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RESEARCH PAPER

Innovation Dynamics and Industry Structure Under Different Technological Spaces

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Abstract The paper presents an Agent-Based model to analyze the reciprocal influence between industry structure and industry innovation patterns. This topic was originally investigated through the seminal models of Schumpeterian competition developed by Nelson and Winter (Am Econ Rev 67:271–276, 1977, An Evolutionary Theory of Economic Change. Harvard University Press, Cambridge, 1982), Winter (J Econ Behav Organ 5:287–320, 1984), and Nelson (National innovation systems. A comparative analysis. Oxford University Press, Oxford, 1993). However, the knowledge accumulation process depicted in these models was extremely simplified. In particular, they did not provide any insight about the direction of firms' technological advancement, within the range of possible alternative technological paths. This aspect is instead of topical importance for the generation of sectoral spillovers affecting the diffusion of innovations and the evolution of the industry structure. Our model aims at filling this gap by amending the framework proposed in Nelson and Winter (An Evolutionary Theory of Economic Change. Harvard University Press, Cambridge, 1982) so to to account for different characterizations of the 'technology structure' of the industry, and their possible influence on the process of Schumpeterian selection. More precisely, technology is represented as a directed network where each node constitutes a batch of technological skills to be learned by firms. The model shows that firms' ability to imitate competitors generates spillover effects whose relevance depends upon the topological structure of Technology Network and firms' specialization trajectories. In turn, by influencing the process of Schumpeterian competition, these spillovers exert a fundamental impact on both the industry innovative performance and the evolution of the industry structure.

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1 Introduction

The paper presents an Agent-Based model to analyze the determinants and consequences of firms' selection process in a market where firms do not only take short-term production and investment decisions, but are also engaged in the search for new technologies (Andersen 1996). This process of 'Schumpeterian competition' was originally investigated by Nelson and Winter in a series of computational models developed throughout the seventies and eighties. Nelson and Winter (1977) wished to examine the evolution of an industry characterized by multiple firms with different innovative behaviors. They considered an industry composed of imitators (investing only in imitative R&D) and innovators (investing both in imitative and innovative R&D). According to the efficacy of their innovative strategies firms experimented different innovative performances, determining different paces of capital accumulation, and different economic performances. The ensuing selection process, in turn, drove the evolution of the sector market concentration. This framework was then further refined in chapters 12 and 13 of Nelson and Winter (1982), where the Schumpeterian trade-off between 'static' and 'dynamic' efficiency was investigated. Winter (1984) then analyzed the process of Schumpeterian competition under different technological regimes, affecting the dynamics of productivity gains.[1] This later version of the model introduced an endogenous firms entry-exit mechanism. Furthermore, it provided on of the first examples—if not the very first—of adaptive heuristics in the field of computational economics as firms were allowed to adaptively change their innovative strategies, based on their past results. Finally, Nelson (1993), building upon this later version, investigated the impact of patents–preventing imitation from competitors during their lifespan—on the process of Schumpeterian selection and industry evolution.[2]

Although the relevance of these contributions is widely recognized, all these models—as we extensively discuss in Sect. 2.2—just focused on the quantitative productivity gains associated to innovation, while totally neglecting the *direction* of firms' technological advancement, and its repercussions on the innovation process itself. Instead, based on a endlessly growing empirical literature, the Evolutionary-Neo Schumpeterian school of thought has stressed that technological change takes place along ordered and selective patterns shaped by technological and scientific principles, as well as by economic and other societal factors (Verspagen 2007). Concepts such as incremental and radical innovations, technological paradigms and technological trajectories (Dosi 1982), natural trajectories (Nelson and Winter 1982), and

[1] In particular, they considered a science-based regime, where the average of the distribution of the 'latent productivity' grew at an exogenous rate, determined by the progresses of science, and a 'cumulative' regime, where the distribution was centered on the on the 'prevailing' productivity of firms.

[2] For an extended literature review on this stream of research see also Cohen (2010).

techno-economic paradigms (Perez 2009) have been developed to capture the patterns of innovation and diffusion across sectors (Breschi et al. 2000), and over time. The analysis of the relationship between sector knowledge base, industry structure, and economic dynamics is thus at the core of the evolutionary approach (Bottazzi et al. 2001; Malerba 2005; Cantner and Malerba 2007) and has allowed to identify typical patterns of industry evolution (Dawid 2006; Malerba 1992).

Our model aims at filling this gap by amending the framework proposed in Nelson and Winter (1982) so to take into account different possible characterizations of the industry 'technological space' in which firms operate (and innovate), and their possible influence on the process of Schumpeterian competition. Firms in our model can experiment different economic performances as a result of their decision to specialize along certain technological paths among all possible ones. In fact, we show that the direction of firms' technological specialization affects their ability to exploit sectoral spillovers through imitation.

The model stresses the relevance of the knowledge structure and knowledge accumulation process: the achievement of an innovation requires the prior acquisition of an ordered sequence of technological skills. Knowledge is cumulative and path-dependent. Each piece of technological knowledge represents at the same time the output and the input of firms' innovative activity. This idea is implemented in the model by representing the industry technology as a directed graph, where different nodes represent technological skills that firms can learn and accumulate, thus allowing them to achieve subsequent innovations.

Our choice of employing a network structure to represent the industry technology brings several advantage (as discussed in Sect. 2.2), in particular for its consistency with the analysis of 'patent citation networks', which opens the possibility of calibrating the network employed in the model so to reflect the actual patterns of specific sectors. However, in this work we present a 'proof of concept' prototype model, employing a set of artificial Technology Networks with different topological structures to highlight their impact on the industry innovation dynamics and evolution process.

2 The Model

Following Nelson and Winter (1982) and later versions, we focus on a single homogeneous product industry.

In each period of the simulation, firms produce using the best production technique at their disposal. All techniques are characterized by constant returns to scale and fixed input coefficients. Firms always produce their output at the full capacity level, this latter being constrained by their current stock of capital $K_{i,t}$. Given the stock of capital, firms then purchase the quantities of complementary inputs required. For simplicity reason, the model assumes that all factors supplies are perfectly elastic, so that all factors prices are constant. Given that each technique requires the same amount of complementary inputs per unit of capital (as input coefficients are fixed), this implies that costs per unit of capital, indicated by c, are constant and equal across firms. What differs is the productivity of capital $A_{i,t}$ which determines, given the stock of capital, the unitary costs of production. Capital productivity varies across firms and over time as *new combinations* are carried out. Therefore firms' productivity and their production costs depend on the efficacy of their R&D activity, by which they come to learn new technological skills.

The state of the generic firm i at period t can thus be summarized by the binary $\{K_{i,t}, A_{i,t}\}$. which determines her output through Eq. 2.1:

$$Q_{it} = A_{it} \cdot K_{it} \tag{2.1}$$

Total output is then given by: 2.2:

$$Q_t = \sum_i Q_{it} = \sum_i A_{it} K_{it} \tag{2.2}$$

The industry faces a downward sloping demand curve with unitary elasticity of prices to quantities. The price is then determined through the product demand-price function as:

$$P_t = D\left(Q_t\right) = \delta / Q_t \tag{2.3}$$

where δ is an exogenous constant parameter representing nominal demand. Firms' profits are given by revenues on sales minus production and innovation costs. By dividing for firms' capital stock, we obtain that firms' rate of profit is equal to the market price multiplied by firms' capital productivity, minus production costs per unit of capital c, minus R&D costs per unit of capital. Innovative and imitative R&D costs per unit of capital, in turn, are given by (r_{in}, r_{im}) respectively, so that the profit rate for firms performing both types of R&D can be expressed as:

$$\pi_{it} = P_t A_{it} - c - r_{in} - r_{im} \tag{2.4}$$

Conversely, firms spending only on imitative R&D have a profit rate equal to:

$$\pi_{it} = P_t A_{it} - c - r_{im} \tag{2.5}$$

In each period, based on the set of technological skills already in her possession, which are collected in a firm-specific list called 'Skill Profile' (SP hereafter), each firm set a 'target' skill to learn (i.e. a target 'innovation node'). However, this may require to set also 'sub-targets' if the firm does not already possess all the prior technological knowledge required to learn it (see Sect. 2.2). Firms can try to learn targets and sub-targets either through innovative R&D activity or by imitating competitors.

The probability of success of innovative R&D is an increasing function of the firm's current expenditure in this activity:

$$Pr\left\{success\right\} = \alpha r_{in} K_{it} \tag{2.6}$$

Alternatively, a firm can try to learn a node through imitation, that is by observing the technology in use among her competitors and trying to copy it. For this sake, she first samples a batch of competitors to 'imitate', and then check if the (sub)target node she is targeting belongs to the SP of anyone of them. If this is the case, imitation is successful and the target node is added to the firm's SP. Otherwise, she tries again in the following period, sampling a different set of competitors. The number of competitors that firms can try to imitate in a given period, N_{it}^{im}, is defined as the maximum between 1 and the value extracted from a Binomial distribution having number of trials equal to the number of competitors in business, and probability of success in each Bernoullian trial increasing with firm's current expenditure on imitation:

$$N_{it}^{im} = Max\left\{1, N_{it}^{im*} \sim Binomial\left(N^{firms} - 1\ ,\ \beta r_{im} K_{it}\right)\right\} \tag{2.7}$$

where N_t^{firms} is the total number of firms. Needless to say, the higher this number, the greater should be the probability of success. Since both policies towards innovation are defined in terms of spending per unit of capital, a firm's total expenditure on innovation and imitation grows or declines according to her size: large firms spend more on R&D than small firms do. In turn, this greater spending implies a greater chance of success. The rationale and the features of the directed network employed to model the industry technological space are discussed, respectively, in Sects. 2.1 and 2.2, whereas firms' behavioral rules related to the choice of the target nodes are outlined in Sect. 2.3.

