Università degli Studi di Torino

Scuola di Management ed Economia
Corso di Laurea in Economics

The complex economics of technology production and adoption: an agent-based simulation.

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Sessione Autunnale
Anno Accademico 2013–2014

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Introduction

Before the booming growth that the western world experienced in the last 200 years, nobody would have forecasted the impact of technological progress on human life, society and economic development. Classical economists drew a rather pessimistic picture, with economic growth inescapably constrained by decreasing returns to capital and limited resources. It wasn't until more recent times – following the Schumpeterian legacy and the developments of modern growth theory – that the evolution of technology entered the field and began to be formalized into economic models. At first, the generative mechanisms at the basis of innovation remained unexplored, and technology was viewed as an exogenous component, affecting the productivity of the production factors, but unable to increase the growth rate of the economy in the long run. During the 80s, the Schumpeterian lesson was recovered and the first models of endogenous growth highlighted the importance of investment in research and innovation as a mean to foster economic growth and social development.

During the same years, a wide strand of literature began to flourish, focusing on the mechanisms governing the evolution of technology and their economic and social determinants. It began to be fully recognized that technological advance responded to economic incentives and, conversely, that economic development was

affected by innovative efforts and knowledge production. This circular mechanism, whose fundamental determinants are difficult to disentangle, proves particularly challenging for policy-makers, who strive to find the most efficient way to foster technological progress and transfer its beneficial effects to the economic and social environment.

Economics has borrowed models and methodologies from other fields – biology, physics, computer science – in its attempt to formalize the complex phenomenon of technological progress, which has interesting emerging properties, but whose determinants are fundamentally rooted in social interactions and human behavior. This duality renders the field particularly interesting, but, at the same time, offer major modeling challenges.

The most recent developments describe technology as an emergent property of the economic environment (Antonelli, 2011) and the economy as emerging from its surrounding technological ecosystem (Arthur, 2009). These two approaches are fundamentally integrated and it is important to study the economic and social environment and the evolution of technology in a parallel way, in order to fully comprehend their circular causal relation and complex interactions.

With these considerations in mind, this thesis work wants to address the topic of technological progress and economic development without establishing a one-way relation, but studying the complex web of interactions and feedbacks between these two systems and its emergent properties. At the core of this attempt is an agent-based simulation developed with Netlogo, which reproduces an economic environment in which a network of firms deals with the decision to adopt existing technologies or produce new ones; these decisions are guided by economic incentives while, at the same time, the technological evolution of the system affect the

performance of the firms. Moreover, the simulation address some policy issues regarding the impact of intellectual property protection measures on the evolution and outcome of the model.

The work is organized as follows: the first part (Chapter 1) offer an overview of some selected topics on the most recent developments of technology economics.

Section 1.1 reviews the major modeling and methodological challenges offered by the field, from the neoclassical approach to the new possibilities opened by the study of complex systems. A more in dept analysis is dedicated to the emergence of mesoeconomics studies – with particular reference to the Schumpeterian and Hayekian legacies – and to complexity theory and its groundbreaking impact on economic modeling.

Section 1.2 addresses the duality between localized and centralized innovation and how it affects the process of decision making of firms and institutions. The section begins with an analysis of the localized diffusion of knowledge and industry know-hows and the dimensions along which externalities and spill over effects unfold and propagate into the economy. The second subsection takes a wider analytical perspective, exploring the main trade offs faced by policy makers and the pros and cons of different policy measures (from laissez-faire to intellectual property protection) to foster innovation. Finally, the third subsection offer an inquire of "big science" programmes (e.g. the Human Genome Project or the more recent European FET-Flagships) which, through empirical evidences, tries to assess their effectiveness and economic efficiency.

The second part (Chapter 2) is dedicated to the simulation. Section 2.1 provides a description of the simulation and its main procedures, with a review of their theoretical ratio. The methodology applied is agent-based modeling (Gilbert

and Terna (2000), Epstein (1996)), together with some insights provided by social network theory and implemented with the support of the NW Netlogo extension. The modeling hypothesis on which the simulation is built are mainly rooted in the literature on evolutionary economics (Nelson and Winter (1982), Arthur (2009)), particularly for what concerns the dynamics of technological progress and its economic determinants, together with some early insights on increasing returns to adoption and the evolution of competing technologies provided by Arthur (1989). Moreover, for what concerns the complex interactions and feedbacks between the technological and the economic environments, Antonelli (2011) and Antonelli (2008) represent fundamental references.

Section 2.2 present the results drawn from the simulation; the first subsection offer a brief visual analysis of the graphical outcomes provided by the interface. The plots produced in the three policy environments are visually compared in order to get an idea of their impact on the outcome of the simulation.

The second and third subsections are dedicated to the statistical and econometric analysis. Data have been collected over five experimental conditions and their descriptive statistics compared in order to draw some conclusions on the impact of different initial settings. Moreover, linear regressions have been performed on four model specifications in order to further analyze some interesting effects highlighted in the previous subsections. Scatterplots have been produced to support the statistical analysis. Finally, the fourth subsection provides an overview and interpretation of some network measures drawn from the simulation.

Keeping in mind that these findings strongly depend on the modeling hypothesis and computational procedures implemented in the simulation, the analysis shows that funding a high number of parallel innovative efforts might prove ineffi-

cient or even detrimental and that a well functioning of technological transfer and diffusion is essential to foster innovation. In fact, data show an inverted u-shaped relation between the percentage of innovators and the economic and technological performance of the system, with the optimal amount of innovating firms located between 40% and 60% of the total.

The simulation also shows that the impact of intellectual property protection policies has to be evaluated with caution, since the positive externalities deriving by imitation and increasing returns to adoption can be an effective engine of growth: in all experimental settings, the implementation of a patent system or secrecy practices results in a reduction of incomes and technological advance. Nonetheless, some amount of protection can be beneficial in order to reduce the detrimental impact of an excessive number of adopters. These results, together with the theoretical and empirical evidences provided in the first chapter, emphasize the desirability of a careful economy- and industry-specific fine tuning of policy measures for innovation.

Chapter 1

Selected topics on technology economics and policy analysis for innovation

1.1 The economics of technological progress

1.1.1 Definitions and modeling challenges

The usual interpretation of technology in economic theory is strictly related with the idea of production function: the technology used by the firm is the way in which inputs are combined to obtain a certain quantity of output. Therefore, from a microeconomic standpoint, technology is modeled as the particular form taken by the production function and by the value of its coefficients and parameters.

At the macroeconomic level, technological progress is one of the key determinants of economic growth, and interpreted either as an exogenous frontier or as an

endogenous element, affected by the aggregate dynamics of the economic system.

However, technology is a multilayered concept and very different ideas such as knowledge, scientific discoveries or new products and processes often receive a uniform treatment. To solve these ambiguities, Arthur (2009) defines an interesting taxonomy that allows for a more rigorous treatment of technology and technological progress. For example, a crucial distinction is the one between technology and what Arthur calls "deep craft":

> Deep craft is more than knowledge. It is a set of knowings. Knowing what is likely to work and what not to work. Knowing what methods to use, what principles are likely to succeed, what parameter values to use in a given technique. [...] This sort of craft-knowing takes science for granted and mere knowledge for granted. And it derives collectively from a shared culture of beliefs, an unspoken culture of common experience.

This distinction may help to understand why, in a world in which information is available to everyone at a negligible cost, some countries or regions lag behind the technological frontier: although a product blueprint can be easily transferred, deep crafts and industry commons are more difficult to build. A nontrivial role is also played by entrepreneurial abilities, a set of behavioral and cultural characteristics through which individuals find opportunity niches, engage in risky ventures to exploit them and convert technological progress into economic development.

An alternative way to define and model technology is offered by Nelson and Winter (1982), who introduce an useful methodological and analytical tool by giving homogeneous treatment to all the concepts above introduced and grouping

them under the definition of "routine". Routines are the techniques applied by the firm in all its processes (production, marketing, sale); the deep crafts deriving from experience, culture and environment; but also the processes the firm undertakes when confronted with the choice between different routines – be it the choice between two alternative production techniques, the level of R&D expenditure and so on.

The choice regarding how to define and differentiate these dimensions of technology is quite discretionary and clearly depends on the purpose of the model and on what kind of behavior and outcomes one wants to highlight. However, both the Darwinian framework of Nelson and Winter (1982) and the combinatorial evolution of technology described by Arthur (2009) (which will be both later explored) imply a departure from the neoclassical view of economic agents as driven by the maximization principle. In a world characterized by heterogeneity, uncertainty and bounded rationality, the optimization problem is misspecified: even if an identifiable, unique maximum existed and even if the means to attain it were clear and perfectly known (which is quite never the case), the complex nature of the structure of economic interactions and the feedback mechanism between the agent and the system ensure that the deck is continuously reshuffled. Economic agents usually have too little knowledge about environmental conditions and limited means to compute the optimal decision within a complex system.

One solution is to use an algorithmic approach: this comes at the expense of analytical solutions, but ensures a more realistic treatment of economic problems and allow for their complex characteristics to unfold.

The evolutionary framework has an influential milestone in Alchian (1950), who identifies in «realized positive profits» the real objective of economic endeavours

and in adaption, imitation and trial and error the most important behavioral mechanisms. According to Alchian (1950) (who also refers to the work of Tintner (1941)):

> Uncertainty arises from at least two sources: imperfect foresight and human inability to solve complex problems containing a host of variables even when an optimum is definable. [...] Under uncertainty, by definition, each action that may be chosen is identified with a distribution of potential outcomes, not with a unique outcome. [...] Essentially, the task is converted into making a decision (selecting an action) whose potential outcome distribution is preferable, that is, choosing the action with the optimum distribution, since there is no such thing as a maximizing distribution. [...] The maximum-profit criterion is not meaningful as a basis for selecting the action which will, in fact, result in an outcome with higher profits than any other action would have.

The departure from the maximization principle does not leave the economist powerless. As Alchian (1950) points out, the central issue becomes the analysis of how firms more or less voluntarily adapt to the economic structure (with plain chance also playing a role) how the environment selects successful firms and what kind of features determine the realization of positive profits in different contexts. The methodological and theoretical tools provided by evolutionary and complexity economics allow to grasp and analyze the patterns and regularities which arise from the simple behavioral routines that firms apply to solve economic problems. To this aim, aggregation under the umbrella of the representative agent can be questioned, in favor of an agent-based approach focused on the interaction of more

or less heterogeneous economic units.

As Nelson and Winter (1982) underscore, it might be the case that these behavioral patterns converge to the very same analytical solution of the standard maximization problem. However, the analytical approach fails to address the structure of interactions between economic agents and its dynamic evolution; this is particularly detrimental when technological change is involved, since innovation and progress make sense only in a non-equilibrium framework, in which unexploited opportunities can be explored or created anew.

1.1.2 Micro and macroeconomics of technological progress

As already introduced, from a microeconomic standpoint, technology is represented by the specific form taken by the production function and/or by the value of its coefficients; therefore, the production function embeds the characteristics of the technology implemented and used by the firm. The choice of some particular form for the production function is not without consequences and, within a framework in which the heterogeneity of agents plays a central role, it is quite detrimental to assume that all firms use the same production technique. Moreover, the production function and its coefficients inevitably change under the pressure of technological progress, economic competition and other environmental conditions.

An alternative approach is the one offered by Nelson and Winter (1982); the firm is represented by a vector of state variables, which are a proxy of relevant characteristics of the agent from both the economic and technological point of view. These state variables influence how the firm acts (choose) and reacts to environmental conditions – that is the market and the structure of available and

potential technologies. Some degree of arbitrariness is indeed necessary in order to define these proxies, but what is relevant is how the characteristics of the system change due to the interaction of heterogeneous firms and whether these interactions lead to the emergence of regularities or specific properties.

For what concerns the macroeconomic layer, the most common approach for the analysis of the interactions between the economic system and technological progress is offered by growth theory, which was mainly developed in the last century within the neoclassical framework. As expectable, the centrality of innovation in economic growth is mostly noticeable in those models in which it is absent. Classical economists failed to acknowledge the role of technological progress and drew a rather pessimistic picture of economic development, constrained by decreasing returns to capital and demographic traps.

We owe to Solow (1956) one of the first formal attempts to include technological progress – viewed as the main engine of economic growth – in the neoclassical framework. In the Solow-Swan growth model, technology is defined a labor augmenting variable, exogenously given to all countries; that is, the technological frontier is considered to be the same for the whole world. Technology grows at a constant rate, which is equal to the rate of growth of capital and output. The main implication is that policy measures have a level effect on output, but not a long run growth effect. These conclusions could not possibly explain the amazing, booming growth that the western economy experienced in the last two centuries.

The more recent strand of literature on endogenous growth offer more interesting insights about the role of technological progress. Some of these models are based on the non-rivalrous nature of knowledge, which allows to implement the modeling hypothesis of increasing returns due to fixed costs and positive external-

ities.

In Romer (1986)'s model, endogeneity of technological progress stems from the fact that, because of positive externalities, knowledge is considered as a capital good with increasing marginal product, that is «production of the consumption good is assumed to be globally convex, not concave, as a function of stock of knowledge when all other inputs are held constant». This is intuitively appealing since, as Romer points out, knowledge will never grow to reach such a low marginal product that it won't be worth to produce it anymore. This model has the interesting feature of capturing the self-generating nature of technology within the economic environment.

However, as Hall (1994) notices, the exogenous and endogenous approaches to technology do not necessarily exclude each other; technology does not "pop up" and enter the production function out of nowhere, but it is also true that technological progress is not entirely driven by economic factors: geographical, cultural and socio-political aspects also enter the picture.

1.1.3 Mesoeconomics and the Schumpeter-Hayek program

Schumpeter collects the neoclassical lesson, in that the basic unit of economic analysis and modeling remains the individual behavior; however, if the neoclassical men is the homo oeconomicus, who decides on the basis of a given set of economic endowments and constraints, but cannot be actively the driver of change, the Schumpeterian entrepreneur brings forth the process of creative destruction which is at the basis technological progress and economic development. Schumpeter (1942) writes that the entrepreneur «incessantly revolutionizes the economic

structure from within, incessantly destroying the old one, incessantly creating a new one. This process of Creative Destruction is the essential fact about capitalism».

Within this framework, the process of knowledge production is endogenous, in that it is the product of the innovative effort of agents reacting to incentives and taking economic decisions. In order to understand this process, one should take into account both the micro level – the decisions of the entrepreneur – and the macro one – the process of creative destruction that diffuse in the economy and generates gales of technological progress. To do so, between the micro and the macro levels, we can address a third layer of analysis – the mesoeconomic one – within which the innovative input of the entrepreneur propagates into the economic environment (through imitation and diffusion) and brings about change. Dopfer (2012) underlines that the main feature of mesoeconomics is bimodality: «there are, on the one hand, ideas, and, on the other hand, matter-energy that is actualized in time and space». Ideas are rules to perform operations and therefore form the (rule) structure of the economy; however, ideas (knowledge, scientific breakthroughs, innovations) need to be actualized in the economic processes to become real drivers of change (Dopfer, 2012). This focus on both structure and process is the main characteristics of mesoeconomics and renders it the ideal theoretical space to analyze technological production and diffusion.

A wide strand of institutional economics literature has focused on mesoeconomics as the layer in which "meso rules" emerge from the micro level and are adopted and diffused in the socio-economic environment. However, the mechanisms that govern the generation of institutions as means to solve problems (and make choices), are still object of investigation (Elsner and Heinrich, 2010) and,

to this aim, a dialogue between the institutional framework and the economics of technology might be mutually useful.

Schumpeter, Dopfer (2012) argues, focus on the active role of the entrepreneur as the one who finds unexplored opportunities and gives actualization to ideas. He deals with the process of creative destruction (the disruption of the status quo through the innovative input) and not with creative construction, at the basis of which is the knowledge production process. Von Hayek (1937) and Von Hayek (1945) fill this gap, since his work introduce a different interpretation of the micro-meso-macro stratification, whose analytical perspective is knowledge: the triad becomes «the neural-cognitive disposition of the individual (micro), the process of knowledge diffusion and adoption (meso), and the engendered change of the economy's division and coordination of knowledge (macro)» (Dopfer, 2012).

The simulation developed in the second chapter tries to implement what Dopfer (2012) calls the «unified Schumpeter-Hayek program», that is to exploit the complementarities of their theoretical architectures and analyze both the process of creative destruction of economic equilibria and the creative construction brought forth by the production of knowledge and technology.

1.1.4 Inside the black box: alternative approaches and methodologies

Complexity theory opens new possibilities to model innovation and technological progress as an emergent property of both the purposeful actions of heterogeneous economic agents – the profit seeking activity – and the structural characteristics of the system within which the individual acts and reacts. Antonelli (2011) provides

a comprehensive definition of complexity theory, which is «a systemic and dynamic approach according to which the outcome of the behavior of each agent and of the system into which each agent is embedded, is intrinsically dynamic and can only be understood as the result of multiple interaction among heterogeneous agents embedded in evolving structures and between the micro and macro level».

One of the fundamental features of a complex system is emergence, that is the development of new rules and properties which are the result of the dynamic interaction of a high number of heterogeneous agents and cannot be understood ex ante by looking at the fundamental laws governing each element of the system. Gilbert and Terna (2000) underscore that a phenomenon is emergent «if it requires new categories to describe it which are not required to describe the behaviour of the underlying components».

Once we begin to think about technological progress as an emergent phenomenon in a complex social system, it becomes clear that its properties cannot by completely understood neither by focusing on the microeconomic level – the technology employed by the firm and its R&D decisions – nor by looking at the macro evolution of technology through historical analysis and economic data. Moreover, complex social systems – differently from physical ones – present an additional challenge: economic and social agents cannot be modeled as a set of mindless automata determining the evolution of the system through action and reaction (e.g. a set of molecules in a room). The role of intentionality must be taken into account when modeling and interpreting their behavior (Antonelli, 2011). That is, although the structural features and laws governing the system are essential to understand the overall outcome, one cannot abstract completely from the intentional profit-seeking activities of economic agents. Moreover, these

activities are not guided by the neoclassical profit maximization, since agents are characterized by bounded rationality and an "optimal" solution is often hardly identifiable; these features determine the already mentioned misspecification of the optimization problem, and force economic agents to learn and evolve through adaptation (to the environment), adoption (from the environment) and trial and errors (Alchian, 1950).

These remarks only provide a hint on the complexity of the processes and mechanisms involved, but may help to understand why it is important to explore new approaches and methodologies in order to get a glimpse into the black box of technological progress. The three main approaches on which this work bases its attempts to investigate the mechanisms involved are evolutionary economics, agent-based modeling and social network analysis.

Antonelli (2011) (referring to the work of Griliches (1961)) provides an useful starting point and states that «innovation takes place when it consists in actions that are able to engender an increase in the value of the output, adjusted for its qualitative content, that exceed their costs». More straightforwardly, an innovation is defined such if it possesses the two attributes of novelty and increased efficiency. Because of that, an increase in total factor productivity is judged as a good indicator of whether the introduction of a new technology has actually resulted in an innovation as above defined. However, the computation of total factor productivity – which still raises a number of methodological issues – is hardly informative on the true nature of the mechanisms involved in technological progress and, more importantly from an economic and social point of view, on what is its impact on economic growth and development and which policies are the most effective to enhance it.

