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Evolution of Knowledge Management Strategies in Organizational Populations: A Simulation Model

Agustí Canals (acanalsp@uoc.edu)
Researcher (IN3-UOC)
Director of Information and Communication Science Studies (UOC)

Max Boisot (boisot@attglobal.net)
Researcher (IN3-UOC)
Sol Snider Center for Entrepreneurial Research (The Wharton School, University of Pennsylvania)

Ian MacMillan (macmillan@wharton.upenn.edu)
Sol Snider Center for Entrepreneurial Research (The Wharton School, University of Pennsylvania)

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ABSTRACT

Knowledge flows among organizations play a key role in the evolution of industries and firms in the information economy. In this paper we develop an evolutionary agent-based simulation model derived from a knowledge-based theoretical framework, the I-Space, and use it to explore the effect of knowledge management strategies on the evolution of a group of knowledge-intensive organizations located in a given geographical area. After introducing the conceptual issues involved, we describe the main features of the agent-based model. We then present the results of different runs of the simulation model. From the analysis that follows, we derive a set of hypotheses on the influence of knowledge management strategies and the degree of development of information and communication technologies on the evolution of organizational populations. We conclude the paper by assessing the adequacy of the simulation approach for these kinds of problems and by suggesting some avenues for further research.

KEYWORDS

knowledge management strategies, knowledge framework, I-Space, ICT

SUMMARY

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Evolution of knowledge management strategies in organizational populations: a simulation model*

AGUSTÍ CANALS

Universitat Oberta de Catalunya

E-mail: acanalsp@uoc.edu

MAX BOISOT

Universitat Oberta de Catalunya

E-mail: boisot@attglobal.net

IAN MACMILLAN

Sol C. Snider Entrepreneurial Research Center, Wharton School, University of Pennsylvania

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ABSTRACT

Knowledge flows among organizations play a key role in the evolution of industries and firms in the information economy. In this paper we develop an evolutionary agent-based simulation model derived from a knowledge-based theoretical framework, the I-Space, and use it to explore the effect of knowledge management strategies on the evolution of a group of knowledge-intensive organizations located in a given geographical area. After introducing the conceptual issues involved, we describe the main features of the agent-based model. We then present the results of different runs of the simulation model. From the analysis that follows, we derive a set of hypotheses on the influence of knowledge management strategies and the degree of development of information and communication technologies on the evolution of organizational populations. We conclude the paper by assessing the adequacy of the simulation approach for these kinds of problems and by suggesting some avenues for further research.

1. INTRODUCTION

In a knowledge-based economy, knowledge creation processes are viewed as fundamental drivers of economic development [Castells, 1996; Leonard, 1995]. Continuous knowledge creation is needed to maintain the competitiveness of organizations [Leonard and Straus, 1997; Sanchez, 2001], regions [Storper, 2000; Audretsch, 2000; Dunning, 2000] and industrial clusters [Porter, 1998]. Yet, knowledge creation is worthless if 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 another point in time and space accurately and in a timely fashion. In an economy where Schumpeter's concepts of "creative destruction" and "new combinations" predominate [Schumpeter, 1934; Teece, 2000], it is the judicious integration of fruitful knowledge creation and effective knowledge diffusion that stimulates business performance and fosters economic growth.

It follows, therefore, that the specific knowledge management strategies adopted by firms and institutions are likely to be important to their survival. They will need to define the appropriate strategic actions that foster the 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 may not even be the most important. The manner in which knowledge is diffused from the organization where it is created to others is also important [Appleyard, 2002; Ciborra and Andreu, 2002]. Even the creation of knowledge is often the outcome of collaborative projects between private firms and public institutions [Matusik, 2002]. External knowledge flows between different economic actors take on a special relevance in this scenario. The management of inter-organizational knowledge flows—which cannot be treated separately from the management of intra-organizational 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 recent years, but often with a primary focus on the intra-organizational level. Of course, the work on strategic alliances takes knowledge issues to be an important factor [Fischer et al. 2002] and particularly the issue of knowledge spillovers [Almeida and Kogut, 1999; Audretsch, 2000; Caniëls and Verspagen, 2001]. However, in the mainstream knowledge management literature, the emphasis has been on knowledge processes that are internal to the organization. Less attention has been given 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. In fact, in a system of organizations, the success or failure of a given strategic choice depends on the strategies adopted by other organizations because they are all competitors in a common marketplace. Our intention in this work is to adopt a supra-organizational perspective to knowledge management that allows us to study this kind of issues.

Some organization theory perspectives such as those of corporate demography [Carroll and Hannan, 2000] and organizational ecology [Hannan and Freeman, 1989] provide a possible alternative to the firm-specific framework by broadening their focus from the individual organization to populations of inter-related organizations. Here, instead of looking at the knowledge management strategies of single organizations, one can now look at the distribution of different knowledge management strategies within a population of organizations. Of course, this is done by reducing the level of detail at which individual organizational strategies are studied. However, in our view it also opens up interesting possibilities that complement the more firm-specific knowledge management studies. First, as stated above, it works well for situations in which knowledge creation and diffusion rely more on networks of organizations in an industrial sector or a region than on individual firms. Second, it allows for the study of different interacting strategies between a given set of firms. Third, it offers an evolutionary perspective on knowledge management processes. Organizational populations evolve: new organizations are created, some organizations survive and others disappear due to their poor performance. As a consequence, some strategic options are selected and others remain residual or disappear.

In the research that we present here we adopt an organizational ecology perspective to study the effects of different knowledge management strategies pursued either by an organizational population as a whole or by subgroups within an organizational population. We make use of a conceptual framework proposed by Boisot [1995; 1998]—the Information-Space or *I-Space* –to develop an agent-based simulation model of an organizational population that creates and shares knowledge. Agents in the model represent individual organizations belonging to a given industrial sector, each with given knowledge management strategies, and each situated at specific locations within a spatial region. Analyzing model runs will highlight how the evolution of organizational populations interacts with the knowledge management strategies of individual agents—that is, organizations. This should allow us to generate potentially fruitful and empirically testable hypotheses.

The structure of this paper is as follows. In the second section, we will introduce the theoretical scaffolding in which we frame our work. Then, we will briefly present in section 3 the *I-Space*—the conceptual framework that underpins our analysis and whose tenets are embedded in our simulation model. Under this light, section 4 will be devoted to the introduction of the different conceptual aspects of strategic knowledge management that will be relevant in our work. After that, in section 5 we will describe the characteristics of the model we have built and in section 6 we will present the main results obtained from several runs of the model.

A discussion of the results will follow in section 7 and we will conclude with the conclusions in section 8.

2. ORGANIZATIONAL POPULATIONS AND KNOWLEDGE

The study of organizational populations introduced a new perspective into the organizational literature [Carroll and Hannan, 2000]. Instead of concentrating on the characteristics of individual firms, the focus was broadened to accommodate a whole industry or set of firms, selected on the basis of some specific criteria. As organizations have to live in an environment that is mostly made up of other organizations such as competitors, suppliers, clients or institutions [Porter, 1980], it makes sense to look at the co-evolution of all of the firms belonging to a geographical cluster, an economic sector or a whole industry.

Research on organizational evolution has been driven by two conflicting approaches [Levinthal, 1991]. One perspective has focused on the process of adaptation of individual firms to the environment, while the other has emphasized the variation and selection of organizational forms as a way for a population of organizations to survive. To the first group belong two works: *The behavioral theory of the firm* [Cyert and March, 1963] and *An evolutionary theory of economic change* [Nelson and Winter, 1982]. The second group is represented by the organizational ecology [Hannan and Freeman, 1989] or organizational demography perspective [Carroll and Hannan, 2000]. Lately, there seems to have emerged a consensus that these two views are complementary [Levinthal, 1991; Amburgey and Rao, 1996]. In this work we will explore this complementarity by analyzing the effects of individual knowledge management strategies on the evolution of organizational populations.

The two competing approaches presented above have adopted different attitudes towards knowledge. The broad perspective adopted by organizational ecologists and demographers of organizations is that, as entities, they are seldom able to adapt to their environment because of their structural intertia [Carroll and Hannan, 2000]. They therefore lack any capacity to learn or create knowledge. This perspective has underplayed the potential contribution of knowledge into the analysis.

Knowledge is viewed as an unchanging characteristic of an organization that makes a fixed contribution to its chances of surviving much as genes do. Never does knowledge management appear to be a means of increasing the probability of organizational survival through the creation of new knowledge and the fostering of its use. The evolutionary theory of economic change proposed by Nelson and Winter [1982] adopts a very different approach. In this case, evolutionary mechanisms are applied not to individual firms in a population, but to elements of organizational knowledge that take the form of *routines*. Here, knowledge management becomes, in a sense, the management of routines. Nelson and Winter, however, do not analyze the impact of such mechanisms on the evolution of the organizational population.

Since organizational populations, as groups of interacting economic actors, can be considered instances of complex adaptive systems [Arthur et al., 1997], we cannot suppose that the effects of low-level knowledge-related processes will scale up in a linear fashion at more aggregated population levels. Merging both the individual adaptation and the population selection perspectives means being able to derive emergent patterns at the level of a population from low-level rules operating at the level of individual members. This is very difficult using traditional methodologies, but the sciences of complexity[1] provide us with new methodological tools such as agent-based simulation modeling [Epstein, 1999]. We propose to pursue a complementary analysis of the two different levels through the use of agent-based simulation modeling. Knowledge management strategies are incorporated into the behavior of individual agents, and their effect at the population level is assessed through the analysis of emergent patterns detected in the population of agents once the simulation runs have been performed.

In order to build a simulation model in which knowledge processes are adequately implemented, we need to base it on a theoretical

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[1] The number of ideas derivable from the new theories of complexity is growing very quickly in the management sciences [Axelrod and Cohen, 1999; Anderson, 1999; McKelvey, 1999; Anderson et al., 1999; McKelvey et al., 1999] and also, particularly, in the knowledge management area [McElroy, 2000; Canals, 2002; Garcia-Lorenzo et al., 2003].

framework that provides us with appropriate knowledge creation and diffusion rules and allows a proper interpretation of the results. As a conceptual framework, the *Information-Space* or *I-Space*, developed by one of the authors, combines a complete modeling of knowledge processes at the level of individual agent with a thorough treatment of the social processes of knowledge diffusion. This makes it a perfect candidate to underpin our simulation model. In the following section we present the main tenets of the I-Space.

3. THE CONCEPTUAL FRAMEWORK: I-SPACE[2]

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. Human knowledge is built up through the twin processes of discrimination and association [Thelen and Smith, 1994]. Framing these as information processes, the I-Space takes information structuring as being achieved through two cognitive activities: codification and abstraction.

Codification articulates the categories that we draw upon to make sense of our world. The degree to which any given phenomenon is codified can be measured by the amount of data processing required to categorize it. Generally speaking, the more complex or the vaguer a phenomenon or the categories that we draw upon to apprehend it—i.e., the less codified it is—the greater the data processing effort that we will be called upon to make [Chaitin, 1974; Gell-Mann, 1994].

Abstraction reduces the number of categories that we need to draw upon to apprehend a phenomenon. When two categories exhibit a high degree of association—i.e., they are highly correlated—one can stand in lieu of the other. The fewer the categories that we need to draw upon to make sense of phenomena, the more abstract our experience of them.

[2] Part of this section draws upon Boisot et al. [2004]

Codification and abstraction work in tandem. Codification facilitates the categorical distinctions and associations required to achieve abstraction and abstraction in turn reduces the data processing load associated with the act of categorization. Taken together, they constitute joint strategies for economizing on data processing. The result is more and usually better structured data. Better-structured data, in turn, by reducing encoding, transmission, and decoding efforts, facilitates and speeds up the diffusion of knowledge while economizing on communicative resources.

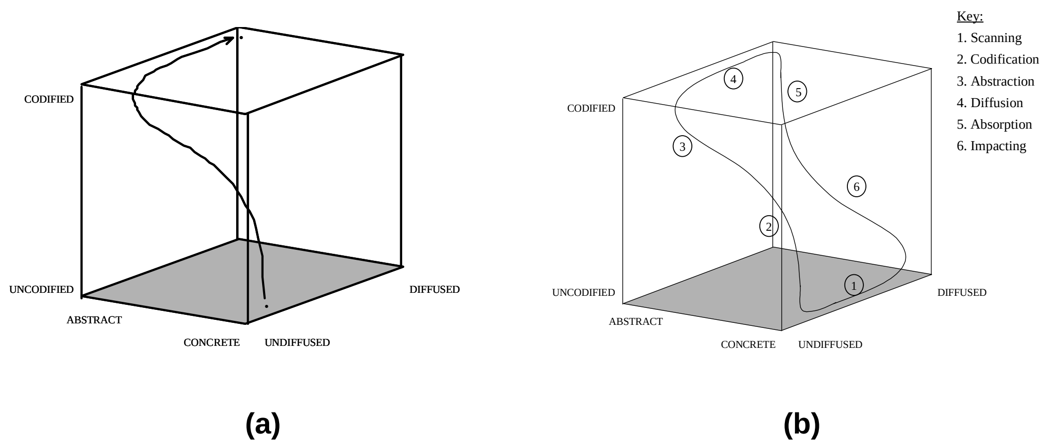

Figure 1 Diffusion curve (a) and Social Learning Cycle (b) in the I-Space

The relationship between the codification, abstraction and diffusion of knowledge is illustrated by the diffusion curve of Figure 1a. 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. Codification, abstraction, and diffusion, make up only one part of a wider social learning process. Knowledge that is diffused within a target population must also get absorbed by that population and then get applied in specific situations. When applied, such knowledge may not fit in well with existing schema and may trigger a search for adjustments and adaptations—what Piaget [1967] described as a process of assimilation and accommodation that we shall refer to as *scanning*. The social learning process that we have just described forms a cycle in the I-Space—the Social Learning Cycle or SLC—that is illustrated in figure 1b and further elaborated in Table 1. It is made up of six steps: scanning, codification, abstraction, diffusion, absorption, and impacting. Many different shapes of cycle are possible in the I-Space, but where learning leads to the creation of new knowledge, however, we hypothesize that the cycle will move broadly in the direction indicated by the figure.

Phases of the Social Learning Cycle	
1. *Scanning*	Identifying threats and opportunities in generally available but often fuzzy data—i.e., weak signals. Scanning patterns such data into unique or idiosyncratic insights that then become the possession of individuals or small groups. Scanning may be very rapid when the data is well codified and abstract and very slow and random when the data is uncodified and context-specific
2. *Problem Solving*	The process of giving structure and coherence to such insights—i.e., codifying them. In this phase they are given a definite shape and much of the uncertainty initially associated with them is eliminated. Problem-solving initiated in the uncodified region of the I-Space is often both risky and conflict-laden.
3. *Abstraction*	Generalizing the application of newly codified insights to a wider range of situations. This involves reducing them to their most essential features—i.e., conceptualizing them. Problem-solving and abstraction often work in tandem.
4. *Diffusion*	Sharing the newly created insights with a target population. The diffusion of well codified and abstract data to a large population will be technically less problematic than that of data which is uncodified and context-specific. Only a sharing of context by sender and receiver can speed up the diffusion of uncodified data; the probability of a shared context is inversely achieving proportional to population size.
5. *Absorption*	Applying the new codified insights to different situations in a "learning by doing" or a "learning by using" fashion. Over time, such codified insights come to acquire a penumbra of uncodified knowledge which helps to guide their application in particular circumstances.
6. *Impacting*	The embedding of abstract knowledge in concrete practices. The embedding can take place in artifacts, technical or organizational rules, or in behavioral practices. Absorption and impact often work in tandem.

