Relational Methodologies and Epistemology in Economics and Management Sciences

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A volume in the Advances in Finance, Accounting, and Economics (AFAE) Book Series

Information Science REFERENCE
An Imprint of IGI Global

Published in the United States of America by
Information Science Reference (an imprint of IGI Global)
701 E. Chocolate Avenue
Hershey PA, USA 17033
Tel: 717-533-8845
Fax: 717-533-8661
E-mail: cust@igi-global.com
Web site: http://www.igi-global.com

Library of Congress Cataloging-in-Publication Data

Names: Biggiero, Lucio, 1955- editor.
Title: Relational methodologies and epistemology in economics and management sciences / Lucio Biggiero, Pier Paolo Angelini, Mario Basevi, Nunzia Carbonara, Antonio Matrogiorgio, Eliano Pessa, Enrico Sevi and Marco Valente, editors.
Description: Hershey, PA : Information Science Reference, [2016] | Includes bibliographical references and index.
Identifiers: LCCN 2015041972| ISBN 9781466697706 (hardcover) | ISBN 9781466697713 (ebook)
Subjects: LCSH: Social sciences--Methodology. | Science--Methodology. | Social epistemology. | Knowledge, Theory of.
Classification: LCC H61 .R45 2016 | DDC 300--dc23 LC record available at http://lccn.loc.gov/2015041972

This book is published in the IGI Global book series Advances in Finance, Accounting, and Economics (AFAE) (ISSN: 2327-5677; eISSN: 2327-5685)

British Cataloguing in Publication Data
A Cataloguing in Publication record for this book is available from the British Library.

Chapter 12
Knowledge Creation, Growth, and Transfer within Industrial Networks of Practices:
The Role of Absorptive Capacity and Direct Centrality

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ABSTRACT

In this chapter we test the hypothesis that uneven links distributions and uneven absorptive capacity between an industrial cluster members provide some kind of competitive advantages. Through an agent-based model has been built and calibrated on real data taken from an aerospace industrial cluster, that hypothesis is contrasted against the normal, the uniform, and the U-shaped distribution. The focus of the model is on knowledge variables, agents' learning capacities, and structural variables, like firms size and proximity. Physical production is not considered, excepted for its degree of complexity, which determines also the degree of knowledge complexity. This work shows that, actually, the best performance in terms of cluster knowledge creation, growth and diffusion is obtained when firms connectedness and absorptive capacity are distributed in a scale-free way. More generally, the more unbalanced are these two variables (especially absorptive capacity), the better is knowledge performance. These results are rather robust, and obtained while keeping all other variables very balanced at the beginning of each simulation.

INTRODUCTION

What appeared more and more evident during the last two decades is that, given its tremendous complexity and methodological heterogeneity, it is very hard to find clear, sound and convergent results from

DOI: 10.4018/978-1-4666-9770-6.ch012

empirical studies on knowledge transfer, industrial clusters and innovation networks, often reciprocally incomparable and theoretically inconclusive. To face with these limitations agent-based simulation modelling (ABSM) are diffusing (Carley, 2009; Davis *et al.*, 2007; Gilbert, 2008; Gilbert & Terna, 2000; Gilbert & Troitzsch, 2005; Harrison *et al.*, 2007; Tesfatsion & Judd, 2006; Uhrmacher & Weyns, 2009), with the hope to build strong and comparable results. When these models are not too abstract, and especially if its parameters are calibrated - inspired by and set up - with real data, results of virtual experiments can dramatically improve and increase our scientific knowledge. This paper adopts this methodological perspective by building KNOWTIC, an agent-based model on knowledge creation, growth, and transfer of industrial clusters (IC).

According to various scholars (Arikan, 2009; Lorenzen & Maskell, 2004; Maskell, 2001; Tallman *et al.*, 2004), the need to build, enhance, and exploit collective knowledge is supposed to be one of IC major drivers. The process of collective knowledge formation occurs through recursive and (mostly) self-organizing mechanisms (Biggiero, 2001, 2006), that is, grounding on largely spontaneous bottom-up forces. After one or more forms of proximity have been established (Boschma, 2005), knowledge creation and transfer (Ernst, 2002) is enabled. Indeed, this picture requires a number of other favourable conditions to occur, and their exploration is just at the beginning. In fact, many IC decline and fail, and many of them loose identity, structure, social cohesion, and competitive advantages. Moreover, nobody knows how many IC could have been formed but never born. In this paper we do not investigate such contextual conditions, and assume that an IC already exists.

The focus is on the way that tacit and explicit knowledge circulates and grows, and how knowledge is employed in collaborative and non-collaborative activities, depending on agents' collaborative propensity, learning attitude, imitation or innovation choice, research expenditure, geographical proximity, size, and a number of other variables whose discussion is succinctly made in the third section. *The core research issue concerns if and how the specific distribution of firms' absorptive capacity (ABC) and connectedness (Dc) influence an IC knowledge performance*. To this aim, a normal distribution of these two variables is benchmarked, ceteris paribus, against a uniform, a U-shaped, and a power-law distribution.

Theoretical supports to our KNOWTIC Model are the following two: the research stream viewing ICs as cognitive systems (Belussi & Gottardi, 2000; Camuffo & Grandinetti, 2011), and the research stream of communities and networks of practices (Agterberg *et al.*, 2010; Anderson *et al.*, 2010; Lave & Wenger, 1991; Wenger 1998), which are combined with the knowledge networks literature (Kreis-Hoyer & Grünberg, 2002; Hildreth & Kimble, 2004; Sammarra & Biggiero, 2008) to ground IC knowledge creation and growth on the firms' micro-level. These theoretical backgrounds are summarized in next section, while the model structure is outlined in section three. Agents' autonomy, cognition, behaviour, and decision making processes are described in the next section, followed by the description of virtual experiments. In section six the main results are evidenced, and then discussed and compared with current literature. In extreme synthesis, the analysis indicates clearly that, ceteris paribus, ABC and Dc nonlinear distributions influence significantly knowledge performance, and the former more than the latter.

THEORETICAL BACKGROUND

We assume the knowledge-based theory of IC formation and evolution (Arikan, 2009; Lorenzen & Maskell, 2004; Maskell, 2001; Tallman *et al.*, 2004). Notwithstanding the variety between and within ICs (Belussi *et al.*, 2003; Belussi & Sammarra, 2005, 2010; Giuliani *et al.*, 2005; Karlsson *et al.*, 2005;

Karlsson, 2008; Porter, 1998a), as a whole and to a higher extent in some of their areas, they share common practices, especially in terms of social, economic, and technological behaviours. These are the conditions that allow and enhance knowledge creation and exchange in a way that, when social, economic and technological factors interact in a virtuous loop, generates IC's competitive advantage (Belussi & Pilotti, 2002; Belussi & Sedita, 2012; Biggiero, 2006; Brenner, 2007; Henry & Pinch, 2006; Malmberg & Power, 2005; Maskell, 2001a, 2001b; Tallman *et al.*, 2004). Practices are common and well performed when knowledge – especially in its tacit form - is effectively and efficiently exchanged and shared (Amin & Roberts, 2008; Biggiero, 2006, 2012; Brown & Duguid, 1991, 1998, 2000; Gertler, 2003; Huysman & de Wit, 2002; Wenger, 1998). And this, in turn, occurs when people trust each other, have short cognitive distance (Nooteboom, 1999, 2000; Nooteboom *et al.*, 2007), and feel a sense of common identity (Camuffo & Grandinetti, 2011; Sammarra & Biggiero, 2001).

These traits make ICs good examples of network of practices (NoP), because their members are nurtured within the same cultural, social, economic and *epistemic* environment (Håkanson, 2005; Thompson, 2005) through recursive and dense interactions. Therefore, ICs are (partially) self-organizing inter-organizational networks (Baker & Faulkner, 2002; Biggiero, 2001b; Capasso *et al.*, 2005; Carayannis *et al.*, 2008; Monge & Contractor, 2003; Nooteboom, 2004; Rycroft & Kash, 2004). These characteristics are much more accentuated when ICs are also industrial districts, because in those contexts socio-economic density is much higher, geographical area narrower, average firm's size much lower, and the degree of industrial specialization higher[1]. Hence, industrial districts are dense and (largely) self-organizing entrepreneurial networks (Biggiero, 2001), where cognitive, cultural, institutional and organizational proximity is very high. This view is fully consistent with Anderson *et al.* (2010), who underlie that entrepreneurial networks and developmental processes are extensively based on shared practices and imitation. These properties show that a substantial aspect of ICs is being also NoPs.

Be them geographically specified or not, NoPs are, at the same time, knowledge networks that usually are structured into sub-networks (Andriessen *et al.*, 2004; Hildreth & Kimble, 2004; Tallman & Chacar, 2011a, 2011b). Therefore, inside them a large amount of common tacit knowledge does circulate in a largely free way, and this aspect is especially accentuated when practices are characterized by complex tasks and behaviors in an uncertain environment. Consequently, ICs can be seen as geographically specified NoPs, whose knowledge creation, growth and exchange depends largely on the complexity of the products and on the underlying industrial and social structure.

The fundamental difference between the way in which the concept of NoP is used here and the way in which it is used in NoP literature – and even more in its precursor literature on communities of practices – is that here NoP's members are organizations while in the original approach they are single individuals. That is, we have applied the same concept to a superior level of aggregation respect to the original formulation. In general, this conceptual transfer hides a lot of subtle epistemological questions, at least because entities lying at different levels of aggregation are ontologically different, and thus, nothing guarantees that they can have the same properties[2]. Therefore, it cannot be accepted automatically. Our rationale for the transfer of NoP concept from individuals' networks to organizations' networks[3] is supported by the three following facts: i) ICs are characterized by a dense net of inner recursive interactions between their constituting organizations; ii) such interactions are quasi-stable practices[4]; iii) such practices are carried on by entrepreneurs, managers, employees, and continually renewed and breed by their mobility between cluster organizations (and marginally, even with non-cluster organizations). Hence, the network aspect, the practice-centered aspect, and the human-embodied aspect all hold also when applying the NoP concept to an IC. As already addressed before, this use of the NoP concept is even more appropriate when the IC is also an industrial district.