For each firm, we can then calculate the 'price-cost' ratio $\rho_{it} = P_t/(c/A_{it})$, which provides an ex-post measure of firm's realized mark-up over unit costs, given the prevailing market price. This ratio concurs to determine, together with firms' market shares $s_{it} = \frac{Q_{it}}{Q_t}$, firms' desired expansion (or contraction) (Eqs. 2.8 and 2.9). Firms' ability to fund investment is constrained by their profitability π_{it}: the greater firms' profitability the greater their ability to persuade capital markets to provide the required funds (Eqs. 2.9 and 2.10).[3]

Since firms produce a homogeneous product and prices are market clearing, firms can only decide the amount of goods they want to produce and sell. In turn, given that they always produce at their full capacity level, this choice depends on their current stock of capital, determined by investment decision which is described by Eq. 2.9. A detailed explanation of this investment function is provided in Appendix A.1. Intuitively, firms' market share enters in the investment function because firms are afraid of 'spoiling' their own market: if they excessively increased their scale of production the market price for their output would shrink, eventually squeezing their profit margin. Therefore, the higher a firm's current market share, the greater the risk of spoiling the market by further increasing production; and then, the higher the price-cost ratio required to induce a given level of expansion. The degree of wariness of firms in taking their investment decision, in turn, fundamentally depends on their assessment of the demand curve elasticity. When firms believe the elasticity of demand to be low, the expected effect on the market price of a further increase in production will be negligible. As a consequence, they tend to invest more for given values of ρ_{it}. The opposite happens if they consider demand elasticity to be high. For simplicity

[3] Notice that, since the rate of profit depends on r_{im} and r_{in}, R&D outlays reduce the funds available to finance investment

reasons, we assume that firms have a correct evaluation of the unitary elasticity which characterizes the demand curve faced by the industry.

Formally, firms' capital stock evolves according to the following first order difference equation:

$$K_{i(t+1)} = I\left(\rho_{it}, s_{it}, \pi_{it}\right) K_{it} + (1-\delta) K_{it} \tag{2.8}$$

where δ is the physical depreciation rate of capital, and investment $I(\cdot)$ is nonnegative and determined by:

$$I(\rho, s, \pi) = Max\left\{0, Min\left[(1+\delta) - \frac{2-s}{\rho(2-2s)}, f(\pi)\right]\right\} \tag{2.9}$$

In Eq. 2.9 $f(\pi)$ indicates firms' financial constraint, which is determined by:

$$f(\pi) = \begin{cases} (\delta+\pi), & \text{if } \pi \leq 0 \\ \left(\delta + B^{regime}\pi\right), & \text{if } \pi > 0 \end{cases} \tag{2.10}$$

$B^{regime} > 1$ is a parameter defining the financial regime: when the rate of profits is nil, firms are able to raise funds just sufficient to replace depreciated capital; when the rate of profit is negative they can replace only a portion of their depreciated capital; finally, if $\pi > 0$ firms can finance a rate of expansion of the stock of capital up to a multiple B^{regime} of their profit rate.

2.1 The Path-Dependent, Firm-Specific Nature of Technological Advance

The generation of knowledge is characterized by specific attributes: knowledge is at the same time the output of a learning process and an input for the generation of new knowledge. In other words, innovation and knowledge creation are highly cumulative and path-dependent.

Firms can enrich their knowledge base by mobilizing both internal knowledge, e.g. through R&D labs, and knowledge located externally, derived from other economic and social actors. Innovation and its diffusion are thus regarded as processes involving the systematic interaction of a wide variety of actors in order to generate and exchange the knowledge relevant to innovation and its commercialization (Cassiers and Forey 2002; Antonelli 2009).

According to Dosi (1982), technology is a broad concept encompassing 'a set of pieces of knowledge, both directly practical (related to concrete problems and devices) and 'theoretical'(but practically applicable, although not necessarily already applied), know-how, methods, procedures, experience of successes and failures and also, of course, physical devices and equipment'. Pushing on a parallel with Khun's 'scientific paradigms, he then proposed the notion of 'technological paradigm', defined as a 'pattern' of solution of selected technological problems, based on selected principles derived from natural sciences, and on selected material technologies. In a nutshell, a technological paradigm is then identified by the generic tasks to which it is applied, the materials it selects, the chemical-physical properties it exploits, and the technological and economic trade-offs it focuses upon. Therefore, technological paradigms shape the basic structure of the technology at stake, delimiting the boundaries in which different 'technological trajectories' can arise.

The notions of 'technological trajectories' plays a central role in our analysis of the Schumpeterian competition process. In Nelson and Winter (1982) model, as well as in its later versions (Winter 1984; Nelson 1993), the final outcome of innovation and imitation processes, when successful, was simply to provide the firm with a 'number' that added up to its current level of productivity. No insight of the 'direction' of technological change by the single firm and the whole industry was provided. Technology was thus described in purely quantitative terms, just focusing on the absolute value of the productivity gains generated by innovations.

This clearly appears if we look at the way imitation was treated. The model implicitly assumed that firms had perfect knowledge of the techniques in use among their competitors, and that they were able to rank them unequivocally in order to identify the best practice of the industry. In reality firms' activity dedicated to 'scan' the technology of competitors is costly and time-demanding, and in most cases it does not allow to attain an unambiguous assessment of the advantages and disadvantages associated to each technique. Even more important, the model assumed that firms doing imitation, when successful, were always and immediately able to adopt the industry best practice, regardless their current gap and the potential discrepancies between their own technological specialization and technology underlying the best practice.

Instead, firms' technological evolution in real world is affected by path-dependency, implying that today's innovative choices not only affect the firm's current performance but, to some extent, 'constrain' her future innovative possibilities, delimiting the paths of technological development that can be feasibly explored. Even within the same industry, firms can experience different technological trajectories, according to their original endowment of technological competences, their past technological path, the set of opportunities and constraints defined by the technological, legal, institutional, and social environment in which they operate, and stochastic factors as well. These trajectories exert a powerful exclusion effects since they tend to restrict innovative efforts in rather precise directions, while being blind to other technological possibilities. Although there might be some complementarity between different trajectories, the more firms are specialized, the more difficult and costly becomes switching from one trajectory to an alternative one.

The paper presents a simple framework to fill the gap discussed above which explicitly considers the topological structure of the technology employed in the industry by modeling the technological space as a directed graph where nodes-representing skills to be learned by firms-are distributed over alternative technological trajectories. In accordance with the empirical observation, in our simulations firms tend to specialize along particular technological trajectories through a search process which goes from less to more specialized technological skills (an in-depth search process). Firms are boundedly rational (Simon 1947) and are not able to evaluate *ex ante* in a precise way the complete set of technological opportunities (i.e. the complete sequence of productivity gains) enabled by each feasible trajectory. Hence, as they face strong substantive uncertainty (Dosi and Egidi 1991), they tend to follow simple heuristics: firms' choice of the trajectory to specialize upon crucially depends on the set of technological skills already in their possession, thus stressing the path-dependent and firm-specific nature of technological advance.

Furthermore, the extent and speed at which firms can explore each trajectory is also affected by the presence of spillovers effects, related to the process of imitation and depending on the number of firms specializing along the same trajectory. The success (or failure) of an innovative strategy thus depends not only on the intrinsic technical 'goodness' of the trajectory chosen, but also on other firms' technological choices, and then on the dynamic of the whole system.

2.2 Modeling a Technological Space as a Network

In order to assess the role of spillovers and to analyze how firms' choices about the direction of their innovative efforts affect the selection process within the industry, we provide an explicit representation of the technological space in which firms operate. Indeed, the industry is initially endowed with a 'Technology Network' (TN): nodes can be thought of as the set of technological skills to be learned in order to achieve a particular innovation while links between them define the dependencies between the pieces of technological knowledge they represent. Indeed, in order to learn a given node firms must already manage all the technological skills embedded in nodes which point to it; that is, they should already have learned all its *'parents'* nodes.

Admittedly, the focus on firms' technological specialization and the analysis of the process of 'competition for adoption' between alternative technologies is not a novelty. Arthur (1988a, b), Silverberg et al. (1988), and Arthur (1989) have stressed the self-organizing and non-ergodic nature of the technology diffusion process, possibly generating multiple equilibria and lock-in phenomena. Since then, several types of models have been proposed to study how spillover effects, learning economies, and network externalities affect the process of adoption of competing technologies. Among the recent refinements of this stream of literature we find history-friendly models (Malerba et al. 1999, 2008; Malerba and Orsenigo 2002) and percolation models of innovation diffusion (Silverberg and Verspagen 2005; Hohnisch et al. 2006; Cantono and Silverberg 2008).

The core of these models still relies on the same fundamental intuition of traditional epidemic models: on the one hand, technology and innovations spread as potential adopters come into contact with existing users of an innovation; on the other hand, the adoption by a larger number of users increases the attractiveness of the technology thanks to increasing returns to adoption of some type. Most of the modeling sophistication proposed in the literature thus relate to how potential users communicate with each other, and how their adoption decisions impact the structure of payoffs associated with competing technologies. The focus in thus on the relationships between innovators, rather than on the relationships between pieces of technological knowledge which are required to manage a technology or to achieve an innovation.

The framework proposed in the present work can be seen as complementary-rather than alternative—to these approaches in that we keep as simple as possible the relationships between technology users, whereas we assign a topology to technology, by placing technological skills on a network structure. This choice may bring several potential advantages. First, most of diffusion models just focus on the case of two alternative technologies competing for a market of adopters, or on the diffusion process of an innovation striving to replace an incumbent technology. The network-based approach proposed here instead allows to consider a wider variety of situations where, for example, several technologies compete and possibly come to coexist. In addition, it also allows to consider possible complementarities or dependencies between competing technologies. Finally, a network-based representation of the technological space has the further potential advantage of being naturally suitable for an empirical calibration based on the evidence provided by the growing literature on 'patent citation networks' (Jaffe et al. 1993; Hall et al. 2001). Over the last decade this literature has continued to grow (Verspagen 2007; Nomaler and Verspagen 2007; Schettino 2007; Fontana et al. 2009; Krafft et al. 2011), allowing to identify several industry-related stylized facts, and to map the main paths of technological evolution of several sectors. Such an empirical foundation of the Technology Network would thus possibly help to enhance the explanatory power of 'history friendly models', which aims at investigating and replicating the actual patterns of evolution of real world industries (Malerba and Orsenigo 2002; Malerba et al. 2008; Garavaglia 2010).

Admittedly, these possibilities are far from being exhaustively exploited in the present work where we present instead a 'proof of concept' prototype model, employing a set of artificial Technology Networks, with different topological structures, to highlight their relevance for the process of Schumpeterian competition and industry evolution.

These networks are generated through a stochastic algorithm,[4] designed to reflect the general features of 'technological paradigms' and 'technological trajectories', as they emerge from the evolutionary literature.