Evolutionary economics tries to deepen our understanding of these mechanisms by borrowing the Darwinian concept of natural selection operated by the environment (the economic and social one) and emphasizing the role of random, successful mutations (new discoveries) in determining technological advance and economic development. One of the milestones of this literature is the already mentioned Nelson and Winter (1982). The risk with this approach is to fail to fully acknowledge the role of the purposeful actions of agents, both those involved in economic decisions (e.g. the firm that invests in R&D) and those involved in scientific/cultural efforts (e.g. the scientist that pursue knowledge). Penrose (1952) interestingly argues that «to abandon [the] development [of firms] to the laws of nature diverts attention from the importance of human decisions and motives, and from problems of ethics and public policy, and surrounds the whole question of the growth of the firm with an aura of "naturalness" and even inevitability».

An answer to these concerns is provided by the most recent strand of evolutionary economics, best embodied in the work of Arthur (2009). The evolution of technology is described as a combinatorial process in which novel discoveries are produced by combination and recombination of existing pieces of knowledge guided by the purposeful action of scientists and inventors. As Arthur (2009) points out, «the pure equivalent in biology would be to select an organ that had proved particularly useful in lemurs, say, and another organ from iguanas, and another one from macaque monkeys, and use these in combination with others to create a new creature». This sort of process happens quite rarely in nature, but is the norm when innovation is involved.

Social network analysis

Social network analysis is an useful methodological tool to understand and model the structural and statistical properties of the complex interactions between economic agents. It is therefore useful to pinpoint some relevant topics in order to further understand the approach implemented in the simulation.

Researchers in a wide number of fields – ranging from biology to sociology and from physics to computer science – strive to understand and reproduce the topology and dynamic behavior of complex networks that emerge in social and biological systems. The behavior of these networks is usually modeled as being governed by probabilistic laws and the two most widely used constructions are the random graph model introduced by Erdos and Rényi (1960) and the small world model developed by Watts and Strogatz (1998). Despite their simplicity, the outcome of these two models show an interesting degree of complexity and is able to capture a number of features of real networks – a peculiar example of which is the "six degrees of separation" rule described by small world networks and noticeable in friendship networks.

Nonetheless, these two models fail to address some essential features of complex networks and this is particularly true when economic and business relations are concerned. In particular, the random network model – in which the probability that two nodes are connected is uniform – misses to address the self-organizational nature of social systems. Small world graphs, instead, are not suitable to model the local nature of many interaction networks – due to myopic agents and/or other natural, cultural and informational constraints. Moreover, both models fail to incorporate two essential characteristic which seem to determine both the observed

scale invariance and self-organization of some real networks: growth and preferential attachment. Erdös–Rényi and small world networks are built with a constant number of nodes, while the structure of edges varies through time following the proper probability distribution. This is particularly detrimental when dealing with economic interaction and the network of evolving technologies, since it rules out innovation and the possibility that a new firm enters the economic competition.

As for preferential attachment – the feature by which a node with a high connectivity has a higher probability of further enlarging its connections – this characteristic has a central role in the observed structure and dynamic evolution of many social systems. This is verifiable both intuitively (e.g. we can easily assume that a production technique which is already employed by a wide number of firms has a higher probability of being chosen by an entrant firm, while true innovators are relatively rare) and from available data. Barabási and Albert (1999) point out that:

> Exploring several large databases describing the topology of large networks that span fields as diverse as the WWW or citation patterns in science, we show that, independent of the system and the identity of its constituents, the probability $P(k)$ that a vertex in the network interacts with k other vertices decays as a power law, following $P(k) \sim k^{-\gamma}$. This result indicates that large networks self-organize into a scale-free state, a feature unpredicted by all existing random network models.

This formal description led to the recognition of power law distributions in a wide number of different systems, both social and natural. These networks are characterized by scale invariance, a feature by which if the argument k is scaled by

a constant factor – say c – the power law relation is only proportionally scaled by a factor $c^{-\gamma}$. Therefore, what characterizes the behavior of the network is the value taken by γ, a number which has been often empirically found in a range from 2.1 to 4 (Barabási and Albert, 1999). The power law distribution is particularly suitable to analyze the behavior of extreme events: in random and small worlds networks, the «probability of finding a highly connected vertex (that is, a large k) decreases exponentially with k; thus, vertices with large connectivity are practically absent» (Barabási and Albert, 1999). Conversely, the long tailed degree distribution of scale-free networks results in a relatively frequent appearance of highly connected nodes.

The scale-free character of these networks is particularly suitable to model the recursive nature of technology described by Arthur (2009) and its dynamical evolution through time. Highly connected nodes represent groundbreaking technological innovations (like the steam engine or computational science), with which a wide number of other techniques and discoveries are related. If we zoom the picture, getting deeper into the relevant *domain*, we find the very same structure, with other crucial and highly connected technologies dominating the network (e.g. the locomotive or the personal computer). If we perform the thought experiment of wiping out one of those groundbreaking, highly connected innovations, we would find that a huge section of the network would collapse and a whole generation of related technologies would disappear together with their offsprings. This help to understand the feature of scale-free network of being particularly vulnerable to directed disruptions, but very resilient to random ones.

As for the dynamic evolution of scale-free networks, growth and preferential attachment ensure that «an initial difference in the connectivity between two ver-

tices will increase further as the network grows» (Barabási and Albert, 1999). This also implies that older nodes further and further increase their connections, while younger ones strive to emerge. This is coherent with the highly path dependent nature of the evolution of innovation (very small, random historical events might have a great impact on the future structure of the model) and with observable lock-in phenomena (Arthur, 1989).

These peculiar characteristics of scale-free networks widen our ability to capture and explain the complex features of social systems emerging from the routinized behavior of myopic agents/nodes. According to Barabási and Albert (1999):

> Similar mechanisms could explain the origin of the social and economic disparities governing competitive systems, because the scale-free inhomogeneities are the inevitable consequence of self-organization due to the local decisions made by the individual vertices, based on information that is biased toward the more visible (richer) vertices, irrespective of the nature and origin of this visibility.

Despite these similarities, one should be careful when applying the features of scale-free networks to social and economic systems. The role of bounded human rationality and (not always successful) intentional profit-seeking activities, together with learning processes or other behavioral routines, crucially influence the outcome of the system. Moreover, the preferential attachment mechanism is often disrupted by the efforts of innovators and entrepreneurs: although lock-in phenomena are present and imitation is still the main process through which firms implement new technologies, the main engine of innovation is the discovery and exploitation of new, unexplored possibilities. When an entrepreneur comes up with

a new business idea, it might strive for a while, since established and widespread technologies are strongly rooted (highly connected) in the market. But if proven successful, the innovation might rapidly catch up and the old techniques be dismissed. Therefore, the structural analysis of the network, although being a useful tool to interpret the meso layer of the model, shall not be the only analytical perspective.

In addition to the above concerns, a crescent number of scholars stress the fact that the widespread diffusion of power-laws in social and biological systems might be actually overstated. The scale-free framework possesses interesting features and provide the researcher with an useful analytical tool to address some particular properties of complex systems. Nonetheless, this intuitive attractiveness might be misleading and the emergence of an actual power-law distribution should be the object of a rigorous, statistical analysis. A clear example of how this kind of analysis might be carried on is provided by Hilbert (2013), who analyzes the network of top-500 supercomputers and the emerging power-law distribution of their performance. As the author notices, intuition and visual analysis of the data show «an inverse linear log-log relation, with (exponentially) many supercomputers of (exponentially) low performance (the so-called "fat-tail") and (exponentially) few supercomputers of (exponentially) high performance (so-called "large events"). The power-law trend lines fit the measurements very well».

Nevertheless, Hilbert points out that visual interpretation and the standard R^2 test might be misleading and perform a statistical test developed by Clauset *et al.* (2009) to detect the actual emergence of a power-law. The results of the test partially confirm and partially contradict the previous conclusions, thus stressing the importance of a rigorous – although not always conclusive – interpretation and

analysis of the data.

Once an actual power-law distribution is detected and tested, another challenge is offered by the identification of the generative mechanism that subtends its emergence. Growth and preferential attachment are not the only forces at play and a number of different solutions have been proposed. In his analysis, Hilbert (2013) browses the main possible generative mechanisms, in order to address whether they fit the case of the top performing supercomputers network. He ultimately proposes an alternative solution, based on the interplay of two exponential processes – technological progress and technological diffusion – which, together, produce the observed power-law. However, this dynamics is far from being a necessary feature of the analyzed system. As he rightly notices:

> It is important to point out that this emerging power-law between exponentially increasing performance and exponential diffusion, stable as it is, is neither automatic, nor the deterministic result of every interplay between exponential progress and social diffusion. [...] a strict Popperian sense of falsifiability still does not allow us to declare deterministic exclusivity on the relation between the proposed mechanism and the empirical data [...].

The integration of intuition, visual analysis and statistical tests, together with a critical interpretation of the data, is fundamental to perform a rigorous social network analysis.

1.2 From localized to centralized technological progress

1.2.1 Dimensions of localized innovation and diffusion

Network externalities and increasing returns to adoption are typically local – both on a geographic dimension and in the Lancastrian knowledge space (Antonelli, 2011). Even if we live in a world where communication is easy and information can be accessed at a negligible cost, much of the knowledge is still tacit or not easily codifiable (Cowan, 2005), particularly for what concerns the manufacturing process. Cultural and linguistic issues also play a role. These features cast some doubts on the public good nature of knowledge and technology – even in the absence of patents regulation or other forms of judicial constraints.

Knowledge flows have been typically analyzed in the literature by looking at the patterns of patent citations. If a patent is cited by a subsequent one, it follows that the technology embedded in the citing patent is built upon the block of knowledge contained in the former (Jaffe *et al.*, 1993). Therefore, looking at the "trails" of patent citations, we can analyze how knowledge diffuses and whether its intuitively appealing local nature is matched by data. Jaffe *et al.* (1993) find large and statistically significant evidences that knowledge diffusion – in the form of patterns of patent citations – is geographically localized. It is worth to notice that simple spatial proximity can be a misleading factor. As Jaffe *et al.* (1993) points out:

> The most difficult problem confronted by the effort to test for spillover localization is the difficulty of separating spillovers from correlations that may be due to a pre-existing pattern of geographic con-

centration of technologically related activities.

A big share of citations might come from the same area in which the patent itself have been produced simply because a wide number of actors involved in knowledge production and diffusion happen to be located in that area – a peculiar example being the Silicon Valley.

Another important role is played by industrial commons (Pisano and Shih, 2009), a multilayered concept related with firm specific manufacturing know-hows, basic and applied R&D capabilities together with engineering and process related skills; it also includes the set of know-hows and logistic processes possessed and developed by other actors that work within a particular industry, such as suppliers or transportation companies. Since most of this knowledge is tacit and embedded in the manufacturing process, these industrial commons are typically geographically localized. Pisano and Shih (2009) notice that

> Once an industrial commons has taken root in a region, a powerful virtuous cycle feeds its growth. Experts flock there because that's where the jobs and knowledge networks are. Firms do the same to tap the talent pool, stay abreast of advances, and be near suppliers and potential partners.

These evidences should warn managers and policy makers: the widespread tendency to outsource the manufacturing sector – in order to concentrate resources and R&D efforts on design – is fundamentally flawed and can jeopardize innovation and the skills necessary to turn an invention into high quality products (Pisano and Shih, 2012). The set of knowledge and know-hows embedded in specific processes, together with professional and social ties, quickly erode, depriving the industry (or

a particular geographical region) of the skills that sustain innovation and growth. Managers should be aware of this kind of shortcomings: financial constraints and short term cost cutting strategies should not be the only criteria when dealing with the outsourcing decision. An useful decisional tool is proposed by Pisano and Shih (2012) and focus on the connection between design and manufacturing: the more interconnected the two processes are – and the more developments in the former also affect the latter and viceversa – the more detrimental is outsourcing.

Together with geography, it is useful to analyze other dimensions along which the local nature of technology diffusion expresses itself. Among these, social proximity has been pointed out as one of the main channels through which information and knowledge diffuse among firms. Departing from the work of Jaffe *et al.* (1993), Breschi and Lissoni (2003) argue that the exchange and diffusion of knowledge can also take place over long distances among workers, scientists and inventors who are linked by social or professional ties. Spatial proximity, therefore, is neither a necessary nor a sufficient condition: even if a firm locates itself near a crucial hub of technology production and diffusion, the social network through which knowledge spreads might be difficult to enter. Moreover, hiring a brilliant scientist might not be enough for the knowledge spillovers to be localized exclusively in the chosen area; the scientist might continue to exchange knowledge with his pre-existing social network, even if geographically distant.

This of course does not mean that spatial proximity is completely meaningless: professional and social links are more likely to be created in a geographically bounded space, «since spatial proximity may help the network members to communicate more effectively and patrol each other's behavior» (Breschi and Lissoni, 2003).

A third research direction focus on the concept of distance in the knowledge space. The closer two firms are (sharing technologies, processes and standards) the easier will be to transfer and exchange information among them. «If a good exhibits network externalities or increasing returns to adoption, two agents will create externalities for each other if they use the same standard or technologies, but not if they do not» (Cowan, 2005).

Therefore, the local nature of knowledge and technology diffusion strongly limit their public good features and led some author to define them either as local public goods (Breschi and Lissoni, 2003) or as a club goods (Cornes, 1996) produced and exchanged among a more or less closed cliques of people tied by professional and social links.

1.2.2 The national level: policies to foster innovation

Some amount of scientific and technological advance originates from publicly funded basic research, but a great deal of innovation is produced by R&D efforts of firms and private actors, which are guided by economic incentives and constraints. It is frequent, in a perfectly competitive environment, for the social value of an innovation to be well above the return expected by the investor firm. The reasons are all more or less related to the peculiar nature of the good produced in the innovation process, that is knowledge. With some caveats which will be further explored, knowledge is often considered as possessing the public good features of non-rivalry – my use of it do not prevent others from using it – and non-excludability – once it is created, one cannot effectively exclude others from using it. Moreover, the original inventor cannot fully appropriate the returns generated by the innovation,

because of positive externalities and spill overs which diffuse in the industrial sector and society in general. Finally, as Posner (2005) points out, the high ratio of fixed to variable costs in the knowledge production process implies that a price equal to the marginal cost is often too low to recover the costs of the investment. This feature either erode the incentives to engage in R&D or, in case of pricing above marginal cost, might cause the inefficient entry of imitators which free-ride on the investment of the incumbent firm.

The two main policy instruments that the policy maker can implement to solve the incentive issues are public subsidies and legal instruments to protect intellectual property. Public subsidies might sound ideal insofar they provide a reward to the innovator without restricting access to and use of the new piece of knowledge, so that it can be freely diffused in the society and further developed; however, they present some relevant drawbacks. First of all, the optimal amount of subsidy can be difficult to compute and often depend on the uncertain commercial success of the innovation. Moreover, the direction of public funds is often guided by political contingencies, rather than criteria of economic efficiency and social development (Posner, 2005). This might induce innovating firm to dedicate time and resources to rent seeking activities in order to obtain the subsidy (legal and agency fees, communication, lobbying and, in the worst case, corruption) rather than to the production of knowledge and technology. Finally, Encaoua *et al.* (2006) notice that the information asymmetry between policy makers and private actors about the actual value and costs of the innovation can induce moral hazard as to the use of the funds and adverse selection of the less performing firms.

Therefore, governments resort to patent systems to provide incentives to innovators, while, at the same time, leaving them with the decision about the direction

of the R&D investment and the consequences of the commercial success (or failure) of their invention. Moreover, the costs associated with the innovation process are bore by its users – who face the higher price implied by the temporary monopoly power enjoyed by the inventor – and not by taxpayers (Encaoua *et al.*, 2006). A third element which makes patents a desirable policy instrument is the disclosure requirement, which forces the innovator to publicly disclose the best practice to obtain/apply its discovery. These characteristics favor knowledge diffusion and the development of cumulative innovation, but also expose the discovery to imitation from competitors, which might try to invent around the patent in order to develop a similar product which do not infringe the intellectual rights of the original inventor.

When it comes to decide between different policy instruments – subsidies, systems of legal protection or even laissez-faire – the crucial point is to assess the magnitude (if any) of the trade off between the distortion generated by the temporary monopoly power granted to the pantentee – and the consequent deadweight loss incurred – and the alleged incentive to innovative investments induced by a system of intellectual property rights. While neoclassical economic analysis is quite straightforward on the assessment of the market and social consequences of monopolistic power, the issue of whether patent systems actually stimulate innovation and technological diffusion is still deeply controversial.

The argument in favor of patent systems usually relies on the public good nature of knowledge and information; since knowledge is non-rivalrous and non-excludable, it can be appropriated by imitators and implemented in their production process with negligible costs. This view implies that technology – products, processes, strategies and so forth – can be almost completely embedded

in blueprints that are easily and freely transferred, communicated or stolen by imitators. Within this framework, laissez-faire is inefficient, since firms may either decide not to engage in R&D (underinvestment), or to keep inventions secret (which is detrimental for technological progress and growth, since it slows down innovation diffusion and development) or the price system collapse into imperfect competition (Nordhaus, 1967).

One on the milestones of this debate is Nordhaus (1967) on the optimal length of patents. Solving the profit maximization problem of the inventor, he finds that the optimal length of a patent is positive and finite, therefore giving theoretical justification to the implementation of a patent system.

In another related framework, the innovation discovery process is represented as fishing from a common pool; «there are many competitive inventors, and the first to make an invention gets the patent on it. Each knows that as others catch (invent) there is less in the pool for her. The result is "overfishing": too many people seeking inventions at once» (Merges and Nelson, 1990). This implies that the act of discovering a new piece of knowledge is rivalrous, in that when the first inventor "catches" it, he precludes the same discovery to others. This feature generates inefficiency, since the race to invention cause duplication and overlaps in the research process. Kitch (1977) contributes to this debate, stating that the explanation provided by the «reward theory» of patent systems – the view according to which patents serve the purpose of rewarding the innovator for its investment – is only part of the story. According to Kitch (1977), patents serve the primary function of increasing the output from resources invested in the innovation process; this is achieved by granting a "prospect", that is the right to develop some technological opportunity, at the early stages of its discovery. This ensures that

the inventor can invest in the development of its innovation without worrying about potential imitators and even coordinate its effort with those of other firms to reduce duplication (Merges and Nelson, 1990).

Reviewing the opposite camp, the most noticeable feature of the relevant literature is that it is extremely rare to find arguments in favor of a complete elimination of the patent system. Quoting Penrose (1951):

> If national patent laws did not exist, it would be difficult to make a conclusive case for introducing them; but the fact that they do exist shifts the burden of proof and it is equally difficult to make a really conclusive case for abolishing them.

However, it is important to underline some controversial features of the patent system and their potential detrimental impact on technological progress and diffusion. Most of the critical arguments rest on the fact that the transfer of knowledge and information is not costless and, in some cases, proves even impossible; most of the knowledge used in the productive processes of the firm is tacit and not codified and cannot be completely embedded in blueprints or transferred in written form. Innovation and knowledge production are often the result of a progressive learning by doing process, in which past experience and established practices play the main role. Moreover, imitation is not costless and often requires extensive adaptation of the technology to the specific processes of the imitator. Finally, Arrow (1962) notices that «no amount of legal protection can make a thoroughly appropriable commodity of something so intangible as information. The very use of the information in any productive way is bound to reveal it, at least in part. Mobility of personnel among firms provides a way of spreading information. Legally imposed

property rights can provide only a partial barrier».

Merges and Nelson (1990) also provide an interesting critique to the prospect theory developed by Kitch (1977); they argue that the assignment of a "prospect" to the first inventor actually slows down the pace of knowledge production, since the competitive pressure of the race to invention is eliminated and the cost of inaction is greatly diminished. Moreover, they focus on the path dependent nature of the discovery process and the tendency of economic actors to learn from past experience: «many independent inventors will generate a much wider and diverse set of explorations than when the development is under the control of one mind or organization». Their argument rests on the fact that, when technological progress is involved, «faster is better», and that the consequences of "underfishing" are more detrimental than duplication in the research efforts.