Of course, an IC is "more" than a NoP, because there are many economic, social, institutional and economic aspects that influence (and are influenced by) its characteristics. However, we can focus only on some cluster traits that depicts it as a NoP: from hereafter we can speak of IC-NoP (IC's NoP). Knowledge creation, growth, and transfer is maybe the most important of these traits, as we said before. Another one is ICs' internal heterogeneity, which has been recently highlighted: Giuliani (2006) for the wine industry, and Biggiero & Sammarra (2010; Sammarra & Biggiero, 2008) for the aerospace industry have shown that trade, collaboration, and knowledge transfer underlying a cluster structure have an irregular topology. Often it follows a power-law structure (Barabasi, 2002; Caldarelli, 2007), and thus, a very unbalanced distribution: few large hubs and many scarcely connected nodes. R&D collaboration networks funded by EU are interesting examples, albeit at regional (supra-national) level (Biggiero & Angelini, 2015). Hence, to the aim of understanding under which structural context knowledge growth is more efficient and effective, it becomes interesting, at the whole cluster level, to discover the appropriate distribution of some key variables, which characterize each IC.

Here we focus on firm's direct centrality (Dc) and absorptive capacity (ABC). The former is considered one of the most important indicators of actor's relevance (Wasserman and Faust, 1994[5]), and thus, of a firm's position in a cluster structure (Sammarra & Biggiero, 2008). The latter is assuming a growing relevance not only at organizational level (Cohen & Levinthal, 1990, 2000; Zahra & George, 2002), but also at inter-organizational and cluster level (Camison & Forés, 2011; Cowan *et al.*, 2004; Giuliani, 2005; Lane and Lubatkin, 1998; Nicotra *et al.*, 2013). The basic idea is that, in order to use the "flowing" or accessible knowledge, and thus, to transform it into innovations or imitations, appropriate knowledge should be acknowledged, acquired, and used. Building mostly on empirical researches, scholars agree – more or less explicitly - that ICs, even respect to knowledge distribution, are not internally homogeneous. Therefore, cluster firms differ either in terms of Dc or ABC. In this perspective we have "customized" the KNOWTIC Model[6] in a way that allows to contrast uneven vs. even distributions of these two variables. Both them have been defined and distributed in relative terms[7].

For we aim at studying the influence of ABC and Dc different distributions on IC-NoP knowledge performance through an agent-based simulation model, we looked for contributions concerning also NoP modelling. However, while there is a plenty of case studies in the field of communities and networks of practices (Jeon *et al.*, 2011; Kodama, 2002; McLure Wasko & Faraj, 2005; Pan & Leidner, 2003; Storck & Hill, 2000; Wenger, 1998; Wenger *et al.*, 2002), there are no formal neither computational models, and most empirical works are hardly comparable, because of their extreme methodological and ontological variety. Indeed, most concepts used in this literature has even not yet defined in formal ways, so to be treated in quantitative or formal approaches.

We looked also for computational agent-based models concerning ICs knowledge dynamics. However, a scouting into what is becoming a rather crowded research area (Albino *et al.*, 2003, 2006; Boero *et al.*, 2004; Borrelli *et al.*, 2005; Brenner, 2004; Brusco *et al.*, 2002; Fioretti, 2001; Merlone & Terna, 2007; Squazzoni & Boero, 2002) has been not very helpful, because there is no any model that, by taking into account all the variables we consider in our model, allows to study the NoP aspect of ICs[8].

As concerning knowledge, we have followed the classical distinction between explicit and tacit knowledge (Amin & Cohendet, 2004; Ancori *et al.*, 2000; Cowan *et al.*, 2000; Gertler, 2003; Lissoni, 2001), and related this latter with inter-firm interactions through collaboration (Malmberg & Maskell, 1999).

We are aware to have adopted an oversimplifying assumption concerning knowledge cumulativeness as a stockpile, that is as a scalar, while it had to be properly considered as a vector of characteristics. However, this assumption adds to the many that are usually required for agent-based modelling, even though not specifically focused on knowledge recombination.

Our model, which is discussed in detail in the next two sections, has the following characteristics:

- It is enough detailed and realistic to be applied to concrete case studies or to be used to explore the theoretical relationships of different variables and so to test different theoretical approaches;
- It combines knowledge network aspects with geographical and economic aspects;
- It distinguishes different types of knowledge (tacit and explicit) and ways to create them (imitations, innovations, patents);
- It allows to explore both emergent properties at the macro level, and the individual (or sub-network level) at the micro level, even taking into account the feedback from the macro- to the micro-level.

Our model overlooks production and trade aspects of ICs[9], and it focuses on 12 structural, cognitive-behavioural, economic, and knowledge variables affecting IC-NoP knowledge performance. Therefore, notwithstanding the lack of production and trade aspects it is enough rich and articulated to be used as a laboratory to explore a vast research area. In this particular contribution it is finalized to shed light on the relative relevance played by the initial level and distribution of ABC and Dc, while keeping stable the other 10 variables. More precisely, this paper answers the following research question:

How does the average level and the distribution of ABC and Dc affect the speed, amount and type of knowledge creation, and the type of its diffusion within an IC-NoP?

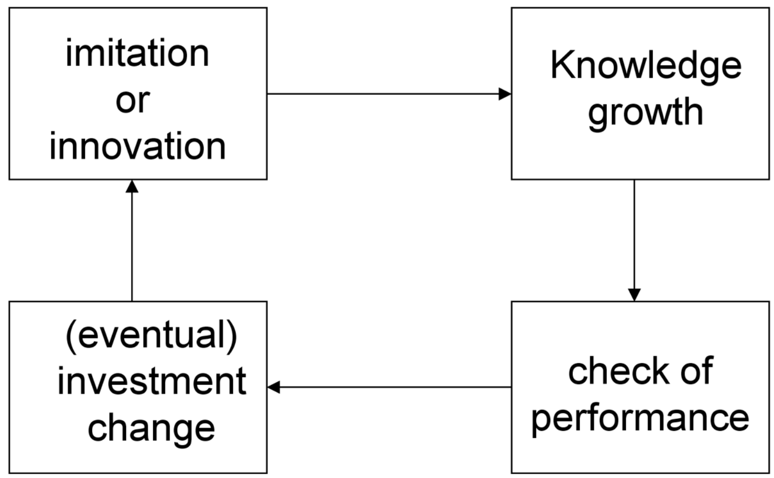
THE KNOWTIC MODEL

General Outline

The core structure of this model is made by a decision-action cycle, which is completed in each step (Figure 1): after comparing his knowledge with the average knowledge possessed by that IC-NoP part that is visible to him, an agent decides whether imitate (if his knowledge is inferior the the average level) or innovate (if it is superior). This decision might lead to knowledge growth and to major profits that can be reinvested in further imitation/innovation, depending on his relative (to the average) performance in terms of knowledge stock. The evaluation of past investments in the light of the actual outcome could determine a reallocation of agent's investments between collaborative or non-collaborative strategies. In short, the model's "engine" is that *agents seek to increase their knowledge, and in order to reach this goal they can allocate a certain amount of research expenditure between collaborative vs. non-collaborative and imitation vs. innovation choices*. By collaborating and imitating, knowledge is transferred and diffused within the IC-NoP, while through innovation it is created ex-novo.

The amount of research expenditure depends on how profitable has been the knowledge they have previously achieved. Knowledge-related variables refer to the distinction between patents, tacit and

Figure 1. A decision-action cycle

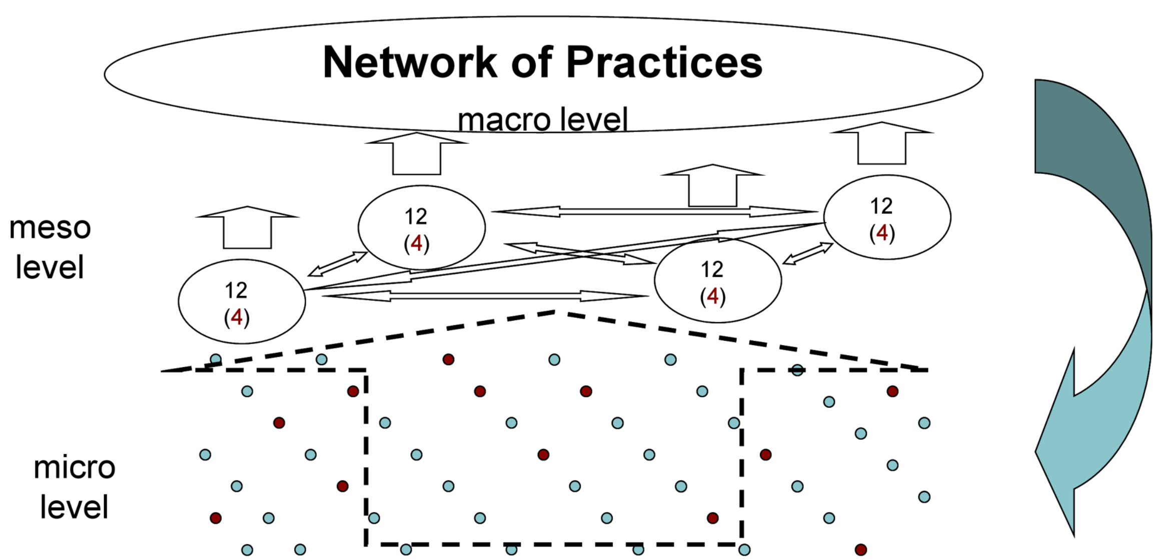


explicit knowledge, and the channels through which it is acquired. Knowledge can be accumulated, and actually this is the main goal of agents.

The model works and can be investigated at *three levels of description* (Figure 2):

- At micro-level, which is made by single agents, with their own characteristics, strategies, and performance;
- At meso-level, which is made by four geographical areas of major proximity;
- At macro-level, which is that of the whole IC-NoP.