First, the dimension of the network is set equal to an exogenously given parameter N. The origin of the network is represented by the 'root node' N_0. This can be thought of as the set of technological skills shared by all firms and representing the basic knowledge of the TN. Other nodes have indexes going from 1 to $N-1$. Then, we draw n direct links from the root node to n initial nodes N_1 to N_n, n being an exogenous parameter.

These nodes represent the first technical skills stemming from the basic knowledge contained in the root node. Remaining nodes (N_{n+1} to N_{N-1}) are sequentially embedded into the TN trough the following procedure:

(i) First, each node samples a *List of Potential Parents* (LPP) among all the possible one. Point ii. explains how the LPP are constructed. Then, each node randomly samples its actual parents from the LPP, their number being equal to a random integer between 1 and the dimension of the LPP. Direct parents are collected in the *Parents List* (PL) whereas its *Genealogy List* (GL) collects its entire genealogy, i.e. the complete list of 'ancestors', from the root node to its 'direct' parents. The genealogy provides the complete list of nodes that must be learned before being able to learn the node under consideration.

[4] A similar algorithm can be found in Morone and Taylor (2010).

(ii) In order to construct the *Lists of Potential Parents* we first split the list of the n initial nodes into j parts. j is randomly extracted from a Binomial Distribution having number of trials equal to n and probability of success P_{Split}, with P_{Split} exogenously given. As nodes are progressively embedded in the network, they are attached to the LPP from which they had sampled, thus becoming themselves the potential parents of following nodes. Therefore, the Lists of Potential Parents change as new 'children' nodes are attached to them. However, before adding new nodes to the network, a random split in a randomly chosen LPP may occur, with probability P_{split}.[5]

By repeatedly splitting the Lists of Potential Parents, as explained in point ii., the Technology Network acquires a branched structure. The higher P_{split}, the more branched the resulting network will tend to be. Different branches can be thought as representing alternative technological paths that firms can explore through their search activity. By branching the network we are then introducing the possibility of having-within the boundaries of a technological paradigm (i.e. the TN)-different and relatively independent technological trajectories.

Figure 1 shows an example of TN generated with this algorithm. The figure displays the root node, marked by index 0 and the $n = 10$ initial nodes radially arranged around it. The branching of the network subdivides it into different and partially independent area, representing different technological trajectories.

2.3 The Direction of Innovation

Once the TN is generated, nodes are endowed with a given productivity gain that firms can obtain by learning the node. For reasons explained in Sect. 3 and related to the purpose of the present work, we assume that all nodes provide the same productivity gain.

Each firm is then endowed with an exogenously given initial number N_{skill} of skill nodes-randomly chosen among the n initial ones-which represent her initial Skill Profile. This also implies that firms have the same initial productivity. Firms in the industry then strive to lower their unit costs of production by increasing their capital productivity. For this sake, they need to enhance their technological knowledge by learning new innovation-nodes. Nodes learned by firms are then attached to their Skill Profile. Firms can try to learn a target node only if they already possess the technology contained in its genealogy, that is only if they have already learned all its 'ancestors'.

The choice of the target node fundamentally depends on the firms' current SP, since they choose the direction of their innovative efforts by comparing the set of nodes already in their possession with the list of nodes required to adopt each 'candidate' node. More precisely:

(i) Firms can choose the target only among the 'children' of the nodes already in their SP.

[5] As a final step, we 'clean' the network by eliminating from the Parents List of each node, parents who are already the ancestors of another parent, so to avoid redundancies.

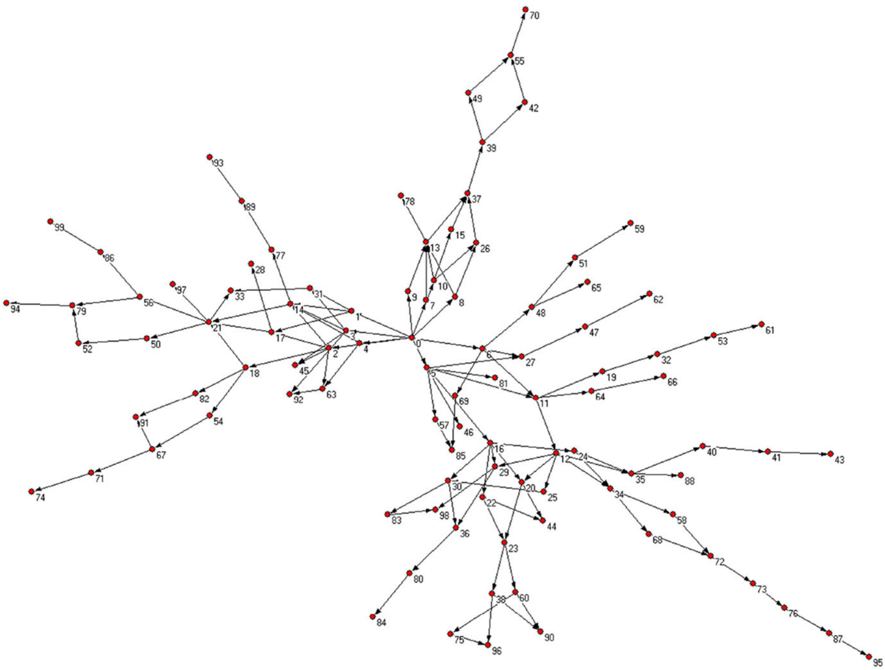

Fig. 1 Technology Network: $N^{nodes} = 100$, $InitialNodes = 10$, $P^{split} = 25\%$

(ii) Firms set as target the nearest node, where the distance from each candidate is given by the number of nodes that are in the candidate's genealogy but not yet in the firms' SP.[6]

Unless the firm already possesses all the nodes in the target's genealogy, she must also choose a 'sub-target' for the current period.[7]

Notice that, since we assumed that every node provides a productivity gain, both targets and sub-targets represent 'innovations'. However, the target determines the overall direction of firms' technological specialization. The procedure by which the target is chosen allows the firm to identify the linkages between different pieces of technological knowledge, i.e. different nodes, in a neighborhood of her current SP. By choosing the target the firm moves forward in the exploration of the network structure that represents the technological paradigm prevailing in the industry.

Given these simple behavioral rules, we expect each firm to specialize along particular trajectories.[8] Which ones depends fundamentally on firm's initial technological

[6] If more than one, they chose the deeper one (i.e. the one with the longer genealogy). Hence they prefer more specialized skills (in-depth search).

[7] For simplicity reasons we assume that firms chose as sub-target the node with the lowest index among those required to implement the target. This trivial rule, while not affecting at all the dynamics of the model, is sufficient to assure that firms will always choose as sub-target nodes that they are actually able to learn directly, given their current SP.

[8] When a firm exhausts all the possibilities of a trajectory, she is allowed to start exploring another one. The choice of the new target is based on the same procedure explained above.

skills but, if more than one possibility are still open, it may also be determined by chance. Therefore, during the simulation, different firms will generally explore different technological trajectories. As a result of the firms' selection process connected to the process of Schumpeterian competition, some of these trajectories will become dominant while others will remain marginal.

It must be stressed that in our model, every innovation produces two effects: first, it raises firms' productivity as in Nelson–Winter models.[9] But in addition, every innovation concurs in defining the direction in which firms are moving within the Technology Network, prompting the firm to specialize along a particular technological path, thereby constraining also the direction of future technological advance by the firm.

As mentioned before, firms can try to learn innovation nodes through either innovative or imitative R&D. At the beginning of each simulation run, imitators select the competitors to imitate randomly. Indeed, at this stage they have no idea of other firms' technological profile. However, a successful imitation may signal that the imitated firm is specializing in a similar region of the Technology Network, thus being likely to provide further opportunities for imitation in the future. Therefore, firms assign to competitors that they have successfully imitated a 'priority' for the next periods: hence, these will be the first competitors to be selected in the firm's next imitative attempts.[10] This priority is scrapped if the imitated firm does not yield any further skill for a given number of subsequent attempts (2 in our experiments). When firms have not succeeded in learning the target node, they sample a different batch of competitors to imitate in the next period.

It is important to notice that imitation generates spillover effects related to the process of diffusion of technological innovations. These spillovers are fundamentally affected by the topological structure of the network which shapes the relationships between different technological skills, and their dimension is largely dependent upon the directions of firms' technological specialization, in a way that was almost neglected in Nelson and Winter's models. Indeed, the probability of learning a target node through imitation of competitors increases when more firms are specializing upon the same technological trajectory on which the node is located. Therefore, firms specializing along densely populated trajectories may have a relative advantage with respect to firms specializing along less densely populated trajectories. On the other hand, firms which also invest in innovative R&D might be disadvantaged if it becomes to easy for competitors to imitate their skills. Our results show that the dimension of spillovers and the shape of these trade-offs significantly vary in relation with the industry structure (i.e. the number of firms operating) and the features of the technology network characterizing the industry (more or less 'branched' networks).

Given that spillovers have a different strength on different technological trajectories, the success or failure of firms' innovative efforts can be fundamentally affected by what competitors do, that is, by the direction of their innovation efforts. This also implies

[9] The increased productivity, in turn, can increases future R&D outlays via profit, investment, and capital accumulation.

[10] In case N_{it}^{im}, the maximum number of competitors a firm can look at when imitating (see Sect. 2), is greater than the number of competitors with 'priority', the remaining ones are randomly sampled. In the opposite case the firm extracts randomly the N_{it}^{im} competitors to imitate among those with priority.

that even firms starting with identical strategies towards innovation and identical initial endowments can experiment very different economic performances as a result of their decisions to specialize along certain trajectories, and not along others.

3 The Setting

The relationship between firms' dimension, market structure, and innovation dynamics was at the very core of Schumpeter's analysis, in particular in *Capitalism, Socialism, and Democracy* (Schumpeter 1950) where he identified in large firms with substantial market power the fundamental engine of technological advance. As stressed by Nelson and Winter (1982), the market structure is endogenous to an analysis of Schumpeterian competition, with the causal link going in both directions. Large firms may have innovative advantages with respect to small firms due, for example, to managerial and R&D economies of scale and to their greater access to credit. In our model large firms spend more on R&D and consequently have a higher probability of carrying out innovations. Furthermore, they also have appropriability advantages, since they can exploit innovations on a larger scale of production. Still, the market structure can influence the ability of innovators to exploit the gains of technological change, affecting the speed at which imitators can catch up and erode innovators' advantage. If there are only few competitors, it is likely that an innovating firm will be able to maintain her technological advantage for a longer period than it would be in a market with more incumbents and more competitive pressure. In turn, successful innovators and imitators can invest their higher profits to increase their dimension so to enhance their primacy in the market, thereby affecting the evolution of the market structure.