These considerations heavily limit the effectiveness of patents to provide a sufficient amount of reward and protection to the original inventor, and therefore their ability to foster technological progress. It becomes increasingly difficult to assess whether the deadweight loss generated by the monopoly power granted by patents has actual economic justification and to what extent.

Turning to the firms' point of view, economic actors that engage in R&D face the trade off between legal protection of their intellectual property, which allegedly grant them a limited in time monopoly power on its use and commercialization, and the drawbacks related with a complete disclosure of their discovery. Also, other less apparent limitations of patenting have to be taken into account; first of all, policy makers can adjust patents' scope to impose a price ceiling: the narrower the patent, the lower will be the price that the firm will be able to charge, since consumers will have a wider array of close substitutes and imitations to choose from.

Moreover, some countries (e.g. China) have implemented a system of compulsory licensing, which force the patentee to grant (in exchange of a «reasonable exploitation fee») a license on the use of its discovery to other firms that might request it (Sorell, 2002). Finally, one should consider the high transaction costs implied in the transfer of intellectual property: «the longer the patent term, the more likely the invention space is to be cluttered with patents, requiring multiple negotiations and creating potential holdout problems» (Posner, 2005). A large public domain within which firms can freely acquire knowledge might be a desirable framework even to the investor worried about the exploitation of his intellectual property. These characteristics might make extensive patenting a rather undesirable choice for innovating firms.

Finally, it must be underlined that legal protection is not necessarily the only, nor the most effective tool to appropriate returns from intellectual property. Secrecy is a viable option, particularly when the invention is complex and hard to imitate; in some cases, it can be made such, through the use of particular strategies to make it difficult for competitors to reverse-engineer the technology embedded in the product. These obfuscation strategies are particularly common in consumer technology and software industry. A second aspect to consider is first inventor's head start, which, thanks to the accumulation of experience and learning by doing, can give to the original inventor a permanent cost advantage over imitators (Posner, 2005). Knowledge can also spill over through workers' mobility, that cause the transfer of experience and know-how to competitor firms; high remunerations are therefore a useful tool to keep intellectual property within the firm's wall.

1.2.3 Big science

It is becoming increasingly frequent to see governments and international organizations involved in gigantic efforts to coordinate and finance Big Science projects, large-scale scientific programmes whose aim is to address and solve grand challenges faced by human kind. These programmes span over a long horizon of time and are usually characterized by a strong multidisciplinarity – requiring the combined effort of scientists from a wide range of fields, enormous costs and highly uncertain outcomes. These features ensure that in order to be undertaken and efficiently performed, these projects require a strong and active involvement of governments and supranational organisms, to finance and coordinate the combined efforts of a network of hundreds of scientists and research institutions. The main goal is to efficiently manage the huge amount of resources invested, create synergies among researchers, avoid overlaps and pool all generated data in publicly available databases. Moreover, these programmes, requiring a huge financial, economic and scientific involvement of national communities, encourage a dialogue between general public, policy-makers and the scientific community, which usually encompass societal and ethical issues. For all these reasons, big scientific programmes have enormous potential to sprout gales of Schumpeterian technological and scientific progress, awake innovative forces in the society and generate new industries and markets. However, a wide range of doubts can be casted on the actual impact of these programs and on whether the set up of such gigantic bureaucratic and economic machines is the best and more efficient way to achieve their visionary goals.

The most representative example of such programmes is probably the Human

Genome Project (HGP), a 15 years, $3.8 billions US investment with the goal of analyzing and map the structure of the human DNA. The project was successful and the complete mapping of the DNA was released and made publicly available in 2003. This achievement had a huge impact on biomedical science and human health, allowing for a better understanding and treatment of genetic diseases and the development of new technology for DNA sequencing and drugs synthesis. Moreover, the project had also wide applications in veterinary medicine and agriculture.

The impact of the project was so widespread that it initiated the so called "genomic revolution", opening up new opportunities niches and applications, both for basic research and business, building industries commons – services for the genomic industries, new markets and suppliers, industrial practices – and initiating a process of day by day learning by doing which led to an extraordinary flourishing of the sector. Some characteristics seem to have been particularly important in the generation of this wave of innovation: first, all produced data were immediately made publicly available in the GenBank database. This allowed for a fast and fruitful diffusion of all generated knowledge in the scientific community and in the industry. Moreover, the project placed particular emphasis on technology production and development, together with efficient transfer to the industrial sector. As the first five-year plan of the project states, «rapid transfer of the technology developed under the human genome program to industries that can develop economically and medically useful applications is a major goal of the project. This will occur in a variety of ways ranging from direct federally funded research at private companies to expedited transfer of new technology into the private sector» (National Human Genome Research Institute, 1991). Finally, the

programme produced a generation of highly trained scientists and professionals in the genomic field, an aspect which will spread long lasting benefits both in the scientific community and in the private sector.

In the late 90s, a new actor entered the road to the mapping of the human genome: Celera Genomics, an information company aiming at the provision under a subscription fee of a database of genes and tools for researchers and pharmaceutical companies, developed a new method for DNA sequencing which proved less costly and faster than the one applied by the publicly funded project. With an investment of only $300.000 and beneficing of the publicly available data provided by the Human Genome Project, Celera Genomics' DNA sequencing effort resulted in the filing of 6500 preliminary patent applications. The event had a disruptive effect on the scientific community and policy makers, which raised concerns about the exploitation of the human genome for profit seeking purposes. Given the particularly sensitive nature of the matter and its high impact on human life and health, the patenting was seen as possibly limiting the availability of data, dampening further research and exposing potentially revolutionary discoveries to exploitation by the pharmaceutical industry. This led to a joint statement of US President Clinton and British Prime Minister Blair, who underlined that the human genome could not be patented.

Although these concerns can be largely shared, some considerations are in order. The emergence of Celera Genomics and its original methodology in the industry surely put a competitive pressure on the Human Genome Project; many observers report an acceleration in the production of data and results by the publicly funded project after 1999. Moreover, the sequences discovered by Celera were available to researchers and pharmaceutical companies under a subscription fee

and were later resequenced – and thus made publicly available – by the Human Genome Project. What gave Celera Genomics a competitive advantage was timing and costs: the company was able to provide its clients with original data faster and with an investment ten times smaller than the costs of the whole HGP, offering new opportunities for further research and drugs synthesis. It is of course unrealistic to believe that a private company – not enjoying public funding – would provide such services without seeking a return on its investment. Finally, the patent applications filed by the company were only preliminary; as J. Craig Venter, President and chief scientific officer of Celera Genomics stated: «A patent will not be issued on the discovery unless an actual patent application is filed within one year of the provisional application filing. During this twelve-month period, Celera will decide with its pharmaceutical partners which genes are medically important enough to file patent applications. This approach is similar to the research strategy taken by pharmaceutical companies» (Venter, 2000). Therefore, the fear that the human genome could be patented seems largely overemphasized, also considering the characters of utility, novelty, and non-obviousness required for patent grants in the US. The concern that these original data could be exploited by pharmaceutical companies at the expenses of citizens and basic research is understandable, but appears more related to the peculiar nature of the US health care system than to Celera Genomics' business model.

These considerations suggest that this might be a case in which scientific progress and profit seeking go in the same direction, but the evidences are still controversial. For example, Williams (2010) «find evidence that Celera's IP led to reductions in subsequent scientific research and product development on the order of 20 to 30 percent». Moreover, a big advantage of publicly funded projects

dealing with such controversial matters is a particular sensitivity to the ethical, social and juridical consequences of the research, which frequently lead to the establishment of ad hoc ethical committees. Companies are usually less prone to deal with such concerns, unless they receive pressures from their clients and shareholders. This order of reasons suggest that there might be space for fruitful collaborations between publicly funded projects and private companies and talks towards this direction were established between the HGP and Celera Genomics. However, the opportunity was largely missed and these talks never resulted in an actual collaboration.

Along the lines of the Human Genome Project, two similarly big and forward looking projects – Graphene and the Human Brain Project (HBP) – were developed within the Horizon 2020 framework, the programme to fund research and innovation which is part of the European growth strategy for 2010-2020. Graphene and the HBP are the two *Flagship* projects of the Future and Emerging Technologies (FET) initiative, a programme for innovation and technological progress characterized by a particular focus in creating synergies between basic research and business opportunities, with great attention for technological development and transfer. As the Horizon 2020 Work-Programme 2014-2015 states, «the combination of a game-changing long-term vision and technological concreteness positions FET research between blue-sky science on the one hand, and research driven by societal challenges or by industrial competitiveness on the other» (Horizon 2020 Work-Programme 2014-2015, 2014).

Similarly to the HGP, the two FET-Flagship projects are characterized by visionary goals, huge investments – amounting at around 1 billion euros for each project over 10 years, active involvement of all member states and the establish-

ment of a fruitful dialogue between society – citizens and policy-makers – and the scientific community. Moreover, in order to ensure a consistent evaluation, rigorous criteria were established for the assessment of excellence, impact and quality and efficiency of the implementation of the single proposals within each project. These are ambitious goals to be achieved within the mammoth bureaucratic machine of the European Union and the scientific community reacted with skepticism. The Human Brain Project, in particular, is the most controversial; its goal «is to combine all existing knowledge about the human brain and to reconstruct it in supercomputer-based models and simulations. The models will offer the prospect of a new understanding of the human brain and its diseases and of completely new computing technologies» (Horizon 2020 Work-Programme 2014-2015, 2014).

The idea behind the development of a simulation of the human brain is visionary, but encountered widespread criticism among a large number of neuroscientists, «because of its focus on an overly narrow approach, leading to a significant risk that it would fail to meet its goals» (Open message to the European Commission concerning the Human Brain Project, 2014). The biggest fear is that the search towards this highly uncertain objective might drain much of European resources dedicated to neuroscience, leaving researchers who focus on alternative – and possibly successful – approaches without funds. Moreover, some doubts are casted on the transparency and accountability of the direction of the funds.

In 2013, another big science project in the field of neuroscience was announced by US President Obama: the Brain Research through Advancing Innovative Neurotechnologies (BRAIN) Initiative. The general vision and objective of the project is to catalyze multidisciplinary efforts in order to «get a dynamic picture of the brain in action and better understand how we think and how we learn and how

we remember» (US National Institutes of Health, 2014). The main difference between the US project and the European one is that the former is less concerned on the development of a simulation of the human brain as a tool to understand its mechanics, but focus on experiments and quantitative and statistical analysis in order to understand and map the dynamics of the neuronal circuits in human and animal brain. The use of simulation is not excluded, but it is part of a wider approach, open to the emergence of new challenges and methodologies as long as the initiative unfolds. Moreover, the first years of the project are specifically dedicated to the development of new technologies and experimental tools to be applied in its later steps; it is in fact recognized that the ambitious goal of the BRAIN initiative is achievable only if the investment will accelerate the emergence and development of an innovation gale similar to the Genomic revolution initiated by the HGP.

The BRAIN initiative might appear less visionary than the HBP, but this is not necessarily a negative feature. An illustrative example of an investment which largely failed to meet its ambitious goals – probably because it was far ahead its times and did not find widespread commercial applications – was the Fifth Generation Computer System (FGCS) project, a groundbreaking initiative undertaken by the Japanese Government during the 80s; the aim of the programme was to build a new generation of computers which, through the implementation of parallel computing and logical programming, would be able to replicate some features of human reasoning and move a step further toward artificial intelligence.

Japanese extraordinary development in the postwar period relied in great extent on the adoption and imitation of foreign state of the art technology. In order to overcome the criticism according to which Japan would exploit foreign technology without contributing with any of its own (Shapiro, 1983) and to develop industry

commons and a new generation of researchers able to produce original knowledge and innovation, the Ministry of International Trade and Industry (MITI) launched this cutting-edge project which encountered both enthusiasm and skepticism among the international scientific community. After an investment of more than $400 million, the project did not take off because of the unexpected acceleration in the development of the computer industry during the late 80s; general purpose computers outperformed the first fifth generation ones at an extraordinary fast pace. However sophisticated, the technology upon which these machines were built was not effectively transfered in the industrial sector – or at least not fast enough – and never entered the mass consumer market. The project is therefore a representative example of how the absence of an efficient transfer between blue-sky research and the industrial sector can lead to the failure of a promising technology. The right timing and fast attainment of a critical mass of adopters in the industrial sector are also crucial features in deciding the success or failure of a new technology – and FGCS seems to have gotten them both wrong.

However, similarly to what happened with the HGP, the actual impact of the research efforts undertaken within the FGCS project are difficult to track and quantify and its legacy might yet have to emerge. First of all, the project raised a generation of highly trained computer scientists and engineers, a pool of specialized workforce which can accelerate domestic innovation and R&D. Moreover, the launch of the FGCS project stimulated the development of similar programmes and private initiatives in other countries, pushed by the competitive pressure and the fear to lag behind the technological frontier. It is the case of the European Strategic Program on Research in Information Technology (ESPRIT), the British Alvey programme, and the US Microelectronics and Computer Technology Corporation

(MCC). Moreover, the beginning of the 21th century saw a rebound of the research on logical programming and most of the technology and scientific knowledge produced within the FGCS project have been recovered for further development. It is however interesting to notice that most of the scientific and economic positive externalities of the programme were not captured by the original investor – Japan – but crossed the border and spilled over the international community.

One of the main issues that decision makers and analysts face when evaluating – both ex ante and ex post – the impact of such investments is the methodology applied to identify and quantify all kinds of returns, both direct and indirect, and externalities deriving from the programme. Impact analysis is still a growing field and new methodologies are constantly emerging; moreover, since the topic is so controversial and since results depend heavily on the econometric and statistical tools applied, this kind of data are easy to manipulate and subject to a wide range of methodological issues.

An illustrative example is the controversial 2011 report on the economic impact of the Human Genome Project prepared by the US Battelle Memorial Institute. Making use of a US specific input-output model, the report analyze the economic impact – both direct, indirect and induced – of the expenditure for the HGP, together with its functional impact on all sectors affected (e.g. the developments made possible in human health, agriculture and biotechnology, among others). The results are striking; according to the report, «the federal investment of $3.8 billion in the Human Genome Project ($5.6 billion in 2010) enabled the generation of more than $796 billion in economic output for a return on investment to the U.S. economy of 141 to 1» (Battelle Technology Partnership Practice, 2011). However, these figures and their interpretation are subject to a wide range of critiques; Julia

Lane, founder and developer of STAR METRICS – a programme aimed to measure the effect of research on innovation, competitiveness and science – notice that what the Battelle report does is to establish a straightforward causal relation between all the subsequent economic activities in the genomic field and the initial investment in the HGP, somehow neglecting the complex interaction between public funding and private initiative. Quoting Lane, «by telling people that funding for science is a slot machine and if you put in money, magic will happen you're really doing a huge disfavor. That's not what science is about. Science is about making mistakes and learning from the mistakes.» (Johnson, 2013).

Chapter 2

Agent-based simulation

2.1 Description

2.1.1 Introduction to the model

The simulation is mainly characterized by a two-mode network, in which firms – the primary node set – are linked with the technologies being used in their productive activities. Technologies have to be understood as any kind of production technique (corresponding to the form of the neoclassical production function), but also products blueprints, logistic procedures, firm-specific routines and know-how, marketing strategies and, more generally, every piece of knowledge that the firm applies in its everyday life to gain a competitive advantage over other firms. The main objective of the model is to analyze how the characteristics of firms and technologies evolve and determine the outcome in a competitive environment and to address the dynamic interplay – inputs and feedbacks – between these two sets of nodes.

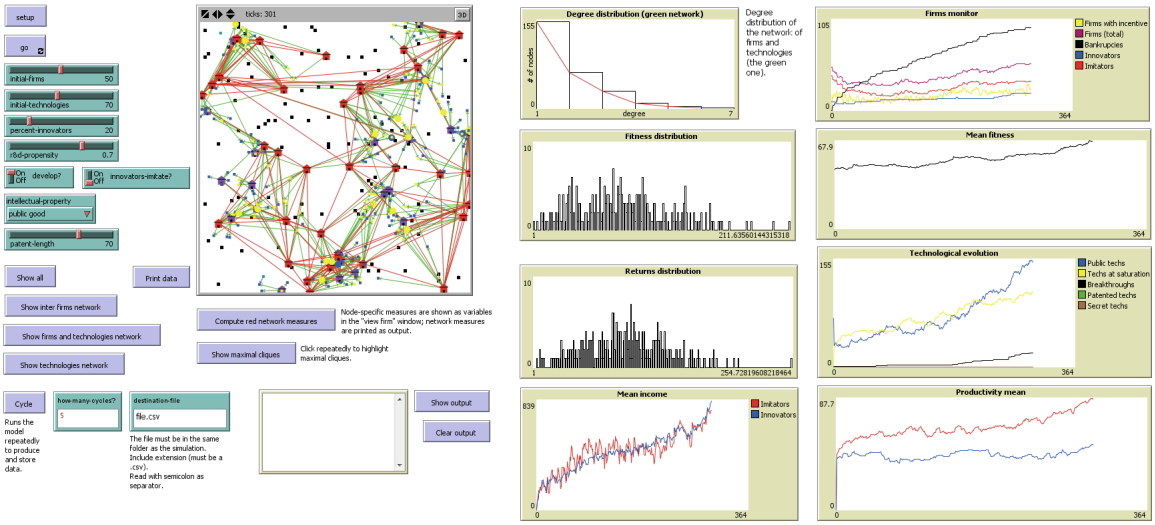

Figure 2.1: Full interface.

The topology of the interactions between firms and technologies can be crucial in determining the economic and technological evolution of the system and because of that, the structure of the network and its statistics has to be taken into account when evaluating the outcome of the simulation. Following the characterization made by Amblard and Quattrociocchi (2013), the interaction topology of the network is explicit, in that the rules governing the establishment of edges between firm and technologies are part of the modeling hypothesis of the simulation.

A second, underlying layer of interactions is the structure which represents the evolution of technological progress – meaning the use and recombination of existing technologies in order to innovate and produce new knowledge. Even if technologies are not properly decision makers, they are actual agents of the simulation, with behavioral rules based on the insights provided by evolutionary economics. Another goal of the analysis is to address how this evolution is influenced by (and send feedbacks to) the economic environment.

Again following Amblard and Quattrociocchi (2013), a distinction can be made between the social structure – the network of social and economic interactions – and the spatial structure, which represents the geographical space. One of the channels through which interactions take place is the social structure: firms that share at least one technology, meaning that they share a common knowledge base or use similar production processes, independently on how far they are on the geographical space, can communicate more easily and establish collaborations in order to innovate or diffuse knowledge. However, geographical distance indeed plays a role and technological progress and diffusion happen to be mainly localized in specific hubs within which knowledge is produced and exchanged. This dimension is also taken into account in the simulation, in that firms prefer to adopt or develop technologies which are located nearby. It is also possible to interpret the space within which the simulation take place as a knowledge space, instead of a geographical one. In this sense, the distance between technologies represents how different is the knowledge base on which they are built and the nearest a technology is to a firm, the easier will be for the firm to decode, imitate and/or develop it.

The dynamics of the simulation is modeled along the lines of the algorithmic 6 steps process of formation of new technological elements described by Arthur (2009), within which innovation emerge as a response to economic and technical needs of the society and, conversely, influence the economic environment which has generated them; this process, as enumerated by Arthur, goes as follows:

1. The novel technology enters the active collection as a novel element. It becomes a new node in the active collection.

2. The novel element becomes available to replace existing technologies and components in existing technologies.

3. The novel element sets up further "needs" or opportunity niches for supporting technologies and organizational arrangements.