Figure 2. Emergence, immergence, and levels of description



Since the three levels are interdependent this model is both "emergentist" and "immergentist", because the influence exerted by each level goes either bottom-up or top-down. Through reciprocal interactions agents determine the structure and performance of the four geographical areas, which in turn interact each other to produce the collective behaviour of the whole NoP. Hence, the model is "emergentist", because macro-behaviour depends on micro- (and meso-)behaviour. However, macro-behaviour enters as a point of reference into agents' learning and decision processes, so that the model is also "immergentist", because the micro-behaviour is influenced also by the macro-behaviour.

Pivotal, Structural, and Economic Variables

Pivotal Variables

The two most important variables are ABC and Dc, because IC-NoP's knowledge performance is analysed in relation to 16 combinations between four different distributions of these two variables. ABC is defined as the capacity an agent has to acquire tacit or explicit knowledge, and it is modelled as a fixed parameter varying between 0 and 1, which can be differentiated among agents. As discussed right below, it is not the only parameter concurring to determine the actual knowledge stock an agent creates or transfers. Dc and other variables contribute to increase or decrease knowledge stock in a different way for tacit and explicit knowledge, and in a different way for collaborative or non-collaborative imitation or innovation.

Dc is defined as the agent's degree of connectivity for collaboration with other agents, and as such intervenes on the ABC that is formed through imitation by collaboration (ABCOLL), according to the following algorithm:

$$ABCOLL = (1-ABS)*Dc \tag{1}$$

This ABCOLL increments an agent's ABC, because it is supposed that his collaboration network expands his capacity to receive others' knowledge. Conversely, if knowledge is acquired without collaboration, Dc loses its role. Besides ABC and Dc, three groups of variables should be introduced and distinguished: structural, economic, and knowledge-related.

Structural Variables

These variables concern agent's size, location, and visibility. Agents' size is given and distinguishes only large from small agents in terms of their visibility to others: the former are visible in the whole IC-NoP, while the latter only in the area of closest proximity in which they are located. Dc is also a structural variable, because it identifies an agent's degree of centrality.

Though small agents at the beginning can be visible only in their geographical area, even a small agent can become visible for all agents if it is a strong knowledge creator. These mechanisms are so powerful that a small agent can become even the IC-NoP's leader, as it happens in some experiment with high initial values and with a scale-free distribution for ABC and Dc. Such a process can also be inverted because of a decline in the agent's ability to innovate or imitate.

Economic Variables

These variables concern investments in collaborative or non-collaborative research and in imitative or innovative activities. Agents start with an initial budget, and receive a certain amount of money in each step independently on their actions, but they acquire new budget depending on their strategies and luck. In this version of the model financial resources cannot be capitalized, because they are spent in each step, adding those eventually gained in the previous step. Further variables refer to the costs of the following variables:

- Knowledge costs, which can be differentiated between non-collaborative or collaborative research;
- Knowledge productivity in terms of expenditure capacity, that is the capacity of a knowledge unit to produce income, which also is supposed to be spent in R&D in the next step.

It is supposed that knowledge acquired through collaboration is more costly because in general collaborating is time and resource consuming to allow partners understanding[10]. The mix between non-collaborative and collaborative research depends on single agents' choices, on their budgets for research expenditures, and on the costs of such forms of collaboration.

Knowledge-Related Variables

Explicit Knowledge

The actual increase of explicit knowledge depends on the amount of available knowledge and on agents' choices between imitation or innovation, and collaboration or non-collaboration (Table 1). The first choice depends on the amount of an agent's knowledge respect to that possessed by the agents visible to it: he chooses to innovate if it is superior, or vice versa to imitate. Firms increment their knowledge stock through creation or acquisition, and in both cases it might be realized by means of an external (collaboration) or an internal way. The decision making process of this (second) choice, which concerns collaborating or non-collaborating, is a little bit more complex than that between innovating and imitating, and it is formally illustrated with the flowchart in Appendix 2. The four combinations of the two couples of variables – imitation vs. innovation and external vs. internal way – correspond to the four possible cases that provide explicit knowledge to agents.

Table 1. Sources of single agents' explicit knowledge

	Collaborative	Non-collaborative
Imitation	Difference between the knowledge possessed by the knowledge leader and single agent's knowledge, multiplied per ABCOLL, and per a random coefficient (between 1 and 2) of misinterpretation	Difference between the knowledge possessed by the knowledge leader and single agent's knowledge, multiplied per ABC, and per a random coefficient (between 1 and 2) of misinterpretation
Innovation	Agent's total knowledge multiplied per the ratio between a random coefficient (between 0 and 1) of misinterpretation and visible agents share, and per ABCOLL	Agent's total knowledge multiplied per the ratio between a random coefficient (between 0 and 1) of misinterpretation and visible agents share, and per ABC

In the case an agent follows a path of collaborative imitation, it is supposed that it increments its knowledge according to the following mechanism:

$$EKG_{imcoll} = \{[(MVAK - SAK) * ABCOLL * RCM_{im}] * UCK\} - ARE \quad (2)$$

where:

EKG_{imcoll} = explicit knowledge increment obtained through collaborative imitation;
MVAK = knowledge possessed by the knowledge leader;
SAK = single agent's knowledge;
RCM_{im} = random coefficient (between 1 and 2) of misinterpretation;
UCK = unitary knowledge cost;
ARE available amount of research expenditure.

It means that when an agent imitates the knowledge leader, it gains a knowledge increment proportional to the gap between its knowledge and that of the leader, moderated by its ABCOLL, which takes into account also its R&D collaborations, and by a random error of knowledge leader misinterpretation. Moreover, for these knowledge units have a cost (UCK), the actual amount of knowledge increment is limited by available resource expenditure (ARE). Otherwise, if agent's choice is still through imitation, but it follows only the internal way, then it gets new knowledge according to the follow mechanism, which differs from the previous one only because ABC doe not take into account agent's collaboration network (Dc):

$$EKG_{im} = \{[(MVAK - SAK) * ABC * RCM_{im}] * UCK\} - ARE \quad (3)$$

Conversely, an innovation choice is expressed by another mechanism because the agent's benchmark is not more the knowledge leader, but rather the mean value between a stochastic number (between 0 and 1) and the share of all agents that it can see respect to all agents. The rest of expression [2] is analogous to that of imitation, and it involves ABC, UCK, and ARE. Notice that here the stochastic number varies in a minor range than for imitation, because it is implicitly supposed that it is harder to innovate than to imitate. This mechanism is a little bit more complex than that of imitation, because it should take into account not just the best agent, but all the agents that are visible to the agent's subjective perspective. In other words, it is plausible to argue that the probability and amount of knowledge obtained through innovation depends also on the knowledge circulating and employed by at least the most visible agents, who – at least partially – are supposed to be the best knowledge performers. In fact, if an agent would not take into account others' knowledge, then it would risk to innovate by creating knowledge that is new for it but already possessed by other agents. This risk decreases as more agents are visible respect to all agents. At the extreme, if all agents were visible, such a risk would be cancelled.

$$EKG_{incoll} = \{[SAK * (RCM_{in}/VAS) * ABCOLL] * UCK\} - ARE \quad (4)$$

where:

EKG_{incoll} = explicit knowledge increment obtained through collaborative innovation;

RCM_{in} = random coefficient (between 0 and 1) of misinterpretation;
VAS = visible agents share.

If innovation were pursued only by internal ways, then the only change in the previous equation is that ABCOLL becomes just ABC. As aforementioned, the actual increment of explicit knowledge depends on the knowledge that could be acquired given the available amount of research expenditure and the unitary cost of knowledge. Explicit knowledge is acquired until the budget allows it, and it is completely employed, because it is supposed that the whole budget is spent in every step. The *available amount of research expenditures* is given by the sum of a fixed budget plus the budget gained in the previous step, which is given by the cumulated degree of knowledge productivity per the knowledge incremented in the previous step. In fact, in this model it is truly assumed that firm's competitiveness is determined by knowledge growth and productivity. The former is given by increments of knowledge stock, while the latter in terms of expenditure capacity.

Tacit Knowledge

It is supposed that this type of knowledge is related only to collaboration activities (Table 2), and it is pulled by explicit knowledge acquired through imitation or innovation. In the former case it is obtained by multiplying the actual increment of explicit knowledge per ABCOLL and per the level of knowledge complexity. In fact, the idea is that through an R&D collaboration it is mutually transferred not only explicit but also tacit knowledge, in a share that depends on knowledge complexity: the more complex the knowledge involved, the higher the share of tacit knowledge, because its characteristic is just to be hardly codifiable (Ancori *et al.*, 2000). Of course, correspondingly to what formalized for explicit knowledge growth, the actually acquired tacit knowledge depends also on agent's ABC, according to the following mechanism:

$$TKG_{imcoll} = EKG_{imcoll} * ABCOLL * KC \tag{5}$$

where:

TKG_{imcoll} = tacit knowledge increment obtained through collaborative imitation;
KC = knowledge complexity.

Analogously, tacit knowledge acquired through innovation is expressed by:

$$TKG_{incoll} = EKG_{incoll} * ABCOLL * KC \tag{6}$$

Table 2. Increment of (collaborative) tacit knowledge

Imitation	Actual increment of explicit knowledge (acquired through the same way) per ABCOLL per knowledge complexity
Innovation	Actual increment of explicit knowledge (acquired through the same way) per ABCOLL per knowledge complexity

Knowledge complexity indicates the degree of true uncertainty (Biggiero, 2012; Yolles, 2006), non-routinization (Amin & Roberts, 2008), interdependence with other activities (Verburg & Andriessen, 2011) and non-codifiability (Biggiero, 2009; Brown & Duguid, 1998, 2000; Butler, 2003; Cowan, 2001; Cowan *et al.*, 2000; Cowan & Foray, 1997) of practices characterizing a specific NoP. Because all these aspects increase the share of tacit knowledge implied by a certain activity, then the higher is knowledge complexity, the higher is the potential amount of tacit knowledge an agent can acquire through collaboration.

