EVOLUTION OF KNOWLEDGE MANAGEMENT STRATEGIES IN ORGANIZATIONAL POPULATIONS: A SIMULATION MODEL

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Abstract

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Keywords: Knowledge Management, Information-Space, Agent-Based Simulation, Information and Communication Technologies, Organizational Populations.

Evolution of knowledge management strategies in organizational populations: A simulation model

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1 Introduction

In a knowledge-based economy, every process related to knowledge acquires a strong relevance. On one hand, knowledge creation processes are the fundamental mechanisms of economic development (Castells, 1996; Leonard, 1995). Continuous knowledge creation is needed in order to maintain the competitiveness of organizations (Leonard and Straus, 1997), regions (Storper, 2000; Audretsch, 2000; Dunning,) and industrial clusters (Porter, 1998). But, on the other hand, knowledge creation is worthless if the adequate processes of knowledge diffusion are not in place (Boisot, 1998; Stein and Ridderstrale, 2001; Winter and Szulanski, 2002). Knowledge created at one point in time and space has to reach the place where it is needed at the time it is needed. It is the adequate combination of fruitful knowledge creation and effective knowledge diffusion that fosters businesses performance and economic growth in an economy where Schumpeter's concepts of "creative destruction" and "new combinations" rule (Schumpeter, 1934; Teece, 2000).

Therefore, knowledge management strategies adopted by firms and institutions are extremely relevant. Indeed, they need to define the adequate strategic actions to foster creation, sharing and use of knowledge within the organization (Davenport and Prusak, 1998). However, in an increasingly networked economy internal processes are not the only ones that matter. Sometimes they are not even the most important. The way and pace knowledge is diffused from the organization where it is created to others has an increasing importance in the present economy (Appleyard, 2002; Ciborra and Andreu, 2002). Even creation of knowledge is often the consequence of collaborative projects between private firms and public institutions (Matusik, 2002). External knowledge flows among different economic actors take in this scenario a special relevance. The management of incoming and outgoing knowledge flows—which cannot be treated separately from the management of internal knowledge flows—must be carefully taken into account in the definition of the strategy.

Strategic knowledge management has been studied from several points of view in the last years, but often looking only at the intra-organizational level. There is, of course, an important tradition in management theory on strategic alliances that takes into account knowledge as an important factor (Fischer et al. 2002) and also a growing concern about knowledge spillovers in economic and management literature (Almeida and Kogut, 1999; Audretsch, 2000; Caniëls and Verspagen, 2001). However, in the mainstream knowledge management literature, the emphasis has been in the processes having to do with knowledge which take place internally to the organization. Less attention has been given, though, to knowledge processes that involve more than one organization and very few to the effects of knowledge-related strategic choices in large groups of organizations or organizational populations. There is, indeed, a gap in the supra-organizational perspective of knowledge management, which is specially important for the analysis of the effect of strategic choices related to knowledge in the development of industrial sectors or regional economies.

Some organization theory perspectives like corporate demography (Carroll and Hannan, 2000) and organizational ecology (Hannan and Freeman, 1989) provide a possible alternative framework to that view in substituting the population of organizations in a given industrial sector or region for the individual organization as a standpoint. Instead of looking at the knowledge management strategies of single organizations, one can look at the distribution of different knowledge management strategies within a population of organizations. Of course, this can be done at the expense of reducing the level of detail in the study of individual strategies. However, in our view it renders also interesting possibilities that complement more traditional knowledge management studies. First, it is an adequate view—as stated above—for situations in which knowledge creation and diffusion relies more in networks of organizations in an industrial sector or a region than in individual firms. Second, it allows for the study of the simultaneous presence of different strategies interacting in a given turf. Third, it permits an evolutionary perspective. Organizational populations evolve: new organizations are created, some organizations survive and others disappear due to their performance.

In the research we present here we use the organizational population perspective in the study of the effects of diverse knowledge management strategies. We make use of the I-Space conceptual framework proposed by Boisot (1995; 1998; 1999) to develop an agent-based simulation model of an organizational population. Agents in the model represent individual organizations, each with given knowledge management strategies, belonging to an industrial sector and situated at specific locations within a spatial region forming a geographic cluster (Porter, 1998).

The analysis of the results on the evolution of organizational populations and knowledge management strategies after running the model will result in the generation of hypotheses that will be able to be eventually empirically tested in further research.

2 Knowledge Management Strategies and Organizational Populations

Nowadays, there is no doubt that the way firms and institutions manage their knowledge has a tremendous impact in their performance. The knowledge management strategies adopted by organizations affect not only their internal processes of knowledge creation and transmission, but also their interaction with other organizations and with individuals.

The degree to which knowledge can be voluntarily transferred to other organizations or the importance of knowledge spillovers will depend, for instance, on the nature of the knowledge used. Explicit, structured knowledge is much easier to use and transfer, but it is also much more susceptible to leak to competitors (Boisot, 1998). Therefore, a strategic preference for working with structured knowledge, that fosters the extraction of value, facilitates also the loose of value of that knowledge through leakages to competitors. A hoarding strategic choice by blocking diffusion through legal instruments like patents or copyrights or just by hiding knowledge can counter-rest this danger. But it can turn out to be not the best choice in a Schumpeterian environment, where sharing can turn out to be a better strategic choice (Boisot et al. 2003).

In the study of the behavior of organizational populations, the individual strategic choices adopted must be taken into account when the objective is describing the mechanisms guiding the evolution of a group of organizations. We want to make use of a simulation model to try and shed some light on how some knowledge management strategies can influence the evolution of a group of firms or institutions. In the following sections we will describe the kind of strategic choices we will consider and the possible effects in the evolution of groups of organizations.

2.1 Knowledge Management Strategies

Knowledge management strategies in organizations can be very diverse and complex. Of course, at least in social sciences, one cannot think of introducing all features of the real world into a simulation model: to be of any utility, a simulation model must be simpler than reality. The model must remain as simple as possible while being able to represent with enough detail the relevant features of the object of study. Thus, we will introduce in our model only the two aspects of the knowledge management strategies whose analysis we consider more relevant in a population of organizations.

The first is diffusion blocking. Firms can adopt a strategy aimed to block the diffusion of knowledge once it has been codified and abstracted—by means, for instance, of patents or simply by hiding it—or they can pose no objection to the free flow of knowledge, hoping that this will influence the sector and the marketplace in their favor.

The second is the level of structuring (codification and abstraction) at which they want to work. Working with highly structured knowledge makes it easier to use and to share it but, by the same token, facilitates knowledge leakages and therefore makes it difficult to extract value from it. The probability of diffusion of a knowledge asset depends on its level of structuring.

2.2 Organizational Populations and Knowledge

The study of organizational populations introduced a new standpoint into the organization theory literature. Instead of focusing on specific characteristics of individual firms, the scope was broadened to a whole industry or to a set of firms selected using some specific criteria. As organizations have to live in an environment which is mostly formed by other organizations like competitors, suppliers, clients or institutions (Porter, 1980), it is no nonsense to look at the joint evolution of all of the firms belonging to a geographical cluster, an economic sector or a whole industry.