Table 1 The Six Phases of the Social Learning Cycle (SLC)

In moving around an SLC, an agent incurs both costs and risks. There is no guarantee that the cycle can be completed. How does an agent extract enough value from its learning processes to compensate for the efforts and risks incurred? If we take the term value in its economic sense, then it must involve a mixture of utility and scarcity [Walras, 1874]. In the I-Space, utility is achieved by moving up the space towards higher levels of codification and abstraction. Scarcity is achieved by keeping the knowledge assets created located towards the left hand side of the diffusion curve. Here we encounter a difficulty which is unique to knowledge goods. As indicated in **¡Error! No se encuentra el origen de la referencia.**, maximum value is achieved in the I-Space at point MV, that is, at the point where codification and abstraction are at a maximum and where diffusion is at a minimum. Yet, as can be seen from the diffusion curve, this is a point at which the forces of diffusion are also at a maximum. The point is therefore unstable and a cost must therefore be incurred—i.e., patenting, secrecy, etc.—to prevent diffusion taking place.

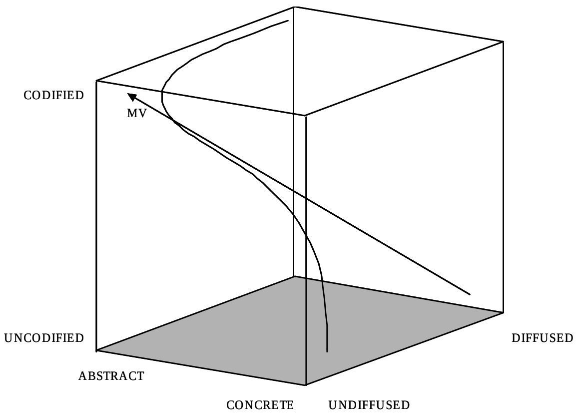

Figure 2Maximum Value (MV) in the I-Space

With a knowledge good, then, and in contrast to the case of a purely physical good, utility and scarcity are inversely related. The greater the utility achieved, the more difficult it becomes to secure the scarcity necessary to extract full value from the good in question. At this point, two strategies are possible for trying to extract the maximum amount of rents from knowledge assets: N-learning and S-learning [Boisot, 1998; Boisot and Canals, 2003; Boisot et al., 2004]. The first consists of trying to maintain our knowledge assets as long as possible in the "maximum value" corner of the *I-Space* by blocking diffusion. The second consists of not blocking diffusion but fostering the speeding up of the Social Learning Cycle to count always with some new knowledge assets at the adequate location in the I-Space.

The introduction of more developed information and communication technologies (ICTs) has as a consequence the shift of the diffusion curve towards the right along the diffusion dimension as shown in **Figure 3**. This shift has two effects. On the one hand, there is a *diffusion effect*: for a given degree of codification and abstraction, a higher number of agents can now be reached with the same information per unit of time than hitherto. Electronic mail, for instance, allows us to reach a much higher number of people than a traditional letter. This is represented in the figure by the horizontal arrow shift. On the other hand, there is a *bandwidth effect*: for a given number of agents targeted, the bandwidth of the message can now be increased. The information transmitted can therefore be both less structured and more concrete, as when we use multimedia instead of written communication. The downward-pointing arrow in **Figure 3** depicts this second effect of an ICT-induced shift of the diffusion curve in the I-Space.

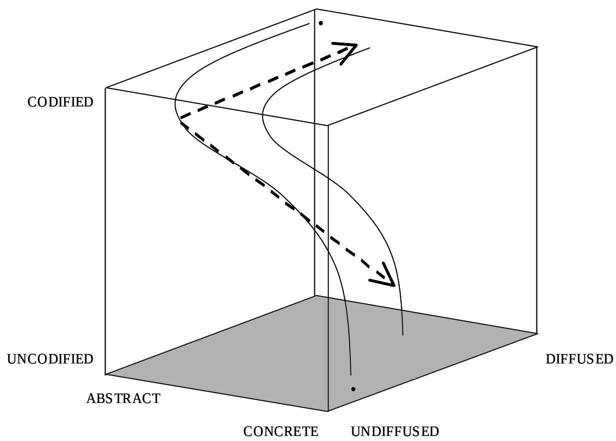

Figure 3 ICTs shift of the diffusion curve in the I-Space

From the analysis of these I-Space formulations we derive two interesting ideas that we will explore with our simulation model. First, we identify two strategic options with respect to the management of one's knowledge. The first concerns an agent's preference for working either with highly codified and abstract knowledge or alternatively, with more tacit and concrete knowledge. The second concerns the possibility of investing in the creation of barriers to the diffusion of one's knowledge—in the real world, these might take the form of secrecy clauses, patents, copyright, etc. In the next section we explain how to introduce these strategic options in our simulation model. Second, we also study the effects of developments in information and communication technologies (ICTs) on the flow of knowledge between organizations.

4. KNOWLEDGE MANAGEMENT STRATEGIES AND KNOWLEDGE DIFFUSION MECHANISMS

Although a full-fledged knowledge-based theory of the firm is still not in place [Spender, 1996; 2002], today, there remains little doubt that the way firms and institutions manage their knowledge has a tremendous impact on their competences and, as a consequence, on their performance [Sanchez, 2001]. The knowledge management strategies adopted by organizations affect not only their internal processes of knowledge creation and transfer, but also their interaction with other organizations and with individuals.

The degree to which knowledge can be voluntarily transferred—or, through spillovers, involuntarily transferred—to other organizations 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 likely to leak out to competitors [Boisot, 1998]. Therefore, a strategic preference for working with structured knowledge, while it facilitates the extraction of value, also facilitates the loss of value of that knowledge through uncontrolled leakages to competitors. A knowledge-hoarding strategy, by blocking diffusion through legal instruments like patents or copyrights or just by hiding knowledge can partly reduce this danger. But it can also turn out to be a sub-optimal choice in a Schumpeterian environment, where knowledge-sharing strategies can result in more profitable long-term outcomes [Boisot et al. 2003].

On the other hand, in addition to the impact of internal strategic choices on the diffusion of knowledge, it can also be affected by external factors such as the physical distance between agents or the degree of development of ICTs. In this section we will describe how we will frame this issues into our simulation model.

4.1. Knowledge Management Strategies

In any study of the behavior of organizational populations, the strategic choices adopted by individual firms must be taken into account when describing the mechanisms guiding the evolution of a group of organizations. We use our 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 their possible impact on the evolution of groups of organizations.

Knowledge management strategies in organizations can be very complex and diverse. Of course, when dealing with complex social sciences problems, one cannot hope to introduce all possibly relevant features of the real world into a simulation model: to be of any utility, a simulation model must always be simpler than reality – and sometimes, much simpler. The model must remain as simple as possible while being able to represent in sufficient detail the key features of the object of study. Thus, we will only introduce in our model two dimensions of a firm's knowledge management strategies whose analysis we consider most relevant to the behavior of a population of organizations.

The first is the level of knowledge structuring at which agents want to operate. Structured knowledge represented in databases, documents or established processes is much easier to transfer, provided that the codes and abstract schemes in which knowledge has been structured are shared. Less structured and more concrete knowledge, like that which is embodied in a craftsman's skills, requires more difficult to transfer since it lacks either clear codification or clear abstraction schemes. In this latter case, the transmission of sensations, feelings or values plays an important part. Face-to-face interaction is then usually required since it provides a "broader bandwidth" that can accommodate all manner of non-verbal communication. Working with highly structured knowledge makes it easier to use and to share it but, by the same token, facilitates knowledge leakages and spillovers and therefore makes it difficult to extract value from it—except, as we will shortly see, when it is possible to put in place diffusion blocking strategies. In general terms, the likelihood that a knowledge asset will diffuse depends on its level of structuring—i.e., on its degree of codification and abstraction. Organizations use both structured and unstructured knowledge, but they can develop a strategic preference for more structured or less structured knowledge. This strategic choice will, no doubt, have an effect on the rents that the organization is capable of obtaining from its knowledge assets.

The second knowledge management strategy that we consider we label *diffusion blocking*. Firms can either adopt a strategy that aims to block the unintended diffusion of knowledge once it has been codified and abstracted—by means, for instance, of patents, copyright or secrecy—or they can allow knowledge to flow freely and unhindered and hope that this will influence the sector and the marketplace in their favor. Again, the choice made will influence the rents obtained from knowledge assets and, therefore, the organization's ability to survive.

4.2. Knowledge Diffusion

Different explanations have been put forward to account for the emergence of clusters of firms that result from agglomeration economies [Krugman, 1991: 37; McCann, 2001: 55; Fujita et al., 1999: 18]. One 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]. In our simulation model, therefore, we will make the probability of successfully transferring knowledge between any two agents depend on the distance between their respective spatial locations. The probability of interaction—and, by implication, of deliberate knowledge transfer or of unintended knowledge diffusion—between two or more agents will be a function of the physical distance between them. Yet, it will also depend on the degree of structuring of the knowledge that has to be transferred or diffused: for a given distance, well codified and abstract knowledge will be much easier to transfer or diffuse than uncodified and concrete knowledge.

An important factor in the effective diffusion of knowledge is the level of development of information and communication technologies (ICTs). The appearance firstly of the telegraph, then of the telephone, and now more recently of the Internet, has made it possible to gradually extend the reach of knowledge across space and time. Information that two hundred years ago could only be transmitted face-to-face through the movement of people can today travel the globe in a matter of seconds. Indeed, technological development constitutes a major factor in the emergence of an information society [Bell, 1973; Castells, 1996; 2001]. The recent increase in bandwidth achieved by new ICT developments points to further improvements in the reach and speed of information transmission.

Although information should not be conflated with either data or knowledge [Boisot and Canals, 2004]—information is what is extracted from data in order to generate knowledge—it is clear that any improvement in the capacity of data transmission implies—other factors remaining equal—a speeding up in the diffusion of information and, concomitantly, in the transfer of knowledge. Our model will reflect this: the dependence of the probability of interaction on spatial distance that we mentioned above will be modulated by the degree of development of ICTs.

But, as already pointed out, many ICT developments also make possible increases in the bandwidth of communication. Bandwidth turns out to be less important when transmitting structured knowledge than when transmitting unstructured knowledge. Knowledge that had to be formally structured to be sent at all, such as mail for example, through improvements in ICT, can now be sent in an informal and unstructured form using, say e-mail or video-conferencing technology. However, this also means that structured information might now readily diffuse beyond our control. The upshot of all this is that the evolution of ICTs can call for a change in the knowledge management strategies that will be appropriate in different situations. The right combination of knowledge structuring and diffusion blocking will thus depend on the degree of evolution of ICTs and cannot be found by analytical means alone.

We build our simulation model using agent-based simulation methods to represent a population of organizations capable of creating and of sharing knowledge assets. Individual agents—here these represent firms or institutions—can each be assigned the different strategic options described in this section, and the environment in which those agents dwell can be adapted to represent the different degrees of dependence of knowledge flows on spatial distance and on different ICT regimes. In the following section we offer a more detailed description of our simulation model.

5. A MODEL OF KNOWLEDGE-BASED ORGANIZATIONAL POPULATIONS[3]

The objective of this research is to use agent-based simulation to study the evolution of specific strategic options within a population of organizations as well as the influence on this evolution of progress in ICTs. Agent-based simulation, as opposed to other simulation techniques which are based on mathematical equations, takes a bottom-up approach made possible through the use of Distributed Artificial Intelligence (DAI) technologies [Brassel et al. 1997]. Agent-based modeling offers the possibility of directly representing individuals or other agents. It is "based on the idea that it is possible to represent in computerized form the behavior of entities which are active in the world, and that is thus possible to represent a phenomenon as the fruit of interactions of an assembly of agents with their own operational autonomy" [Ferber, 1999: 36]. Agent-based simulation, thus, makes it possible to model complex systems whose overall structures emerge from interactions between individuals, something which is not possible using most classical modeling procedures.

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 fields of management and organization

[3] Part of this section draws upon Boisot et al. [2004]

theory, simulation has found many applications. The first uses were in operations research and management-science techniques [Law and Kelton, 2000; Pidd, 1998]. Later, simulation techniques were gradually introduced as a research tool to address theoretical problems in economics and management. Equation-based simulations have been extensively used in economics. Nelson and Winter, for instance, use them in their evolutionary theory of economic change [Nelson and Winter, 1982] and Paul Krugman uses them to deal with some problems in the "new economic geography" [Krugman, 1996]. In management science research simulations remained underutilized [Berends and Romme, 1999], except in specific areas such as Computational Organization Theory [Prietula et al., 1998; Carley and Gasser, 1999] or in applying solutions adapted from other disciplines [Levinthal, 1997]. Lately, however, a clear increase in the use of simulation in management research—and especially of agent-based simulation modeling—can be observed. Such modeling has been used, for instance, to study complex systems problems in organizational design [Rivkin and Siggelkow, 2003], strategy [Rivkin, 2000; Rivkin and Siggelkow, 2002], and strategic knowledge management [Rivkin, 2001]. Finally, simulations have been used in the study of organizational populations [Lomi and Larsen, 1996; 2001]. Yet, although our own previous papers make use of simulation modeling in the field of knowledge management [Boisot et al., 2004], there is in little in this area that deals explicitly with knowledge flows.

The simulation model we propose in the present work, *KMStratSim*, is an extension of *SimISpace* [Boisot et al., 2003a; 2003b; Boisot et al., 2004]. *SimISpace* is an agent-based simulation consisting of a group of agents each possessing different knowledge assets. These are distributed in the I-Space and behave according to its theoretical tenets. The work we present here takes *SimISpace* as a basis for building a more specific model which represents a population of organizations belonging to a given industrial sector and with each organization located in a given spatial region. Each organization manages its knowledge assets by pursuing some particular knowledge management strategy.

KMStratSim extends *SimISpace* in order to study the knowledge management behavior of firms located in space. In *SimISpace*, different agents, each representing a firm, hold a number of knowledge assets and interact in a Schumpeterian regime characterized by the obsolescence of knowledge assets, their uncontrolled diffusion, and a general atmosphere of creative destruction [Boisot et al., 2004]. Agents can either create knowledge for themselves by investing their funds, or they can acquire knowledge assets from other agents through meeting and interacting with them. Agents receive rents from the use they make of their knowledge assets and use those funds either for the creation of new knowledge or for interacting with other agents. The performance of agents in the simulation depends both on their ability to generate funds and to make good use of them. An agent who fails to generate enough funds is removed from the simulation.