In an evolutionary perspective, the study of the connections between market structure and innovative performance has been also fundamentally connected to the analysis of struggle between innovative and imitative strategies. Firms compete in the market and, according to the efficacy of their innovative strategies, they grow or decline, possibly pushing the market towards a more concentrated structure with multiple possible outcomes in terms of imitators' and innovators' shares. The probability to survive and grow of a firm following an imitative strategy mainly depends on her ability to exploit spillover effects. In turn, the dimension of these spillovers is influenced by the number of firms specializing in each feasible trajectory, and hence by the initial market structure. As a consequence, while Nelson and Winter (1982) model—in particular in its 'science-based' technological regime version—depicted a situation where innovative R&D activities were always somewhat unprofitable on average, here different initial market structures may determine a context more or less favorable for either innovative or imitative policies.

For this reason we run several experiments with different initial industry structures: four structures are examined, with respectively 4, 8, 16, and 32 firms. In order to provide the clearest possible explanation of the mechanisms underlying the process of Schumpeterian competition and industry evolution, we set the initial conditions and the parameter values looking for some kind of symmetry across firms' initial situation. For the same reason, we also rule out entry by new firms and we assume that half of firms follow a pure imitative strategy while the other half spend both on innovative and imitative R&D. As already mentioned, in order to give an account of the role played by the network structure in shaping technological spillovers, we assign to every innovation node the same productivity gain.[11] The initial stock of capital is the same for all firms. Each firm is also given the same number of initial skills, chosen randomly among the n initial nodes of the Technology Network. Furthermore, firms have the same initial level of capital productivity. As a consequence, in the first period of the simulation, the levels of production, the market shares, the mark-up ratios, and the desired net investment are also the same for all firms.

Firms' initial capital stock is determined so to ensure that firms' desired net-investment in the first period is equal to zero under each scenario.[12] The parameters r_{in} and r_{im} are then adjusted compensating for the differences in initial levels of capital so to ensure that the initial total expenditure on imitative and innovative R&D is the same in all scenarios. More precisely, following Nelson and Winter, r_{in} is chosen in order to maintain constant the ratio between R&D spending and sales at a level of 0.12.[13] The coefficient α, governing the probability of success in innovating is set so to give, on average and at initial conditions, 1 innovation for the whole system every 4 periods (i.e. a year). Following Nelson and Winter (1982), in order to highlight the cost of doing innovative R&D, we set $r_{im} = \frac{1}{10} r_{in}$ and in order to ensure the symmetry between initial conditions for all simulation runs, we then set β so that the expected value of the Binomial distribution in Eq. 2.7 at initial conditions is equal to one under all scenarios. Therefore, the parameter β depends on the initial number of firms and their initial capital stocks: $\beta = 1/(r_{im} K_{i0})$. This set-up thus assigns to the model roughly the same degree of 'progressiveness' under each scenario. Finally demand elasticity is set equal to 1, formally: $P_t = 67/Q_t$, costs per unit of capital c are set equal to initial capital productivity, and the parameter b_{regime}, defining the finance regime, is set equal to 2.5.

The set-up for the Technology Network generating algorithm employed in the baseline is the following: the network is made up of $N = 100$ nodes, with $n = 10$ initial nodes beside the root one. In each stage of the network generation process the probability P^{split} of splitting one of the Potential Parent Lists is set equal to 25% for the baseline.

Table 1 provides a summary of the parameter values employed for each of the four 'industry structure' scenarios.

Each simulation lasts 100 periods, each period representing a quarter of year, hence for a total of 25 years.

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[11] In this way we rule out any disturbing factor possibly arising from an asymmetric distribution of gains across different branches of the Technology Network. Therefore, the dimension of the spillovers along each possible trajectory does not depend on a pre-determined and arbitrary distribution of productivity gains across nodes. Instead, it depends on the topology of the network representing the industry technological space—which shapes the interdependencies between different technological skills—and on firms' choices about the direction of their search process.

[12] This implies that the initial stock of capital is lower the higher the initial number of firms is.

[13] This value seems to be fairly realistic even today. Some examples: in the previous decade the R&D expenditure as a percentage of sale was about 13.5% for the software and Internet industry, 13,5% for the healthcare industry, 7% for the computer and electronics industry, 5% for the aerospace and defense industry, while it was signifcantly lower for the chemicals and energy industry, about 1%.

Table 1 Initial values under four different initial market structures

	Number of firms			
	4	8	16	32
K	89.73214	48.85417	25.32762	12.87822
r_{in}	0.0224	0.0206	0.01984	0.01951
r_{im}	0.00224	0.00206	0.001984	0.001951
α	0.06219	”	”	”
β	1.6584	1.4216	1.3267	1.2839
c	0.16	”	”	”
δ	0.03	”	”	”

In order to check the robustness of our results under different realizations of the same network generating stochastic algorithm, we consider 5 different Technology Networks obtained with the same specification of the algorithm. For each of these five specifications, we run 100 Monte Carlo simulations under each scenario. The average results and the standard deviations for these simulations are collected in Table 2 in Appendix A.2.

Finally, we also aim at analyzing how different Technology Networks impact the evolution of industry structure, the patterns of innovations, and consequently industry performance. Indeed, as the empirical literature on Sectoral Systems of Innovation has stressed, “Sectoral systems differ in terms of technologies. [...] These technologies affect the nature, boundaries and organizations of sectors. [...] Links and complementarities among technologies, artifacts and activities play a major role in defining the real boundaries of a sectoral system. [...] Then there are dynamic complementarities, which take into account interdependencies and feedbacks. They greatly affect a wide variety of variables in a sectoral system: firms’ strategies, organization and performance, the rate and direction of technological change, the type of competition and the networks among agents.” (Malerba 2004, pp. 18–19). In order to perform such an analysis we change the parameter governing the branching of the network, assuming a probability P_{split} respectively equal to 10 and 40%. For each of these two specifications, we generate 5 different Technology Networks, and re-executed the same experiments of the baseline.

These two further specifications of the stochastic algorithm underlying the construction of the Technology Network affect the degree of complementarity/independence between innovation nodes, generating, respectively, more and less branched networks. Our results show that these changes affect the selection process undergoing in the market and the relative efficacy of imitative and innovative R&D strategies, eventually affecting also the innovative dynamics at the industry level.

4 Results of the Simulations

Our analysis starts by considering a Technology Network with ten initial nodes (besides the root one) and $P_{split} = 25\%$. In order to analyze how industry initial concentration affects the industry performance we compare the results of the simulations under

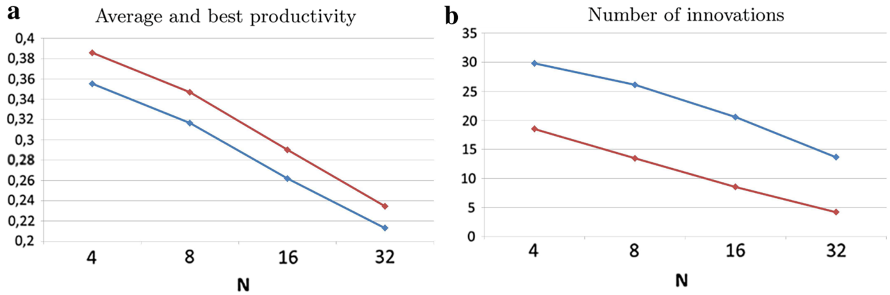

Fig. 2 **a** Average (*blue*) and best practice (*red*) productivity. **b** Total (*blue*) number of innovations in the industry and maximum (*red*) number of innovations by a single firm (color figure online)

the four different experimental scenarios with 4, 8, 16, and 32 firms, taking for this purpose the averages and standard deviations of the end-of-simulation values of the 100 Monte Carlo simulations. These values are displayed in Table 2 in Appendix A.2). For simplicity reasons, the values plotted in figures refer to the network marked by index 1. However, it is easy to verify that results are very robust under the 5 different realizations of the Technology Network for the baseline.

Figure 2a displays the Monte Carlo averages of the end-of-simulations best practice and average productivity. Both markedly decrease as we move from more concentrated to less concentrated industry initial structures: the best practice and the average productivity rise more rapidly when less firms are in business. This result seems to be consistent with the famous *Schumpeter Mark II* argument according to which a more concentrated market structure is the price to pay for a better innovative performance.

In all these cases, the dynamics of the productivity associated to the best practice depends crucially on the innovative R&D activity. Indeed, imitation allows to learn only nodes that have already been discovered through innovation. Therefore, only innovation allows to move forward along technological paths yet to explore, expanding the boundaries of what can be learned through imitation. When the network presents a significant number of independent trajectories, as it happens when the value P_{split} is high enough, imitation exerts a negligible influence on the best practice.[14] Therefore, it is not surprising that the decline observed in the best practice productivity level, as we move towards less concentrated industry initial structures, is accompanied by a fall in both the average number of innovations obtained by the industry as a whole, and the maximum number of innovations obtained by a single firm (see Fig. 2b).

The drop of the industry average number of innovation in scenarios characterized by less concentrated market structures can be explained as a result of the role played by spillover effects in our model: when the number of firms is higher, imitators have less difficulties in finding innovators to imitate. Or rather, it is more likely that innovating firms will be soon imitated by some competitor. This shortens, on average, the time span over which innovators can exploit the quasi-rents deriving from innovations and recover the higher costs incurred for doing innovative R&D. As a consequence,

[14] On the contrary, as we will show in Sect. 4.1, imitation plays a central role when the network is poorly branched and its nodes are more interrelated.

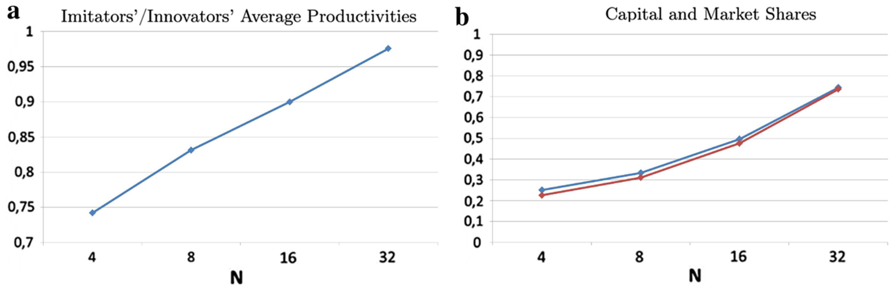

Fig. 3 **a** Ratio between imitators' and innovators' average productivities. **b** Capital (*blue*) and market (*red*) shares of imitative firms (color figure online)

innovators' performance worsen and the deterioration of their profitability negatively impacts on their capital accumulation. Eventually, this reduces the amount of resources devoted to innovation, thereby dampening their innovative performance.