Adaptation and Selection. Research on organizational evolution has been driven by two conflicting approaches (Levinthal, 1991). One perspective has focused in the process of adaptation of firms to the environment, while the other has emphasized the variation in organizational forms as a way to survive on a population basis through a selection mechanism. To the first group belong the behavioral theory of the firm (Cyert and March, 1992) or the evolutionary theory of economic change (Nelson and Winter, 1982). The second group can be represented by the organizational ecology perspective (Hannan and Freeman, 1989) or the organizational demography (Carroll and Hannan, 2000). Lately, there seems to be a consensual opinion that those two views are complementary (Levinthal, 1991; Amburgey and Rao, 1996). In this work we will search this complementarity by analyzing the effects of individual knowledge management strategies in the evolution of organizational populations.

Knowledge, populations and complexity. The two competing approaches presented above have adopted a different attitude towards knowledge. The strictly broad perspective adopted by organizational ecologists or organizational demographers and their view of organizations as entities unable to adapt to their environment as individuals (Carroll and Hannan, 2000)—and, therefore, lacking of capacity of learning or creating knowledge—has hindered the introduction of knowledge into their analysis. Knowledge is seen, in this view, as a fixed and unchanging characteristic of an organization that contributes to its chances of surviving as other characteristics do. Never is knowledge management seen as a means of increasing the probability of survival by improving the creation of new knowledge and fostering its use. A completely different standpoint is adopted by the evolutionary theory of economic change proposed by Nelson and Winter (1982). In this case, evolutionary mechanisms are applied not to individual firms in a population, but to organizational knowledge in the form of *routines*. Knowledge management is, in a sense, the management of routines. Nelson and Winter, however, do not analyze the effect of those mechanisms to the evolution of the population.

Since organizational populations, as groups of interacting economic actors, can be considered complex systems (Arthur, Durlauf, and Lane, 1997), we cannot suppose that the effects of low-level knowledge-related processes will translate in a linear way to the higher level of population. Merging both the individual adaptation and the population selection perspectives means being able to derive emergent patterns at the level of population from low-level rules. This is very difficult using traditional methodologies, but the sciences of complexity provide us with new methodological tools (Epstein, 1999).

The introduction of ideas coming from complexity theories is growing very quickly in the management sciences (Axelrod and Cohen, 1999; Anderson, 1999; McKelvey, 1999; Anderson, Meyer, Eisenhardt, Carley, and Pettigrew, 1999; McKelvey, Mintzberg, Petzinger, Prusak, Senge, Shultz, Bar-Yam, and Lebaron, 1999) and also, particularly, in the knowledge management area (McElroy, 2000; Canals, 2002).

We propose to achieve the complementary analysis of the two different levels through the use of agent-based simulation. The knowledge management strategies are introduced into the behavior of individual agents and its effect at the population level is assessed through the analysis of the patterns detected in the population of agents after the simulation runs have been performed.

Spatial Location and Knowledge. The existence of clusters of firms due to agglomeration economies has been explained by different causes (Krugman, 1991; McCann, 2001: 55; Fujita, Krugman, and Venables, 1999: 18). One of the most relevant is the existence of knowledge spillovers. As Krugman, relying on Marshall (1920), puts it: "[…] because information flows locally more easily than over greater distances, an industrial center generates what we would now call technological spillovers" (Krugman, 1991: 37). Therefore, we will introduce in our model a dependence in the probability of transferring knowledge between agents on the distance that separates their spatial locations. The probability of interaction—and therefore, of knowledge transfer or knowledge unintended diffusion—between two or more agents will depend on the distances among them. Of course, it will depend also on the degree of structuring of the knowledge that has to be transferred or diffused: for a given distance, a completely codified knowledge will be much easier to transfer or diffuse.

Knowledge Diffusion and ICTs Development. An important factor in the diffusion of knowledge is the degree of development of the Information and Communication Technologies (ICTs). The existence of the telegraph, the telephone and lately Internet has made it possible to increase the reach of knowledge diffusion. Information that could only be transmitted face to face or through slow courier systems two hundred years ago can reach nowadays the whole world in a matter of seconds. Indeed, the technological development is a major cause of the raise of the information society (Bell, 1973)(Castells, 1996; Castells, 2001). The increase in bandwidth derived from the ICTs development signifies the improvement of the reach of information transmission. Although information should not be conflated with data nor knowledge (Boisot and Canals, 2004), it is clear that any improvement in the capacity of data transmission carries as a consequence—other factors remaining equal—a facilitation in the diffusion of information and, therefore, in the transference of knowledge. We will also introduce this fact in our model: the dependence on the distance of the probability of interaction that we mentioned above will be modulated by the degree of development of ICTs.

Prior Simulation Modeling Efforts. Simulation techniques have been used to explore several kinds of social science problems (Conte et al.   1997; Axelrod, 1997; Gilbert, 1999; Gilbert and Troitzsch, 1999). In the management and organization theory turfs, simulation has found many applications. The first uses were in operations research and management-science techniques (Law and Kelton, 2000; Pidd, 1998). Later, equation-based simulation and other techniques were introduced in economic and managerial theoretical problems as a research tool (Berends and Romme, 1999; Nelson and Winter, 1982; Krugman, 1996; Prietula, Carley, and Gasser, 1998; Carley and Gasser, 1999; Levinthal, 1997). Lately, management has adopted agent-based simulation modeling when dealing with complex systems problems like organizational design (Rivkin and Siggelkow, 2003), strategy (Rivkin, 2000; Rivkin and Siggelkow, 2002) or strategic knowledge management (Rivkin, 2001; Boisot et al.   2003). Simulations have been used also in the study of organizational populations (Lomi and Larsen, 1996; 2001), but there is a lack of models which take knowledge transference into account.

3 A Model of Knowledge-Based Organizational Populations

The present simulation model is an extension of *SimISpace* (Boisot et al.   ;). *SimISpace* uses an agent-based simulation to represent a group of agents which possess knowledge assets and which behave following the theoretical tenets of the I-Space conceptual framework developed by Max Boisot (1995) and interact in a Schumpeterian regime (Boisot and Canals, 2003)[1].

In this section we will focus on the particular features of the model that are not present in *SimISpace*. A more detailed description of the I-Space theoretical tenets on which the model is based and of the model itself can be found elsewhere (Boisot et al.   ; ; Boisot and Canals, 2003).

[1] Previous versions of SimISpace received the name of *Smart Assets*.

3.1 The simulation model

Our simulation model is the result of extending SimISpace to adapt it to the study of the effect of knowledge management strategic preferences in the organizational population behavior of a group of firms located in a given spatial region.

Because of the importance of spatial location in knowledge diffusion issues mentioned before, we have added a spatial component to SimISpace and we place our agents in a representation of physical space. In the model we present here, agents represent interrelated firms belonging to an industrial sector and located in a given regional space. As we want to assess the effect of knowledge management strategic choices, a new feature has been added to previous SimISpace models: the possibility to assign a preference for a given knowledge management strategy to agents.