Given the importance of spatial factors in the diffusion of knowledge—as mentioned before—we have added a spatial component to *SimISpace*, allowing us to place our agents in a physical space. In *KMStratSim*, agents represent interacting firms belonging to a given industrial sector but assigned to different regional locations. Also, since we are interested in the knowledge management strategies pursued by firms, a new feature has been added to existing *SimISpace* models: the option of assigning different knowledge management strategies to a given agent. Finally, given that they have an obvious effect on knowledge flows, we introduce into our model the possibility of simulating different degrees of development of information and communication technologies (ICTs),

In the following sub-sections we first describe the basic *SimISpace* model and second, the characteristics that are specific to the extended model that we are using here, *KMStratSim*.

5.1. The basic *SimISpace* model

Our agent-based simulation model is characterized by mixture of competition and collaboration between agents. Individual agents aim at surviving and although at this stage in the simulation's development they have no learning capacity, the game as a whole displays elements of evolutionary behavior. Profits are a means of survival and if agents run out of money they are "cropped". They can, however, also exit the simulation while they are still ahead.

How does the model implement and embody the concepts of the I-Space? The I-Space is a conceptual framework for analyzing the nature of information flows between agents as a function of how far such flows have been structured through processes of codification and abstraction. Such flows, over time, give rise to the creation and exchange of knowledge assets. Where given types of exchange are recurrent, they will form transactional patterns that can be institutionalized. In our model, however, we focus on the creation and exchange of knowledge assets *tout court* without concerning ourselves with the phenomenon of recurrence. In later versions of the model, recurrence will become our central concern.

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 transactions with other agents—i.e., buying, selling, licensing, joint-venturing, and merging—who will then use them directly. Agents that fail to make direct or indirect use of such assets in a timely fashion are selected out of the simulation—i.e., they are "cropped". Knowledge assets, somewhat like Dawkins' "memes" [Dawkins, 1999], "colonize" the heads of agents and survive by inhabiting the heads of as many agents as possible. If they fail to occupy at least one agent's head, they die out.

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. Entry and exit are based on the difference in mean revenues between two periods. The rate of entry and exit is a parameter that is set at the beginning of the simulation for every percentage change in mean revenue. Change of rate of entry and exit is a function of percentage change in mean revenue.

The model 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. In what follows, we discuss each model component in turn, starting with agent characteristics. We then describe the knowledge assets component. This is followed by a brief discussion of the agent interaction component.

5.1.1. The agent component

SimISpace operates through a number of agents that, taken together, 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. It would be quite feasible, with suitable parameter settings, to have the agents represent individual employees within a firm and hence to simulate the behavior of such agents within a single organizations. It would also be possible to have an individual agent representing the behaviour of a strategic business unit. Conversely, one could run SimISpace above the firm level and simulate knowledge flows within a population of industries.

As we have already seen, agents can enter or exit SimISpace according to circumstances and can also be cropped from the simulation if their performance falls below a certain threshold. It should be noted here that, as the model looks at rents obtained from knowledge assets and not accounting profits, cropping simply means that agents return to normal profits. That does not mean that they disappear completely from the world in which the simulation is placed. 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. This latter fund constitutes an intangible asset and is non-fungible. Agents modify their wealth either by changing the location of their knowledge assets in the I-Space, and hence altering their revenue-generating potential, or by trading in these assets with other agents thereby enlarging or shrinking their asset base. The details of how this is done are given under the heading of “agent interaction”.

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. Each agent’s preference for drawing from one type of fund or for another is set at the beginning of the game. Each fund, or indeed, both funds can be switched off with a toggle. When a toggle is switched off, the program behaves in a modular fashion.

5.1.2. The knowledge asset component

In *SimISpace*, knowledge assets are represented in a network form. A knowledge network consists of a collection of elements and of relations between elements. We shall refer to the elements of the network as *nodes* and to the relations between elements as *links*. Nodes and links can be combined with certain probabilities to create more complex knowledge assets. A knowledge asset, then, can either be a node or a link between two nodes. Each node and each link varies in how far it has been codified, made abstract, or has been diffused to other agents. Thus each node and link has a unique location in the I-Space that determines its value to the agent and hence its revenue-generating potential. The more codified and abstract a knowledge asset the greater its utility and hence the greater its value. Likewise, the less diffused a knowledge asset, the scarcer it is and hence, again, the greater its value. Agents can enhance the value of their knowledge assets – and hence their revenue-generating potential – in two ways: 1) by investments in the Social Learning Cycle (SLC) that offer the possibility of changing the location of knowledge assets in the I-Space; 2) by combining nodes and links into networks that can be nested and in this way building up more complex knowledge assets. The different locations in the I-Space thus have different revenue multipliers applied to them to reflect their different degrees of utility and scarcity. The proneness of a given asset to diffusion or to obsolescence also varies with its location in the I-Space.

5.1.3. *The agent interaction component*

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 and 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) merge with or acquire 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.

A detailed explanation of the internal functioning of the SimISpace simulation program can be found at [Boisot et al., 2003a; 2003b]. There, one can also find a complete list and description of the parameters of SimISpace.[4]

5.2. The evolutionary model *KMStratSim*: evolution of KM strategies and ICT development

Our interest in studying the effect of knowledge management strategies on the evolution of organizational populations has led us to add several new features to the basic *SimISpace* simulation model, in effect building a new model that we label *KMStratSim*. These features include a representation of the location of agents in a physical space, the possession

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[4] These working papers can be found at the Sol C. Snider Entrepreneurial Research Center website [http://www.wep.wharton.upenn.edu/Research/publications.html]

by different agents of distinct knowledge management strategies, and scenarios that specify different levels of ICT development available to agents. Taking each of these in turn.

5.2.1. The spatial location of agents

Our simulation model represents a population of knowledge-intensive organizations located in a given region of space. As is usual 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 to locate the agents. Several agents can occupy the same cell simultaneously. At this stage of the model's development, we take the space that agents occupy to be isotropic—that is, without geographical irregularities.

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

Both agents created at the beginning of the simulation as well as new entrants in different periods are assigned grid locations at random. New agents created as a result of joint ventures or mergers or as the subsidiaries of other agents, have a higher probability of being assigned a grid location close to one of their parent agents.

We can think of location as having an effect on knowledge flows and transfers because individual locations of firms configure inter-firm distances. Following several studies on the spatial economy, one can plausibly argue that the diffusion of knowledge between two organizations depends, in part, on the spatial distance between their respective locations [Storper, 2000; Audretsch, 2000; Dunning, 2000]. Two different—albeit strongly related—reasons can be invoked for this. First, spatial proximity facilitates face-to-face communication while spatial distance forces one to rely on ICTs to communicate. Since in face-to-face interactions the bandwidth at the disposal of the communicating parties is broader, it seems reasonable to suppose that the diffusion of knowledge will generally be easier. Second, spatial proximity usually implies a greater measure of shared context—cultural economical, social, linguistic, etc. This also facilitates communication and, hence, effective knowledge diffusion. Later we will explain how we implement these ideas in our model.

5.2.2. *The knowledge management strategies of agents*

Strategies for managing knowledge assets—that is, agent preferences for working either at high levels or at low levels of knowledge structuring—i.e., of codification and abstraction—, and agent preferences for either blocking or not blocking the diffusion of knowledge—are represented by two internal variables for each agent. These strategies are fixed for a given agent at the time of its creation and are incorporated in the agent's internal variables. Every time that the agent needs to take a decision related either to the diffusion of his knowledge assets or to their degree of structuring, the stored variables help to shape his decision. In that sense, internal variables act in a way that is similar to the genes of a living creature.

If the *knowledge-structuring-strategy* variable (KSS) for some agent, for example, takes the value 1, each time that the agent makes an investment in research, it goes in the direction of increasing the degree of structuring. If, on the other hand, the value is 0, investments in research go to decrease the degree of structuring and to increase the tacitness of the knowledge in question. The same goes for the *diffusion-blocking-strategy* variable (DBS). If it takes the value 1, the agent's preference will be for blocking the diffusion of knowledge, while if the value is 0 his preference will be for not blocking it. The former choice corresponds to an N-learning strategy in I-Space while the latter corresponds to an S-learning strategy [Boisot, 1998].

Obviously, the knowledge management strategies described have an effect on the actual behavior of organizations. DBSs, for example, affect the level of unintended diffusion of knowledge by firms. KSSs, by contrast, have one of two effects. As we have seen, depending on the option adopted for KSS, any investment in knowledge creation will go towards increasing the mean level of structuring of knowledge assets or towards decreasing it. As the amount of rents an organization is able to extract from its knowledge assets depend on their degree of structuring, this kind of strategic options will have an effect on performance. But the degree of structuring also influences knowledge flows. One of the key propositions of I-Space is that knowledge flows much more easily for higher degrees of structuring than when it remains mostly in tacit form. Thus, while increasing the level of structuring of knowledge will help agent to extract greater benefits from it—at least in the short run—over the longer term, the greater diffusibility of this knowledge will make it difficult to continue extracting value from it.

We have built a model that allows a population of agents to represent a population of organizations belonging to a given industrial sector. Those organizations are located within a spatial region and they can adopt different strategies with respect to either the diffusion or the structuring of their knowledge assets. The exercise of such strategic choices by agents [Child, 1972] introduces an evolutionary process into the simulation. The values of the variables representing knowledge management strategies—i.e., with respect to knowledge structuring and diffusion—remain unchanged over the life of an agent. Furthermore, they are inherited by any agent created by mergers, joint ventures, or subsidiaries, through a mechanism similar to that which underpins genetic algorithms [Mitchell, 1996; Holland, 1992]. In the case of subsidiaries, the values of the parent agent's "genes" are inherited directly by the subsidiary. In the case of mergers and joint ventures, the "genes" assigned to the new agent are those of either parent agent. These are assigned to the new agent with equal probability, thus reflecting the dynamics of Mendelian inheritance of sexual recombination of the genetic endowment of the parents [Mayr, 1982].

Our model, then, exhibits evolutionary behavior. On the one hand, although the strategic preferences of each organization are fixed, their relative importance in the population of organizations in the simulation can vary as a consequence of the evolution of the system over time. On the other hand, an organization's grid location in space, in some cases is inherited—i.e., joint ventures, mergers and subsidiaries are located close to one of the parent organizations. Thus, the spatial location of different members of the population will also evolve over time, and, given, the dependence of knowledge diffusion on spatial distance, this will influence the evolution of knowledge management strategies. What we effectively have is a model capable of describing a co-evolution of knowledge management strategies and locations in an organizational population. In this work, however, we will focus on the implications for the evolution of knowledge management strategies.

Some of the agent strategies will be more effective than others, and firms or institutions adopting these strategies will survive longer and give rise to a greater number of mergers, joint ventures and subsidiaries that subsequently inherit the strategies. In the long run, perhaps only some strategies will survive. Alternatively, after some time, the simulation may settle down in a mix of strategies that remains stable as a consequence of the co-evolution of knowledge management strategies. The fact that we cannot predict the outcome *ex ante* prior to running the simulation demonstrates the utility of simulation modeling when dealing with complex systems. The challenge is then to obtain original insights from the process that lead to the generation of empirically testable hypotheses [Carley, 1999].

5.2.3. ICT development

The effect of ICT development is implemented in our model by focusing on the two effects of the ICT shift of the diffusion curve in the I-Space described in section 3. The *diffusion effect* will be reflected in the fact that, for a given degree of structuring of knowledge, the probability of reaching other agents located at a given distance through knowledge transfers will be higher for a higher level of development of ICTs. This means that more agents will be reached per unit of time for a given level of knowledge structuring. The *bandwidth effect* will be built into the mechanism that will make possible that, for a given number of agents that one has a chance of interacting with, the development of ICTs will increase the probability of successfully transferring knowledge of a given level of structuring. That is, more knowledge will be transferable per unit of time at a given level of codification and abstraction.

We use our model to explore this phenomenon. For this, we introduce a general variable that reflects the extent to which the diffusion of knowledge—both intended or unintended—is impeded or not by the physical distance between interacting agents. Of course, we are aware of the fact that in neither the case of face-to-face communication nor in that of a shared context—cultural or otherwise—is the negative correlation with physical distance necessarily always a strong one. But in the interest of model simplicity we will assume that physical distance constitutes an acceptable proxy for both variables.

The general variable β that we introduce into the model measures the level of development of ICTs. In effect, β is directly associated with the level of ICT development. Higher values for β thus increase both the diffusion effect and the bandwidth effect, facilitating the diffusion of knowledge between agents at different grid locations. As ICTs develop and increase the bandwidth available, the difference in efficiency and effectiveness between face-to-face and ICT-mediated communication begins to shrink. In our model, therefore, the higher the value of β, the higher the level of development of ICTs, and hence the lower the impeding role of spatial friction.

The diffusion of knowledge in *KMStratSim* follows the same logic as that which drives diffusion in *SimISpace*. Knowledge assets diffuse both in an intended way as the result of agents meeting each other and transacting, as well as in an unintended and random way as the result of uncontrollable spillover effects. The latter can result from agent meetings or can take place independently of them. Effective knowledge transfer between agents depends on the interplay of two probability factors. The probability of a knowledge transfer between any two agents is the product of the probability of an interaction between them and the probability of a knowledge transfer given that an interaction has taken place:

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

The probability of a knowledge transfer given that an interaction between agents has taken place depends on the degree of codification and abstraction, that is, the degree of structuring (S) of the knowledge asset involved[5]. So we have:

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

---

[5] 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.

where P_0 includes the random and internal variables dependence. As we will shall see in the following section, the dependence on the degree of knowledge structuring is especially relevant to our study: the more structured—i.e., more codified and abstract—is the knowledge in question, the more probable its diffusion becomes. The calculation of the probability of interaction between agents, therefore, incorporates the influence of spatial distance taking the form of an exponential probability distribution:

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

As might be expected, the equation indicates the dependence of agent interaction both on the spatial distance, r, that separates them and on the variable β. The latter can take on values from 0 to infinity. This probability distribution differs from the exponential distribution often used in simulations [Law and Kelton, 2000 :300] in the fact that always the probability at $r = 0$ is one, reflecting the fact that a knowledge transfer between any two agents occupying the same position in space will always take place. **Figure 4** illustrates the shape of $P(Int)[r,\beta]$ for several values of β. As can be seen from the figure, the effect of increasing the bandwidth—i.e., of more developed ICT regimes—is that the shape of the curve gets modified: the difference between the values for a probability of interaction at shorter distances and for one at larger distances is reduced. This secures the implementation of the I-Space's *bandwidth effect* in the simulation model, and reflects the fact that information and communication technologies help to increase the similarity between long-distance and short-distance interaction.

