The dynamic of innovation networks: a switching model on technological change

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REGULAR ARTICLE

The dynamic of innovation networks: a switching model on technological change

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Abstract In this paper, we introduce an agent-based model where heterogeneous firms compare and modify their innovation strategies, so generating an evolving network structure. By implementing dynamic behavioral switching via a fitness mechanism based on agents' performance, companies can endogenously modify their tactics for technological change and switch among three groups: stand-alone innovators, collaborative innovators and imitators. On the one hand, we study the properties of the emerging networks and we show that they reproduce the stylized facts of innovation networks. Moreover, we focus the analysis on the impact of these three innovation categories on the macro economic aggregate, finding that collaborative companies are those having the highest positive impact on the economic system. On the other hand, we use the model to study the effect of different economic innovation policies in increasing macroeconomic performance.

Keywords Innovation network · Preferential attachment · Economic policy

JEL Classification D8 · L2 · O3 · O4

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1 Introduction

Technological progress has become fundamental for countries' social and economic development (Dosi et al. 1997) and governments are paying increasing attention to incentivizing technological advances in products and production processes derived from firm *R&D* activities (cfr. the "Action Plan 2010" by the European Commision). By contrasts, economic research has had rather little to say about the stylized facts on technological innovation and industrial dynamics, particularly when we consider these issues jointly (Dosi et al. 1997; Klepper and Simons 1997). In fact, the standard Bayesian approach, assuming at the same time (i) rationality of human behavior and (ii) agent's *ex-ante* knowledge on all possible future contingencies, is not able to capture the features of innovation processes, where uncertainty is a key element. Notwithstanding, this inability can be overcome by agent-based models, where each individual can follow different behavior and is able to learn through imitative mechanisms, rather than by using optimization principles. However, despite the merit of this methodology for the *R&D* economics, the number of agent-based models in this area is not large enough (Dawid 2006).

In this paper we aim to fill this gap by introducing a new model with interacting myopic agents. Although firms are not able to conceive all possible outcomes of an innovation project and to generate payoff distributions of different innovation strategies, in our model we assume that agents' technology decisions are influenced by the innovation strategies of other companies that have reported good economic performance, while their own performance depends on their ability to innovate. In particular, we propose a mechanism of behavioral switching through which companies, by comparing their performance with that of other companies, can endogenously change their innovation strategy and switch among three groups: stand-alone innovators, collaborative innovators and imitators. The firms belonging to these groups establish a technological relation with other companies, thus creating a kind of innovation network through which information and know-how on technology flow.

Such switching allows us to study the evolution of the population moving among these three groups and their impact on the aggregate equity level. In this respect, although the empirical literature diverges in the identification of the percentage of innovative firms belonging to each of the groups (for instance, from 1998 to 2000 the innovating companies involved in co-operative research were about 50 % in Finland and 17 % in Germany (Czarnitzki et al. 2007)), we have identified, in line with the literature (Czarnitzki et al. 2007; Foyn 2000), a growing pattern for the number of collaborating firms and a higher impact on the economic outcome of this group. Collaboration, in fact, is seen as the innovation strategy which allows the company to internalize positive externalities, such as technological advances, and share the high costs related to R&D projects occurring in the creation of innovation. Thus, it represents a useful tool to increase the probability of success and the appropriability of research outcomes (Katz 1986; d'Aspremont et al. 1988; Hall 2002). Also the European Union's Framework Programme is promoting collaborative research by direct subsides and indirect fiscal policies (Ebersberger 2005; Czarnitzki et al. 2003) aimed at reducing collaboration costs, such as severance costs, which are usually barriers to joint R&D activities (Koenig et al. 2011).

In addition, we investigate the main innovation network stylized facts, namely: (i) innovation networks are sparse, (ii) innovation networks are clustered and (iii) the distribution of the innovation links is characterized by high heterogeneity with few firms connected with many others. We compare our results with the theoretical literature (Goyal et al. 2003; Konig et al. 2011). However, in contrast with our model, these contributions do not propose mechanisms of behavioral switching among different innovation strategies, but they analyze the behavior and evolution only of the innovators belonging to the collaborative group. Instead, we investigate the features of the whole innovation network, the dynamics of the links and the influence of innovation on aggregate equity. We show that, by varying the firm's trust on its neighbor's performance, linkages self-organize into very different network architectures (cfr. Konig et. al. 2011; Lenzu and Tedeschi 2012). Moreover, in line also with the empirical literature on innovation networks (Fleming et al. 2007; Hanaki et. al. 2010; Roijakkers et al. 2006) we find that, for a high level of trust signal, the network is sparse, clustered and characterized by large variance in the linkages distribution.

