low for this network types. Deffuant et al. (2002) investigated small-world networks with respect to opinion formation and convergence.

Scale-free graphs: However, the way Watts (1999a) generated small-world networks implies that the degree distribution of generated networks has a great deal more regularity and less variance than observed for real social networks.

To generate networks that exhibits degree distributions as observed in many social networks, one needs a process of link formation that differs from pure Bernoulli type process, as observed distributions often exhibit fatter tails. The ideas behind generating distributions with such fat tails dates back to Pareto (1896), for which the standard power distribution is named. Accordingly, generated networks are called power law or scale-free networks.

The characteristic property of scale-free networks is a high global centralization. The distribution of vertices and the number of edges follows a power law: $P \sim k^{-\gamma}$, where γ has no unit. The power law is described by exponential growth, i.e. the number and also the size of the objects which are measured increase exponentially. The size distribution of the objects at each arbitrary point in time obeys a power law. Scale-free networks are considered as relatively failsafe. However, the robustness of such networks is only maintained if vertices randomly drop out. Strategic disconnection of individual vertices which have a high degree of connection (so called "hubs") can lead rapidly to a disconnection of the network into smaller disconnected subnetworks (Barabási, 2003). This is the reason why the breakdown of a small number of routers in the internet can have far reaching consequences. Conversely, the scale-free structure of the Internet entails that if a computer virus reaches such a hub it can spread and diffuse rapidly through the network. It is also assumed that the rapid and far reaching diffusion of HIV in sexual networks takes place similarly, supported by the ability to travel by plane in a short time to nearly every place on earth. Thus epidemiology and disease spreading via infection also takes place within networks. Many works have been done so far in this field. Models on word-of-mouth, viral marketing, spreading of fashion and rumours follow this metaphor.

Hybrid networks: Finally, since purely random graph models do not exhibit the clustering or degree distribution that match many observed networks, while generated small-world networks do not exhibit observed degree distribution and power law or scale free networks do not exhibit observed clustering, hybrid models to generate networks have been developed (Pennock et al., 2002; Kleinberg et al., 1999; Levene et al., 2002; Kumar et al., 2000; Cooper and A., 2003).

Based on these studies an own statistical approach has been developed to generate networks that are closer to empirical observed networks, i.e. have combine the following characteristics: relatively low characteristic path length (diameter), nontrivial clustering, degree distribution that spans between purely random and scale-free networks . This procedure will be briefly described in the next subsection. A detailed description is given in Henning et al. (2007).

4.3 A construction algorithm for a information networks

To construct a information network the modified α-model (Watts, 1999a) is applied which is able to generate hybrid network combining properties of scale-free, small-world and random networks.

According to this procedure, first a basic measure of the propensity that two vertices connect is derived based on the firms' characteristics:

$$p_{ij} = \frac{\mathrm{e}^{\{-A\|X_{IJ}\|\}}}{\sum\limits_{i \geq j} \sum\limits_{j} \mathrm{e}^{\{-A\|X_{IJ}\|\}}} \tag{9}$$

In eq. 9 A denotes a parameter vector that indicates the importance of the different firm characteristics for the propensity that they form a social tie. In detail we used geographical location and branch affiliation as central characteristics to determine the probability in equation 9, where both characteristics have been simulated for the set of firms. The procedure is described in detail in Henning et al. (2007).

Given the basic probabilities of inter-firm relationships, π_{ij}, a specific property of a social network relation is clustering, i.e. the fact that the likelihood of a connection among two firms is correlated with the existing connections among firms. In detail, the higher the number of overlapping connections between a pair of firms, the higher is the probability that these two will form a connection as well.

Obviously, firms' relations are correlated as long as firms are clustered in the character space X. However, beyond the clustering of firms characteristics, a social process is working by implying a correlation among firms' connections.