4. If old displaced technologies fade from the collective, their ancillary needs are dropped. The opportunity niches they provide disappear with them, and the elements that in turn fill these may become inactive.

5. The novel element becomes available as a potential component in further technologies—further elements.

6. The economy—the pattern of goods and services produced and consumed—readjusts to these steps. Costs and prices (and therefore incentives for novel technologies) change accordingly.

With reference to the last passage, it is important to notice that the demand side of the economy is not explicitly modeled in the simulation; nevertheless, the introduction of new technologies – more or less successful – influence the economic performance of the firms, affecting their incentives and the further technical and economic development of the system.

2.1.2 Setup of agents and links

Firms

Firms are the main actors of the system and object of analysis. They are characterized by a vector of state variables that affect their choices, which in turn determine

the aggregate outcome in terms of economic performance and technological evolution. A firm can be an imitator (red), which can only adopt existing technologies, or an innovator (purple), which cannot imitate (unless the innovators-imitate? switch is on), but is able to produce new technologies.

Because of bounded rationality and uncertainty, firms are modeled as a set of myopic agents, which are able to acquire and process only limited information in a very localized geographical and social space; therefore, their behavior follows a procedural approach, based on the available information, their limited computational ability and a certain degree of randomness. The outcome of each decision also depends on the environmental conditions – both local and aggregate – and on the actions of other agents and it is not predictable ex ante by the firm.

Firms are characterized by the following variables and parameters:

- *Techs:* A list which contains the who numbers of each technology used by the firm.
- *Stock:* A measure of the value of the firm, which is computed as the sum of the income at each tick.
- *Innovator:* A dummy variable equal to 1 if the firm is an innovator, 0 otherwise.
- *Imitator:* A dummy variable equal to 1 if the firm is allowed to imitate, 0 otherwise.
- *R&D_propensity:* A variable that can take only two values, 0.2 (low propensity) or 0.6 (high propensity). It is a proxy that represents the firm's propen-

sity to invest in R&D. It influences the amount invested in innovation and the probability to discover a new technology.

- *Productivity_firm:* A measure of the firm's productivity, computed as the geometric average of the fitness values of the technologies used by the firm. On the basis of its current productivity, the imitator firm decides whether to adopt a new, better performing technology, with a procedure which will be later explored.

- *Last_return:* The return to the productive activities of the firm collected in the previous tick. It is computed as the sum of the returns provided by each technology.

- *Last_costs:* The costs bore by the firm in the previous tick.

- *Adoption_temp:* A service list which collects the who numbers of the technologies which are good candidates for adoption.

- *Income:* Income received by the firm, computed as the difference between returns and costs.

- *Incentive:* A dummy variable which takes value 1 if the firm has an economic incentive to innovate or imitate, 0 otherwise.

Technologies

Technologies are broadly understood as every technique or firm-specific routine applied during the different processes in the life of the firm – be it the blueprints of a product, marketing strategies, logistic procedures and so on. The idea at

the basis of technological evolution in the simulation is that when a firm engages in an innovative effort, one of its technologies can sprout an "offspring" that, if successful, will provide the firm with a certain level of competitive advantage and increased returns.

Technologies can take different shapes and colors, depending on their characteristics; a brief legend might come in handy:

- *Square*: identifies basic technologies.
- *Circle*: these are groundbreaking innovations, referred to as "breakthrough"; they have a fitness value at least two times higher than the current average fitness level of the system.
- *Blue*: technologies which are public good, freely adoptable by imitators.
- *Yellow*: technologies which reached their saturation level (later explained).
- *Turquoise*: technologies not currently used by any firm.
- *Green*: patented technologies.
- *Brown*: technologies kept secret.

The most important feature of technologies is the fitness value, which is a measure of the suitability, both from a technical and an economic point of view, of the technology to the current environment. Quoting Arthur (2009): «A candidate solution must technically "work" to be considered for the purpose at hand; and its cost must be in line with what the market is willing to pay for fulfilling the purpose in question. Technologies that fulfill these conditions are potential "solutions" for

the purpose at hand». Since the demand side is not explicitly modeled in the simulation, the fitness value is a comprehensive proxy of both the effectiveness of a technology to fulfill a given technical purpose and its capability of meeting the demand of the market at sustainable costs. The higher is the fitness value, the larger are the returns for the firm.

Technologies are characterized by the following variables:

- *Fitness:* measures the technology's fitness.
- *Return_to_tech:* returns provided by the technology to its users; its computation will be later explored.
- *Adopters:* number of firms which currently use the technology.
- *Cost_adoption:* the cost that have to be payed by imitators to adopt the technology; it is equal to two times the fitness value.
- *Obsolescence:* a variable that counts how many ticks have passed since a technology has been dismissed by all its users. After 20 ticks, the technology dies.
- *Patent_protection:* a variable that counts how many ticks the technology has been under patent protection.
- *Cost_to_secrecy:* costs bore by the firm to keep the technology secret. They are equal to the 20% of the fitness value.

Links

In order to analyze how the economic decisions of the firms and the evolution of technology affects the topology and characteristics of the networks in which economic agents interact, and, conversely, to understand how the structural features of these interactions influence economic development, the simulation has a three layers structure, corresponding to as many networks with different characteristics and functions. The properties and metrics of these networks are mainly computed with the NW Netlogo extension.

It is important to underscore that the networks are not built so that their characteristics correspond to some specific model (e.g. small world); no generators or algorithms are used to produce their structure or keep constant their statistical properties. Instead, networks are left free to develop on the basis of the rules that govern the simulation. Because of the necessary simplifying assumptions on which the model is built, this feature might lead to anomalous or undesirable results, but it is interesting to notice that some intuitively appealing properties indeed emerge.

Three types of links, corresponding to the three networks layers, are implemented in the simulation:

- *Firm_uses (green, directed):* the green links form a two-mode graph characterized by two classes of nodes: firms and technologies. The edge is established when a firm begins to use (imitates or creates anew) a technology and disappears when the firm dismisses it.

- *Parent_of (blue, directed):* the blue links form a one-mode graph between technologies, providing a representation of their evolution; the edge is established when a "parent" technology sprouts an "offspring" and disappears

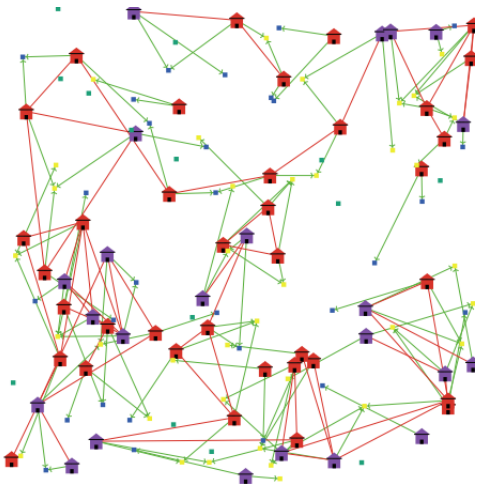

Figure 2.2: View of the simulation after setup and one "go" run

when one of the two technologies dies.

- *Share_tech (red, undirected, weighted):* the red links form a one-mode graph between firms which share at least one technology. The weight corresponds to the number of technologies that the two firms have in common. The edge is established when two firms share at least one technology and disappears when one of the firms goes bankrupt or dismisses the technology that the two share.

Setup

Figure 2.2 shows a typical initial setting of the simulation, with 60 initial firms, 80 initial technologies, 40% of innovators and a value of 0.7 for R&D propensity (meaning that 70% of innovators have high propensity to invest); the view has been exported after setup and one "go" run, since some features are not visible until the simulation is started.

Each firm is initially linked with two random technologies in a radius of 20

patches; this is to favor local technologies (both in the geographical and knowledge space), which are more easily implemented in the productive activities of the firm. If no technologies are found in that radius (rare in this typical setting), the constraint is released to ensure that, at the beginning of the simulation, each firm have two initial technologies.

Links are established following the rules already described and the chosen percentage of innovators is selected randomly among the firms. Moreover, 70% of innovators have been assigned with high propensity to R&D, while the remaining have low propensity. No blue link is present, since no innovation has yet been produced.

2.1.3 Go procedures

Update-tech-features

```
ask technologies [ show-turtle
                   set adopters count in-firm-uses-neighbors

                   ifelse fitness = 0
                      [set return_to_tech 0]
                      [set return_to_tech fitness - (alpha * adopters ^ 2) + (beta * adopters)]]
```

Figure 2.3: Computation of the returns_to_tech variable

This procedure updates the variables characterizing the technologies; the commands are quite straightforward, but some comments are in order for what concerns the computation of the *return_to_tech* variable.

The idea behind the function is that the returns given by a technology are not only a function of its actual usefulness and capability of meeting market require-

ments (represented by its fitness value), but also of the number of its adopters. Following Arthur (1989), technologies might frequently display increasing returns to adoption, so that the more economic agents implement them in their everyday processes, the more experience and know-how are gained and diffused in the industry as positive externalities, and the higher are the returns – in terms of productivity and cost savings – from their utilization.

Increasing returns to adoption have some peculiar and interesting features, such as the possibility that small historical events strongly influence the outcome of the system – leading to the lock-in of an inferior technology – together with non predictability and non-ergodicity. However, these features might have some major drawbacks if implemented into the simulation: a lock-in might drive the system into a static situation in which all innovation and entrepreneurial efforts are frustrated – since increasing returns ensures that the optimal choice is always to adopt an existing technology with the highest number of users, instead of developing a new one. Moreover, non predictability and non-ergodicity might give too much importance to small, contingent events or parameters, which would crucially decide the outcome of the model and completely overcome the results of behaviors and interaction between agents. An opposite effect can intervene to disrupt this self-feeding process and, after some threshold value, prevail – that is saturation. As Antonelli (2011) underscores, «beyond some – changing – levels, congestion, exclusion and saturation may take place and negative externalities become larger than positive externalities». Examples of these negative effects might be the increase in the cost of production factors or market saturation.

These two counteracting effects suggest that a good modeling hypothesis can be to impose a nonlinear relation between returns and adopters. For a small

number of users, the positive effect prevails and increasing returns apply, while, after saturation is reached, returns are decreasing.

These insights are implemented in the simulation, with returns given by the function:

$$returns = fitness + \alpha n_A^2 + \beta n_A, \text{ with } \alpha < 0$$

Where n_A is the number of adopters and α and β two technology-specific parameters which shape the form of the parabola, determining the marginal impact of each newcomer and the number of adopters at which the maximum is reached and returns start declining.

A closer look to this form of the returns – and particularly of its first derivative – can provide with a deeper insight on how the characteristics of the technologies might influence the shape of the parabola and, therefore, the evolution of returns while the innovation diffuse within the economy. Trivially, if a technology has no adopters ($n_A = 0$), then returns are determined only by its fitness value. The first derivative of the function with respect to the number of adopters has the form:

$$y_n = 2\alpha n_A + \beta$$

β expresses the magnitude of the (positive) linear effect of the number of adopters on returns; it can be thought of as representing knowledge spillovers, the creation of industry commons and the emergence of – mainly tacit – know-how through learning by doing. Highly innovative technologies at the early stages of their implementation and development might display a higher β. At this stage, the production process is still not standardized nor explicitly codified and radical product developments are more likely to occur; the entrepreneurial and innovative

effort of the early adopters is highly risky, but, if successful, it is more likely to yield high returns. With a larger β, each new adopter has a stronger positive effect on returns, since the more firms implement the innovation in their everyday processes, discovering and developing its potential, the larger are the benefits for the whole set of adopters.

On the other hand, α represents the marginal strength of the negative impact of adopters on returns; as the number of adopters increases, positive externalities are gradually overcome by the negative effects of saturation. Mature and fully developed technologies, produced within industries with established and well codified practices, might show a higher α, since imitation and market congestion are in this case particularly detrimental.

However, some computational limitations of the simulation must be taken into account; the number of agents that it can currently sustain is too small to result in a smooth and well balanced functioning of the above mechanism. More firms – in the order of hundreds – would result in a more interesting dynamics of the returns.

Update-firm-characteristics

```
ifelse innovator = 0
    [if income < mean [income] of firms with [innovator = 0][set incentive 1]]


    [if income < mean [income] of firms with [innovator = 1] [set incentive 1]
    if income > 1.80 * mean [income] of firms with [innovator = 1] and
    income < 2.5 * mean [income] of firms with [innovator = 1] [set incentive 1]]
```

Figure 2.4: Determination of incentives.

This procedure updates the values of the variables characterizing each firm. Two variables, in particular, deserve a deeper exploration.

The firm's productivity, represented by the *productivity_firm* variable, is set as the geometric average of the fitness values of the technologies used; the ratio behind the use of the geometric average is to avoid the distortionary effect of extremely fit or extremely bad technologies. The resulting variable is then used by imitators to decide whether to adopt a new technology, through a process which will be later explored.

The second variable of interest is *incentive*, a dummy which takes value 1 if the firm has an economic incentive to imitate or innovate, 0 otherwise. The aim of this variable is to guide the creative response of the firm to incentives coming from the economic environment; its theoretical justification is rooted in the Schumpeterian framework.

Antonelli (2011) posits the existence of a quadratic relationship between profits and innovation: firms with low profitability levels «have a strong failure induced incentive to innovate». Their bad economic performance generates the incentive to engage in a creative – instead of adaptive – response and to mobilize resources in order to increase their TFP. This insight is also implemented by Nelson and Winter (1982) in their evolutionary model, within which «only those firms that make a gross return on their capital less than the target level of 16 per cent engage in search». Conversely, firms that enjoy an average economic performance have no incentive to engage in risky innovative efforts. Finally, when profitability is highly above the norm, the incentive is again present, since firms have enough resources to invest in innovation to further increase profits and market power.

As Figure 2.4 shows, these ideas are implemented in the simulation; firms have

an incentive to engage in a creative response when their income is lower than the mean income of their respective category (imitators or innovators). Moreover, innovators with a particularly high income (between 1.40 and 2.5 times the average) have also a positive incentive, because of their stronger propensity to engage in risky innovative activities. A ceiling is set to avoid explosive dynamics.

An interesting feature of this process is the circular causation that it is able to induce: the creative effort of the firms depend on the incentives provided by the economic environment, which, in turn, is affected by the impact of innovation and imitation on firms' profitability. This procedure strongly contributes to one of the objectives of the simulation, which is to establish a two-way feedback mechanism between technological progress and economic development.

Evaluate-techs and adopt-tech

```
ask technologies with [color != green and
                       color != brown] in-radius 20 [ set evaluation_temp fput who evaluation_temp]

foreach evaluation_temp [if member? ? techs
                           [set evaluation_temp remove-item position ? evaluation_temp evaluation_temp] ]

foreach evaluation_temp [if [fitness] of technology ? > productivity_firm
                         and ([cost_adoption] of technology ? < stock)
                           [set adoption_temp fput ? adoption_temp]]

if empty? adoption_temp [ if stock < 500
                           [set stock (stock - 15)]
                          if stock > 500 and stock < 5000
                           [set stock (stock - 200)]
                          if stock > 5000 and stock < 20000
                           [set stock (stock - 2000)]
                          if stock > 20000
                           [set stock (stock - 4000)]

                          set evaluation_temp []
                          ask share-tech-neighbors [ask out-firm-uses-neighbors with [color != green and
                                                                                      color != brown]
                                                      [set evaluation_temp fput who evaluation_temp]]

                          foreach evaluation_temp [if ([fitness] of technology ? > productivity_firm)
                                                   and ([cost_adoption] of technology ? < stock)
                                                      [set adoption_temp fput ? adoption_temp]]
```

Figure 2.5: Section of the evaluate-techs procedure.

These two procedures are the core of the decisional process that governs the adoption of new technologies by imitators. Because of bounded rationality and high uncertainty in the outcomes, economic agents within this context do not solve an optimization problem. Instead, a step-by-step procedure is applied, through which firms acquire incomplete information in a very localized social and geographical space and use their limited computational abilities to decide which technologies are good candidates for adoption.

The full procedure goes as follows:

1. Imitation is costly; the firm pays a fixed amount – adjusted depending on its current stock – to evaluate public good technologies in a radius of 20 patches around it. The technologies are stored in the *evaluation_ temp* list.

2. One by one, technologies are evaluated; if the fitness value of a technology is higher than the current level of productivity of the firm and if its cost is feasible (that is if $cost\_adoption < stock$), the technology becomes a candidate for adoption and is stored in the *adoption_ temp* list. Notice that the firm cannot observe the returns currently given by the technology, nor the ones that will be provided after its adoption; that is, the firm cannot observe the shape of the nonlinear relation between adopters and returns, nor whether the technology is on the increasing or decreasing returns side. The ratio of this limitation is the fact that the full amount of externalities and spillovers provided by a technology and diffused within the industry are often very difficult to assess. The firm can only acquire limited information on the actual usefulness of the technology and of its marketability, characteristics which are represented by the fitness value. However, depending on the number of

adopters, the actual returns might be higher or lower than the fitness value. This uncertainty in the outcome is one of the main features of the decisional process.

3. If no candidate technologies are found browsing the geographical/knowledge space, the firm tries to exploit its social and professional ties. It is hypothesized that firms that share at least one technology can more easily communicate or decode each other's knowledge or, maybe, have established common practices through social or professional exchange. Therefore, the imitator is also able to evaluate technologies which are used by firms with which it is linked by a *share-tech* link. The process of evaluation is again costly (although less than the standard one) and proceeds in the same way as before.

4. If within one of the two evaluation procedures at least one candidate technology is found, the firm tries to adopt one of them. The imitation attempt is successful 60% of the times.

5. If the attempt is successful and the firm is currently using less than 8 technologies, one randomly picked candidate technology is adopted without further constraints.

   If the firm is already using 8 technologies, which is the maximum amount allowed, one of the old ones is dismissed. Notice that the dismissed technology is not the one with the smallest fitness value, but is picked randomly among the techs list. However less likely, it is indeed possible that the new technology has a lower fitness value than the dismissed one and that it contributes

to an overall reduction of the productivity of the firm. This possibility serves the purpose of introducing a further element of uncertainty in the outcome of the imitation attempt. It is reasonable to assume that the new combination of productive processes and technologies used by the firm might not perform as well as the precedent one, no matter how performing the newcomer technology is, since established practices and experience can play a major role in the productivity of the firm.

Innovate

```
ask technologies with [color = grey] [let parent_fitness item 0 [fitness] of in-parent-of-neighbors

                                      ;;fitness of the offspring is distributed as N(fitness of parent, 20)

                                      set fitness random-normal parent_fitness 20

                                      if fitness  <= 0 [set fitness 1]


                                      ;;techs with a fitness 2 times higher than the
                                      ;;mean fitness in the system are identified as breakthrough

                                      if fitness > 2.0 * mean [fitness] of technologies
                                             [set shape "circle"
                                              set size 2
                                              set breakthrough_counter breakthrough_counter + 1]


                                      set cost_adoption fitness * 2

                                      set alpha random (25 - 10) + 10
                                      set beta random (60 - 40) + 40

                                      if intellectual-property = "patent"
                                           [set color green]

                                      if intellectual-property = "secrecy"
                                           [set color brown
                                            set cost_to_secrecy 0.20 * fitness]

                                      if intellectual-property = "public good"
                                            [set color blue]]
```

Figure 2.6: Section of the innovate procedure.