The Conceptual Model: I-Space. As a conceptual framework, the I-Space (Boisot, 1995; 1998; Boisot and Child, 1996) develops a simple, intuitively plausible premise: structured knowledge flows more readily and extensively than unstructured knowledge. The I-Space takes information structuring as being achieved through two cognitive activities: codification and abstraction.

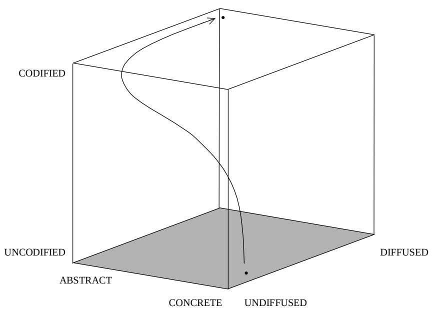

Fig. 1. The Diffusion Curve in the I-Space

The relationship between the codification, abstraction and diffusion of knowledge is illustrated by the diffusion curve of Fig. 1. The figure tells us that the more codified and abstract a given message, the larger the population that it can be diffused to in a given time period.

Agents and assets. The model is populated with agents that carry knowledge assets in their heads. Each of these knowledge assets has a location in the I-Space that changes over time as a function of diffusion processes as well as of what agents decide to do with them. These have the possibility of exchanging their knowledge assets in whole or in part with other agents through different types of dealing arrangements. Knowledge assets can also grow obsolete over time. Agents survive by making good use of their knowledge assets. They can make use of these assets directly to earn revenue, or they can make indirect use of these assets by entering into trades with other agents who will then use them directly. Existing agents have the option of quitting the game while they are ahead and before they are cropped. Conversely, new agents can be drawn into the game if the environment becomes sufficiently rich in opportunities. Here, entry is based on mean revenues generated by the game in any given period.

Model architecture. The has three model components: 1) an agent component that specifies agent characteristics; 2) a knowledge asset component that specifies the different ways that agents can invest in developing their knowledge assets; 3) an agent interaction component that specifies the different ways that agents can interact with each other.

Agents: Smart Assets operates through a number of agents that make up the diffusion dimension of the I-Space. In the model as developed, agents are intended to represent organizations—firms or other types of information-driven organizations—within an industrial sector. Agents can enter or exit Smart Assets according to circumstances and can also be cropped from the simulation if their performance falls below a certain threshold. Agent entry and exit is an important source of variation within the simulation. Clearly, the population that is located along the diffusion dimension of the I-Space will vary in size at different moments in the simulation.

Agents aim to survive within the simulation and to maximize their wealth over the periods of the simulation. Agent wealth is expressed both in terms of money and in terms of knowledge and is taken to be the sum of revenue streams and of revenue-generating knowledge assets. Wealth expressed in terms of money builds up a financial fund. Wealth expressed in knowledge terms builds up an experience fund.

From their financial and experience funds, agents draw budgets for meetings and for investing in knowledge assets. Money that is not spend gets put back into the relevant fund and accumulates.

Knowledge Assets: Knowledge assets have a degree of codification and abstraction. The more codified and abstract a knowledge asset the greater its utility and hence the greater its revenue-generating potential. Likewise, the less diffused a knowledge asset, the scarcer it is and hence, again, the greater its revenue-generating potential.

Agent Interaction: Agents meet each other throughout the game and the frequency of encounters between agents can be varied. They can ignore each other or they can attempt to engage in different types of transactions. In the second case, they need to be able to inspect each other's knowledge assets in order to establish whether a transaction is worth pursuing. Having established that it is, they can either: 1) engage in straight buying as selling of knowledge assets; 2) license other agents to use their knowledge assets; 3) enter into a joint-venture with another agent by creating a new agent that is jointly owned; 4) acquire another agent and convert it into a wholly-owned subsidiary; 5) merge with another agent, thus reducing the number of agents in the simulation. The cost of inspections and of agent interactions will be a function of how codified and abstract the knowledge assets of interacting agents turn out to be.

Spatial location. Our simulation model represents a population of knowledge-intensive organizations located in a spatial region. As is usually done in simulation models (Epstein and Axtell, 1996), our representation of the spatial setting is very schematic. We use a grid 80 cells wide by 80 cells high in which agents are located. More than one agent can occupy the same cell simultaneously. The grid is represented graphically while the simulation is running (see Fig. 2). At this stage of the model, we consider that space is uniform and that geographical accidents are not relevant.

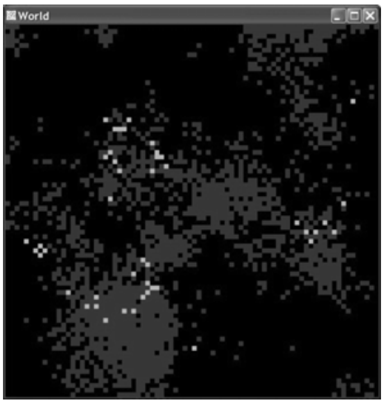

Fig. 2. Image of the simulation graphic representation

At the moment of his creation, each new agent is assigned a location in space that is stored in the variables X and Y belonging to his set of internal variables. The agent will remain at the same position in the grid for his whole life within the simulation.

Agents created at the beginning of the simulation and successive new entrants are located at random. Agents who are the result of joint ventures or mergers or who are created as subsidiaries of other agents are located with higher probability around one of their parent agents.

Knowledge management strategies. Strategies for managing knowledge assets—that is, preference for blocking diffusion or not and preference for working at high levels or low levels of structuring—are represented for each agent by two internal variables. These strategies are fixed at the creation of a new agent and remain stored in the corresponding internal variables of the agent. Every time the agent needs to take a decision related to the diffusion of knowledge or the preference for working at a higher or at a lower level of structuring with its knowledge assets, the stored variables influence the decision. In that sense, those internal variables act in a similar way to genes in living creatures.

If the variable diffusion blocking strategy (DBS) for some agent takes the value 1, the preference of the agent is for blocking diffusion, while if the value is 0 the preference is for not doing it. The same for the variable knowledge structuring strategy (KSS). If it takes the value 1, each time one investment is made in research, it goes in the direction of increasing the degree of structuring. On the other hand, if the value is 0, investments in research go to decrease the degree of structuring and to increase the tacit quality of knowledge.

Introducing evolution. The values of both variables remain the same for the whole life of an agent. And they are inherited by mergers, joint ventures and subsidiaries through a mechanism similar to the one applied in genetic algorithms (Mitchell, 1996). In the case of subsidiaries, the values of the “genes” of the parent agent are inherited directly by the subsidiary. In the case of mergers and joint ventures, the “genes” assigned to the new agent are any of the ones present in the parent agents with equal probability.

We have built a model that allows us the representation of a population of organizations belonging to an industrial sector. Those firms are located within a spatial region and they can adopt different strategies in their preference or not for blocking diffusion and in their preference for increasing or decreasing the level of structuring of their knowledge assets.