Finally, we introduce governmental policies, such as funding technological improvements, to investigate whether they can benefit the economy and spur innovation. Thus, we use our model as a computational laboratory to run experiments on the role of firms' $R\&D$ expenditure and of different incentives on innovation. Several $R\&D$ policies for firms' behavior of innovation have been studied over the last years. From a theoretical point of view, it has been found that $R\&D$ is an important policy (Gaffeo et al. 2008; Russo et al. 2007), public subsidies have a positive impact independently from the fact that these are addressed to collaborative or non-collaborative $R\&D$ activities (Hinloopen 2000, 2001). On the other hand, from an empirical perspective, their impact is ambiguous (Czarnitzki et al. 2007; Gonzalez et al. 2005; Klette et al. 2000). Indeed, in a literature review, David et al. (2000) find that, in around half the cases, innovation policies have the power to trigger additional investments and innovation advances, while in the other half, it is the contrary. For example, in Spain, Gonzalez et al. (2005) find a positive effect only for small companies, while in Ireland Gorg and Strobl (2007) show a positive effect only for small grants and a negative one for large grants. By contrasts, in Germany, Hussinger (2008) finds a positive effect at all, while Hagedoorn and Narula (1996) identify a clear influence of collaborative $R\&D$ innovators on economic growth and in the whole number of participants to innovation. In order to add insights to this literature, we investigate the effects of several economic policies on technology and aggregate equity growth. Irrespective of the governmental treatments chosen, we find that aggregate equity is non-monotonically related with the level of the flat-rate tax on profits; indeed it results to be beneficial only until a maximum level. Furthermore, among the three economic policies we propose, i.e., subsidies only to single innovators or to collaborative innovators or small firms, we find that the policy aimed at encouraging cooperation has a major stimulating effect on the economic growth.

The remainder of the paper is organized as follows. In Section 2, we introduce the model, describing the innovation network, explaining the innovation process and the goods market dynamic. In Section 3.1, we present the simulation results on network dynamics, while in Section 3.2, we show the effect of different economic policies. Finally, Section 4 concludes.

2 The model

We consider an economy in which firms choose their innovation strategies between three main classes: isolated innovation, collaborative innovation and imitation; each is based on an innovation dynamic network. In this network, nodes represent firms, while edges are the connective links between them, through which technology information flows. Links are directional in the case of imitators, i.e. an imitator firm points to another firm with the aim of copying its technological advances and not vice versa. On the other hand, they are bidirectional in the case of collaborative firms. In this last case, indeed, all firms are partners of a unique project and they share all their technological knowledge. In time, the existing links may be deleted and new links created. Firms, by comparing their mutual performances on innovation strategies, have the chance to endogenously switch to an other firm's innovation strategy because it appears to be more advantageous. This mechanism of behavioral switching leads to the emergence of interesting competitive dynamics among the three different groups of innovators and to the replication on diverse stylized facts on innovation networks. The success of the adopted innovation strategy increases the firm's productivity and, therefore, via the goods market, the profits, thus reinforcing the capacity of the strategy to pursue economic growth.

We start the description of the model by explaining the *ex-ante* formation and evolution of the innovation network. Next, we define how the network influences firms' innovation and profits via the goods market.

2.1 The innovation network

We consider an economy in which firms operate in discrete time, denoted by $t = 0, 1, 2, ..., T$. At any time t, the system is populated by a large and constant number of active firms belonging to the finite set $\Omega = i, j, k, ..., \omega$, which produce and sell goods on the market and perform technological innovation. Firms have assigned an innovation strategy that can change over time and, with reference to this feature, can be divided into: (i) stand-alone innovators, i.e. they perform $R\&D$ in isolation without any connection with other companies; (ii) imitators of another firm, i.e they attempt to copy the strategy of more technological advanced firms; (iii) collaborative innovators, i.e they perform innovation in collaboration with other companies (Vega-Jurado et al. 2009; Willoughby et al. 2005).

At time $t = 0$, each firm is assigned an innovation strategy, i.e., we define whether it is an isolated innovator, an imitator or a collaborative innovator, so that the three groups are populated by the same number of firms. In case of firms following one of the last two strategies, we assign them one out-going link to another company. Thus, we identify the firm j that is imitated by the imitator firm i and the partner firm j of the collaborative firm i. Of course, if firm i is a collaborative innovator, it would have an out-going link only to another firm, that is assigned the same innovation strategy.

On the other hand, if firm i is an imitator, it has an out-going link to any other firm in the whole sample - stand alone, collaborative innovators or imitators. Finally, if i is a stand alone innovator, it does not point to any other firm, but can be connected with an in-coming link by a imitator firm. Note that, while there is one single out-going link departing from a firm, the number of in-coming links to a firm could be larger. For instance, a collaborative firm can be partner of more than one firm and be imitated by more than one firm. Again, an isolated innovator or an imitator can be imitated by more than one firm.

At time $t = 1, 2, ..., T$, firms can change their innovation relation and strategy. $R\&D$ tactics are revised at the beginning of each period and we model the evolution of the innovation network by implementing a preferential attachment process, based on a fitness parameter proportional to the firm asset. We define the fitness of each firm at time t as its asset level relative to the asset level of the richest agent A_t^{max}:

$$f_t^i = \frac{A_t^i}{A_t^{Max}}. \tag{1}$$

Each firm i is randomly assigned to a new firm j and if j has a fitness level higher than i's actual connected firm k, $(f_t^j > f_t^k)$, then i could copy j's innovation strategy, removing its link to k. Each firm i definitively changes its strategy and cuts its link with agent k in favor of j with a probability equal to:

$$Pr_t^i = \frac{1}{1 + e^{-\beta^i (f_t^j - f_t^k)}}, \tag{2}$$

while it keeps its existing link with probability $1 - Pr_t^i$. Thus, the probability that a link exists between a pair of firms is equal to the fitted probability from the logit regression (Vandenbossche et al. 2013; Tedeschi et al. 2012; Anderson et al. 1999). The parameter $\beta^i \in [0, \infty]$ in Eq. 2 is the key element generating different network structures. It represents the *signal credibility* and answers the question on how much firms trust the information about other agents' performance. For $0 < \beta < 1$ differences in fitness are smoothed, unchanged for $\beta = 1$ and amplified for $\beta > 1$ (Domencich et al. 1975; Lenzu and Tedeschi 2012).