This procedure, together with the following one, governs the innovative efforts of the firms and the production of knowledge and technology in the simulation. This process is, again, characterized by limited information, uncertainty in the

outcomes and by a procedural approach that guides the decisions of the firm.

The procedure goes as follows:

1. The innovator invest in R&D a percentage of his current stock equal to its R&D propensity, that is 20% in case of low propensity and 60% in case of high propensity.

2. Depending on the amount invested, that is on the R&D propensity of the innovator, the probability of a successful innovative attempt is equal to 10% (in case of low propensity) or 30% (in case of high propensity).

3. If the attempt is successful, a new offspring technology is created, as a development or new version of a preexisting, parent technology that the firm is currently using. This process implements the idea of incremental innovation, that builds upon existing technologies to develop new ones. The innovation inherits some features of the parent technology, but random deviations are likely to occur.

   It is important to highlight the difference between the approach here implemented – which proceeds along the lines of Darwinian evolution – and the combinatorial evolution theorized by Arthur (2009); within the Darwinian framework, the offspring inherits the characteristics of the parent and evolution works through random, successful mutations that are positively selected by the environment. Conversely, in the combinatorial evolution framework, discoveries are the result of the purposeful research effort of scientists and economic agents, that create innovation through the recombination of existing technologies and knowledge. Arthur's approach seems far more appealing

for what concerns the economics of technological progress; however, its operational complexity, characterized in great extent by human creativity and intelligence, are too complex to implement in the current version of the simulation.

Turning back to the code, a parent is randomly selected among the technologies currently used by the firm to generate an offspring. Breakthroughs are excluded (except if no other technology is present), since the next procedure is specifically dedicated to their development. If the firm already uses the maximum amount of technologies allowed (five), the parent technology is dismissed.

4. The characteristics of the newborn technology are then generated: its fitness is selected from a normal distribution with mean equal to the fitness value of the parent and variance 30. It is therefore possible than the new technology performs worse than the dismissed one, indicating an unsuccessful discovery. Conversely, if the technology has a fitness value higher than two times the current fitness mean, it represents a breakthrough.

   The other characteristics of the technology are generated similarly to the setup procedure.

Some commands pertaining the different policy regimes – public good, patent and secrecy – are present in the procedure, but will be separately explained further on.

Develop

```
to develop

  ask firms with [innovator = 1 and incentive = 1]
        [if any? out-firm-uses-neighbors with [shape = "circle"] = true
            [set stock ( stock - (r&d_propensity * stock) )
             if random-float 1 < (r&d_propensity) * 0.5
                    [ask one-of out-firm-uses-neighbors with [shape = "circle"]
                            [let parent_fitness fitness
                             ask patch-here
                                [sprout-technologies 1
                                  [ set color grey
                                    set size 1
                                    set shape "square"
                                    fd random 8
                                    left random 5

                                    set fitness random-normal parent_fitness 20

                                    if fitness  <= 0 [set fitness 1]

                                    if fitness > 2.5 * mean [fitness] of technologies
                                          [set shape "circle"
                                           set size 2
                                           set breakthrough_counter breakthrough_counter + 1]
```

Figure 2.7: Section of the develop procedure.

The develop procedure, which can be turned on or off in the interface, serves the purpose of increasing the impact of the purposeful action of economic agents on the technological evolution of the model. In fact, without this procedure, the technological and economic development of the system depends in great extent on the dynamics imposed by the normal distribution of the fitness values. This is a technically convenient but detrimental modeling hypothesis, since the complexity of knowledge production and technological progress is hardly represented by random mutations drawn from a constant distribution. The path dependent nature of such complex phenomena ensures that these systems «cannot shake off the effects of past events, and do not have a limiting, invariant probability distribution that

is continuous over the entire state space» (David, 1994). In order to disrupt the impact of this modeling hypothesis and weight in the profit seeking ratio guiding the decisions of economic agents, a procedure to dedicate efforts and resources to the specific development of technological breakthroughs is implemented.

As already specified, breakthroughs are those technologies who have a fitness higher than two times the current fitness mean level. Their development is no different than the standard production of innovation introduced in the precedent procedure: from the "parent" breakthrough, a new technology is sprouted, with fitness drawn from a normal distribution with mean equal to the fitness value of the parent and variance 20. All the developments of a breakthrough are kept by the innovating firm, even if exceeding the limit of 5 technologies; they are dismissed only if used to produce a new piece of technology in the standard innovate procedure.

Although the simplifying assumption of a normal distribution of the offsprings around their parent is kept, the idea behind this procedure is that the development of breakthrough would positively disrupt the technological trajectory, engendering gales of innovations.

2.1.4 Policy options

Three policy options affecting the protection of intellectual property are implemented in the simulation, in order to analyze the effect of different regimes on the economic and technological evolution of the system. These three options are public good, patents and secrecy and can be selected through a chooser situated in the interface.

Public good corresponds to the base case, with features no different than those explored in the precedent subsection and therefore will not be further analyzed.

The patent regime

Within this policy regime, innovators are able to patent the technologies they produce and gain an exclusive right to use them; imitators will therefore not be able to adopt the patented technology. Patenting is free, but protects the technology for a limited number of ticks chosen by the user with the *patent-lenght* slider. After that period, the technology becomes a public good and can be freely adopted by imitators.

Patenting is simply implemented by using a green color to identify protected technologies, which are excluded from the evaluation performed by imitators. All technologies produced by innovators are patented, both standard innovations, breakthroughs and their developments. The variable *patent_protection* is used to count the periods of exclusive right. When the specified number of ticks is reached, the technology becomes blue.

It is interesting to notice that the exclusive right to use a technology have its pros and cons: the innovator is shielded from saturation, but is also not able to enjoy the positive externalities and increased returns possibly provided by other adopters, that is a higher position on the parabola that describes the relation between adopters and returns. Whether patenting results in a net gain with respect to the public good regime depends on the shape of the relation, that is on the characteristics of the technology, and on the environmental conditions, that is the number of potential adopters and their economic incentives.

The secrecy regime

With the secrecy regime, innovators protect their intellectual property by keeping it under industrial secret; as in the case of patenting, imitators are not able to adopt the technology. Keeping an innovation secret is quite expensive, since the costs amount to a 20% of the fitness value. These represent all the costs that the innovator bears to make it hard for other firms to reverse engineer or otherwise copy their intellectual property: obfuscation strategies, protection technologies, law fees and so on. Unlike patenting, these practices offer the possibility to maintain an exclusive right on the technology for the whole simulation run. However, in each period (tick) there is a 0.5% chance that the knowledge is leaked and becomes available to imitators as a public good.

Similarly to patenting, secrecy is implemented by using a brown color to identify secret technologies. In case of a leak, the technology becomes blue.

2.2 Results

2.2.1 Visual analysis of the interface

The set of figures in Appendix A shows the plots representing the evolution of a standard simulation with 50 initial firms, 70 initial technologies and 20% of innovators; plots have been exported after 300 ticks. Each triplet shows the outcome in the public good policy regime (first graph), in the patent regime (second graph) and in the secrecy regime (third graph). Some features can be intuitively highlighted from a brief visual analysis.

Figure A.1 shows the firms monitor in the three regimes. The high number of

bankruptcies in the secrecy regime is immediately apparent; moreover, the number of imitators and innovators moves similarly throughout the entire simulation, since it is imitators that bear the highest number of bankruptcies. This is not true in the public good regime, where the number of imitators diverges increasingly.

Figure A.2 shows the evolution of the fitness mean. The dynamics of this variable strongly depend on the contingent evolution of the simulation, but it is clear that the public good regime delivers the best performance, while patents and secrecy seem to have a detrimental effect.

Figure A.3 shows the plots for the income mean of both innovators (blue pen) and imitators (red pen). Again, the secrecy regime is the one in which incomes are the lowest, with imitators income mean showing great variability. Conversely, the public good regime proves to be the most beneficial for incomes, particularly of innovator firms.

Finally, Figure A.5 represents the technological evolution of the system in the three regimes, with public good again delivering the highest number of technologies and breakthroughs.

The main conclusion that can be drawn from a brief, visual inspection, is that the public good regime accommodates for the best performance of imitator and innovator firms, both in terms of incomes and of technological advance. The patent regime follows closely, while secrecy proves to be highly detrimental for the system's outcome. A statistical and econometric analysis of data produced by the simulation is in order to verify these conclusions.

2.2.2 Descriptive statistics

Descriptive statistics tables are shown in Appendix B. The tables refer to data collected from 3 main experimental conditions; moreover, 2 additional sub experiments were performed to address some features that emerged during the analysis.

The experimental conditions are the following:

E1 (low innovators): 50 initial firms, 70 initial technologies, 15% of innovators, 0.7 of R&D propensity; innovators cannot imitate, the procedure develop is on.

E2 (high innovators): 50 initial firms, 70 initial technologies, 75% of innovators, 0.7 of R&D propensity; innovators cannot imitate, the procedure develop is on.

E3 (imitation_ON): 50 initial firms, 70 initial technologies, 15% of innovators, 0.7 of R&D propensity; innovators can also imitate, the procedure develop is on.

- **E3a (imitation_ON + low innovators):** 50 initial firms, 70 initial technologies, 15% of innovators, 0.7 of R&D propensity; innovators can also imitate, the procedure develop is on.
- **E3b (imitation_ON + high innovators):** 50 initial firms, 70 initial technologies, 75% of innovators, 0.7 of R&D propensity; innovators can also imitate, the procedure develop is on.

Appendix B contains 3 tables for each of the main experimental conditions – the public good statistics, the patent statistics and the secrecy statistics – and one

table for each sub experiment (since the focus was not on assessing the impact of different policies, only experiments with the public good regime were performed).

Data have been compared and analyzed along two dimensions: within each policy regime (with the focus being the differences between the conditions) and within each experimental condition (with the focus being the impact of different policies). Results are presented in the following subsections.

The role of innovators

The number of innovators (15% of the total number of firms in E1, 75% in E2) has a significant impact on the outcome of the simulation. An independent samples t-test was performed to compare innovators income mean, imitators income mean and fitness mean in the two experimental conditions. Results are reported in Table D.1 and show that all pairs are significantly different. As a representative example, we can highlight a significant difference in the innovators income means for a simulation with a low percentage of innovators (M=722.52, SD=172.26) and a simulation with a high percentage of innovators (M=626.65, SD=59.94); $t(298)=6.44$, $p < .001$.

Starting from the evaluation of bankruptcies, a low percentage of innovators leads on average to a higher number of bankruptcies, while simulations with a high percentage of innovators tend to show lower figures. However, this variable is not a good indicator of firms' performance, nor of the overall efficiency of the system when simulations with different number of innovators are compared; this is because the structure of the model makes it really difficult (almost impossible) for an innovator to go bankrupt, while imitators' bankruptcies are fairly frequent. This implies that if the ratio of innovators over total firms is high, bankruptcies will

be inevitably lower, independently from the systems' performance. Nevertheless, this variable will be useful when comparing the effect of different policies with a constant number of innovators.

The figures on stock mean are also to be interpreted with caution, since the pace and dynamics of its accumulation strongly depends on whether the firm is an imitator or an innovator. The most apparent feature is that higher levels of stock mean are associated to a high number of innovators. However, the highest stock means are reached within the public good policy regime and when innovators can also perform imitation.

These variables might lead to the conclusion that a high number of innovators has a positive effect on the overall performance of the economic environment represented by the simulation; however, the above mentioned concerns regarding the interpretation of these figures must be taken into account and might here play a major role. In fact, the most striking feature emerging from the descriptive data, is that a high percentage of innovators seems to have a detrimental effect on incomes and on the pace of technological progress within all policy regimes and when innovators cannot imitate.

This interesting feature is most evident from the scatterplots in Appendix C. It can be noticed that for all policy regimes, the relation between the percentage of innovators and innovators' income mean is nonlinear and shows a negative trend. The same relation emerges between the percentage of innovators and fitness mean. Finally, for what concerns innovators and income means of the whole set of firms, it can be noticed that the linear trendline is slightly increasing in the case of patent and secrecy regimes, while it is again decreasing in the public good case. All scatterplots suggest that the ideal amount of innovating firms rests between

40% and 60% of the total.

Particularly interesting is the fact that not only innovators' incomes in condition E2 are lower than innovators' incomes in E1, but also imitators (usually the "weak" firms in terms of income mean) outperform innovators when their percentage is too high. This result, which again must be evaluated in the context of the structure and dynamics imposed to this simulation, can be interpreted as a proof that when technological progress is involved, increasing the amount of parallel innovative efforts might not necessarily be the most efficient solution and can also prove detrimental. An excessive number of innovators might "overcrowd" the system, with a lot of mediocre and similarly fit innovations being produced and little overall advancement both in absolute terms and with respect to the huge amount of resources invested. Imitators have better fortune, since they can select the best innovations of the bunch and dismiss the big crowd of mediocre ones. It seems that in this case, Kitch (1977) "overfishing" problem applies: too many fishers aiming at the same goal generate duplication, overlaps and a great deal of inefficiency. This might also explain why some degree of intellectual property protection – provided by patents and secrecy – contributes to some extent to revert the trend (refer to scatterplots in Figure C.2 and C.3).

This interpretation can be strengthened by looking at the figures on technological evolution, particularly on the number of technologies produced and the count of breakthroughs. Although the case with a high percentage of innovators shows by far a higher number of technologies and breakthroughs, technological progress (in terms of an increase in fitness mean) does not take off.

Innovators engaged in imitation

Among the main experimental conditions, the case in which innovators are also allowed to imitate is the most interesting one.

Bankruptcies reach the largest numbers, since imitation is costly and drags more innovators into failure. Moreover, the mean clustering coefficients are the highest, since widespread imitation brings forth a more interconnected firms network.

The most interesting feature, however, is the notably high innovators income mean, which is, on average, two times larger than innovators income mean when innovators cannot imitate, all other initial settings being equal. This particularly good performance can be traced back to two main causes: first of all, through imitation, innovators become able to perform a more efficient selection of the most fit technologies, although with all the computational and informational limitations imitators are subject to. When they have an incentive to do so, innovators are able to scan the social and geographical space around them, pick a technology with a fitness higher than their productivity level and dismiss an old one, thus introducing an element of further technological evolution to their development.

The second element that can explain such a good overall performance of innovators is an economic one: as already mentioned, imitation is costly and cause the bankruptcy of a higher number of firms. Therefore, innovators that cannot take off in terms of economic performance and technological advance are more likely to just go bankrupt and leave the market. Only the best performing manage to survive, leading to an overall increase in income mean.

It therefore seems that within the present simulation, a steeper process of selec-

tion, both in technological and economic terms, brings forth a better performance. Widespread technological transfer and diffusion, together with the "natural" selection operated by economic incentives and competition, is the most efficient way to achieve technological progress and economic development.

The above conclusions can be also supported by a review of the variables on technological evolution. It can be noticed that the fitness mean reaches higher figures when innovators can also imitate. This is achieved although the number of technologies and breakthroughs is way lower than in the other experimental conditions. Again, a more efficient selection and diffusion of the most fit technologies is way more beneficial than a high number of reckless and expensive innovative efforts.

Finally, it is interesting to notice that in the experimental condition in which innovators can imitate and the policy regime is public good, the returns mean is quite often lower than the fitness mean. This can highlight a saturation problem: since technologies are few and both innovators and imitators converge toward the most fit ones, it is more likely than the decreasing side of the returns function is reached. It must be taken into account that because of the characteristics of the simulation, although saturation is observed quite frequently, it is rare that returns actually fall under the fitness level. A returns mean lower than the fitness mean signals that the saturation is particularly severe and although it is of no big consequences in the simulation, it can be informative of what might happen in some economic environments when imitation is so widespread and intellectual property protection is absent. In fact, within the patent and secrecy regimes, returns are again way higher than the fitness mean; although imitation proves to be beneficial, a certain amount of intellectual property protection is desirable to

dampen the detrimental impact of saturation.

Since condition E3 proved peculiar, two additional sub experiments were performed to compare the outcomes in case of a low number (E3a) and a high number of innovators (E3b).

Conclusions overturned The two sub experiments are particularly interesting since they show that when innovators are allowed to imitate, the conclusions drawn in the precedent section are basically reversed: as the scatterplots in Figure C.4 intuitively display, the relation between the percentage of innovators and income mean show a positive trend. The same can be said about the relation between innovators and fitness mean. Therefore, when innovators can also imitate and technological and economic selection are more efficiently in action, the negative effect of an overcrowding of innovators is dampened and even reversed. More innovators deliver more breakthroughs and more technologies which, in this case, are effective in sprouting technological progress; in fact, fitness mean reaches the highest level of all experimental conditions. All these effects are particularly beneficial for imitators, whose income mean more than doubles in the condition with a high number of innovators. Also saturation seems to be less intense, with returns mean again definitely higher than the fitness mean.

2.2.3 Regression results

Regressions have been performed using four different model specifications, the first two built to assess the impact of the number of innovators and policy regime on income mean and fitness when innovators cannot imitate; the second two, to assess the impact of the number of innovators on income mean and fitness when imitation

is allowed and only within the public good regime. Data have been collected after 300 ticks in simulations with a base setting of 50 firms, 70 technologies and 0.7 of R&D propensity.

These regressions are a useful tool to investigate the direction and magnitude of the relation between the variables involved in the analysis, but some limitations have to be mentioned. As plots D.1 and D.2 in Appendix D show, the regressions are affected by a certain degree of heteroscedasticity and non normality of the residuals, yielding possibly biased standard errors. These undesirable characteristics might be due to misspecification or other biases (notably omitted variables) affecting the models. With these caveats in mind, OLS regressions can nonetheless be informative on the nature of the mechanisms involved.

The first model specification is the following:

$$Income\_mean_i = \beta_0 + \beta_1 Innov_i + \beta_2 Innov_i^2 + \beta_3 Regime\_D1_i + \beta_4 Regime\_D2_i + \varepsilon_i$$

Where $Income\_mean$ is the firms' income mean, $Innov$ is the percentage of innovators, $Innov^2$ is the squared percentage of innovators (to account for nonlinearity), and $Regime\_D1$ and $Regime\_D2$ are two dummy variables used to code the three policy regimes: 0 0 for public good, 1 0 for patent and 0 1 for secrecy.

Results are shown in table D.2. The percentage of innovators and the policy regime explain 44% of the variability of income mean ($R^2 = 0.44$). All coefficients are significant at $\alpha = 0.01$, including the squared term for the percentage of innovators, thus confirming the nonlinear relation between innovators and income mean. In evaluating the positive coefficient attached to innovators, it has to be considered that data are collected along all policy regimes and that, as already noticed from the scatterplots, in the patent and secrecy regimes the increase in the

performance of imitators often more than compensates the decrease in innovators' income mean.

The regression also confirms the detrimental effect of patents and secrecy, yielding on average a reduction in income mean of 66.18 and 131.52 points respectively.

The second model specification is:

$$Fitness\_mean_i = \beta_0 + \beta_1 Innov_i + \beta_2 Innov_i^2 + \beta_3 D1_i + \beta_4 D2_i + \varepsilon_i$$

Results are reported in table D.3. The model is less performing, explaining only 32% of the variability of the fitness mean. Notabily, the role of innovators as explanatory variable is questionable – the coefficient is very low and significant at $\alpha = 0.1$. Again, the negative impact of patents and secrecy is confirmed, even if its magnitude is way lower than in the first specification.