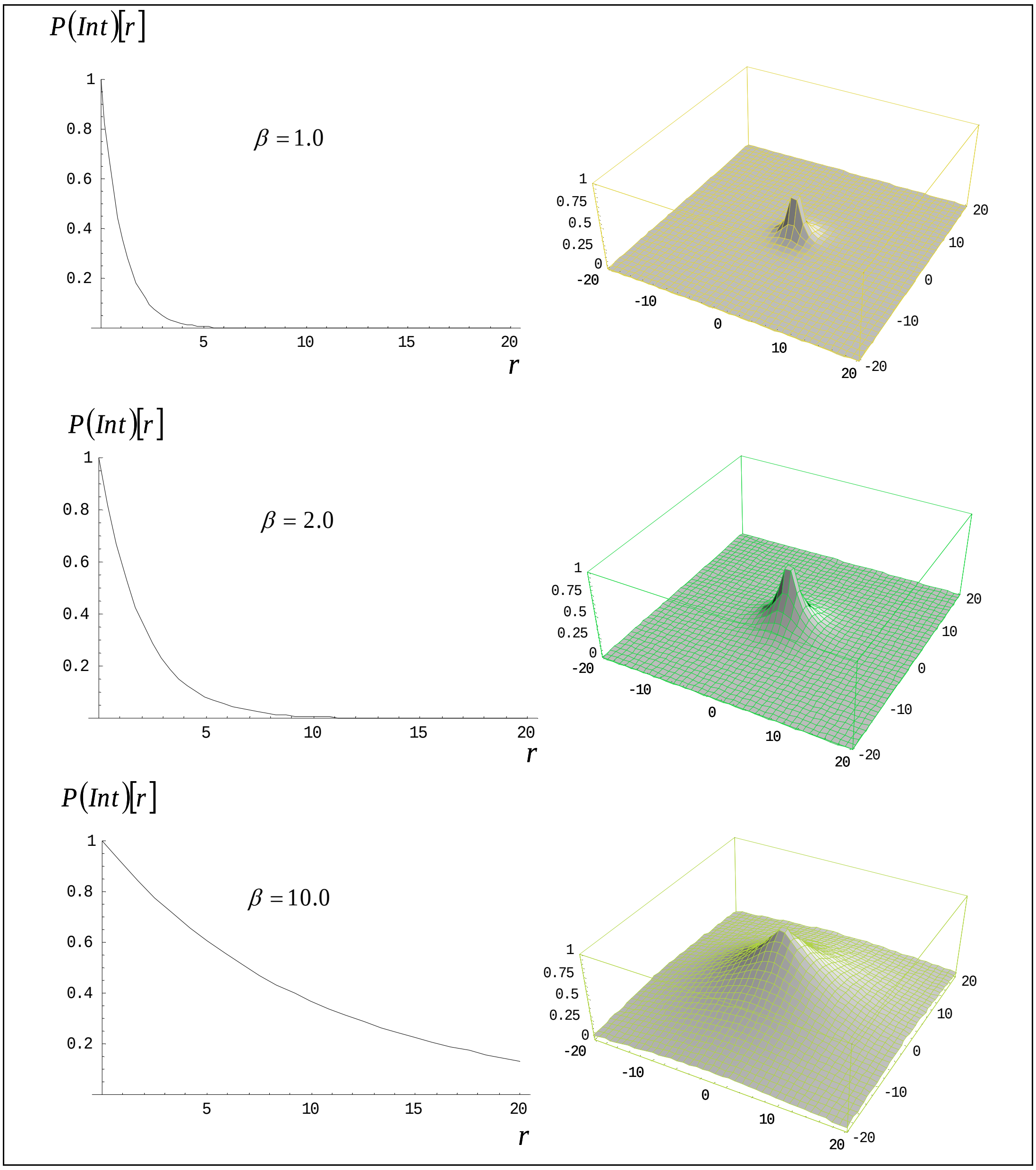


Figure 4 Bandwidth effect: the shape of the probability of interaction $P(Int)[r,\beta]$ for different values of β as a function of the distance *r* between cells.

The variable *r* represents different spatial distances, measured in number of cells; these depend on the nature of the event being described. For diffusion decay, for example, *r* is taken as the distance between the center of gravity of the different agents who possess a given knowledge asset to be diffused and the agent to whom it eventually has to be diffused. For random encounters, *r* is the distance between the two agents for which the probability of a possible encounter is being calculated. Finally, for meetings that have to be arranged in advance, *r* is the spatial distance between a given agent that is evaluating the need to interact with another agent, and this second agent.

Note that the probability of interaction takes the value 1 for $r = 0$ and the value 0 for $r = \propto$. In our interpretation of the model, therefore, in the case of minimal spatial distances, the degree of development of ICTs has less significance—clearly, in face-to-face interactions, even poorly structured knowledge can usually be effectively transferred. However, as spatial distance increases, the probability of effective diffusion decreases and the role of ICTs—and, by implication, their level of development—grows in importance.

Thus, we have a model in which, for a given situation, the probability of transferring knowledge assets between any two firms depends both on the degree of structuring of the assets as well as on the spatial distance between the transacting firms:

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

This expression contains the implementation of the diffusion effect of I-Space, since a higher bandwidth β can compensate for a lower degree of structuring S.

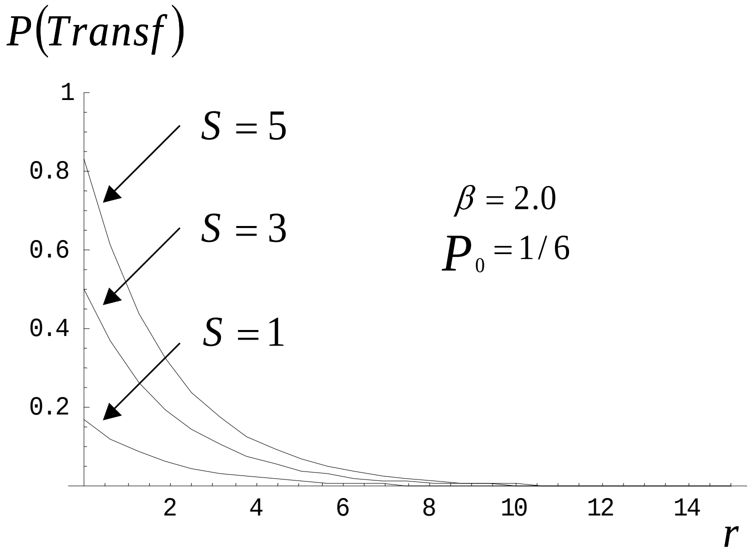


Figure 5 Form of $P(Transf)$

Figure 5 gives the dependence of the probability of transference $P(Transf)$ on the distance *r* for different values of the degree of structuring *S*. For illustrative purposes we have chosen arbitrary values for β and P_0. The value $\beta = 2.0$ corresponds to a medium bandwidth ICT regime and P_0 = 1/6 is the value that makes the probability of transference given interaction $P(Transf \mid Int)$ equal to one for the maximum value of structuring *S = 6*. In the figure it can be seen that, for any given distance, a larger degree of structuring increases the probability of securing a transfer.

As a result of introducing these spatial features, three new parameters have to be added to the initial parameters corresponding to those of SimISpace. The new parameters are the horizontal and the vertical scales that describe our physical space (WORLD_X_SIZE and WORLD_Y_SIZE respectively) and the value of the variable β that represents the degree of development of ICTs (BETA). A complete list of the parameters of our simulation model can be found in appendix 1.

6. RUNS AND RESULTS

In order to explore the influence of different knowledge management strategies on the behavior of a population of agents, we will perform three experiments. First, we will run KMStratSim and compare the general results obtained to those generated by simpler versions of the model—ones in which agent strategies are taken as fixed and identical for all agents. In all cases we select the same value for β. Second, we will look more in depth at the results of the model runs obtained previously and focus on the evolution of the mix of strategies that is present in the agent population. Third, we will run the model for different values of β in order to explore different ICT regimes, that is, different levels of development of information and communication technologies.

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

Robustness. The basic simulation model has been verified and validated following established procedures [Gilbert and Troitzsch, 1999]. This work has been described elsewhere [Boisot et al., 2003a; 2003b; Boisot et al., 2004]. The results reported in this section correspond to a set of simulation experiments that we have performed with the model. The qualitative patterns that we describe here appear to be robust across a wide range of parameter settings and we would be happy to share the complete results obtained with our simulation software with any researcher interested.

For each case that we examine, the run is repeated 50 times in order to be able to obtain statistically meaningful results. We analyze the results of several different cases using ANOVA analysis to ensure that the differences among performance means are statistically significant with $p < 0.001$. In this way we can be confident that any differences found are due to the different parameter settings that characterize each case and not to stochastic variations in the simulated systems—recall that events and decisions in the model are driven by the generation of random numbers. The simulations are programmed to run for a sufficient number of periods to ensure that the system has stabilized. Thus 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 of any given run.

As we present our results, it is important to bear in mind that our aim in this paper is not to demonstrate the generality of any particular results but rather to use any qualitative patterns that emerge as a basis for generating insights on the dynamics of the kind of systems modeled. Thus we use the simulation as a way of generating fruitful hypotheses that could be empirically tested in further research.

6.1. An evolutionary model with mixed strategies vs. simple single-strategy models

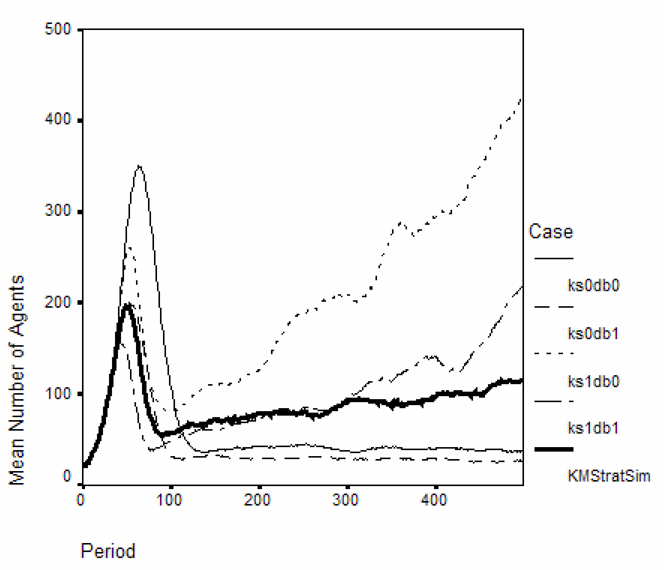
In this sub-section we will look at the general behavior of the evolutionary model *KMStratSim* we have described. Here, we perform all runs using 2.0 as a value for β when calculating the probability of interaction.

In order to analyze the model's overall behavior, we will compare the results obtained in the general case analyzed here with the ones obtained from the four simpler cases in which all agents have identical strategic preference and in which there is therefore no heritable variation. Thus, what distinguishes the general case from the four simpler cases is that, when they are created, agents in the former can make strategic choices both with respect to KSS and with respect to DBS, while in the latter four cases all agents are deemed to possess the same strategic profile—i.e., they have no strategic choices to make. In all cases, the other features and settings remain the same. **Table 2** summarizes the different cases studied relative to the strategic options they implement.

		Diffusion Blocking Strategy (DBS)		
		DBS = 0	DBS = 1	DBS = 0 or 1
Knowledge Structuring Strategy (KSS)	KSS = 0	*ks0db0*	*ks0db1*	
	KSS = 1	*ks1db0*	*ks1db1*	
	KSS = 0 or 1			general *KMStratSim* model

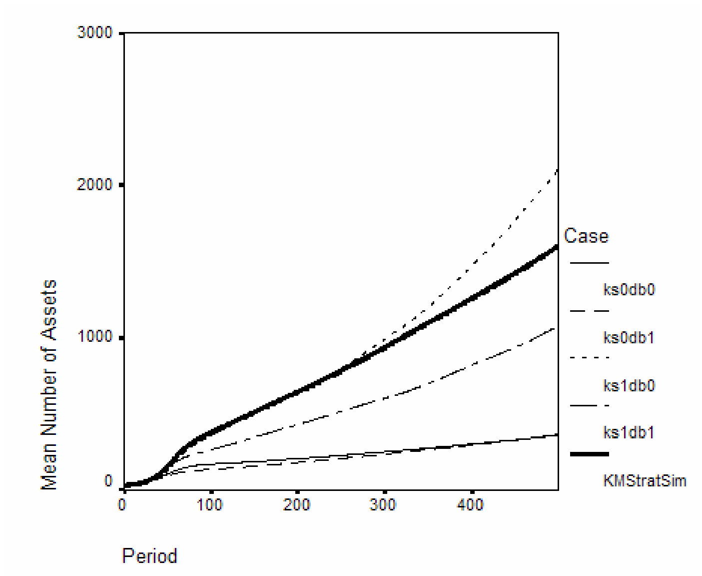
Table 2 Strategic options in the general case *KMStratSim* and the other four restricted cases.

General evolution. In **Figure 6**a to **Figure 6**c, we show the evolution of the model throughout the whole 500 periods. The graphics show the number of agents in the simulation (**Figure 6**a), the number of knowledge assets (**Figure 6**b) and the rents generated (Figure 6c). The curves represent the mean values of these variables for the 50 runs of each model. The thicker curve corresponds to the general KMStratSim model.



Mean Number of Agents
500
400
300
200
100
0
0
100
200
300
400
Period
Case
ks0db0
ks0db1
ks1db0
ks1db1
KMStratSim

(a)



Mean Number of Assets
3000
2000
1000
0
0
100
200
300
400
Period
Case
ks0db0
ks0db1
ks1db0
ks1db1
KMStratSim

(b)

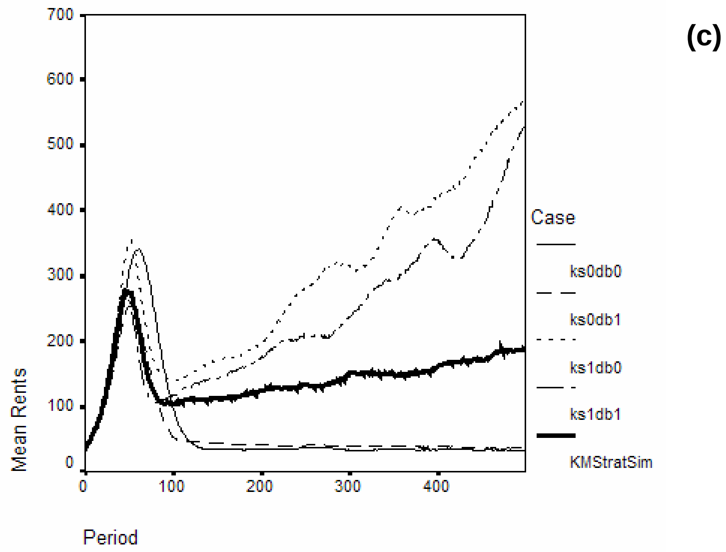


Figure 6 Evolution of a) number of agents, b) number of knowledge assets and c) rents obtained from knowledge assets

The evolution in the number of agents present in the simulation of the general *KMStratSim* case shows a sudden increase in the first 50 periods and then goes 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 that observed in other simulation models [Barron, 2001]. Similar phenomena are also found in organizational ecology models using empirical real data [Hannan and Freeman, 1989; Carroll and Hannan, 2000]. In a simulation exploring organizational fitness in so-called "rugged landscapes", Levinthal [1997] attributes this kind of behavior—in this case, applied to the number of organizational models present in the population—to the emergence of order after an explosive phase in the first periods.