Our model presents evolutionary characteristics. On one hand, although strategic preferences are fixed for each organization, their relative importance in the population of organizations in the simulation can vary as a consequence of the evolution of the system in time. On the other hand, location in space is, in some sense, inherited, since joint ventures and mergers are located between their parents and subsidiaries are located in an area around the parent organization. Thus, location in the regional space of the different members of the population will also evolve in time and, given, the dependence of knowledge diffusion on the distance, will have an influence in the evolution of knowledge management strategies. What we have is a model capable of replicating a co-evolution of knowledge management strategies and locations in an organizational population. In this work, however, we will focus in the results for the evolution of knowledge management strategies.

It is possible that there some of the possible strategies are more effective than others, and therefore firms or institutions adopting those strategies will survive longer and give rise to mergers, joint ventures and subsidiaries inheriting the same strategies. In the long run, perhaps only some strategies will survive. Or, perhaps, after some time, the simulation will tend to reach a situation in which a given mix of strategies remains stable as a consequence of the co-evolution of knowledge management strategies. The fact that we cannot predict which will be the result before running the simulation shows the utility of simulation models of complex systems to obtain sound insights for the generation of original hypotheses. That is what we want to do through the analysis of the simulation runs.

Distance, technological development and knowledge diffusion. Following several studies in spatial economy, it seems plausible that diffusion of knowledge between two organizations depends, partly, on the distance between their spatial locations (Storper, 2000; Audretsch, 2000; Dunning,). Two different reasons—although strongly related—can be appointed for this. First, spatial proximity facilitates face-to-face communication, while distance forces to rely on ICTs (Information and Communication Technologies) for communication. As in face-to-face relationships the bandwidth at disposal of the communicating parts is broader, it seems logical to think that diffusion of knowledge will be easier. Second, closer spatial locations usually means a more similar cultural (economical, social, linguistic,…) context, what also facilitates communication and, therefore, the chance of knowledge diffusion.

In our model we want to have the possibility of studying this phenomenon. For this, we introduce in it a general variable representing to what extent the diffusion of knowledge—both intended or unintended—is difficulted by the physical distance between the agents implied. Of course, we are aware of the fact that in both of the interpretations appointed in the previous paragraph—possibility of face-to-face communication and cultural context proximity—the correlation to physical distance is not one hundred percent direct. But in our aim of simplicity in the model, we consider that our physical distance is an acceptable proxy of at least the first one and probably also of the second.

The general variable β that we introduce in the model represents to how important is distance in hindering the diffusion of knowledge. In terms of the first interpretation, β can be associated to the degree of development of ICTs. As ICTs develop, the difference in bandwidth between face-to-face and ICT-mediated communication shrinks. In our model, the higher the value of β, the lower the development of ICTs.

Diffusion of knowledge in our model is made through several mechanisms. There is an unintended random diffusion decay of knowledge assets and also the possibility of intended diffusion as a consequence of meetings among agents, which can be arranged or at random.

Effective transference of knowledge depends on a probability factor. The probability of transference is the product of the probability of interaction and the probability of transference given that there is interaction:

$$P(Transf) = P(Int) \cdot P(Transf \mid Int)$$

The probability of transference given interaction depends on the degree of codification and abstraction, that is, the degree of structuring (*Str*) of the knowledge asset involved.[2] So we have:

$$P(Transf \mid Int)[Str] = P_0 \cdot Str$$

where P_0 includes the random and internal variables dependence. As we will see in the following section, the dependence on the degree of structuring is specially relevant to our study: the more structured—i.e., more explicit—is knowledge, the more probable is diffusion.

The calculation of the probability of interaction embodies the influence of physical distance:

$$P(Int)[r,\beta] = e^{-\beta \cdot r}$$

As it could be expected, it shows a dependence on the distance, *r*, and on the variable β, which can take values from 0 to infinity. Fig. 3 shows the form of $P(Int)[r,\beta]$ for several values of β.

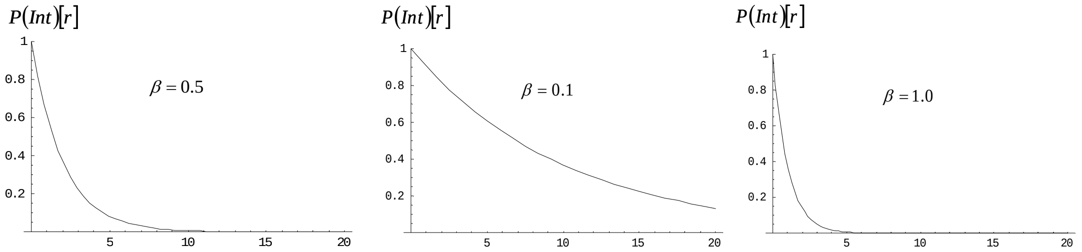

Fig. 3. Shape of $P(Int)[r,\beta]$ for different values of β.

[2] Of course, other factors contribute to this probability, like some internal variables of the model which are related to the kind of event and to the nature and number of agents involved.

The distance *r* represents different things depending on the event. For diffusion decay, *r* is taken as the distance between the center of gravity of the different agents who possess the asset to be diffused and the agent to whom it has to be eventually diffused. For random encounters, *r* is the distance between the two agents for which the probability of the encounter to happen is calculated. Finally, for scheduled arranged meetings, *r* is the distance between the agent that is evaluating the need to interact with another agent and this agent.

Note that the factor takes the value 1 for $r = 0$ and the value 0 for $r = \propto$. In our interpretation of the model, this means that, for minimal distances, the degree of development of ICTs has fewer significance (in face-to-face interaction, even poorly structured knowledge can be transferred) but when distance increases, the probability of diffusion decreases.

So, we have a model in which, for any given situation, the probability of transferring knowledge assets between two firms depends on both the degree of structuring of the assets and the distance in the physical space between firms:

$$P(Transf) = P(Int)[r] \cdot P(Transf \mid Int)[Str] = P_0 \cdot Str \cdot e^{-\beta \cdot r}$$

Fig. 4 shows the form of $P(Transf)$ for different values of Str and for $\beta = 0.5$ and $P_0 = 1/6$.

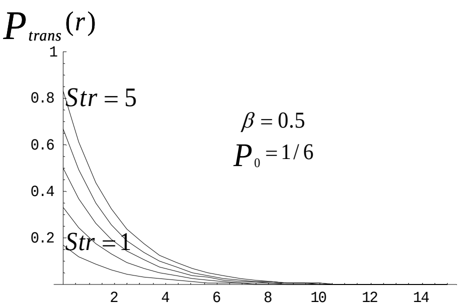

Fig. 4. Form of $P(Transf)$

4 Results

In order to explore the influence of the knowledge management strategies on the behavior of the population of agents, we will perform three experiments. First, we will run our model and compare the general results obtained to the equivalent result coming from simpler versions of the model in which strategies are fixed and the same for all agents. For all cases we choose the same value of β. Second, we will look more in depth into the results of the model obtained previously paying special attention to the evolution of the mix of strategies in the population of agents. Third, we will run the model for different values of β representing different ICT regimes, that is, different degrees of development of information and communication technologies.