This mechanism can be appreciated by comparing the performance of innovative and purely imitative firms across the four scenarios. In Fig. 3a we plot the average ratio of the end-of-simulation average productivities of imitative and innovative firms. The plot shows that moving towards less concentrated industries imitators are able 'to track" innovators' productivity closer and closer.

By recalling our previous discussion on spillovers in the model it is intuitive that the probability of success for an imitative firm is positively affected by the number of firms initially in business. When the number of firms is low, it is more difficult for an imitator to find an innovator specializing along her same trajectory. Consequently, on average, imitative firms find more problematic to enhance their Skill Profile through imitation and they cannot keep up the pace with innovators. On the contrary, when the number of firms is high it should be easier, at least for some imitators, to find someone to copy. Therefore, their performance tends to improve relatively to that of innovators. Figure 3a shows that in the 32 firms case the ratio between imitators' and innovators' average productivities is closed to one.

The observed fall in average productivity can thus be primarily explained as a result of the dampening of innovators' performance. However, it must be noticed that this is also a consequence of the fact that the productivity gains associated to innovations are automatically applied to the firm's entire capital stock. Therefore, the average productivity might also decrease as a consequence of the smaller share of capital affected by each innovation, when the number of firm is higher.[15]

The improved performance of imitative firms is also testified by the inverse relationship between their average capital share and the industry initial concentration (Fig. 3b): imitators' capital share is almost equal to that of innovative firms in the scenario with 16 firms and even higher in the last scenario with 32 firms, despite

15 In Nelson and Winter (1982) this was the only reason explaining the drop in average productivity levels in less concentrated scenarios whereas the best practice productivity was not affected at all by the industry initial structure under the investigated science-based technological regime which exogenously determined the growth of 'latent productivity'. The impact of different initial market structures under a cumulative regime, instead, was not investigated at all.

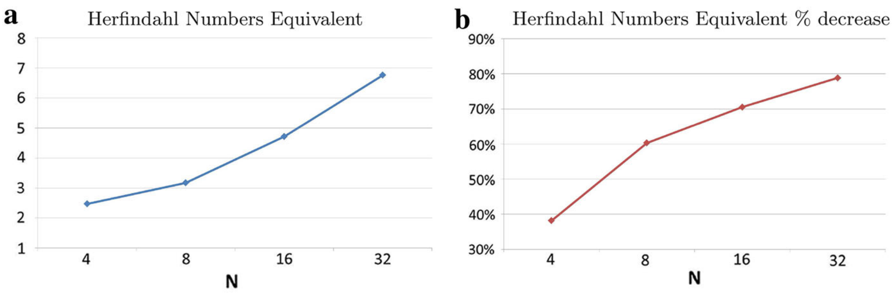

Fig. 4 Herfindahl numbers equivalent end-of-simulations values (**a**) and % reduction (**b**)

the fact that imitators' productivity is still slightly lower than innovators' one. This apparent discrepancy can be explained as follows: according to the desired investment function defined by Eq. 2.9 in Sect. 2, for two firms with the same market share, the firm with the lower production costs (i.e. higher productivity) will have a higher target output and, in turn, an higher target investment. However, investment is constrained by the rate of profit. While imitators spend only on imitative activity, innovators face both innovative and imitative R&D costs, with $r_{im} = 1/10r_{in}$ to highlight the greater financial effort required to perform innovative R&D. This in turn lessens imitators' financial constraint in Eq. 2.9 and stimulates capital accumulation. Therefore, when the ratio between imitative and innovative firms' productivity is close to 90% or higher-as it happens in the last two scenarios—imitative firms' capital share balances or even exceeds innovators' one, on average.

Finally, also the variation of the average market shares of innovators and imitators across the four scenarios shows a similar tendency: in the last scenario with 32 firms, pure imitators outperform innovators. This result is a straightforward implication of the evolution of their productivity and capital shares, discussed above.

While previous results focus on the impact of different industry structures on the industry performance, we also have a reverse causation since the selection mechanism underlying the process of Schumpeterian competition affects the evolution over time of the market structure. Figure 4 displays the average end-of-simulation values of the Herfindahl Numbers Equivalent.[16] When all firms have equal market shares, the Herfindahl Numbers Equivalent is simply equal to the number of firms in the industry. Instead, when firms have unequal shares, it gives the number of equal-sized firms in a hypothetical industry characterized by the same degree of concentration as the actual industry, according to the Herfindahl-Hirschman Index. Results show that in all the scenarios examined, market competition operates as a selection mechanism determining a clear tendency towards higher concentration over the simulation timespan. If we look at the average percentage decrease of the Numbers Equivalent between the beginning and the end of the runs[17] (Fig. 4) we can observe that in the two scenarios

[16] The Herfindahl Numbers Equivalent is formally defined as the inverse of the Herfindahl–Hirschman Index: $HHI = \sum_i s_i^2$.

[17] Note that at the beginning of the simulation total output is equally distributed among firms. Hence the Herfindahl Numbers Equivalent in the first period of each run simply equals the number of firms initially in business.

with 16 and 32 firms the process of Schumpeterian competition results in an end-of-simulation market structure characterized, on average, by a degree of concentration comparable with a market in which more than 70% of the firms have disappeared and the survivors are equally sized. Such a tendency towards increasing market concentration was highlighted also in Nelson and Winter's models. However, in our model it seems to be exacerbated compared to both the science-based and cumulative technological regimes investigated, for example, in chater 12 and 14 of Nelson and Winter (1982). This can be explained by two considerations: first, imitation in our model allows to copy just specific skills (i.e. nodes) of competitors, not their overall level of productivity, so that catching up through imitation is more difficult. Secondly, firms specializing (by bad luck) on very isolated trajectories, are prevented from exploiting spillovers thereby being more likely to suffer a productivity gap which tends to widen over time, causing a rapid fall of their market shares.

Finally, the relatively high values of the standard deviations across Monte Carlo simulations presented in the tables of Appendix A.2, tell us that different stochastic distributions of initial skills among firms may greatly affect the final results of the simulations: although on average different initial market structures determine a situation more or less favorable for the two types of firms, the final outcome of each simulation run is not easily predictable. Even in the less favorable case for imitators (i.e. higher initial concentration-lower number of firms), these latter may have the chance to keep up with innovators if the initial stochastic distribution of skills induce them to specialize upon the same technological trajectories of innovators. In these cases, the final values of best practice productivity and average productivity would be relatively low. Accordingly, the ratio between the average productivities of imitators and innovators would be closer to one, imitators' capital and market shares would be higher, and the final structure of the industry would remain less concentrated. Conversely, even in the large number cases generally more favorable to imitators, an unlucky distribution of initial skills may induce imitative and innovative firms to specialize in different technological areas, making imitation more difficult, reducing the competitive pressure on innovators, and thereby boosting their performance.

This suggests that small stochastic events, here represented by different distributions of initial skills across firms, can exert a huge impact on the outcome of the process of Schumpeterian competition. This impedes to identify *ex ante* both an optimal strategy for the individual firm and the system outcome in terms of final market structure and innovative performance. Given the inherent cumulative nature of firms' technological advance, even firms with identical initial capital stocks and productivity levels, and the same strategy towards innovation, may experiment radically different technological paths and economic performance due to a different initial distribution of skills. This result is in line with the arguments proposed by Arthur (1988a, b, 1989), demonstrating that small stochastic events can exert a huge impact on technology diffusion patterns when path-dependency, network externalities and spillover effects are at stake.

To conclude this section, let us notice again that the results obtained under the five realizations of the Technology Network generated with $P_{split} = 25\%$ (displayed in Table 2) are consistent, suggesting that the trends highlighted are robust under different realizations of the same network generating algorithm.

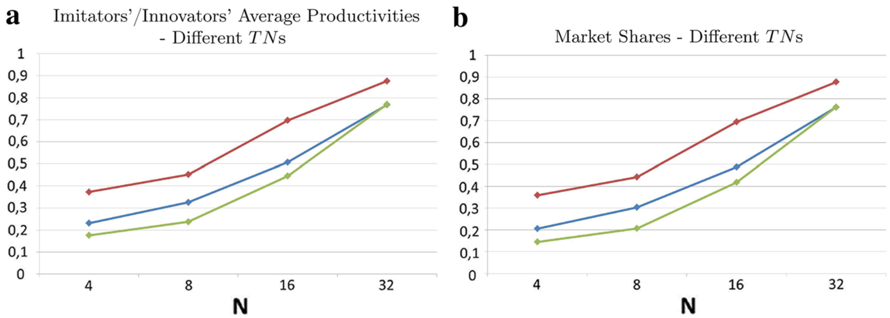

Fig. 5 Ratio between imitators' and innovators' average productivities (**a**) and imitators' market shares (**b**) with different TNs obtained with P_{split} equal to 10% (*red*), 25% (*blue*), and 40% (*green*) (color figure online)

4.1 The Influence of the Technology Network Topological Structure

In order to analyze the possible effects of different characterizations of the Technology Network on the dynamics of innovation and the evolution of industry structure, we re-execute the previous experiments with 5 networks obtained by setting P_{split} at 10%, and 5 networks obtained by setting P_{split} at 40%. As for the baseline, the results of these simulations are presented in Appendix A.2, and collected in Tables 3 and 4.

The outcome of these experiments confirms the tendencies already discussed in the previous section: a greater number of firms initially in business generates, on average, a drop of the average and best practice productivities. As the number of firms increases, the situation gradually changes in favor of imitators. Finally, in all the scenarios we observe a clear-cut increase in the industry concentration.