Our four other test cases exhibit similar behavior, but those in which all agents have a tendency to structure knowledge assets show increases in the number of agents after the early chaotic periods while the cases without that tendency to the structuring present a lower number of agents that remains approximately constant after the first 100 periods. As can be seen from the Figure 6a, the general case using *KMStratSim*—represented in thicker trace—occupies an intermediate position. This suggests that there is a possible direct relationship between the propensity to structure knowledge and the capacity of the system in terms of number of agents.

The number of knowledge assets present in the general case of the *KMStratSim* simulation grows very quickly in the first 100 periods, subsequently adopting a steady and more moderate rate of increase. The number of knowledge assets here is higher than in three of the four test cases, the exception being for the one that shows a preference for structuring knowledge assets but for not blocking diffusion (*ks1db0*).

The total amount of rent obtained by agents from their respective knowledge assets appears to rise in line with the total number of agents, which suggests that both variables are correlated. This is to be expected, since in our model we consider that the marketplace of the population of firms modeled is not limited. Therefore, all agents are able to obtain some rents from their knowledge assets without having to fight each other for a share of the market. This models the case of growing industrial sectors—i.e., computers in the 1980s or software in the 1990s—in which an initially limited number of firms, usually located in technological clusters, were securing large shares of the world market.

Variable		Period					
	Case	0	100	200	300	400	499
Number of agents	*ks0db0*	20,02 *(0,14)*	106,58 *(132,00)*	42,82 *(13,89)*	37,46 *(11,55)*	39,76 *(12,52)*	36,92 *(12,82)*
	ks0db1	20,02 *(0,14)*	31,84 *(18,27)*	29,54 *(8,06)*	28,62 *(8,18)*	28,76 *(8,47)*	26,98 *(7,54)*
	ks1db0	20,02 *(0,14)*	81,70 *(63,91)*	126,38 *(55,61)*	209,48 *(97,12)*	294,02 *(136,83)*	423,44 *(172,75)*
	ks1db1	20,06 *(0,24)*	49,10 *(19,13)*	75,84 *(37,87)*	96,60 *(48,39)*	140,80 *(80,68)*	217,44 *(137,41)*
	KMStratSim	20,00 *(0,00)*	56,88 *(22,03)*	79,10 *(35,44)*	92,54 *(49,06)*	97,46 *(61,99)*	115,12 *(73,52)*
Number of knowledge assets	*ks0db0*	30,58 *(0,76)*	171,20 *(26,97)*	207,42 *(28,95)*	252,58 *(34,23)*	303,78 *(39,61)*	358,84 *(48,00)*
	ks0db1	30,40 *(0,64)*	137,52 *(17,31)*	182,48 *(19,86)*	236,58 *(24,85)*	297,32 *(35,28)*	363,08 *(45,65)*
	ks1db0	30,32 *(0,47)*	381,74 *(207,40)*	641,76 *(323,51)*	991,40 *(432,97)*	1472,70 *(580,09)*	2107,64 *(759,04)*
	ks1db1	30,30 *(0,54)*	266,00 *(133,46)*	428,32 *(186,37)*	601,46 *(240,78)*	819,60 *(331,11)*	1080,32 *(423,64)*
	KMStratSim	30,46 *(0,71)*	374,34 *(217,77)*	642,20 *(327,73)*	935,76 *(430,55)*	1256,48 *(555,97)*	1600,30 *(671,15)*
Rents generated	*ks0db0*	34,13 *(4,88)*	95,26 *(90,03)*	34,90 *(11,52)*	33,12 *(9,80)*	33,86 *(8,26)*	32,22 *(10,93)*
	ks0db1	31,72 *(4,74)*	53,25 *(16,13)*	40,96 *(9,85)*	38,97 *(8,38)*	38,67 *(9,13)*	37,68 *(7,64)*
	ks1db0	34,27 *(5,39)*	139,07 *(81,54)*	196,65 *(75,97)*	315,41 *(126,12)*	416,19 *(165,07)*	573,32 *(223,81)*
	ks1db1	34,17 *(5,90)*	117,66 *(36,27)*	177,59 *(77,50)*	238,30 *(109,58)*	354,71 *(197,17)*	527,53 *(309,55)*
	KMStratSim	34,69 *(5,10)*	104,53 *(29,23)*	124,77 *(39,87)*	152,23 *(59,83)*	160,76 *(73,19)*	186,17 *(91,39)*

Table 3 Evolution of mean values for the number of agents, number of knowledge assets and amount of rents generated with standard deviation.

A general analysis of the final periods. Figure 7a and **Figure** 7b depict the creation of knowledge assets and the generation of rents from those assets in the simulation. The value presented is the average value of the last 100 periods. Afterwards, we calculate the mean value among the 50 runs performed for each model. The plot represents the value and the standard error in the average among all runs with a confidence interval of 95%.

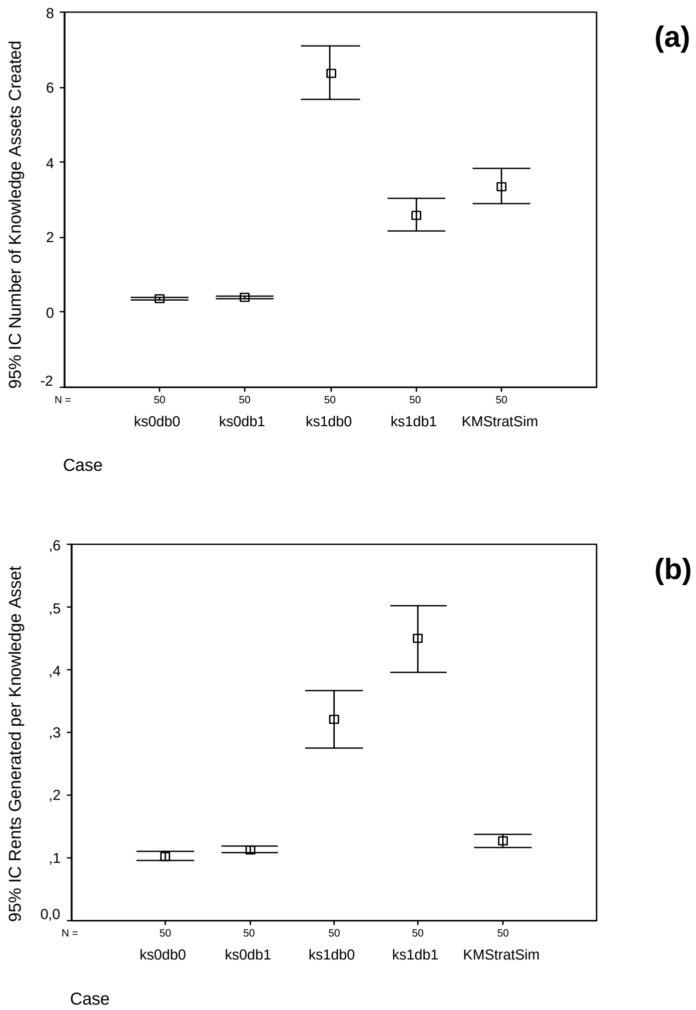
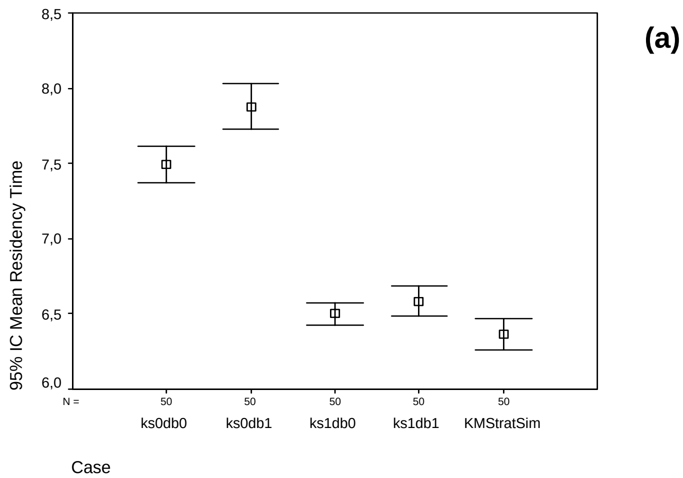


Figure 7 a) Creation of knowledge assets. b) Generation of rents per knowledge asset. Mean values for the last 100 periods.

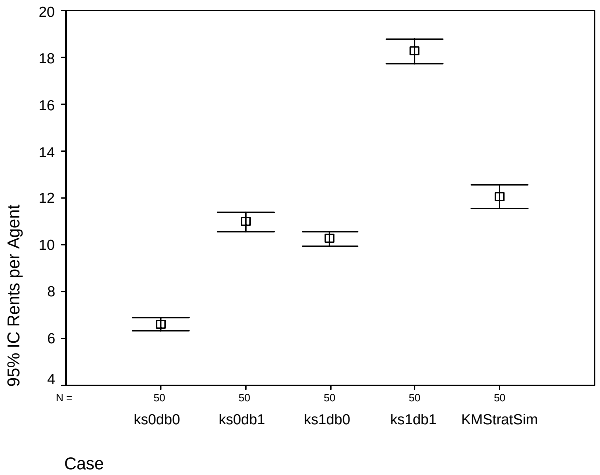
Not surprisingly, knowledge generation in the last 100 periods (**Figure 7**a) shows a similar pattern to the total number of assets (**Figure 6**b). When it comes to knowledge creation, the general case, which allows genetic-like inheritance of different knowledge management strategies, gives the second-best results after the one where agents combine a preference for knowledge-structuring with one for the non-blocking of diffusion (*ks1db0*).

Figure 7b shows the rents generated for all agents in the simulation divided by the number of assets in the simulation. While more than one agent can possess the same knowledge asset, here, this asset will be counted just once. And here again, the cases in which all agents opt for a knowledge-structuring strategy indicate that they enjoy a better performance in extracting rents from the pool of assets.

In **Figure 8**a to **Figure 8**c, we show the average residential times[6] in the simulation of agents still present and active in the last 100 periods of the runs (**Figure 8**a) as well as the rents that those agents obtain both throughout their residency in the simulation (**Figure 8**b) and per period (**Figure 8**c).



[6] We use the expression "residential time" because agents can leave the simulation through two different processes: being "cropped" or deciding to exit. In the second case agents do not properly cease to exist, and therefore we cannot talk of "lifetime". In the range of parameters we are using for this work, however, being cropped is by far the most common way to leave the simulation.



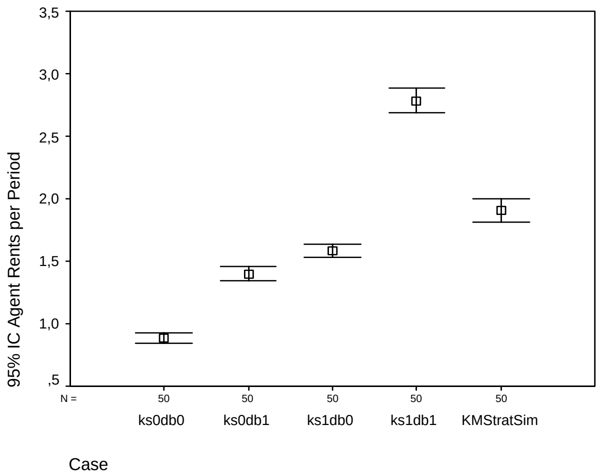


Figure 8 a) Mean residence time of agents b) Rents obtained per agent during their residency time. c) Rents obtained per agent and per period.

The mean residence time of agents in the general evolutionary case is around 6.5 periods, quite close to the mean lifetime in the simulation of the agents in those cases specifying a strict preference for knowledge structuring. By contrast, those cases specifying a thorough preference for not structuring knowledge exhibit a mean residence time of between 7.5 and 8.5 periods.

With respect to the rents generated per agent, the general case is the one in which agents turn in the second-best performance—the best performance being the case in which all agents opt for structuring knowledge and blocking diffusion (*ks1db1*). Obviously, the latter would be not a very realistic case, since once knowledge reaches a certain level of codification and abstraction, it effectively becomes very difficult to prevent its diffusion through leakages, especially in a Schumpeterian environment like the one modeled in our simulations. A similar result is obtained when we look at the rents obtained per period. **Table 4** summarizes the mean values over 50 runs for each case of the main variables studied in the last 100 periods of the simulation with the correspondent standard deviation in brackets.

	Case				
Variable	***ks0db0***	***ks0db1***	***ks1db0***	***ks1db1***	***KMStratSim***
Mean number of agents in a period	39,07 *(8,27)*	26,93 *(3,63)*	350,69 *(117,93)*	160,06 *(68,09)*	105,34 *(58,22)*
Mean number of assets in a period	330,86 *(42,84)*	329,41 *(41,18)*	1777,02 *(661,97)*	941,17 *(367,51)*	1424,39 *(614,19)*
Mean number of assets created in a period	0,37 *(0,11)*	0,38 *(0,12)*	6,38 *(2,53)*	2,60 *(1,51)*	3,36 *(1,68)*
Total amount of rents generated in a period	33,45 *(7,46)*	36,87 *(6,14)*	491,99 *(151,77)*	398,03 *(156,34)*	175,20 *(75,73)*
Mean residency time of agents	7,49 *(0,42)*	7,88 *(0,53)*	6,50 *(0,25)*	6,58 *(0,35)*	6,37 *(0,37)*
Mean rents generated per agent during its residency time	6,62 *(0,93)*	10,98 *(1,45)*	10,26 *(1,05)*	18,26 *(1,80)*	12,05 *(1,78)*
Mean amount of rents generated per agent in a period	0,89 *(0,14)*	1,40 *(0,19)*	1,58 *(0,19)*	2,78 *(0,35)*	1,91 *(0,34)*

Table 4 Mean values and standard deviation for different variables in the last 100 periods.

6.2. Evolution of strategies in *KMStratSim*

In this sub-section we focus on the knowledge management strategies adopted by the agents in the general (evolutionary) case. **Table 5** shows the evolution of the mean number of agents present in the simulation for each of the strategic options contemplated in our study, i.e., the structuring or non-structuring of knowledge assets and the blocking or non-blocking of diffusion of knowledge assets.

Variable	Strategy	Period 0	100	200	300	400	499
Number of agents for each Knowledge Structuring Strategy	KSS = 1	9,42 *(2,12)*	26,94 *(14,03)*	32,56 *(21,09)*	38,40 *(34,27)*	38,50 *(32,08)*	41,86 *(43,18)*
	KSS = 0	10,58 *(2,12)*	29,94 *(16,81)*	46,54 *(30,49)*	54,14 *(35,56)*	58,96 *(46,15)*	73,26 *(58,62)*
Number of agents for each Diffusion Blocking Strategy	DBS = 1	10,22 *(1,96)*	2,54 *(2,94)*	1,10 *(2,01)*	1,02 *(2,12)*	0,84 *(1,88)*	0,80 *(1,68)*
	DBS = 0	9,78 *(1,96)*	54,34 *(22,71)*	78,00 *(35,72)*	91,52 *(49,05)*	96,62 *(62,58)*	114,32 *(73,91)*

Table 5 Mean values and standard deviation of the number of agents for each strategic option.

Since we are more interested in the distribution of the different strategies in the population as a whole, we shall focus on the proportion of agents that pursue each strategy. **Figure 9** depicts: 1) changes over time in the proportion of the population adopting a preference for structuring as opposed to not structuring their knowledge assets (KSS = 1); 2) the proportion of the population adopting a diffusion blocking strategy over time (DBS = 1).