How exactly clustering occurs is a very interesting topic in itself. However, we leave this interesting question for future research and simply assume that clustering occurs and can be implicitly incorporated into our network construction via defining the following transformation of the propensity measure, π_{ij}:

$$R_{ij} = \begin{array}{ll} 1 & , m_{ij} \geq t_i \\ \left[\frac{m_{ij}}{t_i}\right]^{\alpha} (1 - \pi_{ij}) + \pi_{ij} & , t_i > m_{ij} > 0 \\ \pi_{ij} & , m_{ij} = 0 \end{array} \tag{10}$$

In eq. 10 m_{ij} denotes the number of overlapping ties between firm i and j. According to the α-model of (Watts, 1999a), the parameter α determines the clustering of the network. For the special case of $\alpha = 0$ a highly clustered network results. Note that for $\alpha = 0$ R_{ij} becomes 1, whenever two vertices have at least one common connection, $m_{ij} > 0$.

On the other hand, the larger α the more R_{ij} converges against the basic propensity, π_{ij}. Thus, as long as we assume that π_{ij} is sufficiently small for all pairs, a random graph results.

Given the definition of the propensities R_{ij}, the following construction algorithm can be defined:

1. Compute probabilities, π_{ij}, for all pairs $(i, j) \in F^2$.

2. Select randomly a firm i.

3. Compute R_{ij} for all other vertices $j \in F$, where $R_{ij} = 0$, if i and j have already a connection.

4. Sum R_{ij} over all j and normalize each to obtain $P_{ij} = \frac{R_{ij}}{\sum\limits_{k \neq i} R_{ik}}$. P_{ij} can be interpreted as the probability that i will connect with j. Thus, two mechanisms can be applied to select a connection, j, randomly with probability P_{ij}. (a) Divide the unit interval $(0, 1)$ into $(n - 1)$ half open subintervals with length P_{ij}. Generate a uniform random variable on $(0, 1)$. It must fall into one of the intervals, P_{ij}. Connect i with j, the interval that the random variable falls into. (b) select randomly a vertex j, with probability $1/(n - 1$, select randomly a uniform variable on $(0, 1)$, if it is lower or equal than P_{ij} connect i with j. Otherwise start the process again.

This procedure (1) to (4) is repeated until the predetermined number of edges $M = \sum\limits_i t_i$ has been constructed. The vertices i are chosen at random order, but once a vertex i has been chosen it may not be chosen again until all other vertices have taken their turn.

Barabási and Albert (1999) provided a model which constructs scale-free networks. Starting with a small number of vertices m_0 and adding a new vertex at every step. The new vertex will then be connected to m other vertices, where the probability in connecting to a vertex depends on the number of already existing edges of this vertex. This principle is called *preferential attachment* which has similarities to m_{ij} in the α-model of Watts (1999a).

The extended α-model presented in this paper is used to generate small-world networks based on a characteristic space X. A further extension allows us to analyse scale-free networks including a number of s "stars", which are agents that hold a higher degree than the average agent.

The construction algorithm for the network with stars is a nested combination of the original α-model of Watts (1999a, p. 47) where the density of the network is maintained in order to allow for a comparison of the network types:

1. Randomly selection of s stars characterized by t_s information ties.
2. Recalculation of the degree for non-stars and construction of the network by using the α-model algorithm until $M - s\ k_s$ edges are distributed.
3. Applying the α-model algorithm selecting only stars to distribute the remaining network ties, i.e. only the stars are allowed to choose connections respectively ties.

This algorithm keeps the idea of clustering, according to existing ties, which is similar to Watts' approach which seems to be logical for the stars as well. In detail, we assumed that only one star exists, where we vary the number of ties this star forms.

5 Results

5.1 Simulated information networks

To get a better understanding of our main results regarding the impact of network typology on knowledge accumulation and innovation, we first present in the following central network indicators for different simulated networks.