Patents: Another form of knowledge created and transferred within the NoP is represented by patents, and in fact agents can stochastically record a patent if the chance outcome is inferior to its total knowledge share of the whole NoP. This algorithm makes unlikely that an agent with relatively few knowledge obtain a patent, and vice versa.

What Do Agents Do?

At each step agents seek to increase their knowledge through imitation or innovation, which in turn can be implemented through collaborative or non-collaborative R&D activities. In order to decide whether imitating or innovating, an agent compares his own total knowledge with the average total knowledge of the IC-NoP part that is visible to him, depending on the specific NoP sector. Agents can see all the large agents, plus all the small in its area, plus the small ones who became visible anywhere into the community because of an excellent knowledge performance in terms of patents and R&D expenditure. However, excellence can be just temporary, because wrong choices and/or bad luck can lead to temporary or permanent decline. It is supposed that this information is accessible through either informal interactions with other network members or formal publications made by some local government institution or private companies, like those made by trade associations or unions, or public research centres, like universities. If agent's knowledge is superior to the average, then it does not find convenient to imitate, because likely it will not gain new knowledge from others. In this case the agent will follow an innovation strategy. Conversely, an agent decides to imitate from who gets the highest knowledge among the ones it can see.

The imitating agent will spend all the budget to imitate the knowledge leader, trying to fill in the gap. The amount of knowledge acquired by imitation is given by multiplying that gap per a stochastic number between 1 and 2. This number aims to introduce the case of bad or (partially) incorrect imitation. Indeed, the actual knowledge acquired through imitation and innovation depends not only on the amount obtained through the two mechanisms, but also on the agent's degree of collaborative or non-collaborative ABS and Dc, according to what has been discussed in the previous section concerning explicit and tacit knowledge.

What Do Agents Know?

An agent knows its own and the average knowledge possessed by the agents it can see, and that possessed by the knowledge leader. Hence, agents have only partial and local information, limited to the others that are visible in each specific sector of major proximity. Supported by their propensity to collaborate and change, this information makes agents able to decide whether imitate or innovate. The paucity of available information and the simplicity of decision making give these agents bounded and local, albeit intentional rationality (Gigerenzer, 2008; Gigerenzer & Selten, 2001; Simon, 1969, 1977, 1997). Thus, agents cannot find an optimal strategy to increase their knowledge growth rate or their total knowledge, but rather they just tend to increase their current amount of knowledge.

In order to seek this goal, firms employ also a learning capacity, which (see Appendix 2), by looking back at their past outcomes, steers them to eventually change the expenditure mix between collaborative and non-collaborative behavior. However, for they cannot explore all the possibilities and neither gather all necessary information, they are satisfiers and not maximizers in this respect too. Their learning capacity articulates in how frequently they analyze their past performance and compare it with the current one. This parameter addresses to a very important (and realistic) capability of individuals: to look back at past choices, and eventually change decision making. This is what Argyris & Schoen (1996) call double loop learning, and Bateson (1972) calls learning of the first (logical type) level. Either the frequency of past performance analysis or the propensity to change their expenditure mix are parameters that can be varied and differentiated between agents. The path- and perception- and cognition-dependent type of learning processes makes it very close to the situated learning theorized in communities and networks of practice literature (Brown & Duguid, 1991, 1998; Wenger, 1998; Wenger *et al.*, 2002).

CONFIGURATION OF VIRTUAL EXPERIMENTS

In each step a whole cycle of decision-action takes place, and supposing that it can represent a real context in which it lasts one week, 250 steps describe 5 years of NoP's evolution. Besides building a model of collective knowledge dynamics, the primary goal of our contribution is investigating how two strongly nonlinear distributions, like power-law and U-shaped, impact on the amount and speed of both tacit and explicit knowledge, respect to what happens with the normal and uniform distributions. Therefore, experiments are executed varying ABS and Dc distributions while keeping invariant all other variables. Crossing these two variables per the four types of distributions we obtain the 16 different experiments (Table 3).

ABC and Dc are jointly distributed to the same agents, which means that their cardinality varies in the same way for each agent. However, its assignment is given randomly respect to agent's size. In other words, the highest values of ABC and Dc are not necessarily given to large agents, and vice versa. We made this choice to avoid an initial unbalance between large and small agents, even though it would have been quite reasonable and realistic. The advantage of this modelling choice is that results will be even more meaningful, because they cannot depend on biases due to a specific initial assignment of major advantages to large firms. From a field research on the aerospace cluster of the Lazio Region (Biggiero & Sammarra, 2010; Sammarra & Biggiero, 2008) it can be drawn that a Dc mean value of 0.05 can be

Table 3. Synopsis of virtual experiments

		ABC			
		Normal	**Power-law**	**Uniform**	**U-shaped**
Dc	**Normal**	Exp1	Exp2	Exp3	Exp4
	Power-law	Exp5	Exp6	Exp7	Exp8
	Uniform	Exp9	Exp10	Exp11	Exp12
	U-shaped	Exp13	Exp14	Exp15	Exp16

considered quite realistic. We set up it varying from 4 to 7% for the irregular and between 4 and 5% for the regular distributions. Unfortunately, lacking any empirical cues about real ABC values, we chose varying it in the same way of Dc. Then, in order to explore whether and how results are sensitive to parameters scale, we have run experiments with higher values obtained by multiplying per 10 the previous values. Because of the high number of variables and the value that each variable may assume for each agent, it's assumed that virtual experiments differ only in terms of agents' ABC and Dc. All other variables (Table 4) are distinguished between those that are differentiated among agents and those that have the same initialization for all agents. Anyway, it should be underlined that all variables can be differentiated for any single agent, hence giving KNOWTIC Model a high potentiality of experimental research and theory testing.

Variables with different initialization among agents. The community is composed of 48 firms (Table 4), a small number that allows a good control over the simulation. Indeed, this is too the sample size of the abovementioned research on the Lazio Region aerospace IC. The whole cluster was estimated to count around 80 agents, research centers and private/public institutions included, out of which 12 large agents, who are visible by all the others. In our model all agents are divided evenly among the four areas of major geographical proximity, among which large agents are proportionally distributed too. Thus, 16 large and 32 small agents as a whole, partitioned into 4 large and 8 small agents in each geographical area. As stated before, all large agents are visible in the whole network, while small firms are visible only within their belonging area. However, according to the conditions discussed in the previous section, even small firms could be visible at the whole level, if they overcome a *visibility threshold*, which is set up at 0.06, because this value is three times bigger than the value of the share of knowledge and patents an agent would hold in case of an even distribution.

Large firms have been supposed to have more resources, human capital and knowledge stock than others to be employed to learn from their past experiences. Hence, they do it with a frequency of 10% while the others only 5%. Consistently, initial knowledge stock is set up at 100 units for small and 200 for large agents, and research expenditures budget is as well differentiated: 1 for small and 3 for large agents. Thus, since the formers are the double (32) than the latter (16), the amount of initial knowledge is equally distributed between the two groups of agents.

Table 4. Configuration of virtual experiments

Variables with Different Initialization	Variables with the Same Initialization
Geographical structure: agents are evenly divided into four different areas of major proximity.	**Propensity to change the mix of research expenditures**: 10% of the whole budget.
Agents' size: in each experiment we have 16 large agents and 32 small agents.	**Practices (knowledge) complexity**: 0.5 (it can be initialized from 0 to 1).
Visibility threshold (of small agents): 0.06.	**Percentage of non-collaborative expenditure**: 50% of resources.
Learning attitude: 0.10 for large agents, 0.05 for the others (it can be initialized from 0 to 1).	**Knowledge productivity in terms of expenditure capacity**: 0.05 per knowledge unit (it cumulates).
Amount of initial knowledge: 100 for small and the double for large agents.	**Knowledge costs**: 1 for non-collaborative research and 1.2 for collaborative.
Fixed amount of research budget: 1 for small and 3 for large agents.	

Variables with the same initialization for all agents. The percentage of non-collaborative expenditure was set up uniformly to 50% in order to not unbalance simulation from the beginning with a specific preference of expenditure. When agents decide to change their mix of research expenditures, they have a fixed propensity of shifting 10% of their budget from collaborative to non-collaborative strategy, or vice versa. Hence, average and individual propensity to collaborate can and will likely change over time. However, given different agents' size and knowledge stock due to agents' micro-interactions game, nothing can be predicted about the effects of their propensity on the resulting knowledge stock in terms of collaboration channels, as well as their achievement through imitation or innovation.

Practices are supposed to be at an intermediate level of complexity, again in order to keep these simulation neutral respect to this aspect. Knowledge productivity, which determines budget increment (for research expenditure) is fixed at 5%. Knowledge costs, which (in conjunction with the available research expenditure budget) determine the amount of knowledge that could be acquired through collaborative and non-collaborative research, are supposed to be more costly than in the former case, due to human resources employed in collaborating.

Initial knowledge stock, research budget, knowledge cost and its productivity in terms of consequent expenditure capacity are set up in a way that, in the very early steps, it is impossible to increase agent's knowledge more than 5%. This configuration choice aims at getting a balanced initial setting, so to reduce any arbitrary modeling distortion of results. According to the findings of field research on the aerospace IC, it seems a realistic picture if a simulation step represents a working week, as we have chosen. For this analysis is not aimed to study equilibrium conditions, results are distinguished and compared to the 100^{th} and 250^{th} steps. In fact, for all other parameters are supposed unchanged and each step is supposed to equal a working week, it is reasonable that a mature IC and its underlying NoP can keep invariant for five years, at least as concerning its main traits, like density and topology, learning mechanisms, propensity to collaborate, etc.

Most results are referred to the whole community, that is at aggregate level, and they are the average of 100 runs per each experiment, measured in terms of the following indexes:

- Total knowledge (TK),
- Total knowledge realized by visible agents (VIK),
- Total knowledge obtained through imitation (KIM);
- Total knowledge held by the best agent (TKA),
- Non-collaborative knowledge (NCK),
- Total expenditure (TE),
- Tacit knowledge (TaK),
- Imitation (IME) vs. innovation (IVE) events (in average),
- Share of innovators on total firms (INF/TF).