The regressions run on simulations in which innovators can also imitate are more performing, although it has to be considered that data have been collected only within the public good regime, yielding more straightforward results. The first model is the following:

$$Income\_mean_i = \beta_0 + \beta_1 Innov_i + \beta_2 Innov_i^2 + \varepsilon_i$$

Results are reported in table D.4. In this specification, the percentage of innovators explains 78% of the variability of income mean. All coefficients are significant and particularly noticeable is the magnitude of the coefficient attached to the linear term: an increase of innovators of 1 percentage points yields on average an increase of income means of 49.21 points.

The last specification is:

$$Fitness\_mean_i = \beta_0 + \beta_1 Innov_i + \beta_2 Innov_i^2 + \varepsilon_i$$

Results are reported in table D.5. The model explains 73% of the variability of the fitness mean. All coefficients are significant, but the magnitude of the impact of innovators on fitness mean is way smaller.

Overall, the regressions seem to confirm the results drawn from visual analysis and descriptive data; however, it can be noticed that when innovators cannot imitate and their percentage is high, the increase in the performance of imitators on average more than compensate the decrease in innovators' incomes, resulting in an overall small increase in firms' income mean. Finally, the strong detrimental effect of patents and secrecy is confirmed.

2.2.4 Network metrics

Although the following is not a comprehensive network analysis, interesting conclusions can be drawn from the interpretation of some features of the networks and of the metrics computed by the NW Netlogo extension.

The first feature is the seemingly scale free degree distribution shown by the two-mode network of firms and technologies (the green one). Figure 2.8 shows the green network after 300 ticks of a simulation with 50 firms, 70 technologies, 20% of innovators and where imitation is off; the layout has been modified to increase the readability. On the right side, the degree distribution of the network is shown. Although it is methodologically incorrect to report a power law distribution without further statistical inquires, the shape of the degree distribution is quite eloquent, showing a high number of nodes/technologies with 1 or 2 adopters and few hub technologies with 6 or more. It can be hypothesized that the scalefree-like nature of this network is induced by the mechanisms of growth and preferential

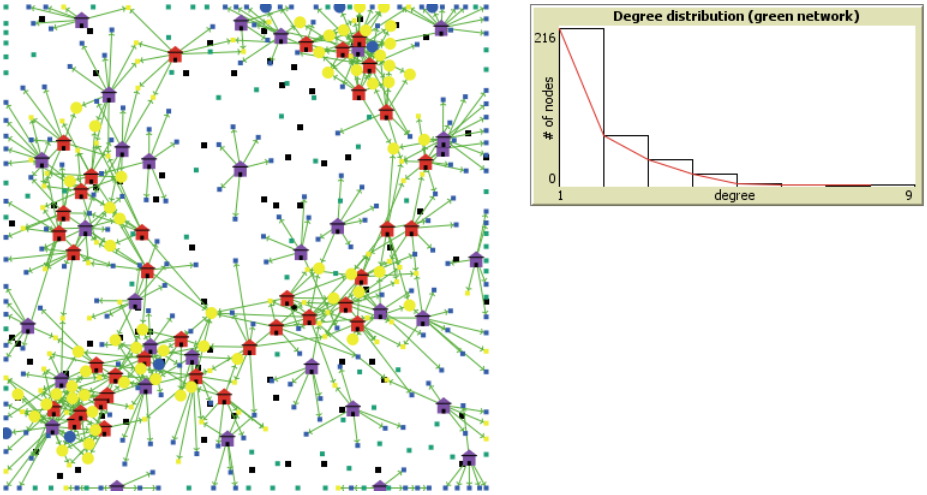

Figure 2.8: The two-mode firms-technologies network and its degree distribution.

attachment which are indeed features of the innovation process as emerging from the economic environment: the network of technologies grows as progress unfolds and the few, fittest technologies are more likely to be adopted by a high number of firms; moreover, economic incentives and positive externalities due to increasing returns to adoption ensure preferential attachment (at least on the increasing side of the returns function).

Although interesting, the analysis of a two-mode network presents a number of methodological issues; therefore, most of the measures collected come from the firms' network (the red one).

The descriptive statistics tables in Appendix B report averaged data on the mean clustering coefficients collected in all experimental conditions. The local clustering coefficient of a node is a number between 0 and 1 that expresses how close are the node's neighbors to being a complete graph (a clique); the mean clustering coefficient is computed as the average of the local ones and can be a representative measure of the connectedness of the graph.

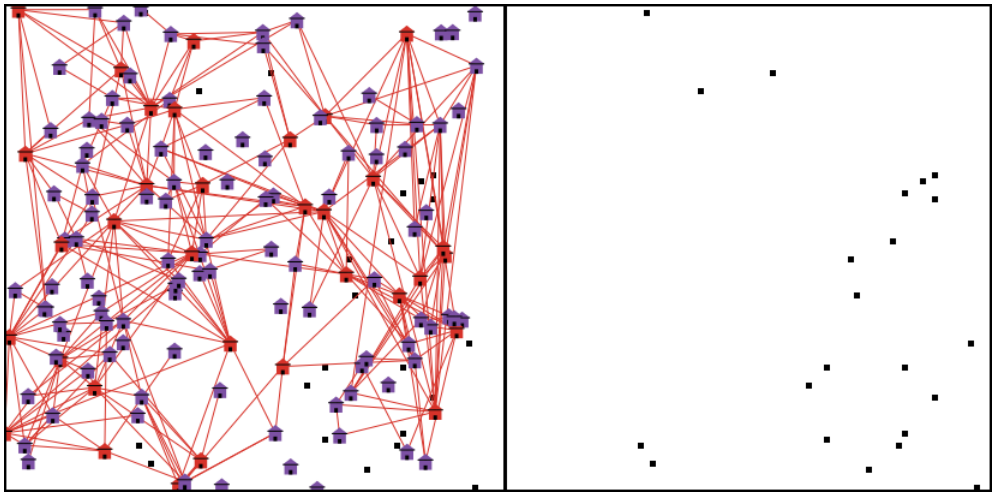

Figure 2.9: Localization of bankruptcies (black patches) in a simulation with mean clustering coefficient = 0.039.

The most apparent feature is the fact that the mean clustering coefficient is on average lower when the number of innovators is high and cannot imitate. These firms rely mainly on their own technologies, leading to a reduced importance of social/professional ties within the system. It would be interesting to assess whether this has an impact on the localization of bankruptcies and – at a visual analysis – this seems indeed plausible: Figure 2.9 show the outcome of a simulation with 50 firms, 70 technologies, 75% of innovators and public good regime after 300 ticks. The mean clustering coefficient is 0.039. It appears that bankruptcies tend to be particularly localized, since firms act mainly within their limited geographical space and bankruptcies are more likely to happen in localized clusters around particularly unfit technologies.

Trivially, the highest coefficients are reached when innovators can also imitate.

To investigate some nodes metrics, data have been collected on each firm's variables in a series of simulations with an initial setting of 50 firms, 70 technologies,

20% of innovators, 0.7 of R&D propensity and imitation off. The most interesting feature emerges from raw data and scatterplots in Figure C.5. It can be noticed that the firms with the highest incomes (> 1500) are always innovators with a local clustering coefficient around the median. Innovators with a coefficient near or equal to 0 or 1 always show inferior performances in terms of income. These observations can be supported by data on the network as a whole. As the left scatterplot shows, the best performances (highest innovators income means) are achieved in correspondence of a median level of mean clustering coefficient.

Concluding remarks

«There is nothing which our infatuated race would desire more than to see a fertile union between two steam engines; it is true that machinery is even at this present time employed in begetting machinery, in becoming the parent of machines often after its own kind, but the days of flirtation, courtship, and matrimony appear to be very remote, and indeed can hardly be realised by our feeble and imperfect imagination».

—Cellarius

In 1863, Samuel Butler writes "Darwin among the machines", a visionary article published on the New Zealand newspaper The Press and from which the above passage is taken. The novelist, writing under the name of Cellarius, paints a gloomy picture of the future of society, dominated by advanced machines that, as benevolent masters, nurture and take care of an enslaved humanity. Cellarius concludes by positing that all machines shall be immediately destroyed and that, if this proves impossible, the process of enslavement has already become irreversible.

This thesis focused on the disentanglement of the generative mechanisms at the basis of technological progress, a process which is inextricably linked with the

incentives and needs emerging from the economic and social environment. The complex nature of this phenomenon, its emergent properties and (to some extent) unforeseeable evolution provide an ongoing challenge to economists and policy makers, who strive to assess the impact of different policies and their actual effectiveness in ensuring the advancement of human society from both the economic and cultural point of view. Together with the analysis of the simulation, theoretical speculation and empirical evidences proved that optimal solutions are difficult to identify and that each policy decision imply trade offs whose magnitude and direction are often difficult to assess. Moreover, the properties of these trade offs crucially depend on the decision maker's perspective – local, national or supranational – and on the level of economic and technological development attained. Economy and industry-specific analysis can and have to be performed in order to design and implement tailored policies for innovation and technological transfer.

In order to address these issues, an excursus of relevant literature and empirical evidences has been performed in the first chapter of this work. The literature review spans from the neoclassical camp to the recent developments offered by complexity economics, with a strong focus on new approaches and methodologies. In the second section of the chapter, the analytical perspective gradually shifts from the local dimension of technology production and diffusion to centralized (national and supranational) measures, in order to address the main challenges faced by decision makers.

An agent-based simulation has been developed with Netlogo and analyzed in the second chapter, in order to model the properties and evolution of an economic environment in which a network of firms deals with the production of new technologies and/or the adoption of existing ones.

In order to focus on the firms' decisions on innovation and imitation, the demand side was not explicitly modeled: following the evolutionary economics framework (Nelson and Winter, 1982) both the actual usefulness and marketability of a technology are represented by its fitness value. Technological progress moves along the lines of Darwinian evolution, with parent technologies transferring their fitness value to their offsprings and random mutations occurring to determine change and evolution. Differently from biological systems, however, this process is brought forth and guided by the purposeful, profit-seeking activities of the firms.

Moreover, the returns provided by the technologies are a function of both their fitness value and the number of firms that use them (their adopters), thus implementing the early insights of Arthur (1989).

With these premises in mind, the aim of the simulation is to analyze how the technological evolution of the system affects the firms' performance and economic incentives and, conversely, how the profit seeking activities of the agents and the structural characteristics of the economic environment affects technological progress. In addition to this, three policy options (that is knowledge as a public good, patent system and secrecy practices) have been implemented in order to assess the impact of intellectual property protection measures.

The main result emerging from the visual and statistical analysis of the data collected from the simulation is that funding a high number of parallel innovative efforts might prove inefficient or even detrimental and that a well functioning of technological transfer and diffusion is fundamental to foster innovation; in fact, an efficient mechanism of adoption and diffusion of existing technologies is as essential as the production of original ones. In particular, descriptive statistics, scatterplots and regression outputs, show an inverted u-shaped relation between the percentage

of innovators and the economic and technological performance of the system: an excessive number of innovators can "overcrowd" the system and result in little advance and great inefficiency.

Extensive imitation proved to be beneficial, since experimental conditions in which innovators are also involved in adoption of existing technologies are the ones that deliver the highest incomes and technological advance; the positive externalities deriving by imitation and increasing returns to adoption can be an effective engine of growth and the impact of intellectual property protection policies should be carefully assessed. Nonetheless, some amount of protection can be beneficial to dampen the negative effect of saturation deriving from an excessive number of adopters.

Finally, the structure of interactions among firms and between firms and the technological environment strongly influence the evolution of the system and, therefore, social network analysis can be an useful research tool. Some network measures have been collected and analyzed through the use of the NW Netlogo extension.

It is important to underline that these findings crucially depend on the specific properties (and limitations) of the simulation and their extendability is subject to a number of issues; nonetheless, the theoretical premises and outcomes of the model can provide with an interesting analytical perspective in order to gain a deeper understanding of the mechanisms involved.

For what concerns the future prospects of this research and simulation, there is wide room for improvement. First of all, Netlogo have some computational limitations that strongly limited the number of agents involved and therefore the well functioning of the mechanisms implemented in the simulation. It would be

also interesting to model the demand side of the economy and move towards a more general framework. To these aims, other object-oriented languages – such as Python – might be a more suitable choice.

Moreover, the social network perspective of the simulation has not been fully explored and developed and can be further improved. Once a more consistent – both internally and externally – and bug free functioning of the simulation has been achieved, more policy options can be implemented and tested.

To conclude (and possibly overcome Cellarius' curse), a final remark. Technological progress per se is a double-edged knife. The attempt to borrow models and methodologies from natural sciences and use them to simulate social systems does not imply that economics shall blindly handle the pulleys and levers of social engineering. The fundamental issue is shifting from "how?" to "what?" and "why?" and economics is deeply involved in this debate. Although innovation has sustained the economic, social and cultural development of society for the last 200 years, new challenges are emerging and, in order to ensure our sustainable survival, a society- and cultural-wide effort is necessary. Technology is not to be viewed as a living ecosystem whose evolution can slip out the active control of mankind, but its complex features and emerging properties render it a challenging horse to ride. Economics and social sciences have an important role to play, so that the fulfillment of human life and the survival and flourishing of the world we live in are put back on top of our priorities and become the main goal of technological progress and economic development.

Appendix A

Interface outputs

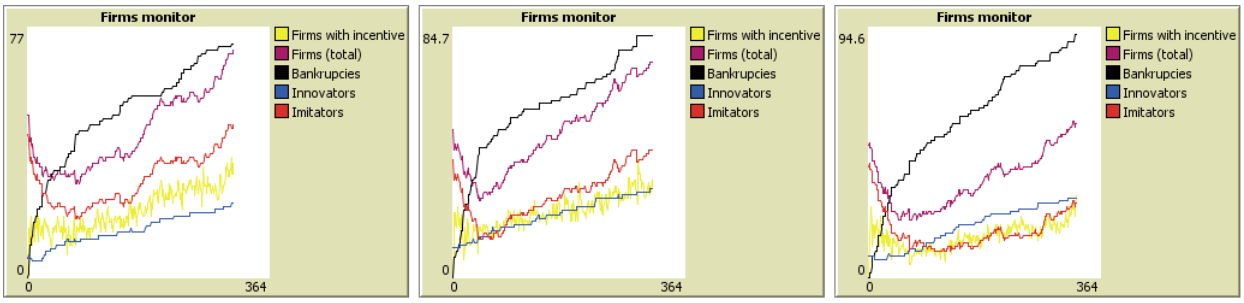

Figure A.1: Firms monitors in the three policy regimes (in order): public good, patent, secrecy.

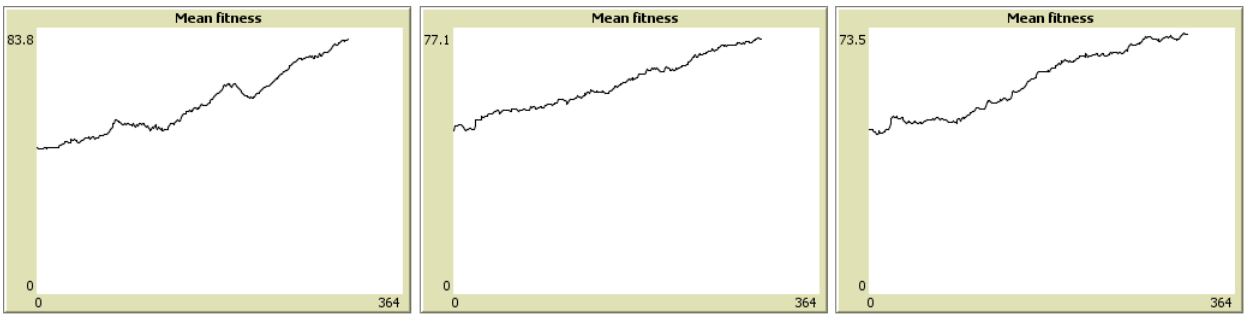

Figure A.2: Mean fitness in the three policy regimes (in order): public good, patent, secrecy.

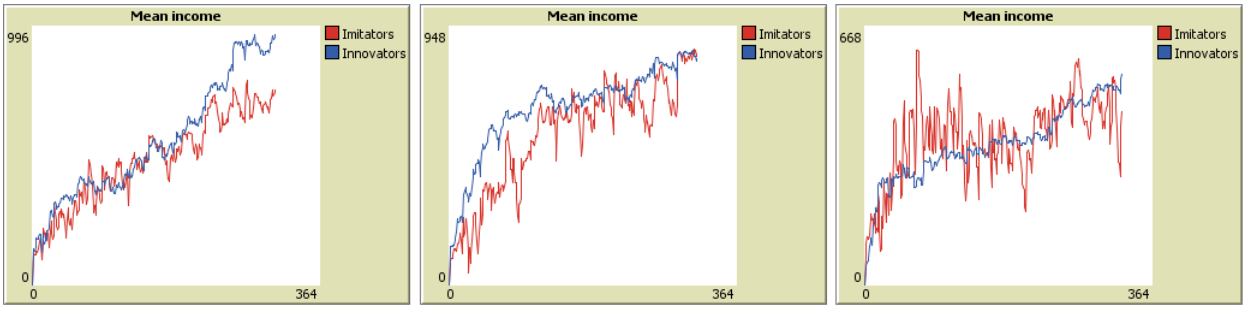

Figure A.3: Mean incomes in the three policy regimes (in order): public good, patent, secrecy.

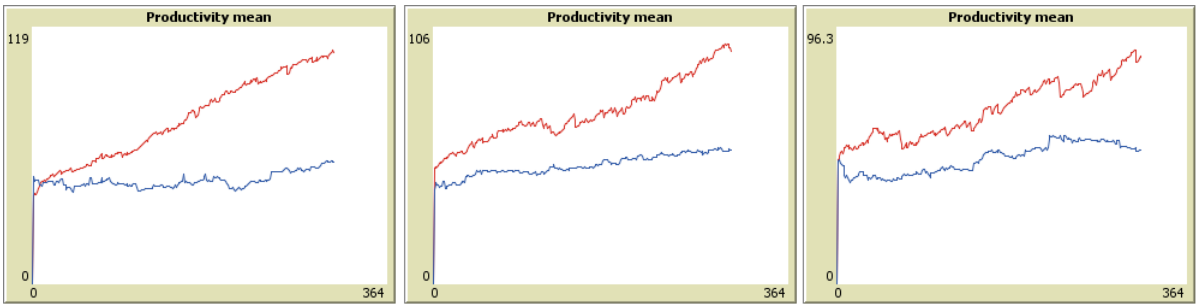

Figure A.4: Productivity means in the three policy regimes (in order): public good, patent, secrecy.

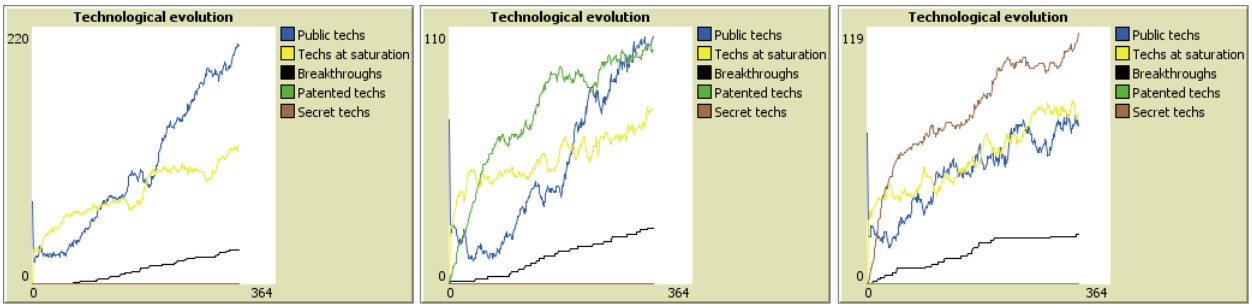

Figure A.5: Technological evolution in the three policy regimes (in order): public good, patent, secrecy.