The algorithm is designed so that successful firms gain a higher number of incoming links and their $R\&D$ strategy prevails. Nonetheless, the algorithm introduces a certain amount of randomness, and links to more successful firms have a finite probability to be cut in favor of links to less successful firms. In this way, we model imperfect information and bounded rationality; indeed firms cannot fully immediately internalize the advances deriving from $R\&D$ activities. At the same time, the randomness also helps unlock the system from a situation where all firms share the same strategy and, therefore, the system remains blocked in a single dominant strategy. Moreover, in order to avoid the disappearence of an innovation strategy, we have defined a minimum number of firms that should always belong to each group and fixed it to be five.

2.2 The innovation process

Once firms have defined their innovation strategies and before the production process, firms update their innovation levels. However, not all firms willing to innovate can obtain access to it. Whether firm i results in a successful innovation or not is determined by a Bernoulli distribution, the parameter of which is given by

$$Z_t^i = 1 - exp(-\gamma \mu_t^i), \tag{3}$$

with $\mu_t^i = \frac{R\&D_t^i}{K_t^i}$, $R\&D_t^i$ being the portion of the firm's profit invested in research and K_t^i the firm's stock of capital (see Section 2.3). As a consequence, the more a firm invests in $R\&D$ higher the probability that it gains access to innovative discoveries (see Dosi et al. 2010; Vitali et al. 2013). It is important to stress that the innovation strategies described in Section 2.1 are just potential or *ex ante* tactics. Equation 2 only generates "potential" links among firms. In fact, given firms' constraints on the realization of their innovation strategies, potential tactics become realized only if firms are successful in completing the innovation *via* Eq. 3. As a results, we can distinguish between **potential** and **realized** innovation networks.

The three groups follow different pathways for innovation advantages:

- an isolated innovator has advances in its technology level if it returns a positive value from Eq. 3. Then, its innovation advance is the realization of a random process:

  $$\phi_t^i = (1 + \xi_t^i)\phi_{t-1}^i, \tag{4}$$

  where ξ is a random variable uniformly distributed on the support $[\delta_1, \delta_2]$.
- for collaborative innovators, the probability of having success depends on the probability of success of all the members. That is: all the members of the collaborative innovation group have technology advances only if they all return a positive value of the Bernoulli distribution. However, the advance is not equal for all the members, but is different for each firm i following Eq. 4.
- The imitators' access to technology advances is also given by a Bernoulli distribution. However, it is possible that the firm does not obtain any advances. Indeed, the imitator i copies the technology of its imitating firm j only if the j's level of technology is higher than its own. Thus, the innovation advance of agent i is the realization of the random process:

  $$\phi_t^i = [1 + (\phi_t^j - \phi_t^i)\xi_t^i]\phi_{t-1}^i. \tag{5}$$

Note that the probability of accessing innovation for each single firm depends only on its own $R\&D$ expenditure. However, collaborators have an additional limitation due to the fact that the partnership is successful only if all the partners have returned a positive value from the Bernoulli. This drawback would recall the high cost of coordination that usually undermines the realization of a technological partnership or joint venture (Koenig et al. 2011). On the other hand, the imitators may have slowed their technology advances because, not having available all the required information, they do not know in advance the true technology level of the imitated firm. Indeed, they decide to link to it only because this company has had a good technological performance in the previous time step.

2.3 The goods market

After that the innovation strategies have been updated, firms make decisions about their productive activity.

Each firm i produces a homogeneous output Y_t^i, according to the following production function:

$$Y_t^i = \phi_t^i K_t^i, \tag{6}$$

with K_t^i being the stock of capital and ϕ_t^i the capital productivity, which depends on firm's innovation, as explained below.

According to Greenwald and Stiglitz (1990, 1993), firms can sell all the output they produce at an individual selling price P_t^i which is a random variable with expected value P_t, i.e., the market price, and finite variance. As a consequence, the relative price $u_t^i = \frac{P_t^i}{P_t}$, is a random variable with expected value $E(u_t^i) = 1$ and finite variance.

Firms are profit seekers and, at any time period t, their profit, in real terms, is equal to:

$$\pi_t^i = u_t^i Y_t^i - g_t^i K_t^i = (u_t^i \phi_t^i - g_t^i) K_t^i, \tag{7}$$

with $g_t^i K_t^i$ being the variable costs and g_t^i depending on the capital productivity, $g_t^i = g_0 \phi_t^i$. The assumption that costs increase over time with ϕ, avoids the possibility that costs become negligible compared to revenues.

If firms make a positive profit, then they invest a portion σ of it in the $R\&D$ activity, with the aim to increase their productivity in the following periods:

$$R\&D_t^i = \begin{cases} \sigma \pi_{t-1}^i & \text{if } \pi_{t-1}^i > 0 \\ 0 & \text{if } \pi_{t-1}^i <= 0. \end{cases} \tag{8}$$

Consequently, after the $R\&D$ expenditure, profit reduces to: $\pi_{t-1}^i = \pi_{t-1}^i - R\&D_t^i = (1-\sigma)\pi_{t-1}^i$. Note that, for sake of simplicity, we are assuming that firms do not use external funding to carry out their investment. In addition, the fact that $R\&D$ investments are financed with internal resources, without resorting to the credit market, is also confirmed by empirical data (Minetti 2011).