For each run, the simulation starts with a population of firms in which the values for the Knowledge Structuring Strategy (KSS) and the Diffusion Blocking Strategy (DBS) are distributed at random, and therefore the initial distribution of strategies in the population is roughly even. Approximately 50% of the agents will have KSS = 0 and 50% will have KSS = 1. The same for DBS. Once firms start creating knowledge and interacting, the system evolves. Bad-performers die and good-performers stay and spread their characteristics through inheritance (except for the cases in which strategies are fixed and the same for all agents). So, one ends up with a different distribution of strategies, resulting from the co-evolution of strategies.

Robustness. The basis of our simulation model has been tested following verification and validation procedures (Gilbert and Troitzsch, 1999). That work has been described elsewhere (Boisot et al. ; ; Boisot et al. 2003).The results reported in this section correspond to a selection of the simulation experiments we have performed with the model. The qualitative patterns we describe have been observed for a broader range of parameters and we would be happy to share the complete results obtained with our simulation software with any researcher interested.

For every case we deal with, the run is repeated 50 times in order to be able to obtain significant mean values of the results. In the comparisons we do of the results of several cases, we use ANOVA analysis to ensure that the differences among mean performances are statistically significant with $p < 0.001$. In this way we make sure that the differences found are due to the different parameters that characterize each case and not to stochastic variations in the simulated systems because of the occurrences that are decided in the model through the generation of random numbers. The simulations are programmed to run for the sufficient number of periods to ensure that the system has reached a stable state and the values used in the analysis correspond—except when we look at the total evolution in time of the system—to the last 100 periods. Having said that, our principal aim in this paper is not to prove the generality of any specific result but to use the qualitative patterns we find to come up with insights on the mechanics of the kind of systems modeled. Through that process, our objective is using the simulation as a methodology for the generation of hypotheses that could be empirically tested in further research.

4.1 Evolutionary model with mixed strategies vs. simple single-strategy models

In this sub-section we will look at the general behavior of the evolutionary model we have described, that in the following we will label as *ksGdbG*. We perform all runs using for β a value of 0.5 in the calculation of the probability of interaction.

In order to analyze the general behavior, we will compare the results obtained to the ones coming from four simpler models that we build in such a way that all agents have only one possible preference for each strategy and, of course, there is no inheritance. All other features are the same of the main model. This leaves us with four additional simple models, one for each of the possible combinations of strategies:

	DBS = 0	DBS = 1
KSS = 0	*ks0db0*	*ks0db1*
KSS = 1	*ks1db0*	*ks1db1*

General evolution. In Fig. 5 we show the evolution of the model throughout the whole 500 periods. Charts show the number of agents in the simulation, the number of knowledge assets and the rents generated. The lines represent the mean values for the 50 runs of each model.

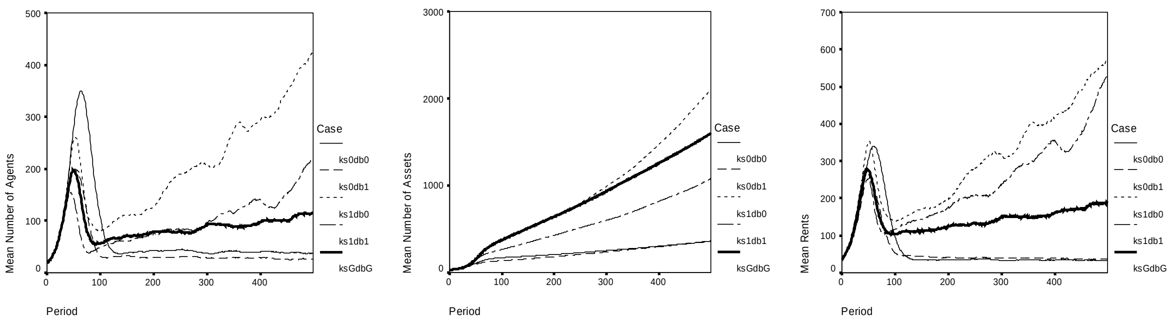

Fig 5. Evolution of the number of agents, number of assets and rents

The evolution in the number of agents present in the simulation of the *ksGdfG* model starts with a sudden increase in the first 50 periods to go down again in the following 50 periods. After that, the number of agents remains more or less stable, with a slight tendency to increase as periods go by. This kind of behavior is equivalent to the observed in other simulation models (Barron, 2001). Similar phenomena are also found in organizational ecology models and real data (Hannan and Freeman, 1989; Carroll and Hannan, 2000). In a simulation exploring organizational fitness in the so-called “rugged landscapes”, Levinthal (1997) attributes this kind of behavior—in that case, applied to the number of organizational models present in the population—to the emergence of order after an explosion phase in the first periods.

The four test models have a similar behavior, but those with tendency to structure knowledge assets present a higher increase in the number of agents after the first chaotic periods while the other two remain stable with a lower number of agents. As it can be seen from the figure, the *ksGdbG* remains in between, what suggests a possible relationship between structuring of knowledge and the capacity of generating a higher number of new assets in the simulation or the carrying capacity of the model.

The evolution of the number of assets present in the simulation for the *ksGdbG* model grows very quickly in the first 100 periods, adopting afterwards a steady, though not so steep, increase. The number of assets is higher than all the test models except for the one that has a preference for structuring knowledge assets and not blocking diffusion.

Total rents obtained by agents from knowledge assets present a very similar form to the number of agents, what suggests that both variables are correlated. This is to be expected, since in the model there are no market boundaries. Therefore, all agents are able to obtain rents from their knowledge assets, without having to fight among them for a market share. This could be the case of a growing sector like computers in the 1990s or software.

4.2 Strategy evolution

In this sub-section we will look at the KM strategies adopted by the agents in our model.

Evolution of strategic mix. The chart in Fig. 6 shows the evolution in the share of the population adopting a preference for structuring knowledge in front of not structuring knowledge (KSS = 1) and in the fraction of the population adopting a diffusion blocking strategy (DBS = 1).

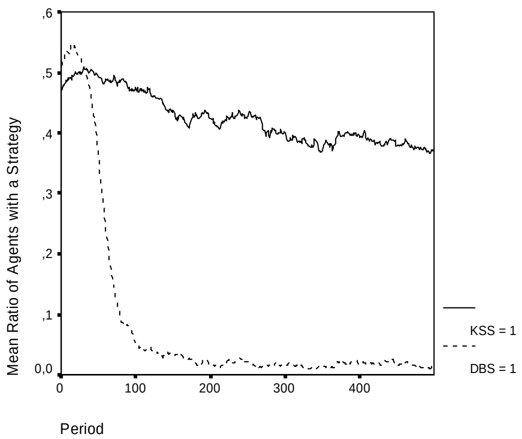

Fig 6. Evolution of the mix of KM strategies in the population

On one hand, it seems clear that the diffusion blocking strategy is strongly suppressed. From a value around 50% (resulting from a random initial endowment of strategic preferences), it goes down very rapidly, remaining lower than 5% after period 100. In presence of the “not blocking diffusion gene”, it looks as if the “blocking diffusion gene” has a much lower capacity for surviving.

