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Knowledge Management Strategies and Spatial Structure of Geographic Industrial Clusters: A Simulation Approach

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ABSTRACT

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KEYWORDS

geographic industrial clusters, spatial structure, knowledge flows, ICT, development

SUMMARY

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Knowledge management strategies and spatial structure of geographic industrial clusters: a simulation approach*

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ABSTRACT

Mainstream economic literature has often neglected spatial issues. Marshall having initiated the study of agglomeration economies, these were then only further pursued in specialized lines of research in economics and economic geography. General interest in them was revived by the "new economic geography" when it applied new economic tools and concepts to their study. However, in order to understand the dynamics of the information economy, we need to introduce the underlying mechanisms of knowledge spillovers into economic models of agglomeration. We propose to do it through the construction of agent-based simulations that implement a theoretical framework designed to understand knowledge flows: the I-Space. Along these lines, we present a simulation model of geographical industrial clusters in which we can study the interrelation between knowledge management strategies and the spatial agglomeration patterns of populations of firms. The application of the model to two well-known high-tech industrial clusters, Silicon Valley and Boston Route 128, offers us insights into the different cultural dynamics of the two clusters. These focus on knowledge transfer and on role played by information and communication technologies (ICTs) at different levels of development.

1. INTRODUCTION

In an information society, knowledge assets occupy the center of the stage in the generation of competitive advantage [Castells, 1996; 2001; Brynjolfsson, 1994]. Because of this, in recent years knowledge has become one of the central elements in the analysis of all kind of economic processes.

In the spatial economy literature, the previous emphasis on logistics, marketplace, or labor force availability (see McCann [2001; 1999] for a review) by degrees has been replaced by a concern with knowledge-related arguments [Dunning, 2000a; Bryson et al., 2000]. Although knowledge spillovers had been already been studied by Marshall in his seminal work on the sources of agglomeration economies [Marshall, 1920], the knowledge factor has been pretty much ignored in economic analysis models until recent times and has only been of interest to non-mainstream approaches.

The consequence has been that studies of the interplay between knowledge and one of the most visible features of firm agglomerations—their location in space—have been neglected. Thus, although firms exist in space, mainstream economic analysis has typically overlooked spatial issues. These were relegated to the literatures in urban economics, in regional science and in economic geography. But even in these traditions—or indeed in more recent attempts to re-introduce spatial issues into the mainstream economic analysis such as Krugman's "new economic geography"—it is difficult to find a treatment that combines in a single model spatial location and knowledge generation and transfer. This is probably due to the challenges both of finding a theoretical framework that can adequately describe knowledge processes and of trying to apply the traditional analytical models associated with the neoclassical economic tradition.

As a consequence, the economic models of industrial districts or clusters seldom include knowledge as one of the relevant factors. In more socio-economic work—i.e., on post-Marshallian Italian industrial districts tradition [Pyke et al., 1990] and in Michael Porter's works on clusters [Porter, 1998]—we can find interesting theoretical and empirical studies that often include insights on how knowledge and location interact in space. But these seldom yield an empirically testable model that could then be generalized to different cases.

In this work we present an agent-based simulation model that explores the interrelation between the knowledge management strategies adopted by firms and their spatial location. A basic feature of our model is the assumption that the probability of effectively achieving a transfer knowledge between two firms is some inverse function of the distance between them. This assumption allows us to link knowledge management strategies with physical location. As interaction at a distance increasingly comes to be mediated by information and communication technologies (ICTs), the dependence of knowledge flows on spatial distance should vary with the level of development of ICTs. We also introduce this consideration into our model.

Our aim is to derive from our model fruitful insights in the form of hypotheses on the influence of the development of ICTs on the interrelationship between the knowledge management strategies adopted by the firms and their spatial location. In order to be able to ground the results of our simulations in real-world cases, we will use as a reference point two well-known cases of high-tech industrial clusters: Silicon Valley and Boston Route 128. Using the salient features of these two different clusters to set the parameters of our model, we will simulate two simplified worlds in which we hope to reproduce—for a given ICT regime—some of the patterns observed respectively in the Californian and the Boston cases relating knowledge management strategies to spatial location. If this happens, it will constitute a first validation of our model. After that, we will vary the level of development of ICTs and see how variations in the ICT regime change the picture. We hope to extract interesting hypotheses from the analysis of the results concerning the future evolution of these kind of industrial clusters.