Applying the extended Watts algorithm to generated information networks among a set of firms we assumed that 1000 firms exists. Further we simulated the spatial distributed of firms as well as firms' distribution over two branches according to specific algorithms described in Henning et al. (2007). Based on firms simulated spatial and branch distribution we applied the extended Watts algorithm described above assuming different values for α. In particular, we vary α in the range from zero to 20, where we kept the average density constant to 0.01, e.g. in average a firm has 10 information ties. Additionally, we assumed that one star exists, with a total number of ties of 100, 250, 500 and 750.

In general, each for each parameter constellation 100 simulation runs have been done and presented values correspond to the mean values over these 100 runs. In detail we receive the following results.

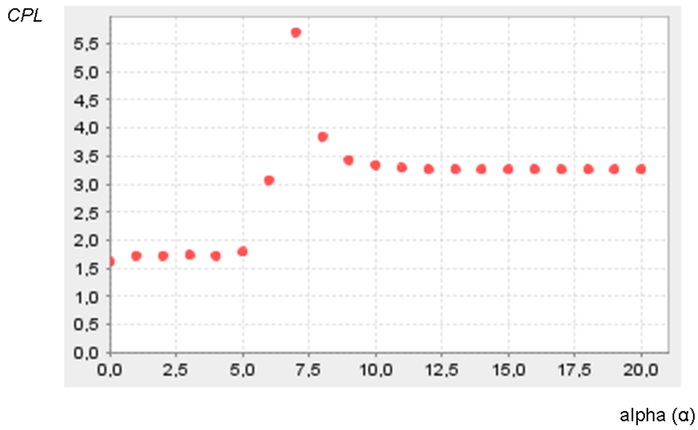
Characteristic path length

"One of the most important statistics of graphs to be considered here is the *characteristic path length* ($L(G)$). It is also assumed that the characteristic path length determines the speed of information diffusion in the regional networks of firms, where speed is defined as the steps which have to be done in order to reach a certain target agent. The characteristic path length differs from network to network.

Figure 1 shows the characteristic path length L for the α-model according to Watts (1999a) , while figure 2 displays the characteristic path lengths for one star with different degrees k.

For small-world networks the characteristic path length first increases and then decreases with α, where the increase in figure 1 is an artifact, since for α-values below 7 the network is not fully

Figure 1: Characteristic path length (CPL) for the α-model of Watts (1999a)

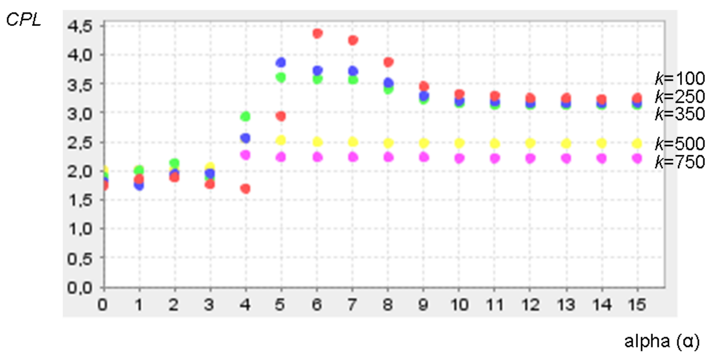


Source: Own source

connected. Therefore, for a connected network characteristic path length decreases with α, i.e the more a network becomes a random network.[2]

In general the same pattern can be observed for hybrid networks. However, a higher centralization generally reduces the characteristic path length, i.e. figure 2 shows a smaller value for higher degrees for the scale-free network with one star.