On the contrary, the system seems to evolve to a situation of coexistence of both the “knowledge structuring gene” (KSS = 1) and the “knowledge unstructuring gene” (KSS = 0). From a 50%-50% mix in the beginning of the simulation it evolves gradually to an approximate 40%-60% more or less stabilized in the last periods.

One could deduce from the results above that while blocking diffusion is not an adequate strategy for the majority of agents in a Schumpeterian setting, in terms of knowledge structuring there is not a preferred strategy for all. The best solution—or, at least, the solution that the system chooses—is one in which there is a coexistence of agents with the two strategies with a slightly higher number of them with a “unstructuring knowledge” strategy.

KM Strategies. Among the 60,000 agents present in the last 100 periods we see a dominance of the “not blocking diffusion” strategy and an equilibrium between the “structuring knowledge” and the “unstructuring knowledge” strategies, slightly biased to the second one. Lifetimes of agents with a preference for blocking diffusion are shorter than their counterparts, which is consistent with the fact that they evolve to a very low share in the population. Also the differences in the lifetimes of “knowledge structuring” and “knowledge unstructuring” agents point to the evolution of strategic mixes in the population (see Fig. 7).

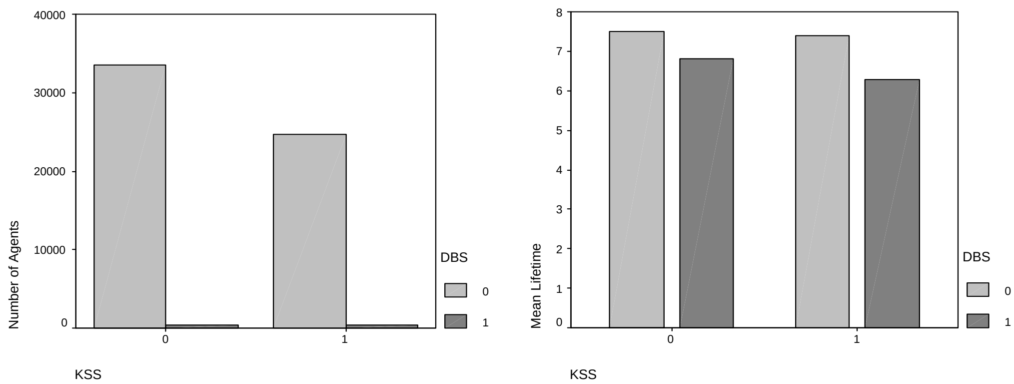

Fig 7. Number of agents with each strategic profile and their average lifetime

4.3 Technological regimes

In this section we will use the model presented before to look at the effect in the behavior of the populations of agents of different ICT regimes by varying the parameter β. Low values of β correspond to high degree of development of ICTs. We run the simulation model for several values of β:

$$\beta = \{0, 0.10, 0.20, 0.30, 0.50, 0.70, 1.00, 2.00, 10.00, 100.00\}$$

General analysis of the final periods. Fig. 8 shows some of the results obtained for the 100 last periods of the simulations.

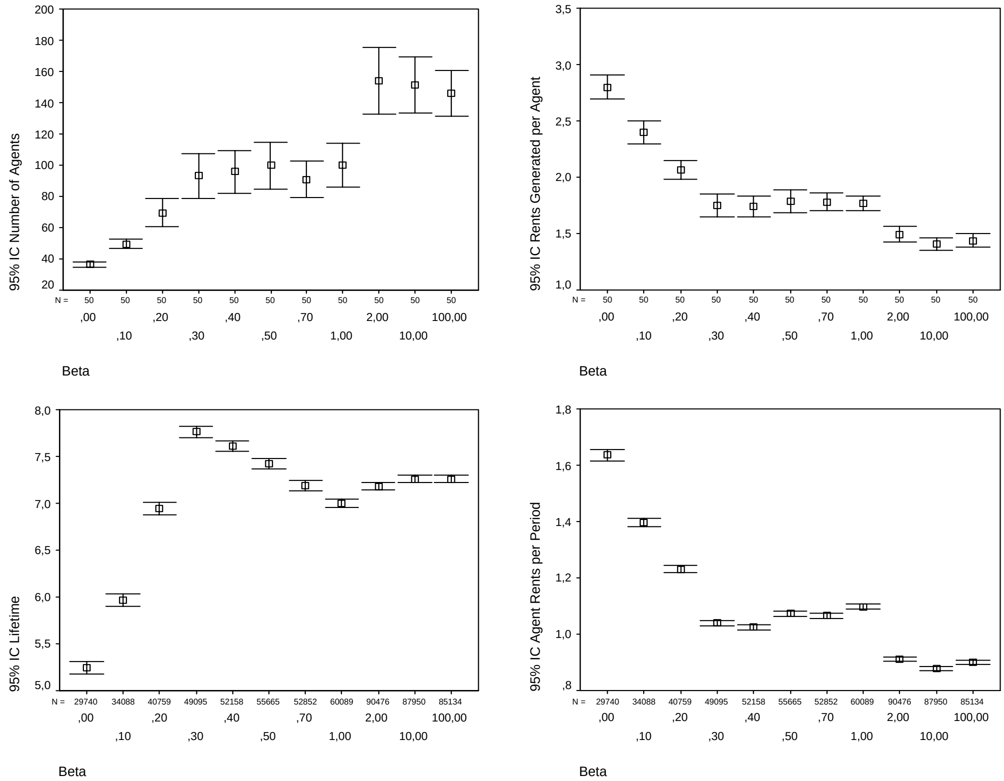

Fig 8. Number of agents, rents generated per agent, average lifetime and agent rents generated per period for different ICT regimes

The most relevant result we obtain is a non-linear behavior. Although the number of agents in the simulation grows with β (and the same happens for the number of assets and the rents generated), the rents generated per agent, the average lifetime of agents and the rents generated per period by each agent show an inflexion point between β = 0.2 and β = 0.4.

Strategic mix. In Fig. 9 we can see that this strong non-linear behavior is also present in the strategic mix.

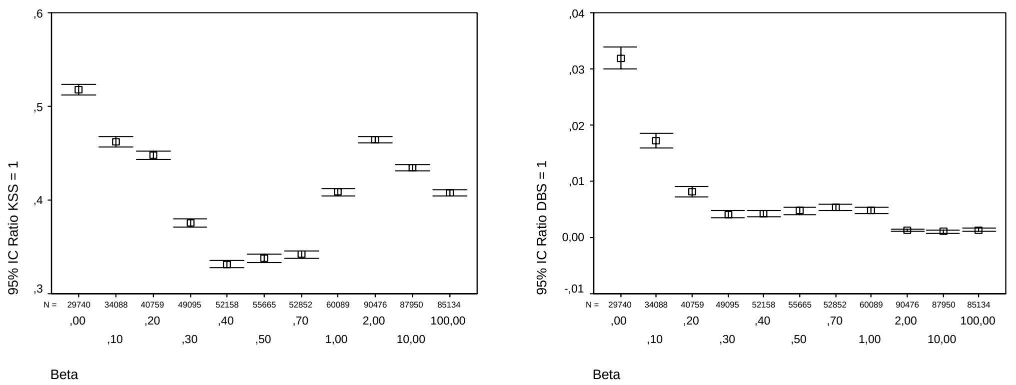

Fig 9. Strategic mixes of KSS and DBS

Focusing in only three of the several regimes studied (β = {0.10,0.50,10.00}), we can see that this particular behavior is strongly related to the strategic mix of the respective populations and the average lifetime of the agents of each strategic profile (see Figs. 10 and 11).