THE MAIN RESULTS

Static Analysis

In average, with ABC and Dc low initial values nothing really changes in all the 16 experiments. Thus, NoPs keep stable and distributions are not able to differentiate outcomes. Conversely, with high initial values, total cumulated knowledge (TK in Figure 3) varies – even if not considerably - among distributions, as indicated by a 17% coefficient of variation. Interestingly, the maximum value corresponds to the most unbalanced distribution, which is the Exp6 when the scale-free holds for both the key-variables (ABC and Dc). The following better scores correspond to Exp14, 2, 10 and 8, but while these are grouped in 20 points of distance, between the first (Exp6) and the second (Exp14) there are 30 points gap. Hence, that gain is much more relevant than what is obtained raising from the fifth to the second best distribution. Even more noteworthy, in all the four experiments (14, 2, 10 and 8) there is still at least one of the two key-variables distributed in a scale-free shape. Conversely, the lowest performance occurs in Exp1, 3, 9 and 11, where ABC and Dc are normally or uniformly distributed. It seems hence that the more unbalanced are the distributions the better the performance, and in fact the scale-free, which is more unbalanced than the U-shaped, gives the major outcomes. Further, in three out of the four experiments the scale-free shape refers to ABC, that is, it seems that, respect to Dc, ABC scale-free distribution is more effective in enhancing the generation of major knowledge. These five best outcomes are also the ones – and matching the respective proportions - in which the increment has been much larger during the second stage (between the 100^{th} and the 250^{th} step). It shows that the unbalance effects occur over time in a reinforcing process.

The highest cumulated knowledge produced by visible firms (ViK), which rounds about 68%, replicates what we found for total knowledge, with an even more accentuated gap between the first and the following four, and with more variability between all experiments (coefficient of variation 27%). Also in this case the major increases occurred during the second stage and was higher for the five better performing distributions, but interestingly the net gain was 3-4 percentage points systematically higher than that for total knowledge. And the best combination (when both ABC and Dc are scale-free) scores an increment about 7 percentage points superior. This means that visible firms are the most benefited by an uneven distribution, and over time they increase their share on total knowledge. In fact, it rounds about 56% across all the 16 combinations at the 100^{th} step, and though it increases about 6-10 percentage points in any experiment, it reaches 25 points more in Exp6, and it is also much higher for the following four second bests (Figure 4 and Table 5 in Appendix 1). Here, as well as for total knowledge, worst performances correspond to the most balanced distributions.

Figure 3. Various types of cumulated knowledge and total expenditure

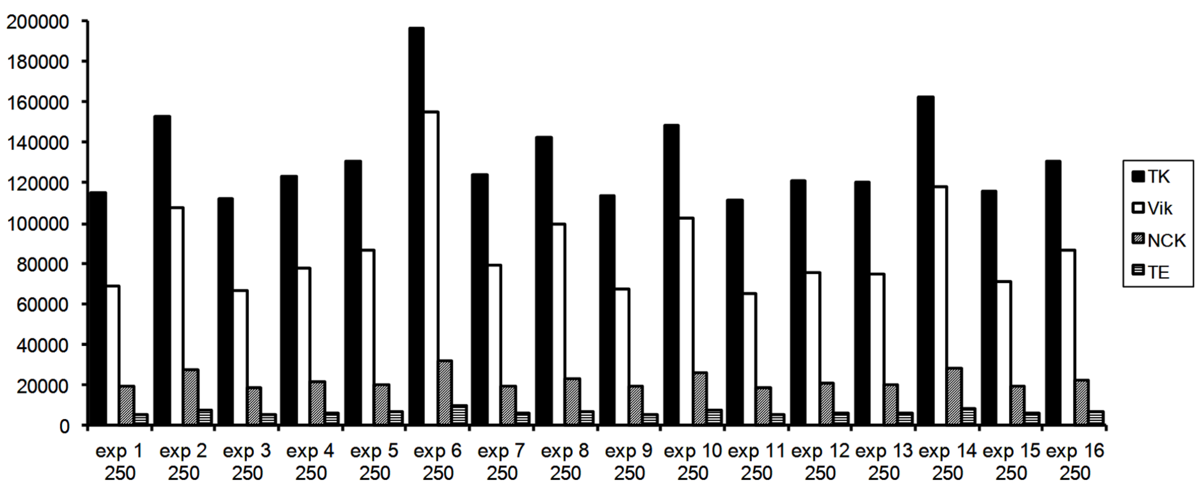


Figure 4. Shares of knowledge of visible firms, leader firms, and tacit knowledge

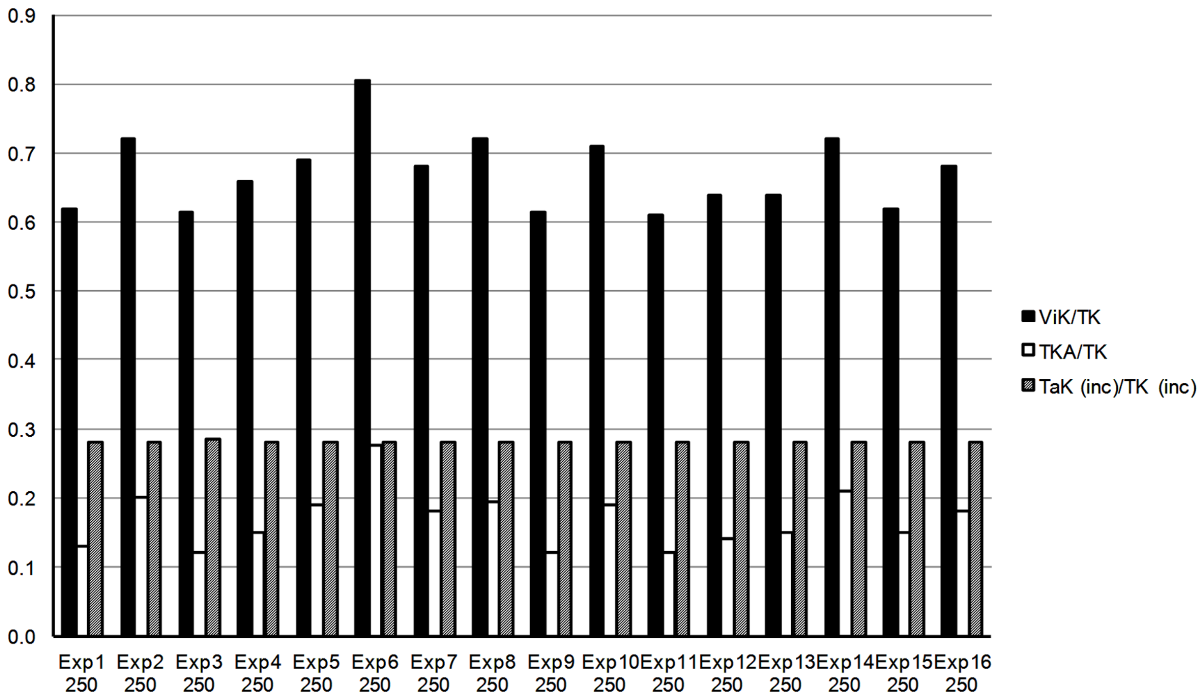


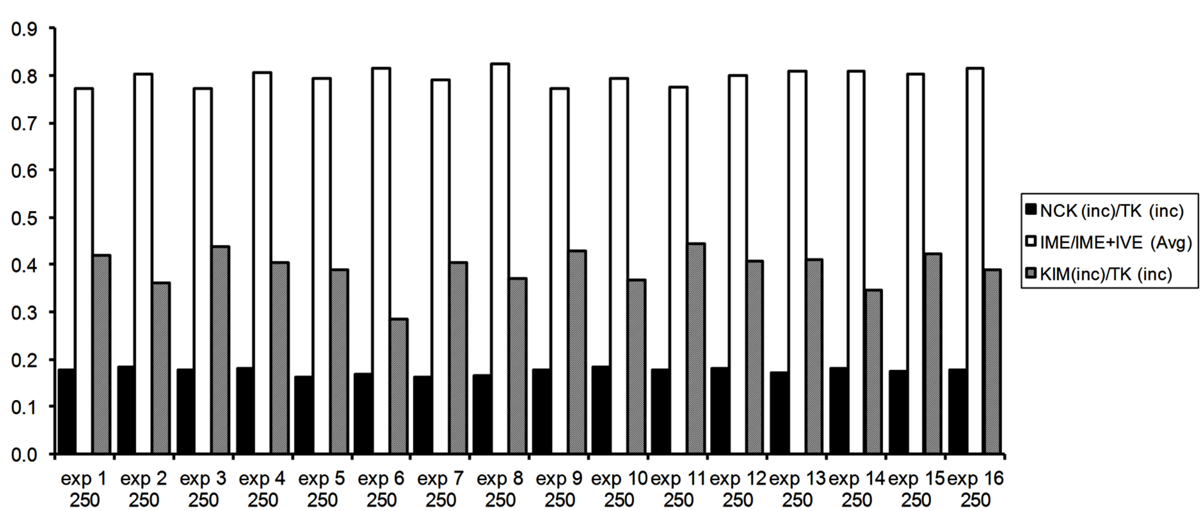
Table 5. Performance ranking of all experiments in terms of TK and ViK

Exp/step	TK	Exp/step	ViK
Exp6 250	196229	Exp6 250	158000
Exp14 250	162653	Exp14 250	120913
Exp2 250	153067	Exp2 250	111148
Exp10 250	148452	Exp10 250	106030
Exp8 250	142292	Exp8 250	102913
Exp16 250	130843	Exp5 250	89260
Exp5 250	130292	Exp16 250	89237
Exp7 250	124003	Exp7 250	82392
Exp4 250	123282	Exp4 250	80890
Exp12 250	121101	Exp12 250	78504
Exp13 250	120090	Exp13 250	77816
Exp15 250	116040	Exp15 250	73787
Exp1 250	115090	Exp1 250	71949
Exp9 250	113848	Exp9 250	70479
Exp3 250	112539	Exp3 250	69421
Exp11 250	111452	Exp11 250	68266

Data shows also that the advantage of unbalanced ABC and Dc distributions benefits especially the best agent, whose share on visible firms (excluding itself) reaches 50% in Exp6 and rounds about 38% for the four (Figure 4). Hence, we can say that the higher knowledge produced is largely due to the faster growing performance of the best firm, and (again) this gain is reinforcing and occurring mostly in the second stage. Moreover, if we consider that at the end of the first stage its share is about 10% in all combinations, in the double scale-free case the leader firm increases five times its share. It means that there is a self-reinforcing process, and that its speed grows following the skewness of the distribution. Noticeably, this does not seem to occur at the expense of the other firms, but mostly by "enlarging the pie", that is by making the cluster more performing in general in terms of cumulated knowledge. Hence, under nonlinear ABC and Dc distributions visible firms pull NOP's knowledge growth. As concerning the differentiation between tacit vs. explicit knowledge, distribution forms and even parameters scales are absolutely irrelevant, holding tacit knowledge at 27% in any case (Figure 4). As well insensitive is the share of expenditure for innovation, which is stably about 50%.