By repeatedly splitting the Lists of Potential Parents in the network creation phase, greater values of P_{split} generate relatively more branched Technology Networks. Therefore, the higher P_{split}, the greater the number of possible technological trajectories on which firms can specialize. In turn, the lower P_{split}, the greater the number of links between nodes, implying a greater complementarity between technological skills and therefore a greater homogeneity of firms' Skill Profiles. Indeed, the average degree is around 3,4 for the 5 networks generated with $P_{split} = 10\%$, around 2.6 for the networks generated with $P_{split} = 25\%$, and 2.3 for the networks generated with $P_{split} = 40\%$. The greater or lower complementarity between technological trajectories can also be appreciated by looking at Fig. 9 which graphically displays the community structure based on edge betweenness (Girvan–Newman) for three types of netowrks: cluseters tend to be less numerous and wider for low values of P_{split}, whereas they increase in number and decrease in dimension for higher value of the paramater.

As a consequence, networks built with $P_{split} = 10\%$ depict a situation relatively more favorable to imitators, while the opposite happens for networks obtained with $P_{split} = 25\%$. This can be appreciated by looking at Fig. 5 which displays the ratio between imitators' and innovators' average productivities, and imitators'

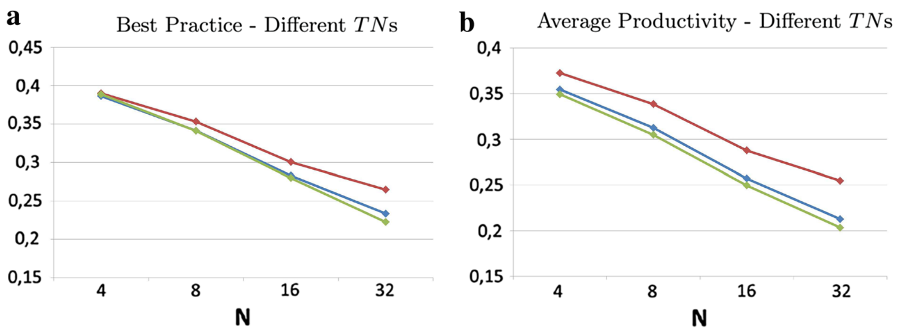

Fig. 6 Best practice (**a**) and average productivity (**b**) with different TNs obtained with P_{split} equal to 10% (*red*), 25% (*blue*), and 40% (*green*) (color figure online)

market shares.[18] A more connected network thus seems to exert an effect on the relative performance of innovators and imitators qualitatively similar to that observed in the scenarios characterized by a reduction of the initial market concentration (i.e. greater number of firms), favoring imitators over innovators.

However, while in the baseline scenario a deterioration of innovators' position relatively to imitators' was associated with a reduction of the best practice and average productivities, since it exacerbated the competitive pressure on innovators, here the opposite happens: networks having a less branched structure tend to favor imitators while being also characterized by higher levels of productivity.

When the Technology Network is highly branched, the number of possible trajectories to explore is relatively higher. These trajectories tend to be clearly distinguishable as they displays very few links between each other, which become even fewer as we move 'in depth' along each trajectory. This appears evident by looking at Fig. 8b, displaying an example of network obtained with $P_{split} = 40\%$. Firms exploring such a network will thus choose one among the many possible trajectories. Since these latter are almost independent from each other, firms' Skill Profile tend to become highly heterogeneous as they specialize. Imitation becomes more difficult, thereby reducing the dimension of spillovers both for imitators and innovators. Firms can thus rely oly on innovation to move forward in the learning process, and the productivity dynamics is dampened (Fig. 6), despite the greater number of innovations achieved by innovators, as displayed in Fig. 7.

The situation is reversed when the network is poorly branched. In this case the nodes of the network appear to be much more interrelated, the number of links increases, and the number of clearly distinguishable-independent trajectories markedly decreases, as one can observe in Fig. 8a displaying an example of Technology Network obtained with $P_{split} = 10\%$. Firms exploring such a network tend to be less specialized and their Skill Profiles tend to be more homogeneous. Since many complementarities exist between alternative technological paths, imitation becomes easier.

[18] The plot for imitators' capital shares, which fundamentally resembles that for market shares, is omitted for space reasons.

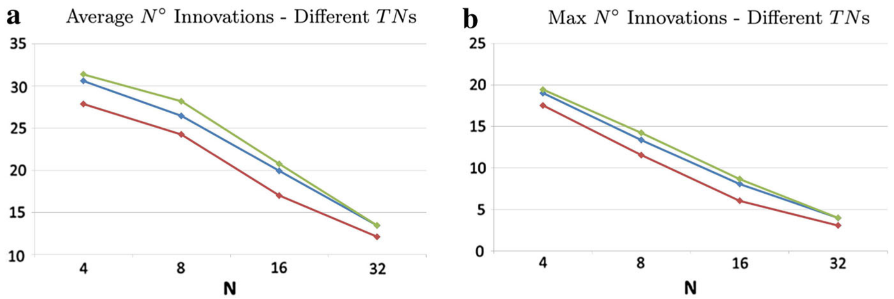

Fig. 7 Total number of innovations (**a**) achieved in the industry and maximum number of innovative draws achieved by a single firm (**b**) with different TNs obtained with P_{split} equal to 10% (*red*), 25% (*blue*), and 40% (*green*) (color figure online)

On the one hand, this favors firms following a pure imitative strategy and plagues innovators, causing a reduction of both the mean and maximum number of innovations achieved over the simulation timespan, as shown by Fig. 7. On the other hand, the greater complementarity between firms' Skill Profiles enhance the dimension of spillovers for both innovators and imitators, allowing technology to spread more and faster thanks to imitation. Figure 6 shows that this latter effect prevails on the slowdown of innovators' innovative performance, causing an improvement of the best and average productivities Fig. 9.

These latter results thus suggest that the topology of the Technology Network characterizing the industry, that is the degree of interrelatedness/complementarity between technological skills required to achieve innovations, plays an important role in shaping the dimension of spillovers, thereby affecting not only the profitability of different innovative strategies (i.e. innovating vs. imitating), but the overall innovation performance of the system as well.

Finally, results in Tables 3 and 4 highlight that less branched technology structures, which make imitation relatively easier, tend to dampen the process of market concentration, whereas highly branched structures which reduce spillovers and make imitation more difficult, tend to exacerbate it. Indeed, a more interrelated-less branched technological structure reduces the risk that firms specialize, by bad luck, on isolated trajectories, being thus prevented from exploiting spillovers. Furthermore, since imitation is easier and firms' Skill Profiles are more homogeneous, catching up becomes relatively easier, thereby narrowing productivity differentials between firms. This in turn dampens the selection process through market competition.

This latter result is broadly comparable to that obtained in the original Nelson and Winter's models under a cumulative technological regime, where hard imitation conditions tended to increase market concentration while easier imitation softened it. On the contrary, the effect of harder/easier imitation conditions on the dynamics of productivity was not conclusive. However, the novelty of the present work lies not so much in the results, but rather in the framework which generates them: in Nelson and Winter (1982) the ease to imitate was exogenously tuned by varying imitation probability of success for given levels of imitative R&D expenses. Here instead, it depends on the pervasiveness of spillover effects, which is fundamentally affected

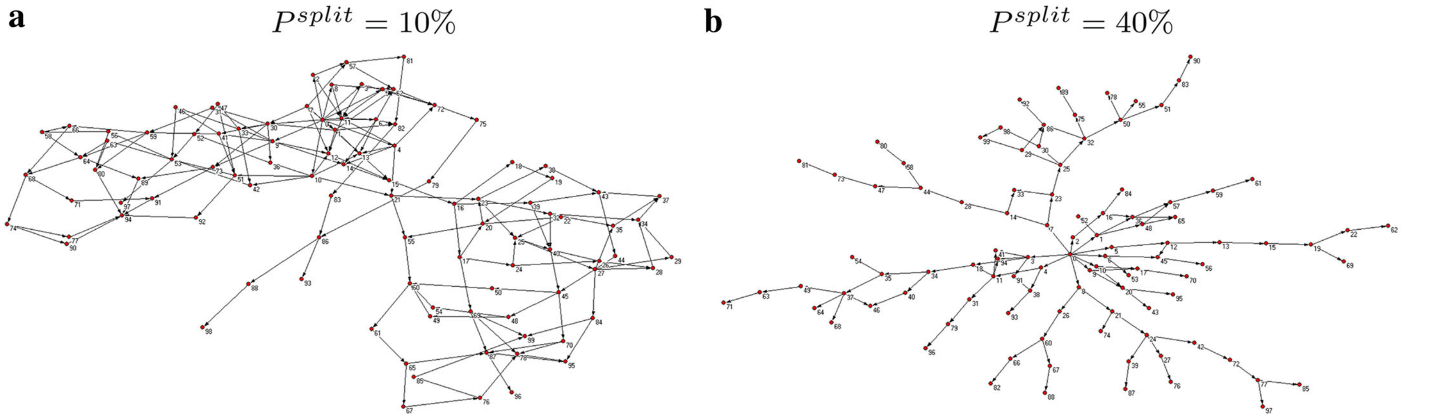

Fig. 8 *Left* **a** Technology Network: $N^{nodes} = 100$, Initial Nodes = 10, $P^{split} = 10\%$. *Right* **b** Technology Network: $N^{nodes} = 100$, Initial Nodes = 10, $P^{split} = 40\%$

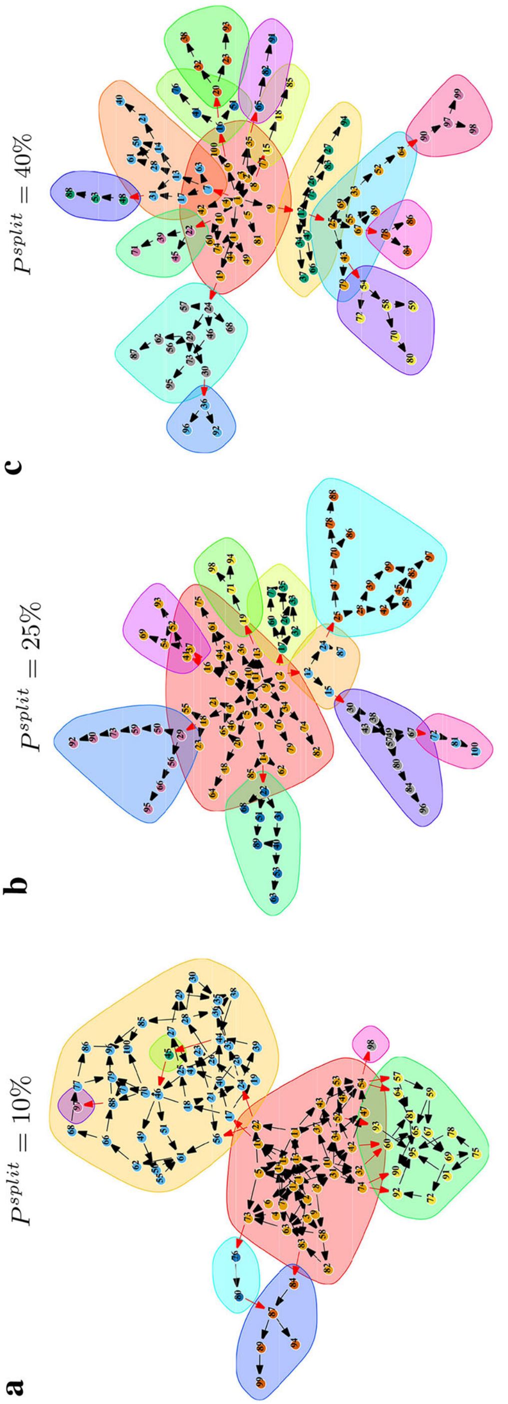

Fig. 9 Community structure based on edge betweenness (Girvan–Newman) for three TN generated with $P^{split} = 10\%$ (**a**), 25% (**b**), 40% (**c**)

by the features of the Technology Network and by firms' technological advancement paths.