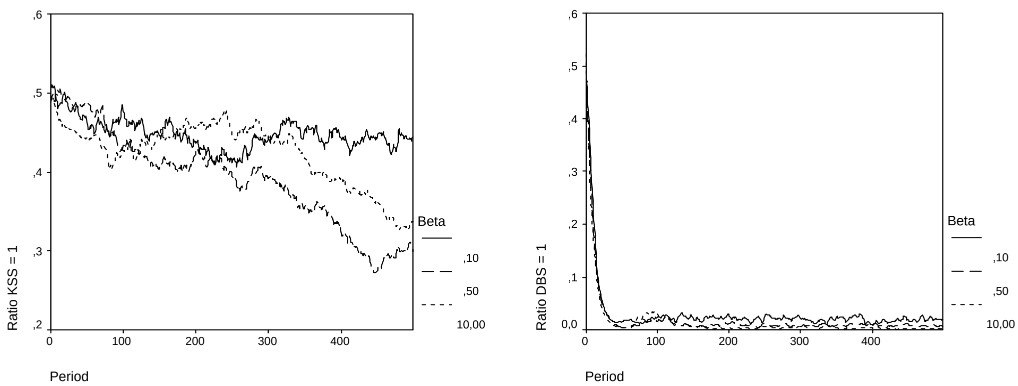

Fig 10. Evolution of KSS and DBS for three selected ICT regimes

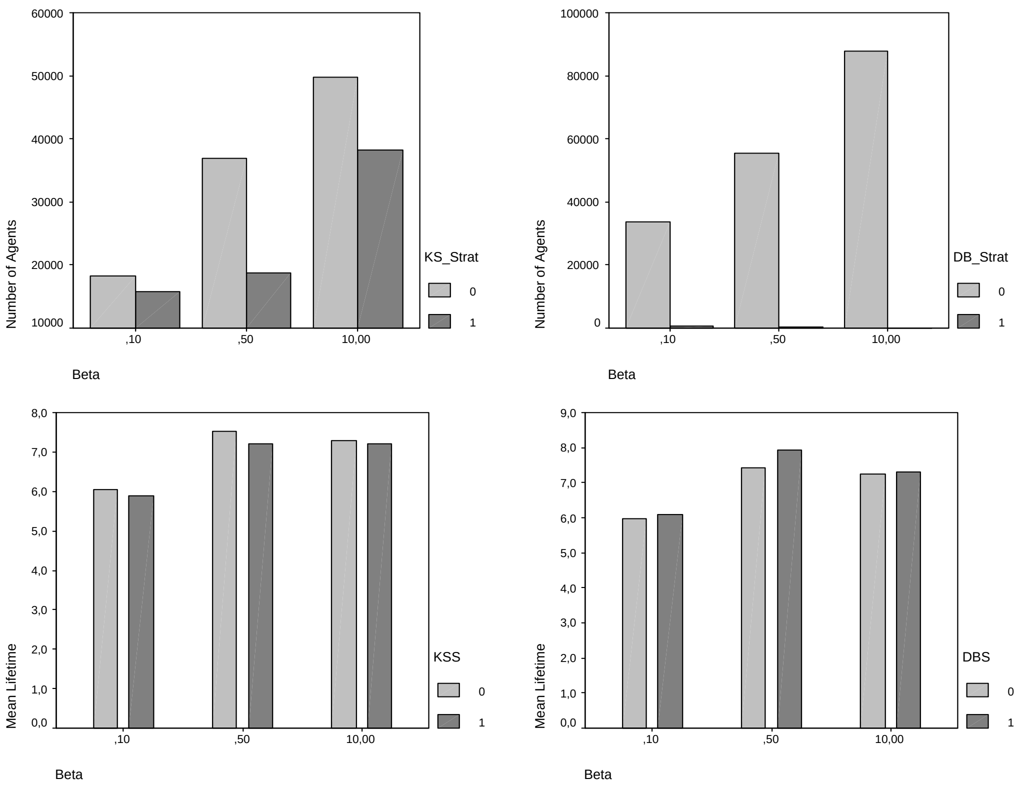

Fig 11. Number of agents and average lifetime for each strategic choice

5 Discussion

From the results of subsection 4.1, we can see that our evolutionary agent-based model of a population of organizations as a complex system in a Schumpeterian scenario shows a consistent behavior. The comparison with less realistic models with single and fixed strategic preferences confirms this fact.

The specific analysis of the evolution of KM strategies in our model in sub-section 4.2 permits to derive very interesting insights. On one hand, they corroborate the common intuition that blocking diffusion is not a very good strategy in Schumpeterian scenarios. The KM strategy DBS = 1 is strongly, reaching a 3% of the population at the most. However, there seems to be always some room for organizations hindering diffusion, and their number could increase slightly with the development of ICTs, although this little proportion of diffusion blocking firms could be occupied just for the newly born organizations that adopt this strategy and have to leave the industry because of it.

On the other hand, although there seems to be an equilibrium—or, at least, a quite flat evolution in the last periods of the simulation—in the mix of knowledge structuring strategies present in the population, it seems clear that this equilibrium is slightly biased towards a bigger number of agents having KSS = 0, that is, a “not structuring knowledge” preference. The possible implications of this could be that both strategies have to coexist in a Schumpeterian environment. We cannot attribute at this point much significance to the fact that there is a bias towards not structuring knowledge, due to the degree of simplification of reality that there is still in our model. However, there is no doubt a signal of the importance of the role that processes working with tacit knowledge play in the economy.

Another observation to be made is that slight differences in the average lifetime of agents with given strategic preferences give rise, in the long run, to a pre-eminence of those preferences. It seems that a some strategic preferences profile give just a slight advantage to the agents adopting them to the others in terms of life expectancy, but this minor difference allows for a greater chance to transmit the preferences to new organizations and, therefore, augmenting their presence in the population as a whole. This is probably favored by the fact that a Schumpeterian scenario fosters interaction and knowledge diffusion. It could happen otherwise in a more Neoclassical environment (Boisot et al. 2003).