Firms accumulate net worth by means of profit[1], according to the following law of motion:

$$A_t^i = A_{t-1}^i + (1-\sigma)\pi_t^i. \tag{9}$$

Because of the uncertain environment, firm i may go bankrupt and bankruptcy occurs if the net worth at time t becomes negative $A_t^i < 0$, that is:

$$u_t^i < \frac{g_t^i}{\phi_t^i} - \frac{A_{t-1}^i}{(1-\sigma)\phi_t^i K_t^i} \equiv \bar{u}_t^i. \tag{10}$$

[1] Under the assumption that firms do not use external finance, the net worth A_t^i is equal to the firm capital stock K_t^i

In other words, bankruptcy occurs if the relative price u_t^i falls below the critical threshold $\bar{u}_t^i$. The Greenwald and Stiglitz (1993) framework, therefore, provides a simple and straightforward way to model the exit process: a firm goes out of the market if its equity level is so low that an adverse shock makes net worth negative, or if it suffers a loss so huge to deplete all the net worth accumulated in the past. Therefore, the probability of bankruptcy is an increasing function of the capital stock and a decreasing function of the equity base inherited from the past. For the sake of simplicity, in the following we assume that u_t^i is distributed uniformly on the interval $(0, 2)$, so we can specify the probability of bankruptcy as $Pr(u_t^i < \bar{u}_t^i) = \bar{u}_t^i/2 = \frac{g_t^i}{2\phi_t^i} - \frac{A_{t-1}^i}{2(1-\sigma)\phi_t^i K_t^i}$. When a firm goes bankrupt, it leaves the market. At the beginning of the next period, failed firms are replaced by newcomers. In line with the empirical literature on entry (Caves 1998; Bartelsman et al. 2005), we assume that entrants are on average smaller than incumbents, with the assets of new firms being a fraction of the average assets of the incumbents. So, entrant size in terms of assets is drawn from a uniform distribution centered around the mode of the size distribution of incumbent companies.

3 Simulation results

We explore the properties of the innovation network modeled above by means of computer simulations. We consider an economy consisting of $\Omega = 300$ firms over a time span of $T = 1000$ periods. Each firm is initially given the same amount of equity $A_{i,0} = 10$. We fix $\phi = 0.15$ and $g = 0.975$. Simulations are repeated 100 times with different random seeds.

The first aim of the paper is to reproduce the salient features of empirically observed $R\&D$ networks and the effect of the parameter β on these topological features. Then, the model is used to study the role of the $R\&D$ expenditure on innovation and economic variables, and the role that different economic policies have on firm's $R\&D$ investments. In these analyses, the model is simulated for different values of the parameter σ.

3.1 Stylized facts on the innovation network

The study conducted in this session concerns the **realized** innovation network rather than the **potential** innovation network as defined in Section 2.2.

Following Koenig et al. (2011), three are the main stylized facts for the $R\&D$ networks in the empirical literature (Fleming et al. 2007; Hanaki et al. 2010; Roijakkers et al. 2006): (i) networks are not complete but only a small number of firms are connected; (ii) there exists highly connected clusters, that is, within a cluster, the firms are highly connected, while there are few connections among clusters; (iii) the number of links among firms is heterogeneously distributed, that is, there are few firms connected to many others, while many remain isolated or marginally connected.

We study these stylized facts by varying the parameter β that indicates the trustworthiness of the innovation firms. By varying this parameter, the network

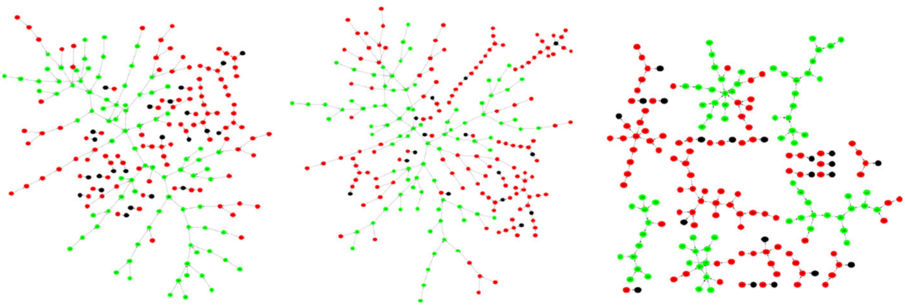

Fig. 1 Network configuration for $\beta = 0$ (*left side*), $\beta = 15$ (*center*) and $\beta = 30$ (*right side*). *Black*, *red* and *green nodes* are, respectively, single innovators, imitators and collaborative innovators. Colors are available on the web site version

self-organizes through different topologies, ranging from the random to the sparse one (cfr. Fig. 1). Thus, it is straightforward how the network architecture depends on the fitness signal strength β. Indeed, this parameter shapes the $R\&D$ network topology by amplifying the signal on firm's attractiveness (see Domencich et al. 1975; Lenzu et al. 2012).

Figure 2, left side, shows the average firm degree, i.e., the firm number of innovation links over 100 runs as a function of increasing values of β. Since the mean degree is inversely related to the sparseness of a graph (Koenig et al. 2011), if we increase the value of the fitness signal, then the network topology becomes more sparse. Moreover, increasing β, a high dispersion of links distribution emerges, as shown by the rise in the degree standard deviation (Fig. 2, right side). Note that this other topological feature captures the second stylized fact on links' heterogeneity.