The model structure and the parameters setting determine a strong prevalence (78%) of imitation over innovation *events* (Figure 5), but, quite interestingly, imitation generates less *knowledge* than innovation (39%). It means that cluster's knowledge is mostly produced by the leader and the visible firms through innovations, while small firms make – as a whole - a lot of imitations, which however do not account more than 25% of total knowledge. Moreover, both these shares are very insensitive to distribution forms, as witnessed by the small coefficient of variation (4 and 10%, respectively). However, if we look closely at their light variations, we see that the minimum KIM (knowledge by imitation) occurs in Exp6 (and in other good outcomes), when total knowledge is maximum, and that IME (imitation events) is maximum in Exp1 (and very high in other bad outcomes). Hence, it is clear that good knowledge performances are determined by innovation events, which, by means of competitive advantages that few visible firms acquire with unbalanced distributions, produce more knowledge than imitation events realized by many small or peripheral firms.

Figure 5. Imitation choices, knowledge through imitation and innovation



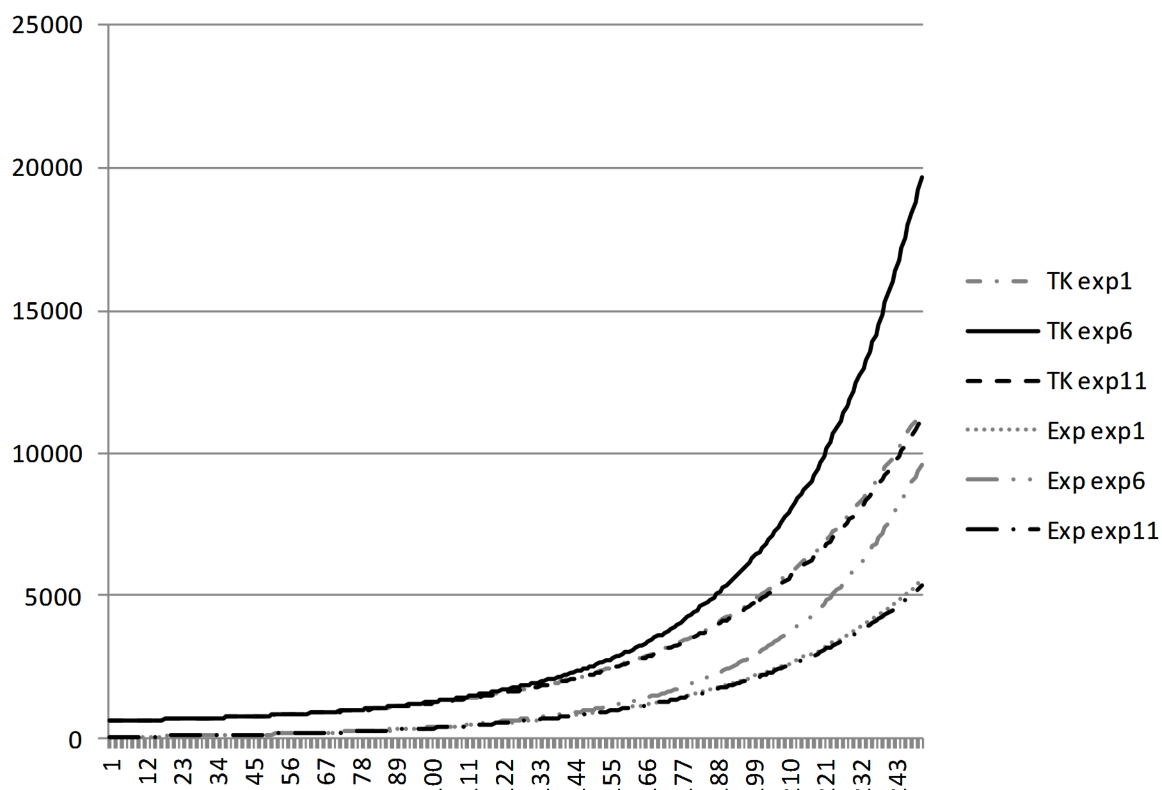
As can be seen from the following table, if we measure NoP performance in terms of cumulated knowledge, experiments lying in diagonal (Table 5) by combining the same distribution of both the key-variables show the most interesting combinations. Both total and visible knowledge rank experiments in almost the same order, in which Exp6 is at the top and Exp16 at the sixth place: that is, the most unbalanced configurations are the best performing. At the opposite, the most even distribution – the uniform-uniform of Exp11 – is the worst one, and the normal-normal (Exp1) is very close to it. Hence, instead of commenting all the 16 configurations, in the following dynamic analysis we will address the attention to all or some of the four in diagonal: Exp1, Exp6, Exp11, and Exp16.

Dynamic Analysis

Shifting the attention to dynamics, we see (Figure 6) that the normal-normal and the uniform-uniform distributions behave in the same way, either in terms of total knowledge (TK) or in terms of economic resources employed to produce it. Conversely, the double scale-free structure produces a fast knowledge growth, and at the same time it consumes an enormous amount of resources, which anyway are produced internally.

As shown in the decision-making process between collaborative and non-collaborative choices, the current model architecture gives a moderate preference for the former, and in fact in all experiments we witness to the following outcomes: 1) the increment of non-collaborative knowledge respect to the

Figure 6. Comparison of total knowledge and expenditure between three key-configurations



increment of total knowledge (NcK(inc)/TK(inc)) significantly declines after the fatal 100th step; 2) non-collaborative expenditure (NcE%) slowly declines; 3) the increment of tacit knowledge respect to the increment of total knowledge (TaK(inc)/TK(inc)) significantly grows after the fatal 100th step, because tacit knowledge is produced only through collaborative behavior. Moreover, these trends are substantially insensitive to the different combinations of ABC and Dc distributions. Therefore, we will not show these indicators when commenting the other experiments. Among the four indicators showed in Figure 7a, the only one that markedly change is that of the productivity of budget expenditure in terms of knowledge increment (K(inc)/Exp), which grows in all experiments remaining between 30 and 40%, excepted for Exp6 where it reaches 50%. Hence, this confirms that when ABC and Dc are very nonlinearly distributed investments are much more productive in terms of knowledge growth (still at the aggregate level).

Figure 7b shows that the share of knowledge produced by visible agents (ViK/TK) constantly grows, and it is followed by that produced by the knowledge leader agent (TKA/TK) covering little less than 10% of the former. A look at the other experiments shows that the same happens in all experiments, but in Exp6 both curves grow more sharply, and in particular that of the knowledge leader. Clearly, the major knowledge growth enhanced by power-law distributions occurs by favouring the pulling role played by visible agents and especially by the knowledge leader among them.

Imitations, which already start at 65% of events, grow up to 80% (IME/IME+IVE(avg)), because the more (few) visible agents produce knowledge over the average, the more followers choose to imitate instead of innovate by themselves. Consistently, the share of innovators over all agents (INF/TF) declines correspondingly. However, the increment of knowledge produced by imitation (KIM(inc)/TK(inc)) slows about the 160th step, and soon starts declining. This effect is due to the fact that, even if the number of imitation events grows their knowledge content is progressively inferior, because realized by agents with a weak capacity to produce knowledge (small budget to be invested, small knowledge productivity of such budgets). As expected, all these trends hold for the other experiment too, but with the usual difference between the more and the less unbalanced distributions: the latter (Exp16) shows the mildest variations, while the former (Exp6) the sharpest. In fact, at the end of simulation time (250th step), in front of 80% of imitation events respect to all events, their contribution to knowledge growth falls down 30% (from an initial 40%).