We structure our work as follows. First, we present the literature on the spatial economy and on knowledge that is relevant to our work, paying special attention to the question of agglomeration economies. In this analysis we highlight the need to build models that accord some primacy to the role played by knowledge flows. To meet this need, we propose the use of agent-based simulation modeling. But if we are to obtain fruitful insights from our simulation efforts, we must inform our models with adequate theoretical formulations of knowledge-related processes. In our work, the *Information-Space* or *I-Space* provide the relevant theoretical framework [Boisot, 1995; Boisot, 1998]. The I-Space is a conceptual framework for the exploration of information flows and the subsequent creation and diffusion of knowledge within populations of agents. Following the presentation of our theoretical framework, we introduce the main focus of our study: the interplay between knowledge management strategies and spatial agglomeration patterns. We then proceed to describe our simulation model and its application to two simplified cases representing respectively Boston's Route 128 and Silicon Valley. Finally, we discuss our finding and put forward some hypotheses. A conclusion follows.

2. THE SPATIAL ECONOMY AND KNOWLEDGE

Firms exist in space and, therefore, spatial issues have to be taken into account when dealing with economic problems. Mainstream economic analysis has often neglected spatial and temporal issues. Although some specific economic traditions have dealt with the spatial economy, these have remained outside the mainstream [Krugman, 1995: 36]. Also, the introduction of a temporal dimension through a dynamic treatment of economic problems has not been successful, probably because of an undue emphasis on equilibrium problems, a key concern of neoclassical economics [Hodgson, 1988: xiv]. In this section we briefly review traditional approaches to the study of geography's role in economic processes. Our focus will be on the importance of agglomeration economies in economics and in economic geography. Next, in the light of new contributions to the subject, we identify some limitations of the traditional approaches. Most of those limitations turn out to be related, in one way or another, to the question of knowledge.

2.1. Agglomeration economies in economics

The relationship between geography and economic processes has seldom been accorded much attention in the economic literature, probably because the problems involved are too complex to be solved with the economic tools available [Fujita et al., 1999: 2]. However, the application of classical—and later, neoclassical—economic concepts and techniques to such problem by a group of diverse authors has, by degrees, produced a number of works that constitute the foundations of spatial economics.

Spatial economic analysis has its origins in Johann von Thünen's "location theory", developed in Germany in the 19th century [Von Thünen, 1826]. The tradition that built up around this work was revived in the 1920's and 1930's with seminal contributions from Alfred Weber [1909], Alfred Marshall [1920], Harold Hotelling [1929], Walter Christaller [1933] and August Lösch [1954]. These provided insights into several aspects of the relationship between economy and space. However, they never much influence the mainstream of the economics profession [Martin, 1999].

After Word War II, the further development of Von Thünen models gave rise to the field of urban economics. The work of August Lösch also provided the foundations for two new fields of economics, namely regional science and economic geography [Martin, 1999]. In the 1990s, a fourth approach was developed, more strongly related to the neoclassical economic tradition: Paul Krugman's "new economic geography". Recently, both increasing globalization and the local organization of economic activities have stimulated contributions from other disciplines to the field of spatial economic. In most of these approaches, agglomeration economies have a relevant role to play. Since they are essential to the formation of industrial districts and geographical clusters, we will briefly examine this role.

Although Alfred Weber had already noted the existence of location-specific economies of scale or agglomeration economies, it was Alfred Marshall [Marshall, 1920] who first described the sources of these in detail [McCann, 2001: 55; Krugman, 1991b: 37; Fujita et al., 1999: 18]. He observed that firms often tend to cluster in given areas, which implies that locating close to other firms offers advantages in terms of both economies of scale and economies of scope. Marshall put forward three different explanations for such advantages—in effect, three kinds of externalities. First, a local agglomeration of firms in a given sector can bring forth local providers of inputs. Second, a concentration of firms fosters the local formation of specialized pools of labour. It then becomes easier to recruit trained workforce in the locality and to attract external experts into the region. Third, spatial proximity facilitates the spread of information. This is especially important when it comes to the informal sharing tacit information since this gives rise to knowledge spillovers. Later, other economists came to make a distinction between pecuniary externalities—covering the first two of the three externalities identified by Marshall and mediated through the market—and pure spillovers—the third kind of externality identified by Marshall and a source of technological economies [Krugman, 1995: 50].