Moreover, such heterogeneity is also recognizable in the study of the decumulative distribution functions of the innovation in-coming links. In particular, by increasing the signal strength, the distribution of the links becomes more heterogeneous, as shown in Fig. 3. It is also possible to identify the presence of increasing heterogeneity

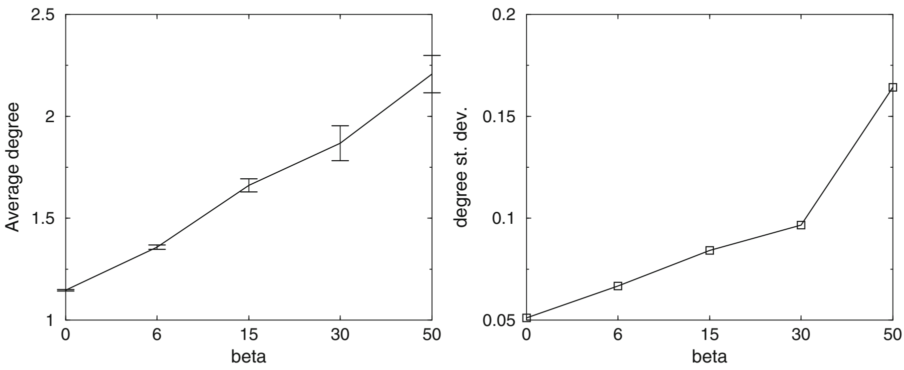

Fig. 2 Average degree +- standard deviation (*left side*) and degree standard deviation across nodes (*right side*), over all time steps and all simulations as function of β

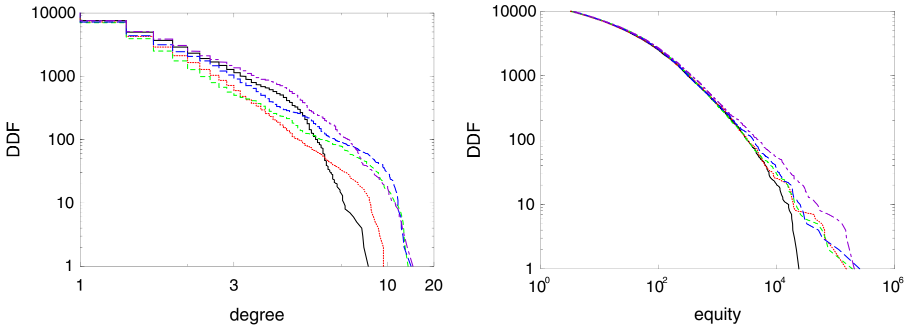

Fig. 3 The decumulative distribution function (DDF) of innovation links and firm equity for $\beta = 0$ (*black solid line*), $\beta = 6$ (*red dotted line*), $\beta = 15$ (*green dashed line*), $\beta = 30$ (*blue long dashed line*) and $\beta = 50$ (*violet dot-dashed line*). Colors are available on the web site version

with increasing values of β by means of the firm equity distribution, since, with high values of β, it follows a power law distribution. To prove that, by increasing β, we obtain a fatter tail on the distribution of equity, we estimate, on the upper tail of the distribution (from the 70th percentile onward), the average exponent α of the power law function and its standard error by means of the Maximum Likelihood Method (MLM), as in Clauset et al. (2009), over 100 simulations. Table 1 shows that, by increasing the signal credibility β, we generate a smooth transition to fatter tails.

Heterogeneity is a fundamental requisite for the emergence of innovative activities. The whole point of innovating for companies is to be able to distinguish themselves from competitors in the market, thereby generating heterogeneity which, in our model, arises from the fitness mechanism. Indeed, although agents initially start with the same amount of equity, when the fitness signal strength β is high, trust generates a fat tail distribution of firms' equity, in accordance with the empirical evidence that market participants are very heterogeneous in size (Axtell 2001).

The existence of clusters of highly interconnected firms is the third strong empirical evidence of the $R\&D$ networks. In this work, a cluster is defined as a group of firms directly or indirectly connected by innovation relationships and corresponds to a so-called "connected component" in network theory jargon. Figure 4, left side, shows that, for small values of β, the network tends to be fragmented in many (23 on average) and small (2 on average) clusters of firms. However, for increasing β, such

Table 1 Maximum Likelihood Method (MLM) estimation of the power law exponents α of the equity distribution tails over the 100 simulations for different values of β and their standard error

	MLM Equity	
	α	s.e.
$\beta = 0$	3.008	0.023
$\beta = 6$	1.222	0.041
$\beta = 15$	1.209	0.041
$\beta = 30$	1.138	0.056
$\beta = 50$	1.104	0.024

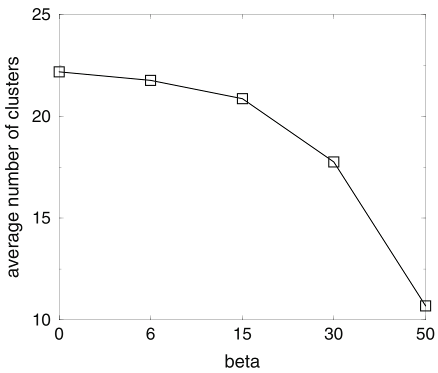

Fig. 4 Average number of clusters (*left side*) and average size of clusters (*right side*), over all times and all simulations as a function of β

clusters decrease in number while they increase in size and the network becomes more clustered (see Fig. 4, right panel).