Figure 2: Characteristic path lengths for one star with different degree k



Source: Own source

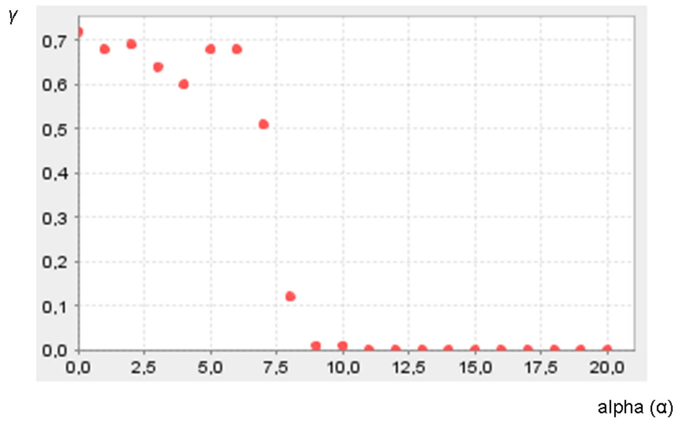
The higher the degree for the star; the lesser the characteristic path length. In the case where the star has a degree of $k = 750$ the characteristic path length is constantly close to 2.

[2]The results attained are similar to the results displayed by Watts (1999a, p. 49) figure 3.4. Some variations in the exact values could be observed due to different implementations in the code, and also due to random number generators. The characteristic path length shows the same stylized facts described by Watts (1999a).

Clustering

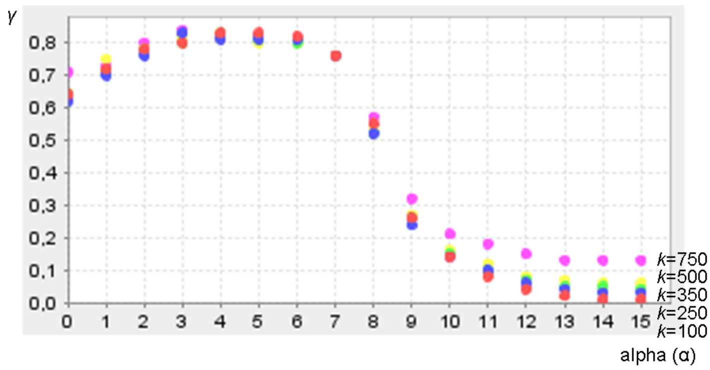
The clustering properties as a function of α are expressed by the clustering coefficient γ, which measures how densely connected the local neighbourhoods are on average. Figure 3 displays the clustering coefficient γ for the α-model of Watts, while figure 4 presents clustering for scale-free network assuming one "star".

Figure 3: Clustering coefficient γ of the α-model according to Watts (1999a)



Source: Own source

Figure 4: Clustering coefficient γ for one star with varying degree k



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While figure 3 basically reproduced the results of Watts (1999a), i.e. clustering values decreases with α, where clustering is extremely reduced once the network is fully connected, i.e. α reached values above 7. Once the network is completely connected the clustering coefficient decreases to a level close to zero exhibiting clustering properties as observed for random networks.

Figure 4 displays the development of the clustering coefficient γ for the scale-free network with one star for different values of α. The figure shows that in general the same relation between clustering and the paramter α can be observed for scale-free networks. However, the curve is significantly smoother for the latter when compared to small world networks.

Centrality

Another important measure is the centralization σ. By construction centralization should be larger for scale-free networks with stars when compared to small-world networks. Accordingly, this result is clearly confirmed by the following figures presenting centrality of both network types.

Figure 5: Centralization σ for the α-model according to Watts (1999a)