A first classification of the different types of agglomeration economies was proposed by Bertil Ohlin [Ohlin, 1933] and Edgar Hoover [Hoover, 1937; Hoover, 1948]. They distinguished three main kinds [McCann, 2001: 57]. The first consist of internal returns to scale: economies of scale that firms achieve simply by reason of their size. This category has no influence on the clustering of different firms at one location. The second consists of economies of localization attained by clusters of firms belonging to the same industrial sector. The third consists of economies of urbanization. These are economies that benefit all firms present in a given agglomeration—whatever sector they belong to—due to the mere fact that they belong to the cluster.

So far, we have identified the first works that describe the sources and types of agglomeration economies. Yet there were also attempts to understand what followed from the presence of such economies in terms of the spatial configuration of economic activities. Perhaps the most representative of these are associated with *central-place theory*.

Economies of scale and transportation costs have a very important influence on the configuration of the spatial economy. Central-place theory studies how these two factors interact to yield a market-efficient spatial distribution of economic activity. The fundamental contributions to central-place theory were those of the two German scholars Walter Christaller [Christaller, 1933] and August Lösch [Lösch, 1954]. Yet, neither Christaller nor Lösch developed any causal explanation of the mechanisms by which the central-place hierarchy is actually built—for example, how it might emerge from individual actions [Fujita et al., 1999: 27]. Nevertheless, their contribution and that of their followers provide interesting insights into the spatial configuration of economic activity.

In urban economics the effects of agglomeration economies are implicit in the bid-rent model, an extension of Von Thünen's ideas concerning the optimal use of land. The bid-rent concept is applied to the modern city to produce the "monocentric city model" [Alonso, 1964], as well as to collections of cities, that is, to urban systems [Henderson, 1974].

Other important issues, concerning for example where cities form and what conditions their spatial relationship to each other, have been neglected by urban economics. However, these kinds of questions have been addressed within another tradition, that of regional science, and developed mainly in the works of Walter Isard [1956] and his followers. Although a source of useful insights, regional science never really got integrated with mainstream economics, or even, for that matter, with urban economics. It became a highly mathematical theory of abstract economic landscapes described in ad hoc equilibrium models and lacking in closure. Nevertheless, despite the lack of any rigorous framework, regional science provided regional planners, transportation departments and other professional dealing with regional issues with a toolbox for practical analysis [Fujita et al., 1999: 33].

2.2. Agglomeration economies in economic geography

In contrast to economics, economic geography adopted a more empirical and multidisciplinary standpoint. In addition to the works of early spatial economists, economic geographers incorporated in the foundations of their discipline the ideas of "economic sociologists" like François Perroux and Gunnar Myrdal. Perroux [1950] had operated on the premise that economic behaviour is "embedded in institutions, norms, and values." He believed, for instance, that one of the most important factors in economic interactions is the asymmetric distribution of power between the actors. Thus for him, spatial agglomeration in economic activities becomes a consequence of the exercise of power in geographical space [Meardon, 2001: 35]. Building on Scitovsky's [1954] distinction between technological and pecuniary externalities, Perroux developed the concept of growth pole. In technological externalities, the output and factor utilization of firm A enter the production function of firm B, while in pecuniary externalities they affect the profits of firm B but do not enter into its production function. A growth pole is a location in economic space in which growth spreads among the firms located in close proximity through pecuniary externalities [Meardon, 2001: 39]. Myrdal based his analysis of agglomeration economies in transnational regions on the concept of cumulative causation [Myrdal, 1957]. In essence, cumulative causation is a variant on the concept of the "vicious cycle" or the "virtuous circle": changes in a social system, instead of triggering countervailing changes aimed at restoring the status quo, call forth changes that take the system further in the same direction, thus amplifying the effects of the initial change. Among possible applications of this concept, Myrdal proposed a theory of agglomeration that invoked the phenomenon of cumulative causation to explain differences in income between countries or regions. He showed how, through the existence of virtuous circles, regions with higher productivity and incomes would progressively increase their advantages over initially less favoured ones [Meardon, 2001: 45]. Both the ideas of Perroux and Myrdal are invoked in Brian Arthur's historical-dependence perspective. In this perspective, "historical accidents" that provoke the initial location of one or two industries in a given place are more important in triggering a spatial agglomeration there than traditional considerations of geographical endowments, transport possibilities or firms' needs. Arthur takes the historical-dependence arguments one step further by modeling them as an instance of increasing returns [Arthur et al., 1997; Arthur, 1994: 50]. The concept of increasing returns refers to the existence of self-reinforcing mechanisms in the economy. As Arthur explains: "[Increasing returns] are mechanisms of positive feedback that operate—within markets, businesses, and industries—to reinforce that which gains success or aggravate that which suffers loss" [Arthur, 1996]. We will see later that increasing returns mechanisms constitute one of the main ingredients of the "new economic geography" led by Paul Krugman.