From the analysis above we propose the following hypotheses:

HYPOTHESIS 1. *Organizational populations behave as complex systems and their behavior can be—at least partially—reproduced using evolutionary simulation models.*

HYPOTHESIS 2. *Blocking diffusion is a minoritary strategy in a Schumpeterian economy.*

HYPOTHESIS 3. *The two strategic preferences for working with structured knowledge and with unstructured knowledge coexist in a Schumpeterian enconomic environment.*

HYPOTHESIS 4. *Lifetime of organizations in a population is directly correlated to the proportion of agents in the population showing their strategic choices.*

The general results for the different ICT regimes (sub-section 4.3) give us also very interesting results. A major consequence of the analysis is that we observe a self-evident non-linearity in the behavior of the model for different values of β. This fact is hardly expectable from the low-level rules that guide the behavior of individual agents. Therefore, we are in front of unexpected emerging high-level patterns, as we could expect from our consideration of the system we model as a complex system.

Attending to the charts in Fig. 8, three main groups of regimes seem to appear. For values of β higher than 1.00, the mean number of agents remains higher and disconnected to the rest. For values of β from 1.00 to 0.30, the mean number of agents remain more or less constant, but with a slight tendency to decrease. This decrease becomes evident for values of β from

0.20 to 0.00. The first group corresponds to undeveloped ICT regimes. Information can only be transmitted face-to-face at very low distances. There is not much difference among the three regimes probably because for values higher to $\beta = 2.00$ a threshold has been crossed that makes the dependence on distance irrelevant. For instance, in terms of communication between human beings, there is not much difference between communicating verbally at 30 cm and doing it at 20 cm or 10 cm. In the second group there is influence of the ICT regime but the values of the number of agents remain very close. In the last group, when the development of ICTs becomes very high, the number of agents is much lower. This is consistent with the fact that with less agents a given territory can be covered when there is more communication capacity.

A very simple interpretation could help to exemplify one possible domain of application of the results. Low values of β could represent something similar to an economy of DotComs in which communication is based in e-mail type and other tools that require highly structured messages. Medium values of β would represent an economy in which communication is made mainly through telephone, in a less structured way. The economy corresponding to low values of β could model economic settings of low technological development, being, for instance, telegraph the more advanced communication tool, which requires again some level of structuring. It is relevant that when looking at rents generated per agent, the higher value is attained for the lower value of β, that is, for the higher level of development of ICTs. In this DotCom's economy and with a high level of ICTs development, less companies would generate less knowledge and less rents but the rents generated for each company would be higher. An interesting point is that with lower rents, what means less cost for society, knowledge is still created.

When looking at the average lifetime, a very clear case of non-linear behavior. Around $\beta = 0.30$ an maximal point appears. To the right—that is, to lower levels of ICTs development—lifetime of agents decreases. But this happens also to the left—to higher development levels of ICTs—but with a much higher pace. One could expect that for economies with a high level of ICT development, companies would have a much shorter life. By all means, this coincides with the experience of the DotComs.

The analysis of the KM strategies mix (see Figs. 9, 10 and 11) gives similar results for all ICT regimes in the sense that diffusion blocking strategies are highly suppressed and the preference for not structuring knowledge dominates over the preference for structuring knowledge. However, there are significant differences among the different cases that have some interest. Concerning the diffusion blocking strategy (DBS), its is noticeable that—

although it remains lower than 5%—the proportion in the population of agents with DBS = 1 grows significantly when β decreases, that is, for higher levels of development of ICTs. This fact, which begins to be specially significant for the lower values of β, could be a hint that, given a certain level of ICT development, for some firms it is more effective to put in place hoarding strategies on knowledge assets, even in Schumpeterian scenarios. The knowledge structuring strategy (KSS = 1) shows a particularly interesting behavior. If for the lower values of β its proportion in the population remains only slightly under the 50%, when β grows, it goes down to values lower than 35%, to afterwards go up again to values over 45%. This is, again, a non-linear effect, what can make us think that it is related to the other behaviors in which we have observed inflexion points. The consequence to be derived from that fact could be that in the first phases of development of ICTs, it pays off for industries or groups of organizations to increase their work with tacit, unstructured knowledge; but it comes a time—when ICTs reach a certain level of development—in which it is advisable to reverse the trend. Of course, the model does not tell us if our society has already reached that point, but taking into account that the higher values of β in our model seem to reproduce some characteristics of a DotComs economy, it could well be that we are already there. The analysis of average lifetimes of the agents having different strategic choices seem to be consistent with this trend.

The hypotheses we derive from this are:

HYPOTHESIS 5. *Non-linear patterns will appear in the response of organizational populations to the gradual increase of the development level of ICTs:*

> SUB-HYPOTHESIS 5.1. *The number of members of the population will show a sudden decrease in the higher phases of development.*
>
> SUB-HYPOTHESIS 5.2. *The rents generated from knowledge assets by firms in the population will increase very rapidly in the same phases.*
>
> SUB-HYPOTHESIS 5.3. *The average lifetime of organizations will increase slightly until it reaches a maximum. Then it will decrease in a quicker way.*
>
> SUB-HYPOTHESIS 5.4. *The rents obtained per period will show a parallel but opposite behavior: a slight decrease up to a point, and then a more rapid increase.*

HYPOTHESIS 6. *In a first phase, the development of ICTs will favor an increase in the strategic preference for working with unstructured knowledge. In a second phase, the trend will reverse.*

HYPOTHESIS 7. *The higher development of ICTs will make diffusion blocking practices to produce more payoff, even in a Schumpeterian economy, although they will remain still residual.*

6 Conclusions

Our research is aimed to assess the influence of knowledge management strategies in the behavior of populations of organizations which are located in a given physical space. Because of that, we need to combine concepts from knowledge management with ideas coming from organizational ecology or spatial economy. Our findings show that this kind of interdisciplinary research can produce results with some interest for all disciplines involved.

The use of agent-based simulation is specially suited for those problems, typically found in complex systems, in which it is difficult to link theoretical frameworks that describe low-level interactions with the observation of high-level patterns of behavior. The influence of knowledge management strategies in organizational populations is one of those problems. This paper illustrates a way to deal with this kind of problems.

In a networked economy, firms and institutions need to be aware not only of their strategic choices, but also of the strategic choices of the other players in the industry and the way all strategies co-evolve. Our contribution, both in the methodology we have used and the results obtained is, in that sense, relevant to the organizations of the Information Society. Some of them reproduce already observed patterns in some industries and others, presented in the form of hypotheses, are to be tested empirically. The unique utility of simulation models here is the generation of grounded insights that would be difficult to obtain otherwise.

This work opens some interesting roads for further research. The inclusion of the model of a spatial dimension in the location of agents and their interaction prepares a way for the analysis of spatial behavior of organizational populations, which is an extremely relevant problem in the study of industrial clusters or regional economy. The specific influence of knowledge management strategies to location patterns constitutes a very interesting turf.

The spatial dimension offers also new possibilities. An extension of the model presented could be considered, in which location of agents were not in a physical space but in some sort of “cultural” space. In that space, distance should represent the difficulty in transmitting knowledge due to cultural barriers.

Our hope is that this line of research using simulation modeling will contribute to the development of knowledge management both in setting it in a sound theoretical foot and to apply it to complex real problems.

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