Finally, the charts in Fig. 5 report the results on the volatility, correlation and importance of the different innovation groups at different values of β: for $\beta = 0$ (first column), $\beta = 15$ (second column) and $\beta = 30$ (third column). In particular, the first row shows fitness time series of single innovators (black solid line), imitators (red dotted line) and collaborative innovators (green dashed line). Increasing β, the model is able to generate a strong volatility among the fitness of different groups. Then, the fitness dynamic drives the number of firms belonging to each class: the higher the fitness in a single class, the higher the number of participants in that innovative class (see the middle panel of Fig. 5). A natural way to assess the co-movement between the increase (decrease) in fitness and the increase (decrease) in the participants' number is to study their correlation. We find that the average Person correlation coefficient over 100 simulations for each group is an increasing function of β and reaches a value of 0.62 when the fitness signal strength is significant. A strong co-movement also emerges between the number of participants in innovative classes and the equity time series, as shown in the bottom row of Fig. 5 and confirmed by a positive correlation coefficient of 0.82 for $\beta = 30$. These results on the evolution of the network are in line with other works (Brock et al. 1998; LeBaron et al. 2009; Gerasymchuk et al. 2010; Tedeschi et al. 2012).

3.2 The role of $R\&D$ expenditure and of the impact of economic policies on innovation

To analyze the role of the $R\&D$ expenditure on the economic variables, we run 100 independent simulations for different levels of σ, i.e. the parameter which defines the firm expenditure in $R\&D$. In this experiment, β is uniformly distributed in the discrete interval [0, 50], while the other parameters are kept fixed as in the previous case.

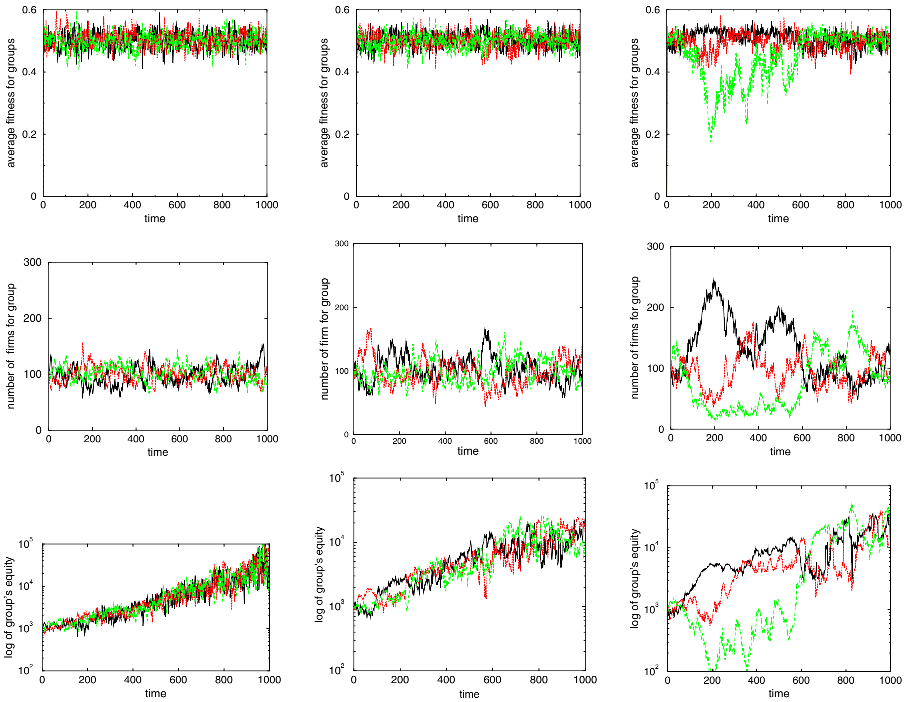

Fig. 5 Fitness time series (*top row*), number of agents in each innovation group (*middle row*) and equity time series (*bottom row*) for $\beta = 0$ (*first column*), $\beta = 15$ (*second column*) and $\beta = 30$ (*third column*). Single innovators are highlighted in *black solid line*, imitators in *red dotted line* and collaborative innovators in *green dashed line*. Colors are available on the web site version

The results reported in the top left panel of Fig. 6 display the existence of a non linear relationship between the efforts in $R\&D$ and the average equity. This behavior holds for all three classes of innovators. More in detail, for increasing values of σ, ranging from 0.005 to 0.025, the average equity level increases, but for values of σ higher than 0.025, the equity level drops. Thus, the relation between $R\&D$ expenditure and equity level is not monotonic, but depicts an inverse U-shaped curve. Indeed, a too high value of σ corresponds to a decreasing equity level, via Eq. 9, and to less investment, leading to an higher probability of bankruptcy, as shown in Fig. 6 (bottom left panel). Moreover, by comparing the different performances of single innovators (black circle), imitators (red square) and collaborative innovators (green triangle), in terms of equity, we observe that all the three groups perform such non-monotonic relation. In particular, the collaborative innovator group shows a dynamic that recalls closely that of the whole system. This is mainly justified by the large number of its members (Fig. 6, top right panel) and by the higher average productivity of such group (Fig. 6, bottom right panel). Indeed, over time, innovators who have become more technologically advanced also experience higher equity than others. Then, such firms have a higher probability to being linked to a partnership, according to our preferential attachment mechanism.