Figure 7. The dynamics of some main indicators in Exp1 and Exp6

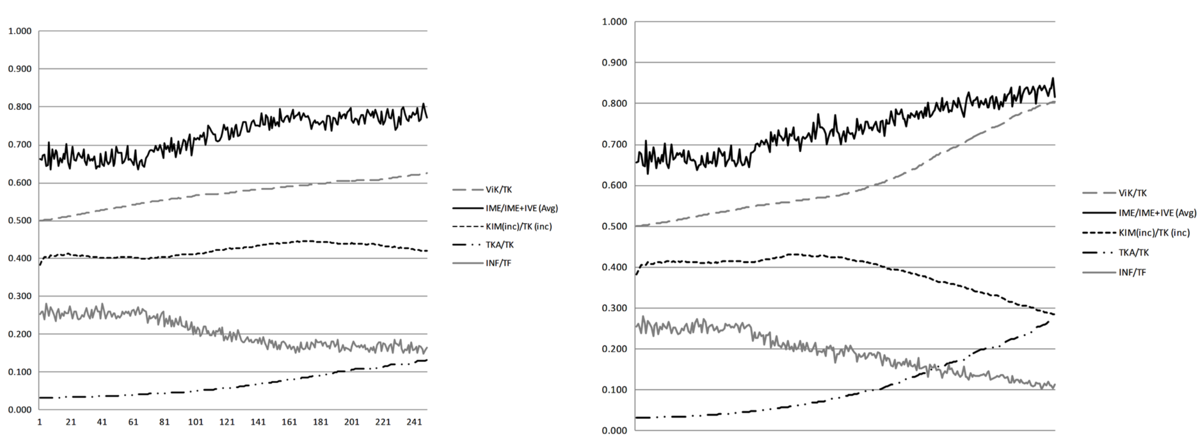
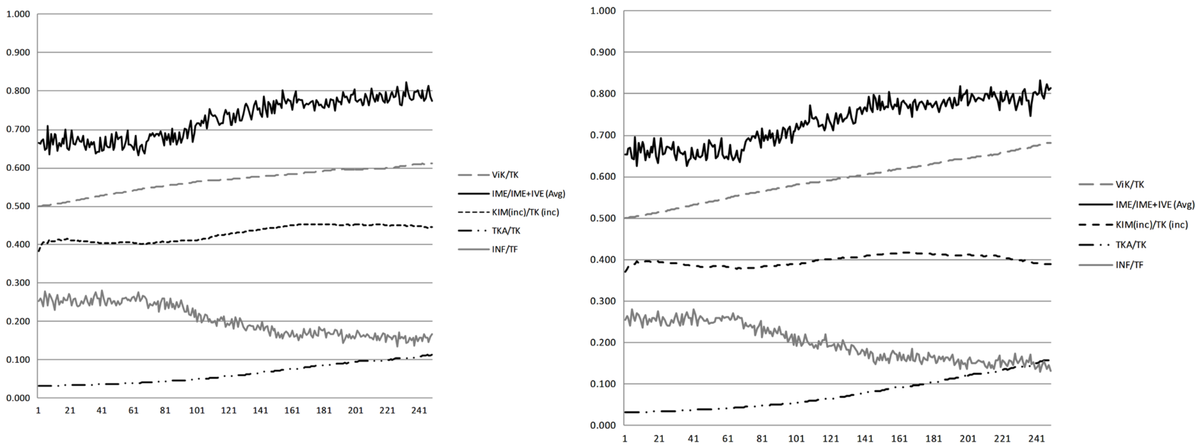


Figure 8. The dynamics of some main indicators in Exp11 and Exp16

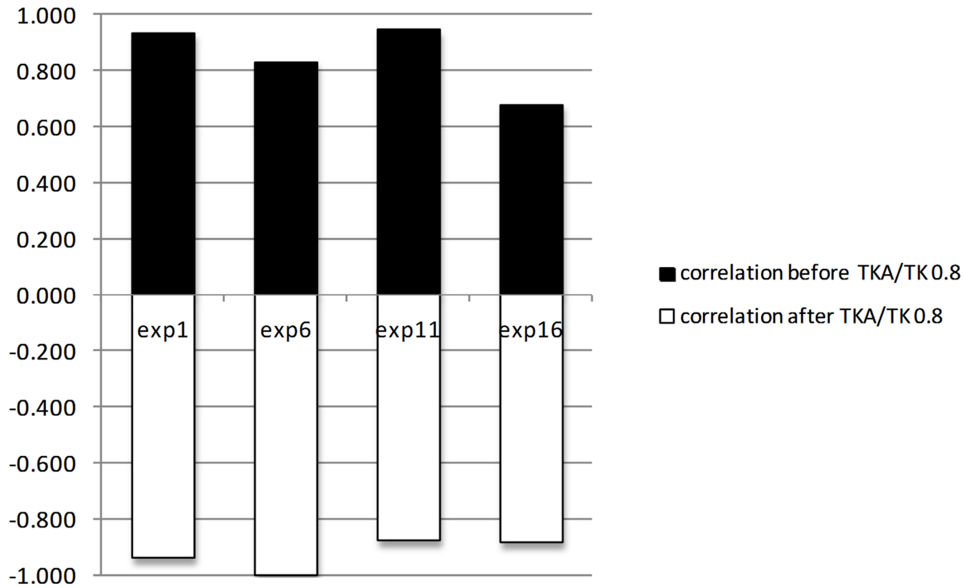


As shown in previous analysis, all relevant changes appear around the 80th step: some variables strongly accentuate their slope, like TKA/TK, while others even revert it, like KIM(inc)/TK(inc). In order to focus the trends of these two interesting variables, we have calculated their correlation before and after the 80th step (Table 6 and Figure 9). This correlation is particularly instructive, because it shows that the leader's knowledge share is highly correlated with knowledge increments by imitation respect to total knowledge increments. However, before the 80th step correlation is positive while after it is negative. It means that, because good knowledge performers (not only the leader[11]) do innovate and not imitate, as far as their share of total knowledge grow, imitation events (and the corresponding knowledge share produced that way) decreases, and NoP becomes more and more innovative. More interestingly, before the breakpoint the four highest correlations occur with the most linear distributions, expressed by Exp11 (double uniform), Exp3 (uniform-normal), Exp9 (normal-uniform), and Exp1 (double normal). Conversely, after the 80th step the four highest correlations correspond to the most nonlinear distributions: Exp6 (double power-law), Exp14 (power-law with U-shaped), Exp8 (U-shaped with power-law), and Exp10 (power-law with uniform). Therefore, nonlinearity divaricates the trends of leader's knowledge and imitation events. Moreover, even in this case, when comparing the influence of ABC and Dc nonlinearity, we see that the former is much more influential, because it appears in any of the early eight experiments showing the highest (negative) correlation values after the breakpoint.

Table 6. Correlation between TKA/TK and KIM(inc)/TK(inc)

	exp1	**exp2**	**exp3**	**exp4**	**exp5**	**exp6**	**exp7**	**exp8**
correlation before TKA/TK 0.8	0.935	0.914	0.937	0.803	0.883	0.833	0.896	0.795
correlation after TKA/TK 0.8	-0.941	-0.994	-0.928	-0.853	-0.994	-0.999	-0.992	-0.995
	exp9	**exp10**	**exp11**	**exp12**	**exp13**	**exp14**	**exp15**	**exp16**
correlation before TKA/TK 0.8	0.937	0.918	0.945	0.815	0.847	0.900	0.855	0.682
correlation after TKA/TK 0.8	-0.946	-0.995	-0.879	-0.792	-0.940	-0.998	-0.883	-0.885

Figure 9. Correlation zooming on the four critical experiments with identical distributions



DISCUSSION AND CONCLUSION

We can summarize the most important results as follows:

- The more nonlinear are ABC and Dc distributions the better the performance, and in fact the scale-free, which is more unbalanced than the U-shaped, gives the major outcomes, while worst performances correspond to the most balanced distributions of ABC and Dc;
- Visible firms - and especially the knowledge leader - are the most benefited by nonlinearity, and over time they increase their relative share on total knowledge;
- Better performances corresponding to the strongly nonlinear distributions configurations are obtained by improving and speeding up the whole network, and not at the expense of less performing agents: under nonlinear ABC and Dc distributions visible firms pull NOP's knowledge growth;
- ABC and Dc distribution leaves untouched the partition between tacit and explicit knowledge;
- Though imitation events outrank innovation events, good knowledge performances are determined by innovation events, which, by means of competitive advantages that few visible firms acquire with unbalanced distributions, produce more knowledge than imitation events realized by many small or peripheral firms;
- Assuming the two variables at the same level, ABC distribution is more influential than Dc distribution;
- In more performing combinations knowledge production considerably increases;
- In order to allow an IC-NoP significant growth and to produce differences between the various combinations, average level of capabilities in terms of ABC and average level of connectedness should be sufficiently high. In other words, IC-NoPs characterized by lowly connected firms which have weak absorptive capacity do not evolve

- Finally, it should be noticed that all these results have been obtained by varying the distribution shape, and only very marginally value ranges: just two points in the maximum value. Moreover, simulations have been designed in order to keep, at the beginning and early stages, all variables very balanced, excepted ABC and Dc in some experiment.

The model discussed by Cowan *et al.* (2004) is not directly comparable with ours, because it does not consider the same variables and it is aimed at investigating other issues. Moreover, while they put an inverse relationship between ABC and TaK, we supposed a direct relationship. However, our results are compatible with their and with the other scholars who investigated the role of ABC at cluster level (Camison & Forés, 2011; Giuliani, 2005; Lane & Lubatkin, 1998; Nicotra *et al.*, 2013). As well compatible it is with Carbonara's results of next chapter, but while the two models allow in principle to design experiments to test some common hypothesis the actual experiments designed here and there address different issues, and thus, it is not possible a strict comparison.

In short, we can say that when both ABC and Dc are distributed in a scale-free form, in few years NoP's knowledge creation and innovation capacity speeds up, and investments in innovation become more efficient. However, this outcome is obtained at the price of a sharp and progressive polarization of the NoP structure and roles. Even though the distribution of the two key-variables did not change – as in our model – small firms (and some large too) will shift even more peripherally, and subordinate to what the leader and some large firms will do. Similar (but smoothly) results would be obtained from a combination of scale-free and U-shape distributions. Conversely, with more balanced distributions NoP grows slower and less efficiently, even though more balanced in terms of innovation/imitation and collaboration/autonomy ratios. Absorptive capacity and degree centrality distributions cease to produce any distinction if their values are low, because NoPs fall down in a very static state.

Of course, these results cannot be generalized too much, because there can be many other counterforces that balance nonlinear effects of absorptive capacity and degree centrality. Some of them could be explored with the KNOWTIC Model as it is now, just varying in a future research agenda all the other variables that here have been kept fixed. A further interesting analysis could be done by distinguishing the analysis per the four sub-cluster areas with higher proximity. Among the others, it could allow to answer to the relevant question whether the outcomes split uniformly between them or concentrates in high- and low-performing areas. It would be also very interesting to investigate scale effects regarding agents number, and some initial conditions about the proportion between large and small firms, and many other initial or structural conditions. However, notwithstanding its simplicity, this model can give interesting suggestions and establishes some clear conceptual relationship concerning the ways in which knowledge is produced and distributed under the given assumptions. In this perspective, the present contribution underlines the fundamental role played by ABC and Dc distribution. In particular, the strong positive effect given by the scale-free distribution seems very consistent with the empirical fact that many (most?) real inter-organizational R&D collaboration networks, like the EURJVs, are scale-free shaped, likely in many sectors, and certainly in the aerospace sector (Biggiero & Angelini, 2014).