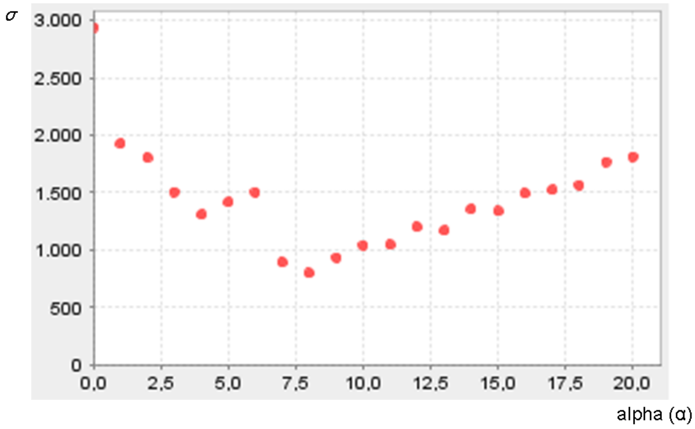

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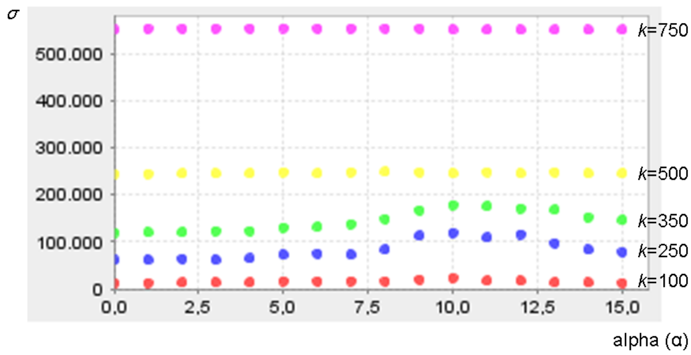
Figure 6: Centralization σ for one star with different degrees k



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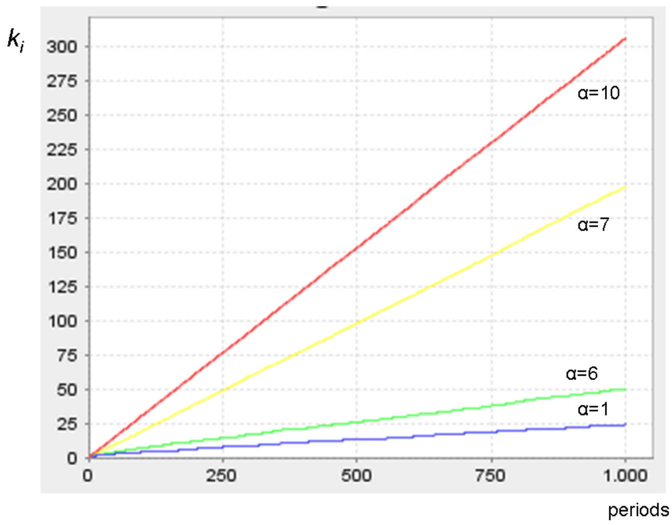
In the case of $k = 100$ the centralization σ is relatively low, whereas in the case of $k = 750$ the centralization increased rapidly.

5.2 Network typology and knowledge accumulation

The key question of our simulation analysis is how different network typologies influence the accumulation of knowledge in the regional economy. Thus, a first indicator of knowledge accumulation would be the maximal knowledge accumulated by a regional firms, i.e. $Max\left\{\sum_{i\in F} K_{it}\right\}$, where for simplicity we have assumed that each information signal equals 1, i.e. $k_t = 1$. Accordingly, assuming further that the accumulated knowledge in period 1 is zero for all firms, it follows that the maximal knowledge a firm can accumulate until a given time period T just equals T.

Figure 7: Highest accumulated knowledge in regional firm network assuming different small-world network typologies



Source: Own source

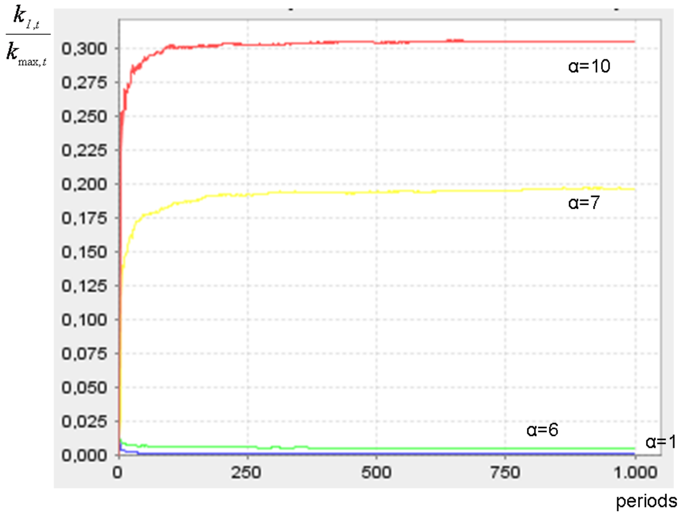
As can be seen from figure 7 the typology of information networks has systematic impact on information accumulation, where average accumulated information increases with alpha. However, the relevant indicator for the speed of knowledge accumulation in the regional economy is the relation of the average accumulated knowledge by regional firms to the knowledge generated in the leading region:

$$\frac{\bar{K}_T}{K_{T\max}} = \frac{\sum\limits_{i\in F} K_{it}}{\sum\limits_{t=1}^{T} k_t} = \frac{1}{T}\sum_{i\in F} K_{it}$$

Figure 8 displays the relation of average to maximal accumulated knowledge for the different simulated values of α.

The greater the value of α, the greater is c.p. the average accumulated knowledge in the regional economy in relation to the accumulated generated knowledge in the leading region. Moreover, for any α this relation approximates a constant in the long run. For unconnected networks, i.e. $alpha < 7$, this relation is close to zero, i.e. relative accumulated knowledge in the regional economy is extremely lagging behind the accumulated knowledge of the leading region.

Figure 8: Information accumulation for small-world network typologies



Source: Own source

For connected information networks, i.e. $\alpha > 7$, this constant ranged between 0.2 for $\alpha = 7$ and 0.3 for $\alpha = 10$, that is average accumulated knowledge in the regional economy stabilizes between one fifth and one third of the knowledge generated in the leading region.

Thus, in contrast to neoclassical approaches to regional spillovers according to our theory catching-up does generally not occur at least not in small-world networks.

Obviously, given the assumed process of information transmission and knowledge accumulation this result is also intuitively understandable, since the speed of knowledge transmission form the leading region to the peripherial regions crucially depends on the speed of information diffusion in the regional network, which in turn is mainly determined by the average path length among firms. The lower the average path length the faster information diffuses through the regional network and the faster new information injected by the leading region can be processed by randomly chosen firms.

Applying this logic to hybrid networks characterized by free-scale properties implies that in average the speed of knowledge accumulation should increase with network centrality, since this reduces the average characteristic length of the network. Figure 9 represents maximal accumulated knowledge in a free-scale network assuming one star with 250, 500 and 750 information contacts. As regard content a star could be a large firm dominating business relation in the region, i.e. a trading company to which most regional firms deliver their products, or a business organization of which most firms are a member of.

As can be seen from figure 9 and 10 our theoretical hypotheses are confirmed. Introducing stars into small-world networks generally increased both the absolute accumulated knowledge in regional networks and also the relation of average accumulated knowledge in the regional network and generated knowledge in the leading regions. Furthermore, in general the same relation between the α-parameter and accumulated knowledge in the regional economy results for scale-free networks. Please note that the latter can not be seen from figure 9 and 10, for which a constant $\alpha = 7$ is assumed.

Figure 9: Highest information for the scale-free network with one star and different degrees (growth paths for different scale-free networks with different degrees k of the star)