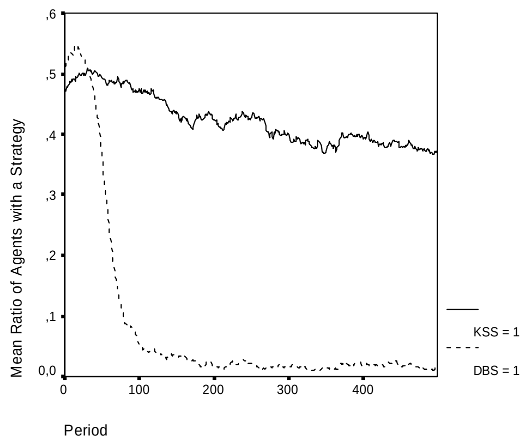


Figure 9 Evolution of the mix of KM strategies in the population

Clearly, the diffusion-blocking strategy is quickly "selected out" and only remains present at a low level until the end of the simulation. From an initial value of around 50% (resulting from a random initial endowment of strategic preferences), it goes down very rapidly, remaining below 5% from period 100 onward. In competition with the "not-blocking-diffusion gene", it appears that the "blocking-diffusion" gene has a much lower prospect of surviving.

By contrast, the system seems to evolve to a situation of peaceful coexistence between the "knowledge-structuring gene" (KSS = 1) and the "unstructured-knowledge gene" (KSS = 0). From a initial 50%-50% mix at the beginning of the simulation it gradually evolves to a mix of approximately 40%-60%. This gets more or less stabilized in the last periods.

One can infer from the above results that while a diffusion-blocking strategy is not attractive for the majority of agents in a Schumpeterian setting, when it comes to structuring or not structuring knowledge, there is no strategy that is strongly preferred by all agents. The two strategies appear to co-exist with a slightly higher number of agents exhibiting a preference for an "unstructured knowledge" strategy.

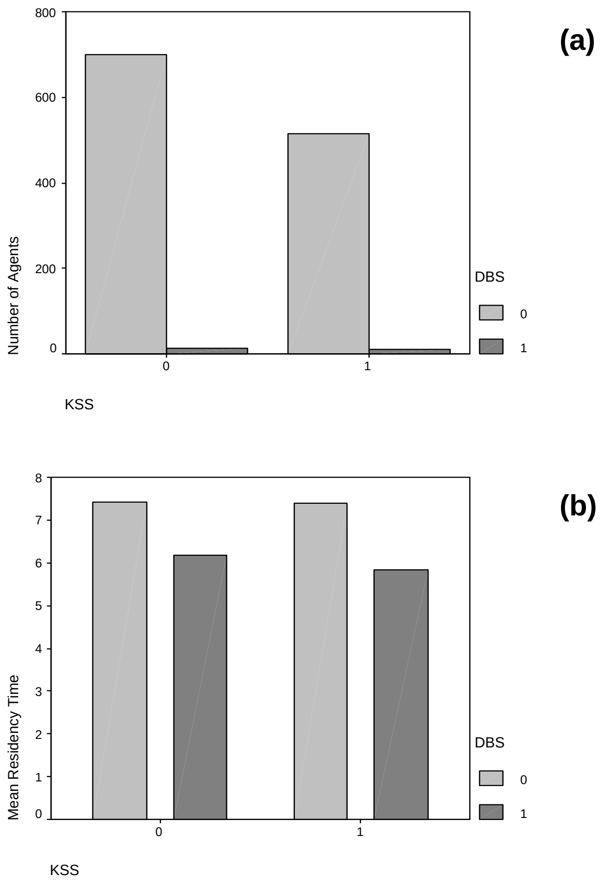


Figure 10 a) Number of agents of each strategic profile within the last 100 periods of the simulation
b) Mean residency time of those agents

Among the 1,200 agents that are present on average in the simulation during the last 100 periods, we see a clear dominance of the "not-blocking-diffusion" strategy, and a broad equilibrium between the "knowledge-structuring" and the "knowledge-unstructuring" strategies, but one slightly biased in favor of the second one (**Figure 10**a). The residence time in the simulation of agents with a preference for blocking diffusion is clearly shorter than that of their non-diffusion-blocking counterparts (**Figure 10**b), which is consistent with the fact that they evolve to a very low proportion of the population. However, no significant differences are found between the residency times of "knowledge-structuring" and "knowledge-unstructuring" agents.

6.3. ICT regimes

In this section we look at the behavior of agents under different ICT regimes by varying the parameter β. Recall that low values of β correspond to high degree of development of ICTs. We run the simulation model for several cases corresponding to different values of β:

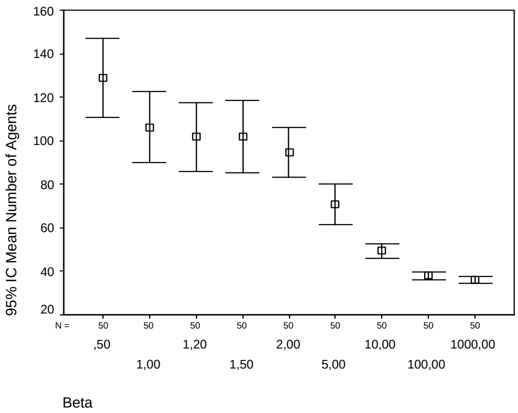
$$\beta = \{0.50, 1.00, 1.20, 1.50, 2.00, 5.00, 10.00, 100.00, 1000.00\}$$

Table 6 shows the mean values—with the corresponding standard deviation—obtained of selected variables in the 100 last periods after running the simulation 50 times for each case.

ICT regime	Variables			
	Number of agents in a period	Total rents generated per agent	Mean residency time	Agent rents generated per period
β = 0.50	128,72	9,88	7,18	0,92
	(63,93)	*(17,54)*	*(6,25)*	*(0,99)*
β = 1.00	106,27	11,47	7,01	1,10
	(57,40)	*(20,19)*	*(6,09)*	*(1,16)*
β = 1.20	101,68	11,47	7,09	1,09
	(55,70)	*(20,55)*	*(6,11)*	*(1,15)*
β = 1.50	101,75	11,49	7,26	1,07
	(58,24)	*(20,43)*	*(6,20)*	*(1,14)*
β = 2.00	94,67	12,42	7,35	1,13
	(39,97)	*(22,00)*	*(6,46)*	*(1,18)*
β = 5.00	70,74	13,04	7,01	1,20
	(33,07)	*(24,75)*	*(6,87)*	*(1,24)*
β = 10.00	49,49	13,12	6,02	1,37
	(11,87)	*(25,77)*	*(6,47)*	*(1,41)*
β = 100.00	38,05	13,89	5,32	1,63
	(6,38)	*(27,25)*	*(5,82)*	*(1,65)*
β = 1000.00	36,09	13,98	5,27	1,63
	(5,49)	*(27,75)*	*(5,82)*	*(1,66)*

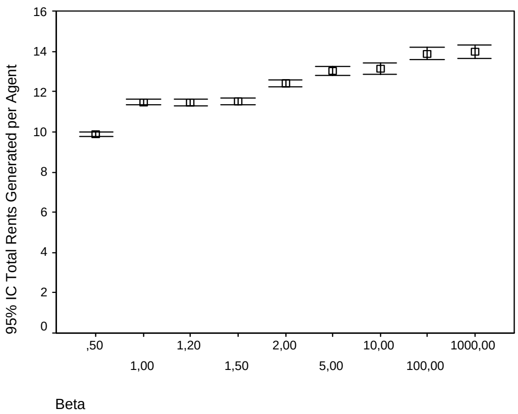
Table 6 Mean values and standard deviation of selected variables for several cases corresponding to different ICT regimes.

Figure 11a to **Figure 11**d show some of the results obtained for the agents present in the 100 last periods of the simulations.



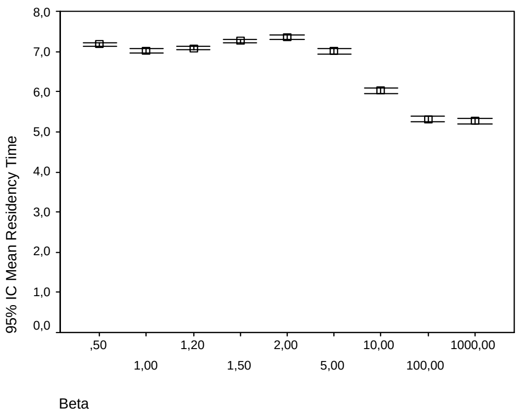
95% IC Mean Number of Agents
160
140
120
100
80
60
40
20
N = 50 50 50 50 50 50 50 50 50
,50 1,00 1,20 1,50 2,00 5,00 10,00 100,00 1000,00
Beta

(a)



95% IC Total Rents Generated per Agent
16
14
12
10
8
6
4
2
0
,50 1,00 1,20 1,50 2,00 5,00 10,00 100,00 1000,00
Beta

(b)



95% IC Mean Residency Time
8,0
7,0
6,0
5,0
4,0
3,0
2,0
1,0
0,0
,50 1,00 1,20 1,50 2,00 5,00 10,00 100,00 1000,00
Beta

(c)

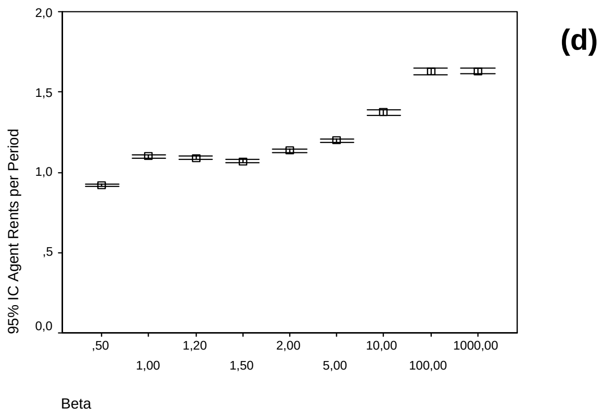


Figure 11 a) Number of agents, b) rents generated per agent, c) average residency time and d) agent rents generated per period for different ICT regimes within the last 100 periods of simulation

Our results point to non-linear behavior.[7] Although the number of agents in the simulation grows with β—the same goes 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 = 1.20 and β = 2.00. If, for example, we look at the agent rents generated per period (**Figure 11**b), we see that after the value corresponding to β = 1.00 there is a slight decrease until the value for β = 1.50. From then on, the agent rents generated per period clearly start to increase with increases in the value of β.

This strongly non-linear behavior is also evident in the mix of knowledge management strategies, especially for the "knowledge-structuring strategy". In **Figure 12**a we note a clear minimum in the fraction of agents having a KSS = 1 strategy at around β = 1.50. For lower and higher values of β, the ratio turns in superior values. Less self-evident

[7] We will exclude from some of our analysis the values corresponding to β = 0.50 since we consider that their relatively detached behavior can be attributed to the fact that probabilities of interaction are strongly suppressed for this value and this makes that the dynamics of the system in that case not comparable to the rest.

inflexion points also exist for the “diffusion-blocking strategy” (**Figure 12**b).

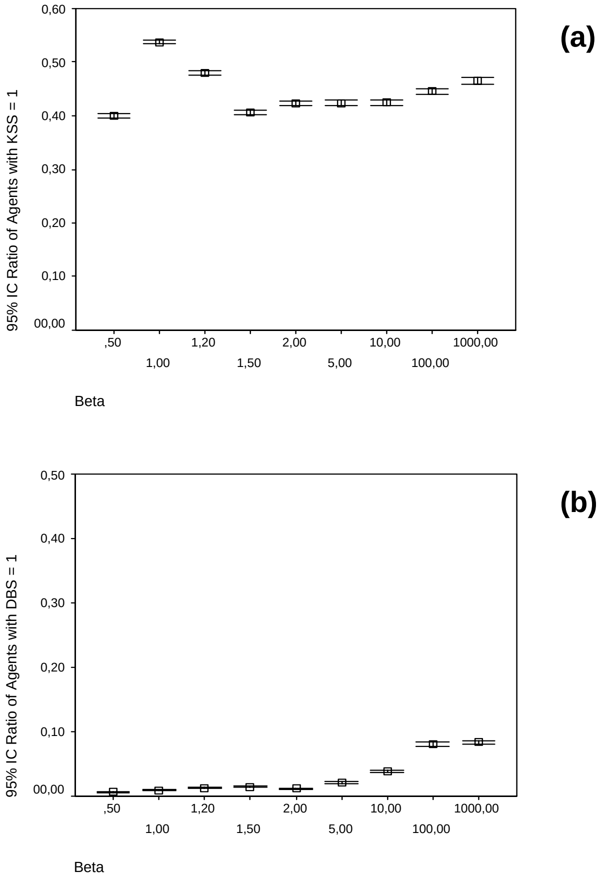


Figure 12 Strategic mixes of a) KSS and b) DBS

Focusing on three of the several regimes studied, β = {0.10,0.50,10.00}, we can see that the non-linearities are strongly related to the mix of strategies of the respective populations (see **Table 7** and **Figure 13**a and b and **Figure 14**a and b) as well as to the mean residential time in the simulation of agents pursuing different strategies (see **Figure 14**c and d).

Case			Period					
	Variable	**Strategy**	**0**	**100**	**200**	**300**	**400**	**499**
β = 0.50	Number of agents for each Knowledge Structuring Strategy	KSS = 1	9,28 *(2,20)*	22,14 *(14,08)*	35,78 *(24,99)*	41,24 *(44,16)*	47,28 *(50,59)*	53,90 *(65,17)*
β = 0.50	Number of agents for each Knowledge Structuring Strategy	KSS = 0	10,72 *(2,20)*	28,50 *(12,16)*	51,56 *(30,97)*	62,94 *(46,94)*	69,66 *(39,77)*	81,92 *(43,67)*
β = 0.50	Number of agents for each Diffusion Blocking Strategy	DBS = 1	10,60 *(2,66)*	4,12 *(3,52)*	1,88 *(2,58)*	0,90 *(2,25)*	0,90 *(2,15)*	0,80 *(1,87)*
β = 0.50	Number of agents for each Diffusion Blocking Strategy	DBS = 0	9,40 *(2,66)*	46,52 *(16,08)*	85,46 *(41,44)*	103,28 *(61,64)*	116,04 *(61,54)*	135,02 *(86,89)*
β = 2.00	Number of agents for each Knowledge Structuring Strategy	KSS = 1	10,26 *(2,33)*	26,18 *(16,99)*	38,12 *(30,69)*	42,34 *(46,86)*	32,78 *(31,63)*	39,96 *(43,46)*
β = 2.00	Number of agents for each Knowledge Structuring Strategy	KSS = 0	9,76 *(2,31)*	25,42 *(12,23)*	32,40 *(17,92)*	42,30 *(25,00)*	55,40 *(35,06)*	54,96 *(36,71)*
β = 2.00	Number of agents for each Diffusion Blocking Strategy	DBS = 1	9,66 *(2,06)*	3,14 *(4,09)*	1,32 *(2,28)*	1,52 *(2,92)*	0,66 *(1,35)*	1,18 *(2,68)*
β = 2.00	Number of agents for each Diffusion Blocking Strategy	DBS = 0	10,36 *(2,07)*	48,46 *(17,02)*	69,20 *(31,53)*	83,12 *(49,48)*	87,52 *(41,42)*	93,74 *(51,00)*
β = 10.00	Number of agents for each Knowledge Structuring Strategy	KSS = 1	10,24 *(2,27)*	23,48 *(13,18)*	21,40 *(16,34)*	20,56 *(14,53)*	21,08 *(16,15)*	20,42 *(18,13)*
β = 10.00	Number of agents for each Knowledge Structuring Strategy	KSS = 0	9,72 *(2,29)*	25,08 *(11,24)*	26,26 *(13,90)*	26,18 *(11,87)*	28,68 *(18,09)*	29,90 *(16,26)*
β = 10.00	Number of agents for each Diffusion Blocking Strategy	DBS = 1	10,04 *(2,38)*	3,08 *(3,14)*	1,56 *(1,94)*	1,82 *(2,50)*	1,26 *(1,80)*	1,82 *(2,26)*
β = 10.00	Number of agents for each Diffusion Blocking Strategy	DBS = 0	9,92 *(2,40)*	45,48 *(10,93)*	46,10 *(15,18)*	44,92 *(12,81)*	48,50 *(14,55)*	48,50 *(18,08)*

Table 7 Mean values and standard deviation—in brackets—of the number of agents for each strategic option at different ICT regimes.