The experiments presented in the paper thus confirm that the analysis of the technology structure and the direction of technological advance undertaken by firms is crucial to understand industries evolution and its relationship with innovative dynamics. This claim is in line with the empirical evolutionary literature which has insisted on the heterogeneity of the knowledge base, learning and diffusion processes, and technological structure as a key factor in shaping the boundaries, organization, and evolution of sectors.[19]

5 Concluding Remarks

The paper proposed a simple AB framework to analyze the relationship between innovation and the evolution of market structure under different characterizations of the industry technology structure, following the *generativist approach* of Agent Based Models (Esptein 2006). Results show that more concentrated initial market structures tend to outperform less concentrated ones, by reducing the competitive pressure on innovators. Furthermore, the increase of market concentration caused by the process of Schumpeterian competition is more marked than in the Nelson and Winter's family of model when we account for firms' specialization, which constrains firms' ability to exploit technological spillovers through imitation. Furthermore, we show that more connected-less branched Technology Networks reduce firms' specialization and enhance technological spillovers, allowing to improve the dynamics of productivity in the industry and to dampen the process of market concentration, despite the relative worsening of innovators' performance. The opposite occurs under less connected-more branched networks.

Our results thus confirm the topicality of firms' technological specialization and industry technological knowledge structure for the analysis of industry evolution and innovation dynamics. Despite the over-simplified nature of the model presented here, we believe that the proposed framework might be worthy of several other applications and extensions.

In particular, we have discussed the suggestive opportunity provided by the empirical literature on patent citation networks (Hall et al. 2001; Verspagen 2007; Fontana et al. 2009) to improve the realism of the Technology Network employed in the model, thus possibly deepening our understanding of the relationship between innovation diffusion patterns, knowledge spillovers, and the evolution of industry structures across real world sectors, in the wake of 'history friendly models' (Malerba and Orsenigo 2002; Malerba et al. 2008).

A further possible application is represented is to the design and regulation of Intellectual Property Rights (e.g. patents) which faces a trade-off between appropriability incentives guaranteed by IPRs, which spur R&D investments by increasing the quasi-rents of innovations, and the exploitation of network externalities and spillovers

[19] For an extended review of this literature see Nelson (1993), and more recently Malerba (2004) and Hall and Rosenberg (2010).

generated by the process of knowledge diffusion. The framework proposed is particularly suited for this type of analysis, since it explicitly models knowledge flows between innovations by means of the network structure which defines the relationships between different pieces of technological knowledge.

Finally, since the model accounts for the firms' search process by which they tend to specialize along certain trajectories among all the possible ones, this makes it suitable to investigate the competition process between alternative technologies and thee potential emergence of inflexibilities, lock-in effects, and inefficiencies in the pattern of technological advance, as originally advocated by Arthur (1988b, 1989).

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A Appendix

A.1 Investment

As explained in the text the function defining desired investment reflects the idea that firms are afraid of 'spoiling' their own market if they increase too much the scale of production, thereby reducing the market price and possibly their own profit margin. Assuming that the demand curve has a constant elasticity η and firm's market share is equal to s, the elasticity of the residual demand facing the firm, under the firm's conjecture that other producers will maintain constant their output, is given by: $\frac{\eta}{s}$ Given that $\pi = (P(Q) - \frac{c}{A})sQ$, the firm maximizes her profit when it chooses a level of output such that:

$$\frac{\partial \pi}{\partial Q} = \left(\left(\frac{\partial P}{\partial Q}\frac{Q}{P}P + P\right) - \frac{c}{A}\right)s = 0 \Rightarrow \left(-\frac{1}{\eta/s} + 1\right)P = \frac{c}{A} \Rightarrow$$
$$\Rightarrow \frac{\eta}{\eta - s} = \frac{PA}{c} = \rho \tag{A.1}$$

If instead firm's conjecture is that the rest of the industry consists of price-takers that respond along a supply curve with constant elasticity ψ we obtain a more general results. The profit maximizing price-to-marginal-costs ratio is given by:

$$\rho = \frac{\eta + (1-s)\psi}{\eta + (1-s)\psi - s} \tag{A.2}$$

Notice that, when $\psi = 0$, we obtain the previous equilibrium condition. The right-hand side of the above equation can be interpreted as the target mark-up $\rho^T(s)$ of the firm, expressed as a function of the firm's market share.

Hence, desired investment can be expressed as:

$$I_D = \delta + 1 - \rho^T \frac{c}{P_t A_{it}} \tag{A.3}$$

When the realized mark-up $P_t A_{it}/c$ is exactly equal to the target mark-up $\rho^T(s)$ the firm considers herself to be in a profit maximizing equilibrium at the current level of production and her desired investment is simply equal to the amount required to replace depreciated capital. Instead, when the realized mark-up is greater (smaller) than the target one, the desired net investment will be positive (negative). Equation (2.8) in Sect. 2 was obtained by setting $\eta = 1$ and $\psi = 1$.

A.2 Tables of Results

Table 2 Results of the simulations-5 networks generated with $P_{Split} = 25\%$ & *Initial parents number = 10*

	Network	Number of firms			
		4	8	16	32
Best practice	1	0.386	0.347	0.290	0.235
		(0.055)	(0.054)	(0.057)	(0.035)
	2	0.395	0.336	0.273	0.229
		(0.059)	(0.057)	(0.049)	(0.034)
	3	0.385	0.337	0.276	0.233
		(0.062)	(0.052)	(0.053)	(0.040)
	4	0.381	0.349	0.295	0.247
		(0.050)	(0.044)	(0.043)	(0.031)
	5	0.386	0.338	0.281	0.224
		(0.055)	(0.054)	(0.050)	(0.040)
Average productivity	1	0.355	0.317	0.262	0.213
		(0.056)	(0.049)	(0.050)	(0.026)
	2	0.362	0.307	0.249	0.212
		(0.058)	(0.052)	(0.043)	(0.029)
	3	0.349	0.309	0.252	0.214
		(0.055)	(0.048)	(0.045)	(0.033)
	4	0.356	0.325	0.274	0.221
		(0.052)	(0.038)	(0.039)	(0.027)
	5	0.350	0.306	0.249	0.203
		(0.052)	(0.052)	(0.044)	(0.031)
Ratio average productivity: imitators/innovators	1	0.742	0.891	0.899	0.976
		(0.218)	(0.181)	(0.132)	(0.068)
	2	0.682	0.840	0.918	0.981
		(0.234)	(0.168)	(0.120)	(0.087)
	3	0.677	0.829	0.903	0.975
		(0.215)	(0.186)	(0.133)	(0.085)
	4	0.798	0.884	0.967	1.007
		(0.224)	(0.158)	(0.080)	(0.058)
	5	0.646	0.723	0.829	0.966
		(0.209)	(0.199)	(0.148)	(0.085)

Table 2 continued

	Network	Number of firms			
		4	8	16	32
Industry total innovations $N°$	1	29.80	26.10	20.55	13.65
		(6.42)	(6.71)	(7.75)	(4.38)
	2	31.80	25.56	19.10	13.57
		(6.83)	(6.67)	(6.65)	(5.48)
	3	31.12	26.52	19.11	13.48
		(7.07)	(6.53)	(6.55)	(6.38)
	4	29.00	26.35	19.23	12.88
		(6.33)	(7.26)	(6.20)	(4.86)
	5	31.33	27.78	21.60	13.61
		(5.96)	(6.90)	(6.57)	(5.18)
Max $N°$ innovation by a single firm	1	18.51	13.44	8.53	4.19
		(3.45)	(4.03)	(4.06)	(2.61)
	2	19.72	13.01	7.54	3.89
		(4.07)	(3.94)	(3.40)	(2.51)
	3	19.03	13.42	7.84	4.16
		(4.03)	(3.64)	(3.61)	(3.28)
	4	18.54	13.02	7.33	3.40
		(3.84)	(3.99)	(3.48)	(1.94)
	5	19.25	13.88	9.00	4.17
		(3.66)	(3.74)	(3.92)	(2.97)
Imitators' capital share	1	0.251	0.334	0.496	0.744
		(0.172)	(0.171)	(0.206)	(0.152)
	2	0.217	0.339	0.549	0.783
		(0.175)	(0.165)	(0.203)	(0.163)
	3	0.206	0.323	0.515	0.728
		(0.172)	(0.174)	(0.208)	(0.199)
	4	0.304	0.387	0.590	0.839
		(0.180)	(0.191)	(0.187)	(0.139)
	5	0.178	0.246	0.385	0.743
		(0.168)	(0.182)	(0.188)	(0.177)
Imitators' market share	1	0.226	0.311	0.476	0.736
		(0.176)	(0.182)	(0.223)	(0.165)
	2	0.190	0.316	0.532	0.777
		(0.179)	(0.174)	(0.217)	(0.176)
	3	0.177	0.301	0.496	0.720
		(0.177)	(0.184)	(0.224)	(0.212)