Appendix B

Descriptive statistics

Table: Valid cases = 50 cases with missing value(s) = 0.

Variable	N	Mean	Std Dev	Variance	Minimum	Maximum
Bankrupcies	50	86,16	11,45	130,99	66	121
Mean_CC	50	0,08	0,01	0	0,05	0,11
Saturation	50	100,48	23,19	537,56	49	148
Stock_mean	50	25336,18	7957,92	63328470,64	14457	44602
Innovator_income_mean	50	802,64	205,88	42387,87	399	1269
Imitators_income_mean	50	708,14	92,11	8483,8	508	882
Returns_mean	50	89,5	9,88	97,68	68	106
Fitness_mean	50	75,92	11,34	128,48	53	98
Breakthroughs	50	19,94	9,34	87,16	3	36
Innovators_final	50	16,94	4,19	17,57	7	27
Imitators_final	50	34,88	7,68	58,92	16	48
Public_techs	50	269,18	67,09	4500,64	113	412

Table B.1: Condition E1, public good regime.

Table: Valid cases = 50 cases with missing value(s) = 0.

Variable	N	Mean	Std Dev	Variance	Minimum	Maximum
Bankrupcies	50	94,26	9,3	86,44	77	115
Mean_CC	50	0,07	0,02	0	0,04	0,12
Saturation	50	69,94	16,58	275,04	42	106
Stock_mean	50	22181,44	5802,75	33671916,99	11938	41484
Innovator_income_mean	50	720,64	161,12	25961,01	451	1186
Imitators_income_mean	50	600,58	96,45	9303,27	445	819
Returns_mean	50	85,88	8,9	79,21	65	107
Fitness_mean	50	68,4	9,4	88,33	49	90
Breakthroughs	50	15,48	7,97	63,52	2	38
Innovators_final	50	17,88	4,21	17,7	9	30
Imitators_final	50	27,34	6,52	42,56	16	42
Public_techs	50	174,38	45,16	2039,38	86	283
Patented	50	76,38	20,3	411,91	34	117

Table B.2: Condition E1, patent regime.

Table: Valid cases = 50 cases with missing value(s) = 0.

Variable	N	Mean	Std Dev	Variance	Minimum	Maximum
Bankrupcies	50	96,68	9,42	88,75	70	117
Mean_CC	50	0,07	0,01	0	0,05	0,1
Saturation	50	60,52	11,29	127,48	43	99
Stock_mean	50	22364,06	5302,43	28115795,65	11114	33612
Innovator_income_mean	50	644,28	95,31	9083,51	478	908
Imitators_income_mean	50	538,64	84,6	7156,44	314	713
Returns_mean	50	86,76	7,8	60,84	64	102
Fitness_mean	50	68,14	7,89	62,29	48	82
Breakthroughs	50	13,78	5,72	32,66	3	26
Innovators_final	50	16,68	3,68	13,53	11	24
Imitators_final	50	25,48	4,3	18,46	18	39
Public_techs	50	155,44	28,12	790,9	108	245
Secret	50	83,3	18,28	334,09	50	138

Table B.3: Condition E1, secrecy regime.

Table: Valid cases = 50 cases with missing value(s) = 0.

Variable	N	Mean	Std Dev	Variance	Minimum	Maximum
Bankrupcies	50	14,34	5,37	28,84	6	26
Mean_CC	50	0,03	0,01	0	0,02	0,05
Saturation	50	155,36	15,92	253,42	126	195
Stock_mean	50	38919,36	7185,52	51631708,52	28954	59948
Innovator_income_mean	50	656,08	45,59	2078,73	569	790
Imitators_income_mean	50	903,54	76,16	5800,5	784	1080
Returns_mean	50	85,4	4,08	16,61	77	95
Fitness_mean	50	62,3	4,45	19,77	54	74
Breakthroughs	50	87,78	15,76	248,5	53	132
Innovators_final	50	97,64	7,42	55,05	81	114
Imitators_final	50	26,84	4,67	21,81	18	37
Public_techs	50	843,66	58,63	3437,9	753	1011

Table B.4: Condition E2, public good regime.

Table: Valid cases = 50 cases with missing value(s) = 0.

Variable	N	Mean	Std Dev	Variance	Minimum	Maximum
Bankrupcies	50	19,48	5,13	26,34	7	33
Mean_CC	50	0,03	0,01	0	0,02	0,05
Saturation	50	108,96	13,76	189,35	77	145
Stock_mean	50	35684,1	6431,81	41368131,36	21431	51021
Innovator_income_mean	50	639,12	61,97	3840,35	530	826
Imitators_income_mean	50	828,74	79,02	6244,48	665	1034
Returns_mean	50	85,34	5,55	30,8	74	101
Fitness_mean	50	61,46	5,64	31,85	51	77
Breakthroughs	50	75,78	16,63	276,66	39	109
Innovators_final	50	95,86	9,37	87,71	76	121
Imitators_final	50	22,34	4,24	17,98	14	37
Public_techs	50	535,18	61,29	3756,48	397	664
Patented	50	287,26	42,86	1836,65	223	417

Table B.5: Condition E2, patent regime.

Table: Valid cases = 50 cases with missing value(s) = 0.

Variable	N	Mean	Std Dev	Variance	Minimum	Maximum
Bankrupcies	50	21,32	5,89	34,67	11	34
Mean_CC	50	0,03	0,01	0	0,02	0,04
Saturation	50	94,32	10,54	111,16	69	116
Stock_mean	50	33132,8	4385,72	19234572,61	25814	45851
Innovator_income_mean	50	584,76	46,61	2172,59	472	689
Imitators_income_mean	50	737,04	82,22	6760,28	528	914
Returns_mean	50	84,42	4,5	20,25	71	95
Fitness_mean	50	60,76	4,55	20,72	47	73
Breakthroughs	50	82,22	12,81	164,22	60	114
Innovators_final	50	98,28	8,86	78,57	72	115
Imitators_final	50	21,3	3,64	13,28	14	31
Public_techs	50	462,32	37,57	1411,73	373	553
Secret	50	396,48	35,9	1288,95	307	491

Table B.6: Condition E2, secrecy regime.

Table: Valid cases = 50 cases with missing value(s) = 0.

Variable	N	Mean	Std Dev	Variance	Minimum	Maximum
Bankrupcies	50	98,36	14,37	206,52	57	123
Mean_CC	50	0,11	0,02	0	0,08	0,18
Saturation	50	87,92	37,7	1421,38	30	197
Stock_mean	50	29284,72	12834,17	164715999,8	8298	76468
Income_mean	50	947,56	327,38	107178,62	388	1822
Innovator_income_mean	50	1679,66	937,02	877997,37	453	4921
Imitators_income_mean	50	783,64	224,81	50538,72	368	1379
Returns_mean	50	127,26	29,94	896,52	67	200
Fitness_mean	50	126,76	31,98	1022,68	65	193
Breakthroughs	50	6,22	4,68	21,93	0	23
Innovators_final	50	7,92	4,04	16,32	1	21
Imitators_final	50	30,92	10,92	119,26	11	55
Public_techs	50	168,9	76,11	5792,34	48	403

Table B.7: Condition E3, public good regime.

Table: Valid cases = 55 cases with missing value(s) = 0.

Variable	N	Mean	Std Dev	Variance	Minimum	Maximum
Bankrupcies	55	103,09	12,64	159,75	66	125
Mean_CC	55	0,1	0,02	0	0,06	0,16
Saturation	55	76,53	29,44	866,77	23	157
Stock_mean	55	27542,4	10053,33	101069367,02	11419	59164
Income_mean	55	939,93	247,51	61263,59	393	1417
Innovator_income_mean	55	1537,27	519,88	270275,42	484	3060
Imitators_income_mean	55	758,53	188,17	35408,59	365	1151
Returns_mean	55	129,27	23,53	553,76	68	185
Fitness_mean	55	121,64	23,66	559,64	59	177
Breakthroughs	55	5,65	4,43	19,64	0	25
Innovators_final	55	9,16	3,86	14,88	2	21
Imitators_final	55	27,96	9,73	94,74	10	57
Public_techs	55	151,67	63,05	3975,74	45	348
Patented	55	33,04	16,14	260,41	6	101

Table B.8: Condition E3, patent regime.

Table: Valid cases = 51 cases with missing value(s) = 0.

Variable	N	Mean	Std Dev	Variance	Minimum	Maximum
Bankrupcies	51	107,47	12,59	158,49	77	141
Mean_CC	51	0,1	0,02	0	0,07	0,15
Saturation	51	62,94	25,24	637,26	25	133
Stock_mean	51	27208,53	8045,66	64732605,25	12846	49805
Income_mean	51	772	236,81	56078,4	326	1332
Innovator_income_mean	51	1204,04	567,21	321722,88	405	3275
Imitators_income_mean	51	629,33	156,91	24620,75	273	936
Returns_mean	51	123,59	26,02	676,85	74	188
Fitness_mean	51	112,84	26,63	709,01	74	180
Breakthroughs	51	6,2	5,13	26,32	0	21
Innovators_final	51	8,25	3,75	14,07	2	15
Imitators_final	51	23,04	7,81	61	10	46
Public_techs	51	126,69	51,25	2626,5	46	266
Secret	51	33,59	19	361,09	3	94

Table B.9: Condition E3, secrecy regime.

Table: Valid cases = 50 cases with missing value(s) = 0.

Variable	N	Mean	Std Dev	Variance	Minimum	Maximum
Bankrupcies	50	98,08	16,23	263,46	73	132
Mean_CC	50	0,11	0,02	0	0,07	0,17
Saturation	50	86,8	38,26	1463,47	22	174
Stock_mean	50	30644,66	13176,91	173631076,35	3828	77871
Income_mean	50	961	383,51	147081,84	289	1749
Innovator_income_mean	50	1570,7	930,31	865483,81	161	3933
Imitators_income_mean	50	822,14	273,34	74713,55	302	1442
Returns_mean	50	127,42	37,96	1440,7	70	217
Fitness_mean	50	124,32	39,76	1581,16	63	218
Breakthroughs	50	6,4	5,77	33,31	0	25
Innovators_final	50	7,96	3,85	14,86	1	15
Imitators_final	50	30,74	12,17	148,16	9	56
Public_techs	50	167,46	76,44	5842,91	43	345

Table B.10: Condition E3a, public good regime.

Table: Valid cases = 50 cases with missing value(s) = 0.

Variable	N	Mean	Std Dev	Variance	Minimum	Maximum
Bankrupcies	50	35,46	7,16	51,27	19	50
Mean_CC	50	0,05	0,01	0	0,04	0,06
Saturation	50	253,7	29,63	878,01	191	335
Stock_mean	50	49615,28	13500,07	182251850,61	30542	95833
Income_mean	50	2223,8	295,47	87305,1	1588	3114
Innovator_income_mean	50	2360,58	340,27	115783,27	1624	3488
Imitators_income_mean	50	1821,26	203,43	41384,03	1353	2170
Returns_mean	50	218,08	17,73	314,36	181	255
Fitness_mean	50	203,48	17,44	304,05	169	238
Breakthroughs	50	18,14	7,01	49,18	5	35
Innovators_final	50	79,34	7,27	52,88	64	94
Imitators_final	50	26,62	3,85	14,81	19	37
Public_techs	50	775,28	107,72	11603,68	557	1017

Table B.11: Condition E3b, public good regime.

Appendix C

Scatterplots

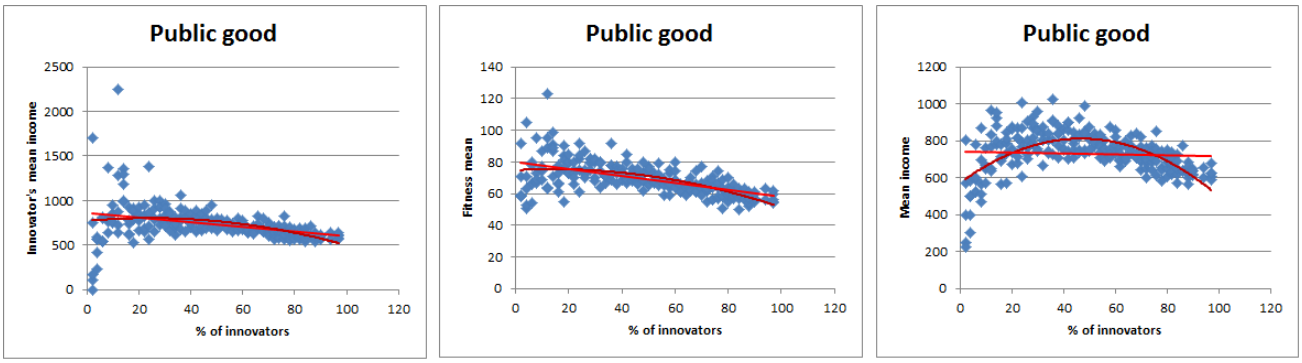

Figure C.1: Scatterplots on public good regime.

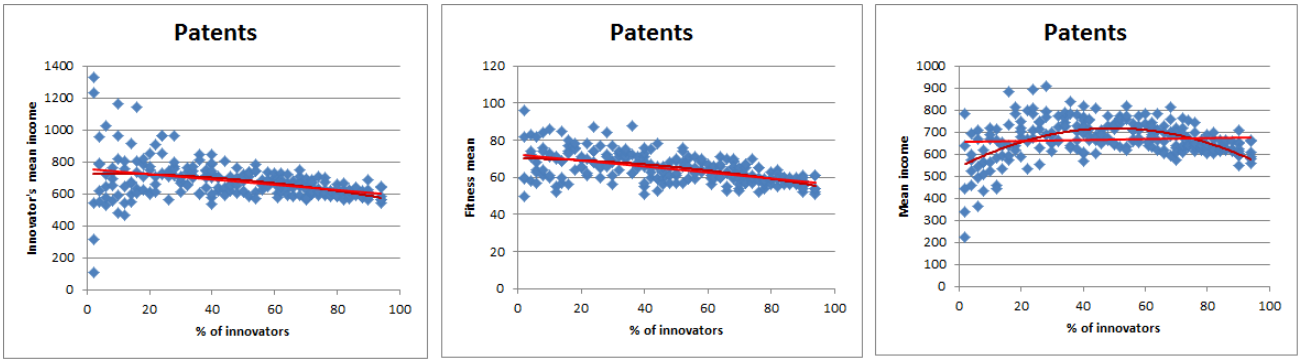

Figure C.2: Scatterplots on patent regime.

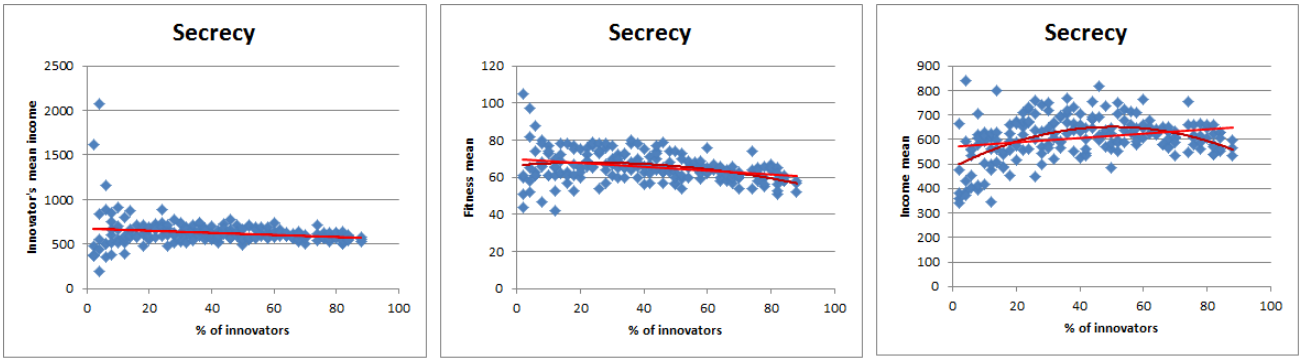

Figure C.3: Scatterplots on secrecy regime.

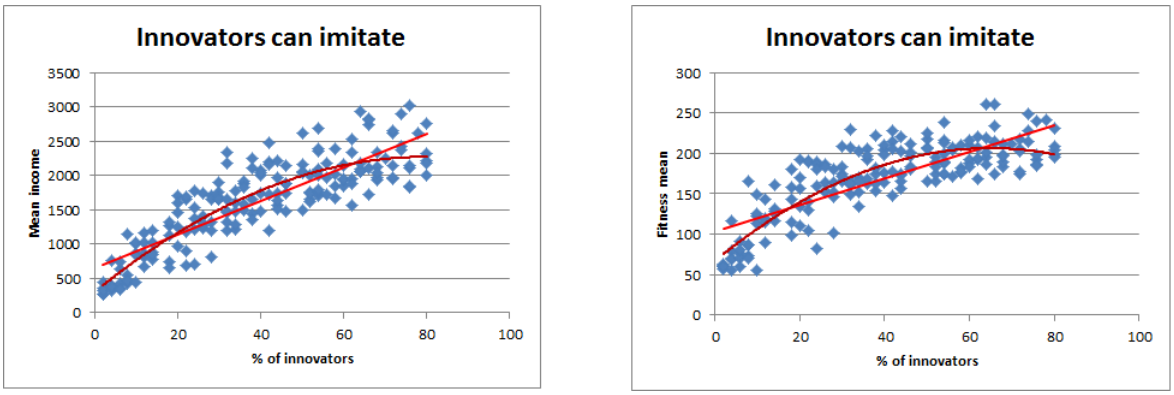

Figure C.4: Scatterplots, innovators can imitate.

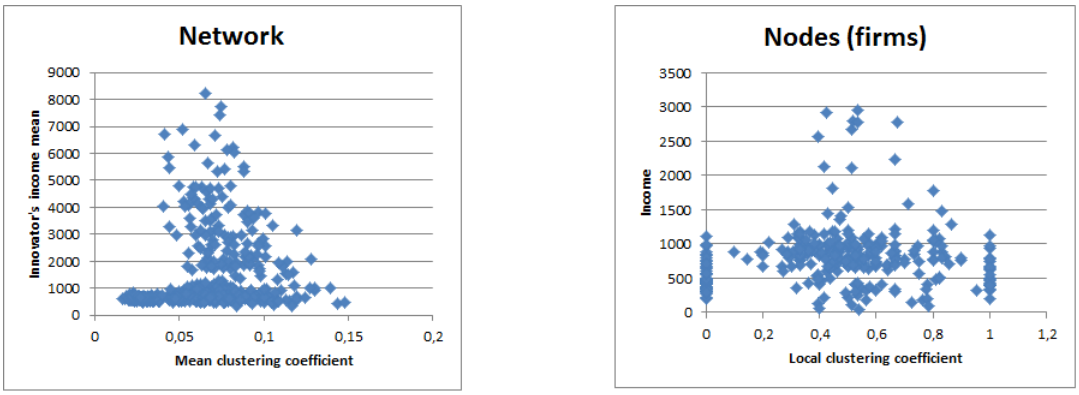

Figure C.5: Scatterplots, clustering coefficient measures.