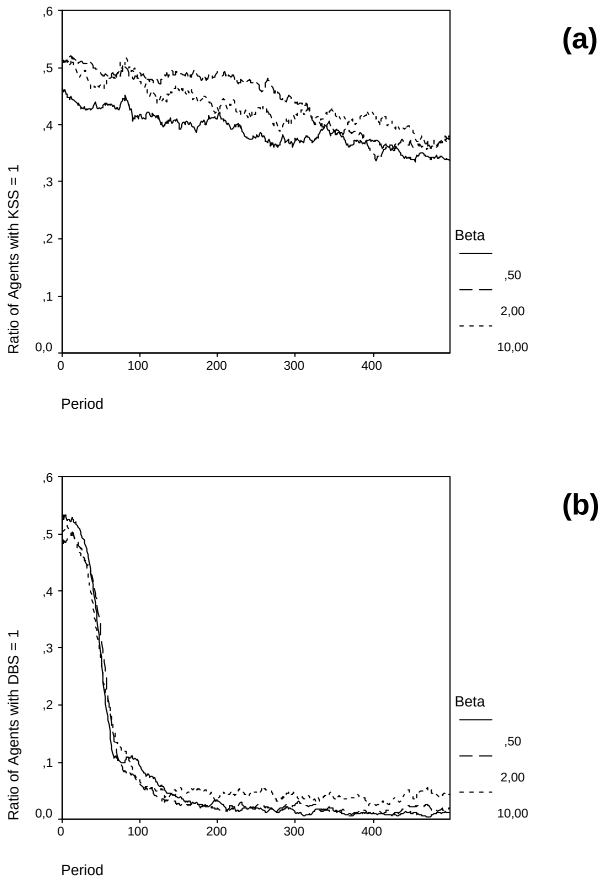
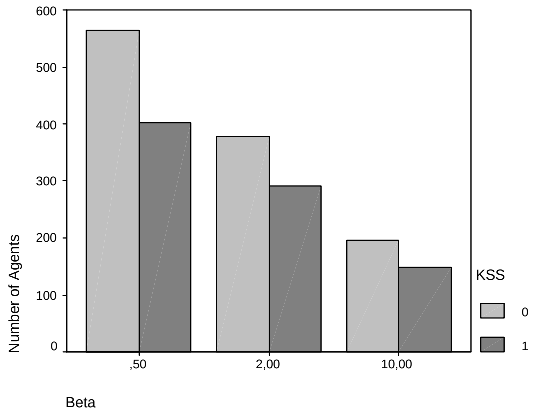


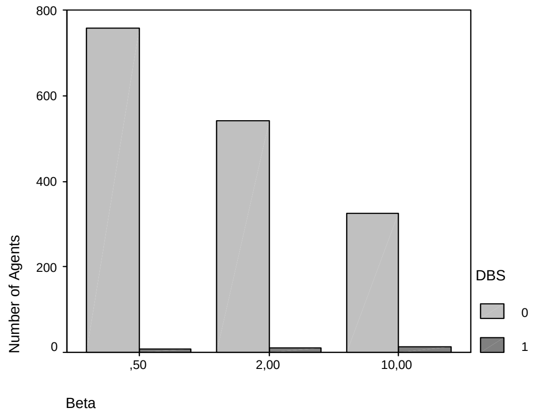
Figure 13 Evolution of a) number of agents and b) mean residential time for each strategic choice.

A clear illustration of this relationship is given by the fact that for β = 2.00 the mean residency time of agents with a KSS = 1 strategy is longer than that for their counterparts with a KSS = 0 strategy, while for β = 0.50 and for β = 10.00 the opposite is true (see **Figure 14**c). This points to the internal characteristics of the populations of agents as possible causes of these non-linear effects. We explore this issue later on in our discussion.

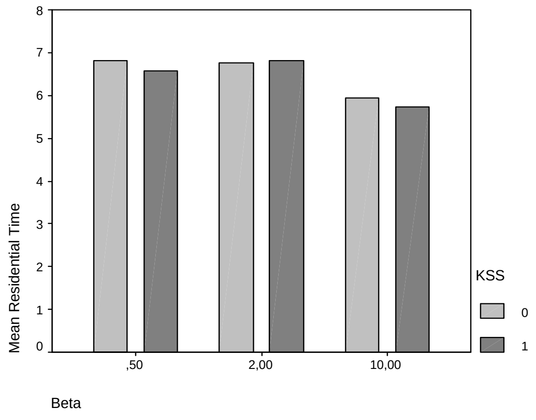
(a)


600
500
400
300
200
100
0
Number of Agents
,50
2,00
10,00
Beta
KSS
0
1

(b)


800
600
400
200
0
Number of Agents
,50
2,00
10,00
Beta
DBS
0
1

(c)


8
7
6
5
4
3
2
1
0
Mean Residential Time
,50
2,00
10,00
Beta
KSS
0
1

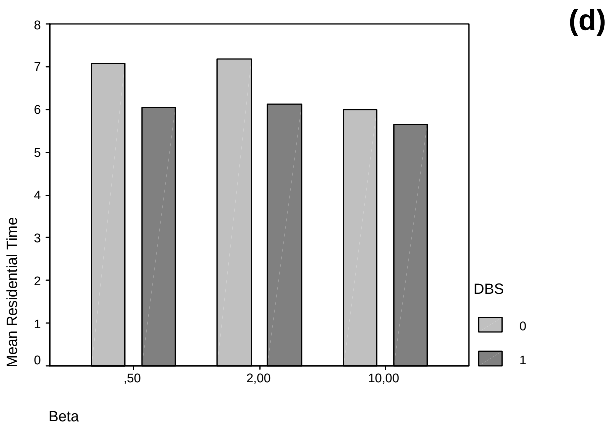


Figure 14 a) Number of agents adopting each KSS choice. b) Number of agents adopting each DBS choice. c) Mean residential time of agents adopting each KSS choice. d) Mean residential time of agents adopting each DBS choice. Data corresponding to the last 100 periods for each strategic choice.

7. DISCUSSION

From the results of subsection 6.1, we can see that our evolutionary case—i.e., a population of organizations as a complex system in a Schumpeterian environment—exhibits a consistent pattern of behavior. A comparison of this case with less realistic ones, those exhibiting a single and fixed strategic preference common to all agents, confirms this fact.

Organizational populations behave as complex systems and we have shown that some aspects of their behavior can be replicated using evolutionary simulation models. Simulations offer an alternative approach to the study of complex social systems. Our case, however, presents a peculiarity not usually found in simulations of this kind. Here, agents do not follow simple ad-hoc rules that are solely derived from and conceived of for a given simulation model. Rather, the behavioral possibilities of agents are specified with respect to a prior and independent theoretical framework, the I-Space. This feature alone gives them a measure of generality and should enhance the simulation's explanatory power.

The specific analysis of the evolution of KM strategies in sub-section 6.2 permits to derive a number of insights. On one hand, they corroborate the common intuition that blocking diffusion may not be a very good strategy in a Schumpeterian environment. The KM strategy DBS = 1 is strongly suppressed and ends up being pursued by 3% of the population at most. Although there always seems to be some scope for organizations that want to block diffusion—and, to be sure, their number increases somewhat with the development of ICTs—the low proportion of diffusion-blocking firms could be attributed to the paucity of new entrants into the simulation that adopt this strategy but that are then compelled to quit the simulation because of it. Examining the specific histories of some of the simulations performed, we observe that the survival problems of agents prone to "diffusion-blocking" are not related to their rent-producing abilities. Indeed, the mean level of rents obtained by agents with a diffusion-blocking strategy is considerably higher than for their counterparts with a preference for not blocking diffusion. One plausible interpretation is that blocking diffusion is a high-risk/high-return strategy that is worthwhile for but a few players. The difficulties that these players encounter come from the high costs they have to incur in order to maintain diffusion blocking. From this we derive the following hypothesis:

> ***Hypothesis 1.*** *A general knowledge management strategy based solely on the protection of intellectual property rights (diffusion blocking) is not sustainable in an information economy due to the high costs of maintaining blocking mechanisms. Any Investment in such mechanisms is only worthwhile for specific knowledge assets in industry-specific circumstances.*

The preceding hypothesis flags up the difficulties of blocking diffusion in a Schumpeterian economy. The high costs of establishing, maintaining and enforcing diffusion-blocking mechanisms such as copyright, patents or simply secrecy, can quickly outweigh the benefits of possessing knowledge assets in exclusivity. In some cases, a strategy aimed at taking advantage of "creative destruction" and fostering the generation of new knowledge from previously diffused knowledge can yield a higher payoff.

The difficulties encountered in blocking the diffusion of knowledge assets often depend on the nature of those assets. On the one hand the copyright of musical productions has today become very difficult to enforce because of the phenomenon of file sharing through peer-to-peer mechanisms on the Internet. On the other hand, knowledge assets that can only be replicated though large sunk cost investments, or through hard-to-imitate processes can easily be protected from diffusion. All of this suggests that diffusion-blocking strategies need to be viewed as knowledge protection mechanisms that are specific to a given industry rather than being of general applicability.

Firms therefore need to be selective when choosing to use a diffusion blocking strategy. A diffusion blocking strategy pays off when one possesses unique knowledge assets. Thus, one can think of investing in diffusion-blocking for a selection of good quality assets which are unique to the firm while not investing in diffusion-blocking for the rest. The residency time or lifetime within the simulation offers a measure of the degree of "fitness" of an agent and can provide us with some clues to explain the patterns encountered. As has been pointed out before, the observed differences in the residency times of agents according to the diffusion blocking strategy they adopt (**Figure 10**b) are consistent with the observed suppression of the DBS = 1 strategy. But to understand the real causes of this relationship requires a deeper analysis. For that, we look at the mean residency times of the four different types of agents we have in the simulation—new agents created from scratch, from joint ventures, from mergers and from the creation of subsidiaries—during the lapse of time in which the evolutionary process is stronger, i.e., within the first 100 periods (see Table 8).

Diffusion Blocking Strategy	Agent type	Variables	
		Number of agents	Mean residency time
DBS = 0	**Joint Venture**	221 *(124)*	6,57 *(0,75)*
	Merger	71 *(41)*	11,74 *(1,20)*
	Normal	5 *(2)*	18,20 *(7,56)*
	Subsidiary	65 *(28)*	9,55 *(1,23)*
	Total	91 *(104)*	11,51 *(5,78)*
DBS = 1	**Joint Venture**	117 *(80)*	7,01 *(0,93)*
	Merger	40 *(27)*	10,91 *(1,49)*
	Normal	6 *(2)*	20,94 *(7,67)*
	Subsidiary	22 *(13)*	9,79 *(2,13)*
	Total	46 *(60)*	12,16 *(6,65)*

Table 8 Mean values and standard deviation—in brackets—of the number of agents and their mean residency time for each type of agent strategic option in the first 100 periods of the simulation.

Surprisingly, for three of them the mean residency time in the simulation turns out to be longer if they adopt a DBS = 1 strategy than if they do not. Only mergers yield a shorter residency time for agents in the simulation if they choose to block diffusion. And although agents created through mergers come only second in terms of frequency (see Table 8), their impact ends up dominating the whole system. But, what explains the distinctiveness of mergers? A careful analysis of the dynamics of the simulation gives us some hints. Recall that in a merger formed by two parent agents, the new agent receives all of its knowledge assets from both parents but inherits its KM strategy from *only one* of the parent agents. The mergers that happen to perform badly, and therefore reduce the mean residency time of created agents, are those that proceed from parent agents with different DBS, but that then adopt a DBS = 1. The costs associated with blocking diffusion for *all* the inherited knowledge assets when one of the parents had gathered its share of them without incurring this initial cost burden often has fatal consequences for the new agent. Translating this into a hypothesis:

> ***Hypothesis* 2.** *The merger of two companies with different knowledge management strategies, one with a preference for blocking diffusion of its knowledge assets and the other with a preference for not blocking this diffusion, will incur a higher cost of blocking diffusion relative to the average value of the merged knowledge assets if the merged entity chooses to pursue a diffusion-blocking strategy.*

The cost of blocking diffusion—i.e., of defending intellectual property rights—can therefore impose a growth limit on the firm, i.e., on its size. This could be one of the reasons why, in places like Silicon Valley, one finds a larger number of small and medium-sized firms with a reduced number of key knowledge assets, rather than very large corporations with broad ranging capabilities.

Looking at the evolution of the evolution of Knowledge Structuring Strategies (KSS), there seems to be something of an equilibrium—or, at least, a highly attenuated evolution in the last periods of the simulation—in the mix of knowledge-structuring strategies present in the agent population. This equilibrium appears to be somewhat biased in favor of agents having KSS = 0, that is, a "not-structuring-knowledge" preference. However, given the simplified reality that characterizes our model, we cannot at this point attribute too much significance to the fact that there is a slight bias against the structuring of knowledge. Nevertheless, it could signal the continuing importance of tacit knowledge in the economy, and the consequent need to achieve a balance between investing in structured and investing in unstructured knowledge.