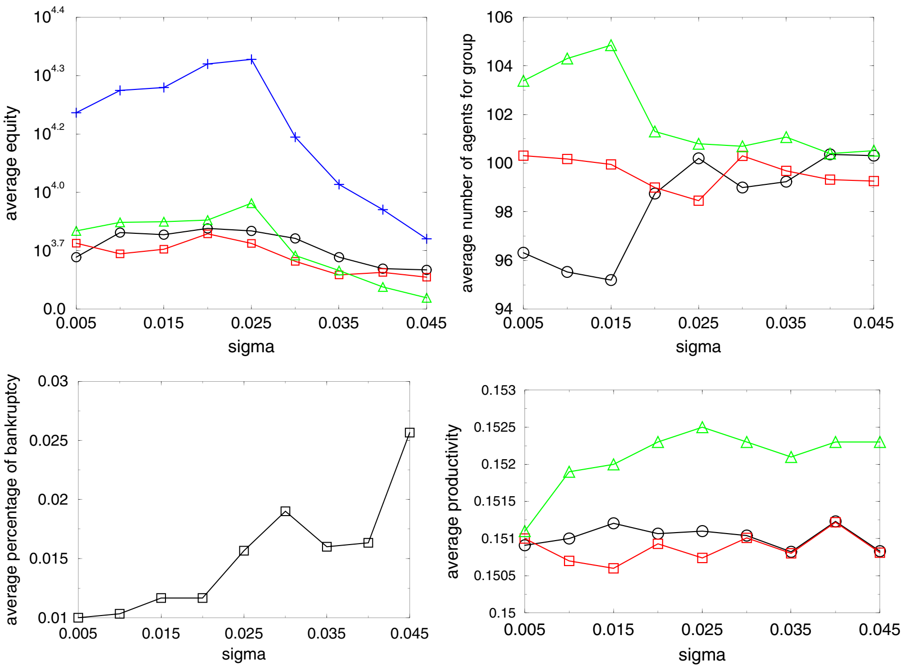

Fig. 6 Average equity (*Top left side*), average number of agents for group (*Top right side*), average percentage of bankruptcy (*Bottom left side*) and average productivity (*Bottom right side*), for single innovators (*black circle*), imitators (*red square*), collaborative innovators (*green triangle*) and the system (*blue plus*), over all times and all simulations as a function of σ. In this experiment, $\beta \sim U[0, 50]$, while the other parameters are kept fixed as in the previous case. Colors are available on the web site version

Finally, we find that when firms collaborate to carry out a new technology, the average technology follows an increasing trend and largely departs from what happens with stand-alone innovators and imitators[2] (Czarnitzkietal 2007; Foyn 2000). Note that these results are in line with the recent empirical literature finding a growing number of companies creating joint ventures for and collaborating in $R\&D$ projects and having remarkable technological advances (Czarnitzki et al. 2007).

We now investigate the role that economic policy has in influencing innovation and economic growth, by simulating the impact of different innovation policies. To this aim, we introduce in the model the "public sector", the role of which consists in collecting tax revenues from firms and redistributing such funds to selected firms during the same period. The redistributive policy is used to advance the technology level of the economy by increasing the firm spending on $R\&D$, and, consequently, to enhance growth.

We focus our attention on three potential public policies. On the one hand, the State applies a flat tax rate (τ) to all firms' profits; on the other hand, tax revenues

[2] Such a result is robust at different values of σ.

are redistributed, on a per-capita basis, as cash incentives for investing in $R\&D$, only to one of the following groups:

- single innovators (Treatment 1),
- collective innovators (Treatment 2),
- small firms (Treatment 3), identified taking the first quartile of firms ranked by equity. Indeed, while large firms are usually able to set aside money for investing in innovation, small firms have very few resources.

It is important to emphasize that these redistributive policies do not imply any cost to the Government. In fact, the State collects tax according to firms' profits, if positive (i.e., we have 300 firms that pay taxes proportionally to their profits) and, then, redistributes this amount among the different groups on the basis of the applied treatment.

Our results reproduce the outcome of 100 simulations, with increasing levels of tax rate τ parameter, starting from 0 % to 25 % with steps of 5 %. In these experiments σ=0.025, while all the other parameters remain fixed as previously defined.

The left panel of Fig. 7 shows that all three redistributive policies affect positively the aggregate output growth rate, but only at low levels of taxation. The effect is reversed as the tax rate is raised to more than 10 %. The turning point takes place because the growth enhancing effect associated with the redistribution of resources is more than counteracted by the increase in the firm financial fragility, associated with lower net worth. Indeed, firms suffer by a too high taxation and do not have enough financial resources for goods production and investment in $R\&D$. This fact is reflected in an increase in bankruptcies, as shown in the right panel of Fig. 7. However, these policies impact differently the output. In particular, when the collaborative innovation firms receive public funds (Treatment 2, red square in Fig. 7), the economy performs better than when the appointees are single innovators (Treatment 1, black circle) or small firms (Treatment 3, green triangle).

Finally, in order to investigate deeply the benefits of these economic policies on the three groups of innovators, we analyze the effect that each of these treatments has on them. Figure 8 shows, for each economic policy, the average equity of every

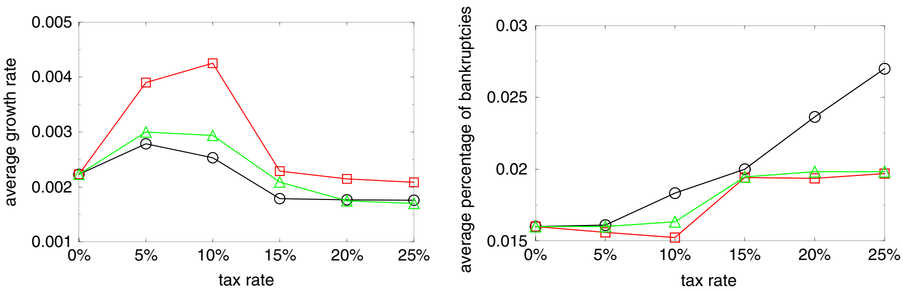

Fig. 7 Average growth rate (*left side*) and average percentage of firm bankruptcy (*right side*), respectively, for Treatment 1 (*black circle*), Treatment 2 (*red square*) and Treatment 3 (*green triangle*), over all times and all simulations as a function of the tax rate. Colors are available on the web site version