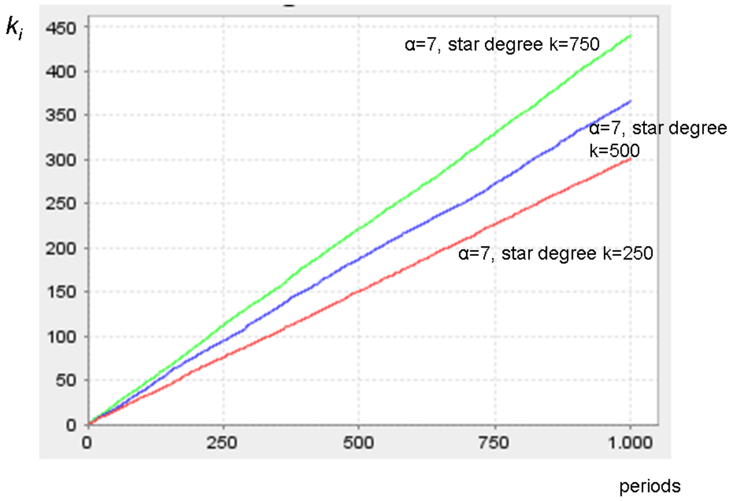


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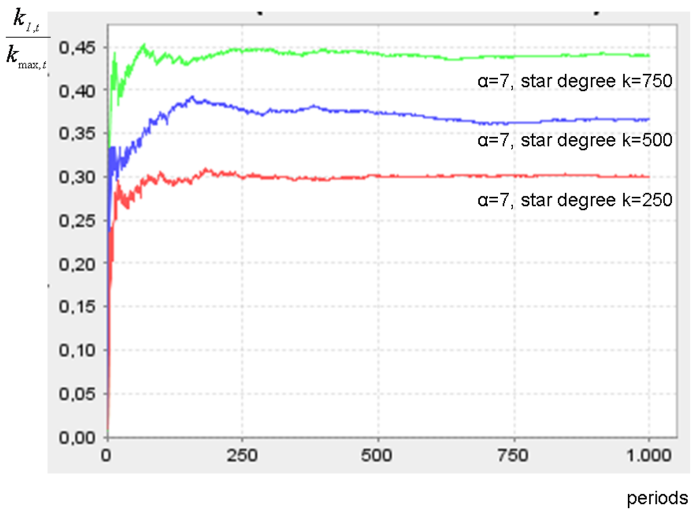
Figure 10: Information accumulation for the scale-free network with one star and different degrees



Source: Own source

However, please note that also for highly concentrated networks catching-up is not observed given a constant relation of 0.45 for average and maximal accumulated knowledge assuming a star with 750 in formation contacts, e.g. that is directly related to 75 percent of the regional firms.

Finally, notice that also we observe a constant relation between knowledge accumulation in the peripherial and leading region, the difference of accumulated knowledge in this two regions is still not constant, but increases constantly over time:

$$K_{max,t} - \bar{K}_t = K_{max,t} \cdot (1 - z_\alpha) = t\,(1 - z_\alpha) \tag{11}$$

, where

$$z_\alpha = \lim_{t \to \infty} \frac{\bar{K}_t}{t}$$

This indicates that the difference between the accumulated knowledge in the perhiperial and leading region increases linearly over time.

5.3 The impact of network typology on regional economic growth and the regional share in total production

Finally, we analyze the impact of network structure on regional growth and the development of regional share in production. Obviously, this impact depends crucially on the properties of the function A(), i.e. how accumulated knowledge translates into production output.

Here, it is common in the neoclassical growth theory to assume an exponential function for A():

$$A_i = e^{w \cdot K_{it}} \tag{12}$$

where w is a common exponential growth rate.

Alternatively, we also assume a linear form for A():

$$A_i = w \cdot K_{it} \tag{13}$$

Accordingly , w denotes the linear growth rate in eq.13.

Now giving our assumption above regarding regional knowledge accumulation, the long term growth rate of regional production in total production, w_x, can be expressed as a function of speed of knowledge generation in the leading region, w_{k_o}, and the long term relation of regional accumulated knowledge and generated knowledge in the leading region, i.e. z_α:

$$\begin{aligned} &w_x = w\ z_\alpha\ w_{K_0} \\ &\tfrac{K_{it}}{K_{0t}} = z_\alpha \\ &w_{K_0} = 1 \end{aligned}$$