We should also note that slight differences in the mean residency time of agents with a strategic preferences for structuring knowledge, in the long run, give rise to those preferences pre-dominating. It seems that whatever advantage is conferred on a given agent itself by its strategic preferences in terms of residence time in the simulation, it creates the opportunity to transmit such preferences to new organizations, thus augmenting their frequency in the population as a whole. A Schumpeterian environment that fosters collaboration as well as competition between agents would favor such developments whereas a purely competitive "neoclassical" environment might not [Boisot et al., 2004]. A greater residency time, however, does not imply more rents obtained. In fact, in our simulations we observe that agents with a strategic preference for unstructured knowledge earn a higher level of rents per period. We therefore propose the following hypothesis:

> ***HYPOTHESIS* 3.** *In a stabilized population of firms there is a positive correlation between the mean lifetime of firms using a given knowledge structuring strategy and the fraction of firms within the population showing a preference for that strategy. However, there is no positive correlation between the former and the amount of rents obtained by firms inclined to use the given strategy. There is a trade-off between survival and rent maximizing that benefits the population as a whole but not specific firms.*

In any stable situation that follows an evolutionary process, the dynamic equilibrium achieved maintains both the KSS = 0 and the KSS = 1 strategies in similar proportions. This leads us to think that any deviation from these proportions exerts a pressure to revert to the equilibrium situation. Through evolution, therefore, the system reaches a state of co-existence between strategies. Such a stabilization of strategies could be a consequence of co-evolutionary effects. This result challenges the popular assumption that the structuring knowledge through codification and abstraction is always going to be better strategy than keeping it unstructured and tacit. Both strategies can perfectly well co-exist within a sector or geographical cluster.

Different ICT regimes (sub-section 6.3) also give us interesting results. For different values of β we observe a clear non-linearity in the behavior of the model This fact is not predictable from the low-level rules that guide the behavior of individual agents. We are thus dealing with unexpected, high-level, emergent patterns—as could be expected when modeling a complex system.

The presence of these non-linear patterns is particularly important. They point to aggregate behaviors of the system that cannot be predicted from the rules adopted by individual agents. On one hand, this tells us that the simulation model we are using is able to capture the behavior of a complex system. On the other hand, this kind of results allows the generation of hypotheses that cannot be easily derived by other means.

A closer analysis allows us to develop more specific hypotheses. Looking at the graphics of **Figure 11**a, three types of regime appear. For values of β lower than 1.00, the mean number of agents in the simulation remains much higher than for other settings of β. For values of β from 1.00 to 2.00, the mean number of agents remains more or less constant, but with a slight tendency to decrease. This decrease, however, becomes quite evident for values of β higher than 2.00. The first case corresponds to undeveloped ICT regimes where information can only be transmitted face-to-face over very short distances where a threshold located between $\beta = 0.50$ and $\beta = 1.00$ probably operates. For values lower than $\beta = 1.00$ this threshold has not been crossed, which makes any dependence on spatial distance irrelevant. In most interactions between human beings, for example, there typically is not much difference between communicating verbally at a distance of 30 cm and doing so at a distance of 20 or 10 cm. In the second case the influence of different ICT regimes makes itself felt but the values for the number of agents remain close to the earlier ones. In the last case, when the development of ICTs becomes very advanced, the number of agents is much lower. This is consistent with the idea that a given territory can be covered through fewer agents when there is more communication capacity available. Given the above, in our interpretation of the results, we will exclude the $\beta = 0.50$ case since we consider it does not contribute significant information on the impact of ICT evolution.

***Hypothesis 4.** ICT development decreases the carrying capacity of an industrial sector in terms of the total number of firms that can be accommodated.*

The observation of detailed data from the simulation runs shows us that the decrease in number of agents with growing β especially affects the number of joint venture agents. The formation of joint ventures seems to be a sensible way of covering a market when it gets difficult to transfer knowledge at a distance. With the development of ICTs, the number of joint ventures decreases since a lower number of firms is now sufficient to cover the market. And, as we will presently see, they do so at a higher payoff.

> ***Hypothesis* 5.** *With ICT development, the rents that firms receive from their knowledge assets increase.*

When looking at the simulation data in detail, we observe that this phenomenon is mainly due to an increase in the rents obtained by one particular type of agent: one created by mergers. A simple interpretation could help to illustrate one possible domain of application of these results. The economy corresponding to low values of β could represent economic settings characterized by low levels of technological development, and where, say, the use of the telegraph—here taken as the ICT of choice—would requires a fairly high degree of message structuring. Medium values of β would represent an economy in which communications take place primarily through the telephone, in a less structured, and hence a less codified and abstract way—China's current mobile phone mania suggests that such an economy exists. Finally, high values of β could represent something akin to an economy of large DotComs, in which communication is based on e-mail-related technologies as well as on other software tools that require a fairly high degree of message formalization and structuring. The development of ICTs, by making it possible for fewer firms to operate in the system on account of their greater "reach", would then create an incentive to merge. In an economy of large DotComs, firms tend to be global players—Cisco and Google come to mind as examples. Interestingly, when looking at the rents generated per agent, the higher rental levels are actually attained at higher value of β, that is, for higher levels of ICT development.

In this economy of large DotCom's and a high level of ICTs development, fewer firms would generate less knowledge and lower rents, but the rents generated per company would be higher. An interesting point is that lower overall rents—which translate into lower costs to society for a given amount of created knowledge—do not appear to impede the creation of new knowledge.

In our simulation, as we have just seen, ICT developments have an important impact on the structure of an industrial sector or geographical cluster. While the relative number of joint venture agents decreases, the relative number of subsidiaries increases. Thus, instead of growing through joint ventures firms choose to grow through subsidiaries, i.e., through organic growth.

> ***HYPOTHESIS 6.*** *ICT development favors organic growth instead of mergers or joint ventures.*

One possible interpretation of this is that some ICT developments remain inside firms instead of diffusing out in the market. This might be the case for specialized ICTs, which are internal to an industry and not available to the public.

When looking at the average residency time of agents in the simulation (**Figure 11**c), we see a very clear case of non-linear behavior. At around $\beta = 2.00$ a maximum point appears. Towards the left—that is, at lower levels of ICT development—the mean residency time of agents decreases. But this also happens towards the right—at higher levels of ICT development—and it is more pronounced. One might therefore expect that in economies with a high level of ICT development, firms would have a much shorter life. This is consistent with the empirical evidence provided by the overall DotComs experience. It is also consistent with the behavior of the rents obtained per period in our model (**Figure 11**d). After a slight decrease from the $\beta = 1.00$ to the $\beta = 1.50$ case, the trend is clearly towards a sustained increase in rents.

An analysis of the knowledge management strategy mix (see **Figure 12**a and b) gives similar results for all ICT regimes in the sense that diffusion blocking strategies remain out of favor and a preference for keeping knowledge unstructured predominates over one for structuring knowledge. However, significant differences remain among the different cases that are of some interest.

The knowledge structuring strategy (KSS = 1) is of particular interest. If for the low degrees of ICT development (β = 1.00) the proportion of the population adopting this strategy reaches a peak value higher that 50%, then it goes down to a value around 40% for β = 1.50, to afterwards go up again to values of over 45%.

One possible interpretation of that phenomenon is that in the first phases of development of ICTs, it pays for industries or groups of organizations to increase the tacit or unstructured knowledge component of their work; but when ICTs reach a certain level of development, there eventually comes a time when it becomes advisable to reverse the trend – the benefits of "reach" are then too important to forgo. Of course, the model does not tell us whether our society has already reached that point, but taking into account that the higher values of β in our model do seem to reproduce some characteristics of a DotComs economy, it could well be that we are already there. An analysis of the average residency time of agents having different strategic choices seems to confirm the trend. This is, again, a non-linear effect, which leads us to think that it is related to the other behaviors for which we have observed inflexion points.

> ***HYPOTHESIS 7.*** *In a knowledge-intensive industrial sector, the early stages of ICT- development will favor knowledge-unstructuring strategies, but in the later stages of ICT-development the trend will reverse, and favour the pursuit of knowledge-structuring strategies.*

From this we can draw one clear implication: future trends in a global economy where ICTs are highly developed are unlikely to favor—as some might expect—an increase the use of tacit knowledge, but rather to further favor the use of structured knowledge.

Turning now to the diffusion blocking strategy (DBS), it is noticeable that while it manifestly remains the less preferred strategy, the proportion of agents in the population with DBS = 1 grows significantly when β decreases. Figure 12b shows that it goes from around 1% for β = 0.50 to more than 7% for β = 1000. That is, for higher levels of development of ICTs:

> ***Hypothesis 8.*** *The higher levels of ICT-development will increase the payoff to diffusion-blocking strategies, and this, even in a Schumpeterian economy. Such strategies, however, will remain a minority preference.*

This fact, which gains in significance at lower values of β, suggests that beyond a certain level of ICT development, it becomes more attractive for some firms to pursue a strategy of hoarding knowledge assets, even in Schumpeterian scenarios—the current travails of the music business readily comes to mind as an example.

8. Conclusions

Our research aims to assess how the knowledge management strategies of agents—individuals or organizations—might vary as a function of their location in physical space. In this paper, we have combined knowledge management concepts with ideas coming from organizational ecology or spatial economic to explore this. We have shown that this kind of interdisciplinary research can produce results of relevance to all the disciplines involved.

The use of agent-based simulation is well suited to these kinds of problem, typically those associated with complex systems, in which it is difficult to link theoretical frameworks that describe low-level interactions and behaviors of individual agents with observations of high-level or aggregate patterns of behavior in an analytical way. The influence of individual knowledge management strategies on organizational populations is just such a problem. Our paper illustrates one approach to this kind of problem.

In a networked economy, firms and institutions need to be aware not only of their own strategic choices, but also of that of other players in their industry, as well as of the way that all these strategies co-evolve. Our contribution, both in the methodology that we have used and in the results that we obtained has relevance for the new types of organization that characterize the Information Society. Some of our results reproduce patterns readily observable in some industries, while others, presented in the form of hypotheses, can be tested empirically. The utility of simulation models here resides in how they stimulate the generation of grounded insights that would be difficult to secure by intuition alone.

Of course, our approach has obvious limitations common to most of the attempts at simulating social systems. Our results are not predictions or outcomes from competing theories. Rather, they are propositions that now need to be matched against empirical data. The value of agent-based simulation models resides in their ability to capture the kind of processes that are present in complex systems. Because they are often counter-intuitive nature, these complex processes are often beyond the grasp of unaided intuition. It is through their heuristic function that simulation models acquire real value in research problems of this kind. Given the nature of complex systems and the large quantity of parameters of our model, we cannot be sure that our simulation results will mimic reality; but with a process of validation and a sensible calibration based in the observation of real systems it is possible to reproduce the relevant aspects of real systems.

Another clear limitation of our work is that we only take into account two possible strategic dimensions of knowledge management: knowledge structuring and diffusion blocking. And for each of these we only examine binary choices (0 or 1). Clearly, the management of knowledge is a complex and subtle affair. But simplification is the price that we have to pay if we are to extract any consequences at all from simulations, especially in these early attempts. Further refinements must await the future development of our model.

This kind of research opens up new perspectives as well. For example, it can be argued that there are other factors apart from physical distance that intervene—and probably more importantly—in establishing the probability of interaction between agents. If so, one could extending the model so that the location of agents did not occur solely in a physical space but also in some sort of “cultural” space. Here, “distance” would then act as a proxy measure of the difficulties encountered when transmitting knowledge across cultural barriers.

Our paper points to some other interesting avenues for further research. The inclusion in the model of a spatial dimension in the interaction of agents facilitates an analysis of the spatial behavior of organizational populations, something highly relevant to the study of industrial clusters or regional economies. The specific influence of knowledge management strategies on spatial location patterns constitutes a promising avenue of research. The simulation model we have developed can be used to model more specific problems like the evolution of knowledge-intensive industrial districts or geographical clusters in terms of knowledge management strategic options and location patterns. Applying the simulation to more concrete problems would allow for a better calibration of the model using real data and, consequently, for an easier and more fruitful interpretation of the results.

Our hope is that this line of research using agent-based simulation modeling will contribute to a form of knowledge management theorizing that is both robust and empirically relevant.

9. APPENDIX 1: PARAMETER SETTINGS FOR *KMSTRATSIM* MODEL

In the following table we show the values of the simulation parameters we have chosen for the *KMStratSim* general model whose results we present in section 6.1. The results presented in section 6.2 are obtained with the same set of parameters except for BETA, which takes a whole range of different values.

Parameter group	Parameter	Value
Global switches	ASSET_MANAGEMENT	0
	MOD_DISCOVERY	0
	MOD_RESEARCH	0
	AGENT_INTERACTION	0

	MOD_OBSOLESCENCE	0
	MOD_DIFFUSION	0
Main variables	INIT_AGENT_NUM	20
	INIT_NODE_NUM	20
	INIT_LINK_NUM	10
	MODEL_PERIODS	500
	MAX_AGENT_NUM	300
	MAX_NODE_NUM	10000
	MAX_LINK_NUM	7000
Asset variables	MAX_COMPLEXITY	7
	COMPLEXITY_COST	0.001
	NEW_LINK_PROB	0.15
	MOVE_POSSIBILITIES	2
	PASSIVE_CARRY_MULT	0.50
I-Space world variables	BASE_REV_MULT	10
	ASSET_SHARE_PROB	0.20
	OBSOLESCENCE_DECAY	0.005
	DIFFUSION_DECAY	0.001
	DIFFBLOCK_COST_MULT	0.001
	AGENT_ENTRY_THRESHOLD	0.15
	AGENT_ENTRY_RATE	0.10
	AGENT_EXIT_THRESHOLD	45
	AGENT_EXIT_RATIO	-0.005
	MAX_AGENT_ENTRIES	5
	AGENT_ENTRY_NODES	2
	AGENT_ENTRY_LINKS	1
I-Space matrix variables	ABSTRACT_DIM_SIZE	5
	CODIFY_DIM_SIZE	5
	DIFFUSE_DIM_SIZE	4
	DIFFUSE_FACTOR	2
Linkage probability variables	ABS_NONZERO_VAL	0.20
	COD_INCREASE_VAL	0.20
	ABS_NONZERO_PROB	0.05
	NEW_ASSET_THRESHOLD	1.40
Agent variables	INIT_FINANCIAL_FUNDS	20
	INIT_EXPERIENCE_FUNDS	20
	FINANCIAL_ALLOCATION	0.80
	ACTIVE_SET	12
	PASSIVE_SET	5
	ISPACE_MOVE_PROB	0.03
	ISPACE_MOVE_COST	0.03

	JOINT_VENTURE_RETURN	0.10
	SUBSIDIARY_RETURN	0.20
	PAR_FUND_THRESHOLD	15
	PAR_ASSET_THRESHOLD	0.50
Agent meeting	MEETING_ARRANGE_COST	0.005
	MEETING_FIXED_COST	0.005
	PRESENT_COST_MULT	0.005
	EXAMINE_COST_MULT	0.005
	TRADE_VALUE_MULT	1.75
	LICENSE_VALUE_MULT	0.25
Meetingspace variables	PROB_RANDOM_MEETING	0.25
	MAX_RANDOM_MEETINGS	5
	TRADING_SET_RATIO	2
DM variables	MIN_PREFERENCE_LEVEL	0
	MAX_PREFERENCE_LEVEL	1
Research DM variables	PROB_MOVE	0.10
Meeting DM variables	PROB_POSITIVE	0.10
	PROB_NEGATIVE	0.20
	HIGH_COOP_MULT	0.50
	JOINT_VENTURE_INVEST	0.25
	SUBSIDIARY_INVEST	0.25
Physical space variables	WORLD_X_SIZE	80
	WORLD_ Y_SIZE	80
	BETA	2.00

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