The risk to oversimplify real phenomena crosses scientific research and grow in social and natural sciences since ever, and it heavily impacts on agent-based simulation modelling. In this perspective, this model doesn't accomplish the KISS (Keep It Simple, Stupid) requisites, because it is already too complex. It's much more complex than that built by Cowan and colleagues (2004). It's complexity is closer to that built by Brenner (2004) into the (near) field of ICs formation and growth. KNOWTIC can be defined as a rich middle-range model, which can deal with a large class of phenomena concerning how various types of knowledge are produced and distributed inter-organizational R&D collaboration networks.

The major limitations of this model, which could be indeed overcome by enriching this model towards a more realistic, are the following:

- There is no any turn-over of agents, that is nobody enters or exits the community;
- Agents cannot increase or decrease their size, and neither move among the four geographical areas;
- ABS and Dc are fixed during the simulation;
- Production and trade of goods are neglected;
- There is not a true topology, because the various distributions are built just varying quantitative ABC and Dc values. Therefore, it was not possible to concern also the small-world structure, which indeed is the other interesting hypothesis to be tested, due to its wide diffusion among real inter-organizational R&D collaboration networks.

However, these limitations are moderated by the assumption that the hypothesized NoP is mature and it is observed for a limited time run. Other major limitations are the following: i) knowledge is not distinguished in technological, market and managerial or other types of categorizations; ii) single innovations and their possible imitations cannot be traced; iii) agents spend all the budget in each step preventing the accumulation of R&D capital; iv) there is not a portfolio strategy among different types of knowledge acquisition. The latter two aspects play more severely regarding large agents. Finally, knowledge is oversimplified in a scalar, instead of being articulated in a vector of characteristics, so to enable complementarity and specificity effects.

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ENDNOTES

1. To know more about the – currently inconclusive – debate about the differences between ICs and industrial districts, see: Belussi & Caldari, (2009), Biggiero (1999), Markusen (1996), Paniccia (2002), Porter (1998a, 1998b), Storper (1995). Indeed, as anticipated by Nooteboom and colleagues (2007) and recently confirmed by Broekel and Boschma (2012) proximity should not be too short, because the advantages become obstacles to innovation and growth.
2. For further remarks on this issue, see the Chapter 1 of this volume.
3. It could be said also: from intra- to inter-organizational networks.
4. They could be seen also as evolving routines between organizations.
5. For a better understanding of the importance and interpretation of direct centrality in network topology, see also other references on network analysis, and especially on social network analysis discussed in the Chapter 2 of this volume.
6. This model has potentialities that go far beyond the specific use we made in this paper.
7. For details, see next two sections on the model architecture and main variables.
8. Perhaps, one of the nearest model is that presented in Chapter 14 by Nunzia Carbonara.
9. Indeed, it overlooks many other aspects, namely: social, and institutional, technological, financial, demographical, and other aspects related to the competitive environment faced by the cluster. Moreover, even the 12 variables dealt with are not modelled at fine grain, otherwise they would generate dozens new variables, and a consequent overwhelming complexity. On the other hand, IC are entire economies on a small scale, with the consequent untreatable complexity. Therefore, each agent-based cluster model drastically simplifies the cluster representation.

[10] Indeed, there can be many contexts where, especially for radical or pioneering in-house innovations, collaborations would be cheaper.

[11] Indeed, a similar correlation would occur if we substituted TKA/TK with ViK/TK, that is leader's knowledge share with that of visible firms.

APPENDIX 1

Tab. 7 Scores of the main parameters at the 100th and 250th step

(10 simulations Avg)	Exp1 100	Exp1 250	Exp2 100	Exp2 250	Exp3 100	Exp3 250	Exp4 100	Exp4 250	Exp5 100	Exp5 250	Exp6 100	Exp6 250	Exp7 100	Exp7 250	Exp8 100	Exp8 250
TK	12704	115090	12985	153067	12667	112539	12876	123282	12783	130292	13094	196229	12726	124003	12950	142292
StD (last step)	573.0	15750.1	570.9	19150.3	564.5	14429.7	601.4	17945.7	589.3	17717.4	595.9	37640.0	574.7	16227.6	608.6	17436.9
ViK	7177	71949	7298	111148	7140	69421	7390	80890	7240	89260	7386	158000	7188	82392	7436	102913
ViK/TK	0.56	0.63	0.56	0.73	0.56	0.62	0.57	0.66	0.57	0.69	0.56	0.81	0.56	0.66	0.57	0.72
TKA	616	15124	734	30275	609	13457	659	17705	676	24385	824	52871	658	21648	714	27554
TKA/TK	0.05	0.13	0.06	0.20	0.05	0.12	0.05	0.14	0.05	0.19	0.06	0.27	0.05	0.17	0.06	0.19
NcK (inc)/TK (inc)	0.24	0.18	0.25	0.18	0.24	0.18	0.25	0.18	0.24	0.16	0.25	0.17	0.24	0.16	0.24	0.17
NcE% (Avg)	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.48	0.49	0.48	0.49	0.49	0.49	0.49
NcE% (last step)	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.47	0.48	0.47	0.48	0.47	0.48	0.48
TaK (inc)/TK (inc)	0.25	0.27	0.25	0.27	0.25	0.27	0.25	0.27	0.25	0.28	0.25	0.28	0.25	0.28	0.25	0.28
IME/IME+IVE (Avg)	0.67	0.72	0.68	0.73	0.70	0.77	0.70	0.81	0.67	0.73	0.68	0.74	0.71	0.79	0.71	0.83
KIM (inc)/TK (inc)	0.41	0.42	0.43	0.36	0.41	0.44	0.40	0.40	0.41	0.38	0.43	0.29	0.41	0.40	0.40	0.37
(10 simulations Avg)	**Exp9 100**	**Exp9 250**	**Exp10 100**	**Exp10 250**	**Exp11 100**	**Exp11 250**	**Exp12 100**	**Exp12 250**	**Exp13 100**	**Exp13 250**	**Exp14 100**	**Exp14 250**	**Exp15 100**	**Exp15 250**	**Exp16 100**	**Exp16 250**
TK	12691	113848	12955	148452	12657	111452	12853	121101	12780	120090	13065	162653	12736	116040	12968	130843
StD (last step)	576.1	15595.1	566.7	18207.6	564.8	15332.3	600.3	16946.8	607.5	18069.9	598.8	20752.1	588.4	15324.3	597.7	18266.0
ViK	7157	70479	7262	106030	7127	68266	7363	78504	7284	77816	7406	120913	7241	73787	7503	89237
ViK/TK	0.56	0.62	0.56	0.71	0.56	0.61	0.57	0.65	0.57	0.65	0.57	0.74	0.57	0.64	0.58	0.68
TKA	613	13873	720	27833	606	12668	652	16270	645	17534	751	33510	635	15541	699	21028
TKA/TK	0.05	0.12	0.06	0.19	0.05	0.11	0.05	0.13	0.05	0.15	0.06	0.21	0.05	0.13	0.05	0.16
NcK (inc)/TK (inc)	0.24	0.18	0.25	0.18	0.24	0.18	0.25	0.18	0.24	0.17	0.25	0.18	0.24	0.17	0.24	0.18
NcE% (Avg)	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.48	0.49	0.49	0.49	0.49
NcE% (last step)	0.48	0.48	0.48	0.47	0.48	0.48	0.48	0.48	0.48	0.47	0.48	0.48	0.48	0.48	0.48	0.48
TaK (inc)/TK (inc)	0.25	0.27	0.25	0.27	0.25	0.27	0.25	0.27	0.25	0.28	0.25	0.27	0.25	0.28	0.25	0.27
IME/IME+IVE (Avg)	0.70	0.77	0.71	0.79	0.69	0.77	0.69	0.80	0.70	0.81	0.72	0.81	0.70	0.80	0.71	0.81
KIM (inc)/TK (inc)	0.41	0.43	0.43	0.37	0.41	0.44	0.40	0.41	0.40	0.41	0.43	0.34	0.40	0.42	0.39	0.39

APPENDIX 2

The choices between innovation or imitation and between collaborative and non-collaborative behavior have been discussed in section 3. The former choice is quite simple: the agent compares his own total knowledge with that possessed by the agents that are visible to him. Then, he innovate if his knowledge is superior and imitate if it's inferior, because it is likely that he can find competitors with better products, able to generate more knowledge. The latter choice, instead, deserves a further deepening, because it implies to consider also economic variables, as represented by the flow chart in Figure 10. Let's focus on the first step: budget control. For agents don't activate their learning function every step, budget control is not always activated. If yes, then the agent compares his own with others' average knowledge in the last step, and if it results superior he doesn't change his expenditure mix between collaborative and non-collaborative. Conversely, if he finds to be under the average, then he wonders whether his investments in knowledge are more or less productive respect to the past: that is, he compares his last knowledge/budget ratio with that he got during last 9 steps. If they equal, then he choose a stochastic expenditure mix change. Conversely, if the last investment has been more or less productive than in the past, then he decides to make an analogous comparison, now restricted only to the non-collaborative part of expenditure. In both cases – more or less productive – if the non-collaborative part of expenditure in the last step was equal than in the past, then he choose a stochastic expenditure mix change.

If last knowledge investment was more productive than in the past and if non-collaborative expenditure is too higher than in the past, then the agent concludes that this choice was successful, and thus, he decides to increase it. Analogously, if last non-collaborative expenditure was lower than in the past, then the agent concludes that this choice was successful, and thus, he decides to further reduce it. Conversely, if the last knowledge investment was less productive than in the past 9 steps, the previous reasoning should be just reversed.

Figure 10. Agent's decision making between collaborative and non-collaborative behavior