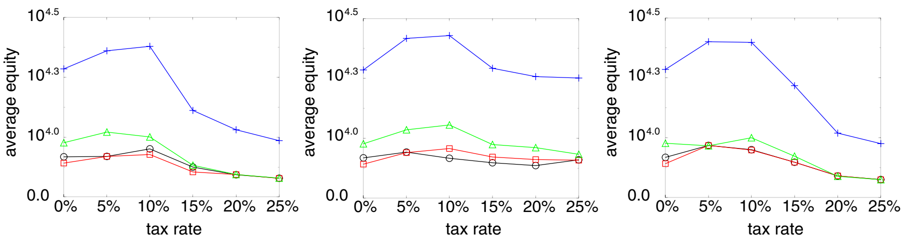

Fig. 8 Average equity, respectively for Treatment 1 (*left side*), Treatment 2 (*center*) and Treatment 3 (*right side*), for single innovators (*black circle*), imitators (*red square*), collaborative innovators (*green triangle*) and the system (*blue plus*), over all times and all simulations as a function of the tax rate. Colors are available on the web site version

innovation group over time and the number of simulations as a function of τ. We find that equity is non-monotonically related to the level of the flat rate tax on corporate profits, i.e., equity increases with the level of the tax rate up to a threshold, which can be thought as the pseudo-optimal level, and then reduces. Moreover, collaborative innovators (green triangle) have slightly greater benefits from economic policies then the others. Indeed, collaborative innovators have the highest performance from all tax treatments. However, the leading role on economic growth is preserved in Treatment 2. The reason why collaborative innovators benefit more from the economic policy is related to the higher number of companies participating in this class. However, the number of agents per group comes from the endogenous switching and

Table 2 Average, standard deviation, minimum and maximum equity level of each innovation group across 100 Monte Carlo simulations for different economic policies

Groups	Treatment 1	treatment 2	Treatment 3
Single innovators			
avg. equity	5559.5	6460.8	5983.9
st.dev.	1759.4	701.64	1099.4
min	3131.1	5435.8	3016.3
max	8036.8	7680.8	8694.5
Collaborators			
avg. equity	7028.2	9557.6	6852.9
st.dev.	2069.5	1701.8	2698.7
min	3148.8	7315.7	2991.1
max	10853	12215	9980.3
Imitators			
avg. equity	5102.2	6860.1	5799.2
st.dev.	1510.1	863.15	2069.5
min	3121.3	5651.7	2993.1
max	7102.3	8278.6	8705.3

is an emergent property of the system. It is interesting to see that, even when the innovation policies benefit single innovators and small firms (Treatment 1 and 3), the advantage of the redistributive policy is not sufficient to make them more competitive than the collaborative innovation firms. With regard to Treatment 2, one might think that to redistribute revenues to collaborative innovators and to see that they perform better is an expected result. If, in fact, as a group, they are the ones with the highest aggregate redistribution, it is also true that, as a group, they are the ones with the highest aggregate tax contribution, which makes the results of this policy not a priori obvious. More details are reported in Table 2, where the average equity, its standard deviation, the minimum and maximum values for each treatment and for each group are shown.

4 Conclusions

Our results allow us to conclude that the interaction among myopic agents is a key element to reproduce important stylized facts about technological change and industrial evolution. When one considers the process of technological change in an industry, in fact, it is crucial to look at a highly decentralized dynamic search process under strong uncertainty, where numerous heterogeneous agents search in parallel for new innovation strategies, but are interlinked through market and non-market interactions. The endogenous behavioral switching introduced in our model allows different innovation strategies to rise and fall in popularity over time and compete among themselves in superiority. Our simulation results, in line with empirical studies (Czarnitzki et al. 2007; Foyn 2000; Hagedoorn et al. 1996), underline the key role played by $R\&D$ collaborative companies on technology innovation and economic growth.

Moreover, by changing the firm's trust on its neighbor's performance captured by the parameter β, we identify the parameter range in which the stylized facts of $R\&D$ networks emerge. Our findings show that, for high level of fitness signal strength (i.e. signal credibility), our dynamic is able to reproduce sparse and clustered network topologies with heterogeneous degree distributions. This is particularly important since these patterns are in no way explicitly incorporated into the model, but are emergent properties of the aggregate behavior, which is built upon "simple" micro foundations: the bottom-up approach (see Delli Gatti et al. 2011). The fact that our model is able to reproduce empirically observed aggregate behaviors becomes particularly relevant if we use it to predict and evaluate the effects of policy measures that change the market environment. For more details about evolutionary agent-based models see Dawid (2006); Pyka et al. (2003).

To address this question, we use our model as a computational laboratory to investigate the role of alternative governmental policies on macro variables. In particular, we add to the modeled economy a public sector that levies taxes on corporate profits and redistributes revenues to benefit firms' $R\&D$ investments. We find a non-monotonic relation between the flat-rate tax on profits and the aggregate output. Indeed, a too high level of taxation corresponds to higher financial fragility. Furthermore, our findings show that different economic policies impact the economy with different intensity. Indeed, the most profitable policies are those that go to benefit collaborative groups .

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