Appendix D

Regressions and tests

Table: Group Statistics					
	Experiment	N	Mean	SD	S.E. Mean
Innov_income	E1	150	722,52	172,26	14,07
	E2	150	626,65	59,94	4,89
Imit_income	E1	150	615,79	114,63	9,36
	E2	150	823,11	104,17	8,51
Fitness	E1	150	70,82	10,24	0,84
	E2	150	61,51	4,92	0,4

Table: Independent Samples Test						
		Levene's Test		t-test for Equality of Means		
		F	Sig.	t	df	Sig. (2-tailed)
Innov_income	Equal variances assumed	89,57	0	6,44	298	0
	Equal variances not assumed			6,44	184,56	0
Imit_income	Equal variances assumed	3,63	0,058	-16,39	298	0
	Equal variances not assumed			-16,39	295,31	0
Fitness	Equal variances assumed	57,49	0	10,04	298	0
	Equal variances not assumed			10,04	214,24	0

Table D.1: Independent samples t-test for incomes and fitness in conditions E1 and E2.

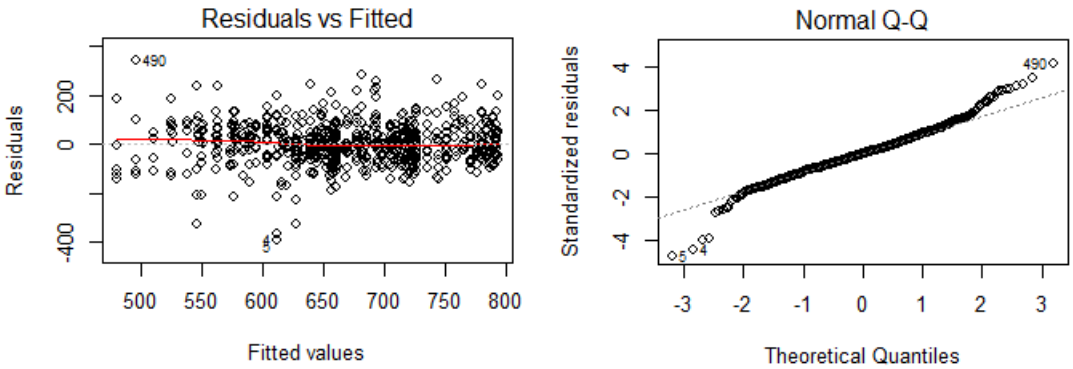

Figure D.1: Analysis of residuals for the first specification.

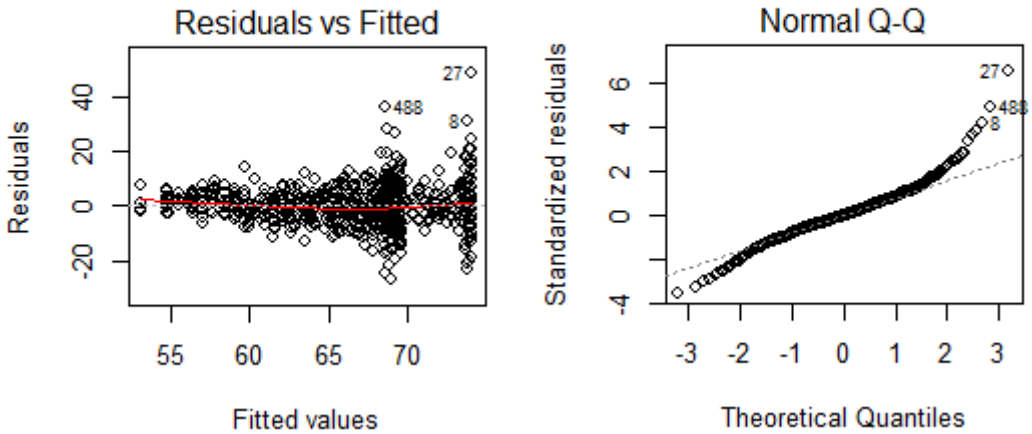

Figure D.2: Analysis of residuals for the second specification.

Model Summary (Income_mean)

R	*R Square*	*Adjusted R Square*	*Std. Error of the Estimate*
,67	,44	,44	82,34

Coefficients (Income_mean)

	Unstandardized Coefficients		*Standardized Coefficients*		
	B	*Std. Error*	*Beta*	*t*	*Sig.*
(Constant)	596,77	10,65	,00	56,05	,000
innov	8,18	,48	1,97	17,10	,000
innov2	-,09	,00	-1,98	-17,20	,000
Regime_D1	-66,18	7,50	-,29	-8,83	,000
Regime_D2	-131,52	7,94	-,54	-16,57	,000

Table D.2: Regression results for the first specification.

Model Summary (Fitness_mean)

R	*R Square*	*Adjusted R Square*	*Std. Error of the Estimate*
,57	,32	,32	7,52

Coefficients (Fitness_mean)

	Unstandardized Coefficients		*Standardized Coefficients*		
	B	*Std. Error*	*Beta*	*t*	*Sig.*
(Constant)	73,57	,97	,00	75,68	,000
innov	,07	,04	,21	1,69	,092
innov2	,00	,00	-,73	-5,75	,000
Regime_D1	-4,47	,68	-,24	-6,53	,000
Regime_D2	-5,12	,72	-,26	-7,06	,000

Table D.3: Regression results for the second specification.

Model Summary (Income_mean)

R	*R Square*	*Adjusted R Square*	*Std. Error of the Estimate*
,88	,78	,78	306,07

Coefficients (Income_mean)

	Unstandardized Coefficients		*Standardized Coefficients*		
	B	*Std. Error*	*Beta*	*t*	*Sig.*
(Constant)	304,34	70,05	,00	4,34	,000
innov	49,21	3,97	1,71	12,40	,000
innov2	-,31	,05	-,88	-6,42	,000

Table D.4: Regression results for the third specification.

Model Summary (Fitness_mean)

R	*R Square*	*Adjusted R Square*	*Std. Error of the Estimate*
,85	,73	,73	24,49

Coefficients (Fitness_mean)

	Unstandardized Coefficients		*Standardized Coefficients*		
	B	*Std. Error*	*Beta*	*t*	*Sig.*
(Constant)	66,97	5,60	,00	11,95	,000
innov	4,30	,32	2,05	13,53	,000
innov2	-,03	,00	-1,31	-8,63	,000

Table D.5: Regression results for the fourth specification.

Appendix E

Simulation code

To ease readability, most of the comments have been eliminated. For the complete code, refer to the .nlogo file.

```
extensions [nw]

globals [temp_techs2 counter breakthrough_counter]

breed [firms firm]
breed [technologies technology]

directed-link-breed [firm-usess firm-uses]
undirected-link-breed [share-techs share-tech]
directed-link-breed [parent-ofs parent-of]

share-techs-own [weight]

firms-own
[techs
 stock
 innovator
 imitator
 r&d_propensity
 productivity_firm
 last_return
 last_costs
 adoption_temp
 income
 incentive
```

```
 betweenness_centrality
 local_clustering_coefficient]


technologies-own
[fitness
 alpha
 beta
 return_to_tech
 adopters
 cost_adoption
 obsolescence
 patent_protection
 cost_to_secrecy
 cost_to_tech]






;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;;                 SETUP                    ;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;





to setup

  clear-all

  setup-patches

  setup-tech

  setup-firms

  reset-ticks

end
```

```
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;;           SETUP PROCEDURES              ;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;



to setup-patches

  ask patches [ set pcolor white ]

end




to setup-tech

  create-technologies initial-technologies

              [ set color blue
                set size 1
                set shape "square"
                setxy random-xcor random-ycor

                set fitness random (80 - 15) + 15

                set alpha random (25 - 10) + 10
                set beta random (60 - 40) + 40

                set cost_adoption fitness * 2]
end






;; A chosen number of firms is created


to setup-firms
```

```
  create-firms initial-firms

        [ set color red
          set size 3
          set shape "house"
          setxy random-xcor random-ycor
          while [any? other turtles-here]
                  [ fd 1 ]
          set techs []
          set stock 500
          set imitator 1


          repeat 2
           [ifelse one-of technologies in-radius 20 != nobody
             [create-firm-uses-to one-of technologies
                                          in-radius 20]
             [create-firm-uses-to one-of technologies]]

          let temp_techs []
          ask out-firm-uses-neighbors
              [set temp_techs fput who temp_techs]
          foreach temp_techs [set techs fput ? techs]
          set techs remove-duplicates techs

          if random 100 < percent-innovators
              [ set innovator 1
                set color violet
                ifelse innovators-imitate?
                    [set imitator 1]
                    [set imitator 0]

                 ifelse random-float 1 < r&d-propensity
                    [set r&d_propensity 0.60]
                    [set r&d_propensity 0.20] ]  ]

   ask firm-usess [set color green]

end
```

```
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;;                    GO                    ;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;


to go

 ;; a new firm enter the system with 30% probability
     create-new-firm

 ;; technologies variables are updated
     update-tech-features

 ;; firms variables are updated
     update-firm-characteristics

 ;; a list containing candidates for adoption is created
     evaluate-techs

 ;; one of the candidates (if any) is adopted
     adopt-tech

 ;; technologies that reached saturation level
 ;; are detected and signaled (yellow)
     detect-saturation

 ;; innovation procedure
     innovate

 ;; breakthroughs are developed
     if develop?
          [develop]

 ;; create a share-tech link between firms
     inter-firm-link

 ;; update the weight of the link among firms
     update-inter-firm-weight

     set-colors

     tick
```

```
end




;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;;             GO PROCEDURES               ;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;





;; with  30% probability, a new firm is created


to create-new-firm

  if random-float 1 < 0.30

      [ create-firms 1
           [ set color red
             set size 3
             set shape "house"
             setxy random-xcor random-ycor
             while [any? other turtles-here]
                     [ fd 1 ]
             set techs []
             set stock 500
             set imitator 1

             repeat 2
               [ifelse one-of technologies with
               [color != green and color != brown]
                in-radius 20 != nobody
                   [create-firm-uses-to one-of technologies
                    with [color != green and color != brown]
                    in-radius 20]
                   [create-firm-uses-to one-of technologies
                   with [color != green and color != brown]]]

             let temp_techs []
```

```
            ask out-firm-uses-neighbors
                [set temp_techs fput who temp_techs]
            foreach temp_techs [set techs fput ? techs]
            set techs remove-duplicates techs

            if random 100 < percent-innovators
                [set innovator 1
                 set color violet
                 ifelse innovators-imitate?
                     [set imitator 1]
                     [set imitator 0]

                 ifelse random-float 1 < r&d-propensity
                     [set r&d_propensity 0.60]
                     [set r&d_propensity 0.20]] ]

    ask firm-usess [set color green]  ]


end





to update-tech-features

  ask parent-ofs [hide-link]

  ask technologies
    [show-turtle

     set adopters count in-firm-uses-neighbors

     ifelse fitness = 0
       [set return_to_tech 0]
       [set return_to_tech fitness - (alpha * adopters ^ 2)
                           + (beta * adopters)]]
```

```
   ask technologies with [color = turquoise]
    [hide-turtle

    set obsolescence obsolescence + 1
    if obsolescence > 20 [die]]

  ask technologies with [color = green]
    [set patent_protection patent_protection + 1
     if patent_protection > patent-length
        [set color blue]]


end





to update-firm-characteristics

;; the list techs is updated

  ask firms [ set techs []
              let temp_techs []
              ask out-firm-uses-neighbors
                [set temp_techs fput who temp_techs]
              foreach temp_techs
                [set techs fput ? techs]
              set incentive 0


;; returns are computed

             let temp_return 0
             ask out-firm-uses-neighbors
                [ set temp_return
                     (temp_return + return_to_tech) ]

             set last_return temp_return
```

```
;; costs are computed

             let temp_costs 0
             ask out-firm-uses-neighbors
                [ set temp_costs
                     (temp_costs + cost_to_secrecy) ]

             set last_costs temp_costs



;; productivity is updated

              ifelse count out-firm-uses-neighbors = 0

                 [set productivity_firm 0]

                 [let temp_productivity 1
                  let n 0
                  ask out-firm-uses-neighbors
                   [set temp_productivity
                       (temp_productivity * fitness)
                    set n (n + 1) ]
                  set productivity_firm
                       (temp_productivity ^ (1 / n))]



;; income is computed

             set income (last_return - last_costs)

             ifelse innovator = 0
               [if income < mean [income] of firms
                with [innovator = 0]
                       [set incentive 1]]

               [if income < mean [income] of firms
               with [innovator = 1]
                       [set incentive 1]

                if income > 1.80 * mean [income] of firms
                with [innovator = 1] and
```

```
                 income < 2.5 * mean [income] of firms
                 with [innovator = 1]
                        [set incentive 1]]




;; stock is updated

             set stock (stock + income)
]


end





to evaluate-techs


  ask firms with [incentive = 1 and imitator = 1]

      [let evaluation_temp []
       set adoption_temp []

       if stock < 500
          [set stock (stock - 30)]
       if stock > 500 and stock < 5000
          [set stock (stock - 300)]
       if stock > 5000 and stock < 20000
          [set stock (stock - 3000)]
       if stock > 20000
          [set stock (stock - 6000)]

       ask technologies with
             [color != green and
              color != brown] in-radius 20
                  [ set evaluation_temp fput
                    who evaluation_temp]
              foreach evaluation_temp
```

```
                [if member? ? techs
                    [set evaluation_temp remove-item
                    position ?
                    evaluation_temp evaluation_temp] ]

            foreach evaluation_temp
                [if [fitness]
                 of technology ? > productivity_firm
                 and ([cost_adoption]
                 of technology ? < stock)
                  [set adoption_temp fput ? adoption_temp]]

             if empty? adoption_temp
             [ if stock < 500
                 [set stock (stock - 15)]
               if stock > 500 and stock < 5000
                  [set stock (stock - 200)]
               if stock > 5000 and stock < 20000
                  [set stock (stock - 2000)]
               if stock > 20000
                  [set stock (stock - 4000)]

               set evaluation_temp []
               ask share-tech-neighbors
                  [ask out-firm-uses-neighbors
                   with [color != green and color != brown]
                      [set evaluation_temp fput
                       who evaluation_temp]]

               foreach evaluation_temp
                 [if ([fitness]
                 of technology ? > productivity_firm)
                 and ([cost_adoption]
                 of technology ? < stock)
                   [set adoption_temp fput ? adoption_temp]
                   ]]]

end
```

```
;; the firms try to adopt a new technology

to adopt-tech

  ask firms with [incentive = 1 and imitator = 1]
     [if not empty? adoption_temp
        [if random-float 1 < 0.60
            [ set techs shuffle techs
              set adoption_temp shuffle adoption_temp

              ifelse length techs >= 8
                 [ ask out-firm-uses-to technology
                   item 0 techs [die]

                   create-firm-uses-to technology
                   item 0 adoption_temp

                   set techs replace-item 0 techs
                   item 0 adoption_temp

                   set stock (stock - [cost_adoption]
                   of technology item 0 adoption_temp)]

                 [ create-firm-uses-to technology
                   item 0 adoption_temp

                   set techs fput item 0 adoption_temp techs

                   set stock (stock - [cost_adoption]
                   of technology item 0 adoption_temp)]] ]]

end
```

```
;; technologies at saturation are signaled with yellow color

to detect-saturation

  ask technologies with [color = blue]
    [if (- 2 * alpha * adopters + beta) < 0
        [set color yellow]]

  ask technologies with [color = yellow]
    [if (- 2 * alpha * adopters + beta) > 0
        [set color blue]]



end





to innovate

  ask firms with [innovator = 1 and incentive = 1]
     [ if length techs > 5 [set color grey]
       set stock ( stock - (r&d_propensity * stock) )
       if random-float 1 < r&d_propensity * 0.5
           [ask patch-here
               [ sprout-technologies 1
                    [ set color grey
                      set size 1
                      set shape "square"
                      fd random 8
                      left random 5] ]

           create-firm-uses-to one-of technologies
           with [color = grey]

           ifelse any? out-firm-uses-neighbors with
           [color != grey and shape != "circle"] != false
                [ask one-of out-firm-uses-neighbors with
                [color != grey and shape != "circle"]
```

```
                    [create-parent-of-to one-of technologies
                     with [color = grey]
                     if any? firms with [color = grey]
                          [ask link-with one-of firms
                          with [color = grey] [die]] ]]

                [ask one-of out-firm-uses-neighbors with
                [color != grey]
                     [create-parent-of-to one-of technologies
                      with [color = grey]

                      if any? firms with [color = grey]
                           [ask link-with one-of firms
                           with [color = grey] [die]]]]

            ask technologies with [color = grey]
              [let parent_fitness item 0
               [fitness] of in-parent-of-neighbors

               set fitness random-normal parent_fitness 20
               if fitness  <= 0 [set fitness 1]

                    [set shape "circle"
                     set size 2
                     set breakthrough_counter
                     breakthrough_counter + 1]

                set cost_adoption fitness * 2
                set alpha random (25 - 10) + 10
                set beta random (60 - 40) + 40

                  [set color green]
               if intellectual-property = "secrecy"
                  [set color brown
                   set cost_to_secrecy 0.20 * fitness]
               if intellectual-property = "public good"
                  [set color blue]]]

   ask firms with [color = grey] [set color violet]]

end
```

```
;; breakthroughs are developed to exploit their potential

to develop

  ask firms with [innovator = 1 and incentive = 1]
    [if any? out-firm-uses-neighbors
     with [shape = "circle"] = true
       [set stock ( stock - (r&d_propensity * stock) )

        if random-float 1 < (r&d_propensity) * 0.5
           [ask one-of out-firm-uses-neighbors
            with [shape = "circle"]
                [let parent_fitness fitness

                 ask patch-here
                    [sprout-technologies 1
                       [ set color grey
                         set size 1
                         set shape "square"
                         fd random 8
                         left random 5

                         set fitness random-normal
                         parent_fitness 20

                         if fitness  <= 0 [set fitness 1]
                         if fitness > 2.5 * mean [fitness]
                         of technologies
                            [set shape "circle"
                             set size 2
                             set breakthrough_counter
                             breakthrough_counter + 1]

                          set alpha random (25 - 10) + 10
                          set beta random (60 - 40) + 40

                          set cost_adoption fitness * 2] ]

                          create-parent-of-to
                          one-of technologies
```

```
                          with [color = grey]]

                          create-firm-uses-to
                          one-of technologies
                          with [color = grey]]]

   ask technologies with [color = grey]
    [ if intellectual-property = "patent"
          [set color green]
      if intellectual-property = "secrecy"
          [set color brown
           set cost_to_secrecy fitness * 0.20]
      if intellectual-property = "public good"
           [set color blue]]]

end




to inter-firm-link

;;firms who share at least 1 technology are linked

  ask share-techs [die]

  ask technologies
    [ let sharingfirms in-firm-uses-neighbors
      ask in-firm-uses-neighbors
        [ create-share-techs-with other sharingfirms ] ]

  ask share-techs [set color red]


end
```

```
to update-inter-firm-weight

  ask share-techs
    [ set weight 0

      let temp_weight 0
      ask end2 [ set temp_techs2 []
                 foreach techs
                   [set temp_techs2 fput ? temp_techs2] ]
      ask end1 [ foreach techs
                   [ if member? ? temp_techs2
                        [ set temp_weight temp_weight + 1]]]

      set weight temp_weight ]

end









to set-colors

    ask parent-ofs  [set color blue]
    ask firm-usess  [set color green]

    ask technologies
       [set adopters count in-firm-uses-neighbors
        ifelse adopters = 0 [set color turquoise]
                            [if color = turquoise
                                [set color blue
                                 set obsolescence 0]]]

    ask technologies with [color = brown]
       [if random-float 1 < 0.005
          [set color blue
           set cost_to_secrecy 0]]

    ask firms [if stock < 0 [ask my-links [die]
                             ask patch-here [set pcolor black]
```

```
                             die]]

end







;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;;;        INTERACTIVE PROCEDURES           ;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

;; interactive procedures are not reported
```

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