Table 2 continued

	Network	Number of firms			
		4	8	16	32
	4	0.284	0.372	0.582	0.839
		(0.188)	(0.202)	(0.197)	(0.134)
	5	0.150	0.218	0.352	0.734
		(0.171)	(0.189)	(0.202)	(0.196)
Herfindahl number equivalents	1	2.473	3.175	4.715	6.765
		(0.427)	(0.787)	(1.445)	(2.087)
	2	2.326	3.353	5.194	7.261
		(0.368)	(0.872)	(1.634)	(2.145)
	3	2.360	3.320	4.779	7.032
		(0.453)	(0.862)	(1.455)	(2.156)
	4	2.615	3.810	5.446	7.434
		(0.534)	(0.933)	(1.175)	(1.49)
	5	2.250	2.978	4.353	7.634
		(0.336)	(0.743)	(1.558)	(2.901)

Table 3 Results of the simulations-5 networks generated with $P_{Split} = 10\%$ & *Initial parents number = 10*

	Network	Number of firms			
		4	8	16	32
Best practice	1	0.403	0.377	0.320	0.285
		(0.043)	(0.040)	(0.035)	(0.027)
	2	0.390	0.349	0.306	0.277
		(0.056)	(0.047)	(0.035)	(0.023)
	3	0.397	0.360	0.309	0.250
		(0.051)	(0.052)	(0.046)	(0.035)
	4	0.380	0.329	0.273	0.247
		(0.056)	(0.041)	(0.029)	(0.012)
	5	0.380	0.351	0.295	0.265
		(0.049)	(0.042)	(0.036)	(0.022)
Average productivity	1	0.392	0.366	0.308	0.275
		(0.044)	(0.038)	(0.036)	(0.027)
	2	0.373	0.335	0.294	0.266
		(0.057)	(0.044)	(0.033)	(0.023)
	3	0.370	0.338	0.290	0.237
		(0.049)	(0.051)	(0.041)	(0.031)

Table 3 continued

	Network	Number of firms			
		4	8	16	32
	4	0.367	0.320	0.267	0.242
		(0.056)	(0.040)	(0.027)	(0.014)
	5	0.360	0.334	0.280	0.254
		(0.052)	(0.043)	(0.034)	(0.022)
Ratio average productivity: imitators/innovators	1	0.941	0.963	1.010	1.037
		(0.116)	(0.073)	(0.037)	(0.034)
	2	0.878	0.964	1.003	1.033
		(0.200)	(0.070)	(0.035)	(0.036)
	3	0.805	0.878	0.972	1.047
		(0.222)	(0.166)	(0.119)	(0.064)
	4	0.909	0.969	1.005	1.021
		(0.189)	(0.068)	(0.018)	(0.021)
	5	0.817	0.905	0.984	1.031
		(0.225)	(0.155)	(0.054)	(0.044)
Industry total innovations $N°$	1	27.08	24.75	16.35	12.76
		(6.23)	(6.70)	(5.12)	(3.52)
	2	27.02	22.30	16.36	11.88
		(6.73)	(6.49)	(5.52)	(3.43)
	3	28.87	25.44	19.07	11.96
		(6.39)	(7.15)	(7.24)	(4.18)
	4	28.05	23.40	16.11	11.41
		(6.69)	(6.40)	(4.20)	(3.36)
	5	28.34	25.35	17.11	12.45
		(6.21)	(6.81)	(5.77)	(4.12)
Max $N°$ innovation by a single firm	1	17.21	11.90	5.55	3.18
		(3.91)	(3.61)	(2.61)	(1.25)
	2	17.04	10.78	6.16	3.14
		(3.94)	(3.54)	(3.16)	(1.30)
	3	18.03	12.43	6.90	3.13
		(3.83)	(3.68)	(3.43)	(1.66)
	4	17.43	10.54	5.06	2.63
		(3.85)	(3.47)	(2.02)	(0.89)
	5	17.90	12.02	6.42	3.16
		(3.78)	(3.09)	(2.83)	(1.50)

Table 3 continued

	Network	Number of firms			
		4	8	16	32
Imitators' capital share	1	0.420	0.481	0.745	0.887
		(0.151)	(0.168)	(0.135)	(0.054)
	2	0.391	0.497	0.718	0.870
		(0.173)	(0.158)	(0.134)	(0.078)
	3	0.329	0.383	0.607	0.862
		(0.195)	(0.191)	(0.231)	(0.108)
	4	0.405	0.484	0.764	0.900
		(0.155)	(0.165)	(0.129)	(0.037)
	5	0.321	0.414	0.650	0.858
		(0.186)	(0.180)	(0.166)	(0.118)
Imitators' market share	1	0.412	0.475	0.746	0.890
		(0.160)	(0.173)	(0.140)	(0.055)
	2	0.377	0.490	0.717	0.873
		(0.182)	(0.164)	(0.138)	(0.081)
	3	0.309	0.367	0.600	0.865
		(0.204)	(0.201)	(0.245)	(0.113)
	4	0.395	0.479	0.764	0.902
		(0.164)	(0.170)	(0.131)	(0.037)
	5	0.304	0.402	0.645	0.859
		(0.196)	(0.189)	(0.174)	(0.123)
Herfindahl number equivalents	1	3.105	4.625	6.535	8.610
		(0.554)	(0.903)	(0.999)	(1.595)
	2	2.998	4.577	6.131	8.134
		(0.646)	(0.972)	(1.106)	(1.690)
	3	2.678	3.674	5.251	7.587
		(0.571)	(0.899)	(1.193)	(1.935)
	4	3.001	4.686	6.881	10.171
		(0.638)	(1.009)	(1.233)	(2.342)
	5	2.705	4.112	5.668	8.097
		(0.570)	(0.900)	(1.089)	(1.703)

Table 4 Results of the simulations-5 networks generated with $P_{Split} = 40\%$ & *Initial parents number = 10*

	Network	Number of firms			
		4	8	16	32
Best practice	1	0.389	0.342	0.286	0.224
		(0.054)	(0.055)	(0.055)	(0.034)
	2	0.389	0.346	0.284	0.224
		(0.058)	(0.049)	(0.051)	(0.029)
	3	0.391	0.336	0.273	0.222
		(0.053)	(0.050)	(0.053)	(0.037)
	4	0.388	0.336	0.284	0.223
		(0.055)	(0.053)	(0.050)	(0.035)
	5	0.386	0.347	0.272	0.220
		(0.052)	(0.053)	(0.051)	(0.026)
Average productivity	1	0.347	0.306	0.254	0.205
		(0.048)	(0.049)	(0.045)	(0.027)
	2	0.352	0.318	0.259	0.210
		(0.052)	(0.048)	(0.043)	(0.024)
	3	0.351	0.293	0.242	0.202
		(0.049)	(0.044)	(0.043)	(0.027)
	4	0.349	0.301	0.252	0.201
		(0.051)	(0.048)	(0.043)	(0.025)
	5	0.346	0.306	0.242	0.199
		(0.048)	(0.045)	(0.043)	(0.019)
Ratio average productivity: imitators/innovators	1	0.618	0.722	0.815	0.978
		(0.189)	(0.196)	(0.157)	(0.080)
	2	0.699	0.796	0.901	1.008
		(0.233)	(0.196)	(0.134)	(0.071)
	3	0.579	0.708	0.845	0.961
		(0.180)	(0.161)	(0.142)	(0.107)
	4	0.619	0.721	0.853	0.960
		(0.211)	(0.191)	(0.145)	(0.90)
	5	0.629	0.703	0.867	0.977
		(0.179)	(0.171)	(0.132)	(0.077)
Industry total innovations N°	1	31.78	28.46	21.73	14.15
		(6.04)	(7.41)	(7.20)	(5.02)
	2	30.39	27.95	19.82	12.54
		(6.32)	(6.63)	(6.05)	(4.23)
	3	31.73	27.23	21.18	13.92
		(5.92)	(6.60)	(6.88)	(4.97)

Table 4 continued

	Network	Number of firms			
		4	8	16	32
	4	31.95	28.26	21.19	13.49
		(6.68)	(6.51)	(6.75)	(4.02)
	5	31.10	29.07	19.83	13.17
		(6.14)	(6.46)	(6.90)	(4.47)
Max $N°$ innovation by a single firm	1	19.77	14.32	8.87	4.14
		(3.78)	(3.80)	(3.97)	(2.79)
	2	18.77	13.70	8.07	3.27
		(3.66)	3.42)	(3.72)	(1.57)
	3	19.90	14.35	8.64	4.30
		(3.52)	(3.84)	(4.12)	(2.58)
	4	19.59	14.02	9.25	4.23
		(3.65)	(3.68)	(3.94)	(3.02)
	5	19.10	14.70	8.42	3.90
		(3.27)	(3.78)	(3.72)	(2.21)
Imitators' capital share	1	0.167	0.230	0.398	0.760
		(0.156)	(0.177)	(0.223)	(0.174)
	2	0.230	0.284	0.498	0.823
		(0.179)	(0.172)	(0.209)	(0.145)
	3	0.144	0.227	0.428	0.742
		(0.146)	(0.156)	(0.204)	(0.191)
	4	0.162	0.224	0.434	0.745
		(0.164)	(0.159)	(0.194)	(0.170)
	5	0.174	0.223	0.469	0.783
		(0.158)	(0.159)	(0.194)	(0.153)
Imitators' market share	1	0.134	0.201	0.366	0.753
		(0.153)	(0.186)	(0.239)	(0.189)
	2	0.204	0.261	0.479	0.822
		(0.184)	(0.183)	(0.224)	(0.154)
	3	0.111	0.191	0.398	0.732
		(0.142)	(0.157)	(0.220)	(0.210)
	4	0.135	0.194	0.406	0.732
		(0.170)	(0.166)	(0.209)	(0.188)
	5	0.141	0.188	0.442	0.775
		(0.154)	(0.162)	(0.209)	(0.169)

Table 4 continued

	Network	Number of firms			
		4	8	16	32
Herfindahl number equivalents	1	2.225	2.883	4.281	7.069
		(0.353)	(0.686)	(1.516)	(2.365)
	2	2.356	3.127	4.831	7.556
		(0.421)	(0.734)	(1.546)	(1.797)
	3	2.153	2.770	4.550	7.013
		(0.291)	(0.563)	(1.594)	(2.498)
	4	2.205	2.911	4.230	7.316
		(0.315)	(0.672)	(1.519)	(2.551)
	5	2.263	2.843	4.632	7.486
		(0.342)	(0.629)	(1.696)	(2.263)

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