Assuming a linear form for A(), w_x corresponds to a linear growth rate and accordingly a constant regional production share results in the long run:

$$\frac{\sum\limits_{i\in F} X_{it}}{X_{0t}} = \frac{w\ z_\alpha\ t}{w\ t}\frac{\sum\limits_{i\in F} g_i}{g_0} = z_\alpha\ \bar{g} \tag{14}$$

However, if a exponential form for A() is assumed, w_x corresponds to an exponential growth rate and regional production share tends towards zero in the long run:

$$\frac{\sum\limits_{i\in F} X_{it}}{X_{0t}} = \frac{\mathrm{e}^{(w\ z_\alpha\ t)}}{\mathrm{e}^{(w\ t)}}\frac{\sum\limits_{i\in F} g_i}{g_0} = \mathrm{e}^{-((1-z_\alpha)wt}\ \bar{g} \underset{t\to\infty}{\to} 0 \tag{15}$$

6 Summary and outlook

Stimulated by new evolutionary economic approaches to innovation and technical progress the paper analyzed the impact of different information network typologies on regional knowledge spillovers, knowledge accumulation and technological progress.

Technically, a rather simple ACE-model is derived that particulary focus on the role of information networks in the accumulation of knowledge by regional firms. New technological knowledge is exogenously generated in a leader region and randomly transmitted to regional firms. Within a region transmission of technological know-how occurs in information networks. Following central findings of existing ACE literature on innovation (Dawid, 2006) we assume that firms can only transmit information that they were able to process, where firms' capacity to process new technological knowledge depends on accumulated technological know-how. Therefore, given an exogenous rate of generation of new technological information in the technological leader regions, the speed of information accumulation within a region crucially depends on the speed of information transfer within the regional firm network, where the latter depends on network structures. Applying our simple agent based model we simulate the impact of different network typologies on spatial diffusion of knowledge and regional technological. In particular, we simulate two different network types, i.e. small-world and free-scale networks, varying global network structures, which are clustering and centralization. Main results of our simulation studies are the following:

(i) Information network structures have a significant impact on both spatial information diffusion and regional technological progress.

(ii) Information diffusion in networks is only imperfect, i.e. accumulated knowledge in regional networks correspond only to a constant fraction of technological knowledge generated in leader regions.

(iii) In particular, this fraction is c.p. higher for scale-free networks when compared to small-world networks. Moreover, this fraction increased for scale-free networks with the preferential attachment parameter and for small world networks with the α-parameter.

(iv) In contrast to classical catch-up models our network approach to spatial diffusion of technological knowledge implies that except for extreme centralized or dense networks catching-up does not occur. In contrast, depending on the concrete typology of regional information networks a constant productivity gap to the technological leader is stabilized or regions characterized by extremely clustered information networks are even increasingly falling behind.

Although in the new ACE-literature on innovation the importance of established informal and formal interfirm network structures for knowledge accumulation has clearly been recognized, it is still fair to conclude that there hardly exists studies analyzing the role of networks in regional knowledge spillovers. In this regard the paper certainly contributes the existing literature.

However, to focus on the role of information networks in knowledge spillovers the paper applies a rather simple model neglecting other important factors determining innovation processes. In particular, beyond knowledge spillovers, innovation involves other mechanisms, i.e. in-house R&D or learning by doing which have been neglected in our approach. Moreover, our approach simply assumes that accumulated knowledge is the key factor of technical progress, although beyond knowledge technical progress often requires investment in new capital goods. These investment is often characterized by a fundamental uncertainty, i.e. firms have to form beliefs regarding future states of the world without knowing ex ante the set of all possible future contingencies. Therefore, firms decision to invest in innovation can be better captured by ABM-approaches assuming strong substantive and procedural uncertainty than by dynamic optimization models with Bayesian updating or even perfect foresight.

Social networks have also a significant impact on agents' belief formation and thus on firms' investment decision regarding innovation project. However, these aspects of the impact of social networks on innovation have not been considered in this paper, and we consider this as an interesting topic for future research.

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