In opposition to "geographical economics" or to the "new economic geography", traditional economic geography does not rely only on purely economic concepts such as equilibrium location theory or new growth theory. Because of the difficulties experienced by neoclassical mathematical models when attempting to incorporate the complexities of the spatial economy, and also because of its interest in empirical research, economic geography developed a more eclectic approach to the matter, incorporating concepts imported from "alternative" branches of economics and even from other disciplines for inspiration. Thus, it emphasized the role of social, institutional, political and economical factors in regional development and industrial agglomeration. The influences acting on the discipline are numerous and diverse. Ron Martin [Martin, 1999: 79] identifies at least six lines of influence present in economic geography:

- The new industrial-technological paradigm based on the "flexible specialization" concept by Piore and Sabel [Piore and Sabel, 1984]

- The works of a group of Italian neo-Marshallian economists on industrial districts in Italy. Their approach is grounded in detailed empirical work on specific regions, work that stresses the role of social, cultural and institutional factors on local industrial growth

- The French regulation school of political economy with the concept of "post-Fordism" and the stress on the role of social regulation

- The technological learning literature addressing themes such as technological spillovers, the circulation of knowledge, technical know-how, learning and the concentration of innovation within area-based networks or "learning regions"

- The economics of sunk costs

- The cultural bases of industrial organisation and corporate behavior

With this gradual separation of economic geography from economics, spatial economic analysis itself never found a home in mainstream economic analysis. With neoclassical economics maintaining its predominance, spatial issues were gradually put aside, probably because of the difficulties of incorporating them in the sophisticated mathematical models used in economical analysis [Krugman, 1995]. Thus, little by little spatial economy issues disappeared from the economic literature and, until the birth of the so-called "new economic geography" in the 1990s, they were left to geographers.

This divorce has had undesirable consequences for economics. Since the birth of the discipline, its ability to deal with spatial problems has lagged far behind what has been achieved in other fields. But has also constituted an important drawback for economic geography. The emphasis on empirical studies and the eclecticism of its theoretical approaches has made it more difficult to secure the required level of formal rigour and generality in the models used. As we will see in the next section, the "new economic geography" offered a way to address both problems.

2.3. The "new Economic Geography": Krugman's Geographical Economics

In the 1990s, a group of mainstream economists leaded by Paul Krugman turned their attention to the implications of geography in economic analysis. The reason for their sudden interest lies in the growing importance of the concepts of increasing returns introduced by Brian Arthur [1997; 1994] and imperfect competition, developed among others by Joan Robinson [1933]. As Krugman himself points out [1996; 1991a; 1995; 1998], technical developments in the treatment of these two concepts allow a more meaningful modeling of the spatial economy. This has given rise to a considerable economic literature, known as "the new economic geography" by its protagonists and as "geographical economics" by more critical economic geographers [Martin and Sunley, 1996].

The relevant technical developments have been outlined by Krugman in "Dixit-Stiglitz, icebergs, evolution, and the computer" [Krugman, 1998: 164]. Dixit-Stiglitz is a model of monopolistic competition—location making it difficult to achieve perfect competition—that offers a way of dealing with transportation costs and dynamic processes rather than static equilibria—Arrow-Debreu models cannot deal with spatial issues—as well as some mechanic help in addressing the more complicated models that appear.

The "new Economic Geography" has been subject to a fair amount of criticisms, mainly from the more "traditional" economic geographers [Martin and Sunley, 1996; Martin, 1999; Ottaviano and Puga, 97; McCann, 1995; Meardon, 2001]. Ron Martin, one of the most persistent critics summarizes his view with the following words [Martin, 1999: 65]: "This 'new economic geography' […] is neither that new, nor is it geography. Instead, it is a reworking (or re-invention)—using recent developments in formal (mathematical) mainstream economics—of traditional location theory and regional science. As such, it is quite opposed to, and difficult to reconcile with, the work on regional development and industrial agglomeration being carried out in economic geography proper."

Although it might indeed be difficult, it is worth working towards such a reconciliation. The development of a new approach incorporating the multidisciplinary insights and empirical bases of traditional economic geography on the one hand, and the formal rigor and connection to mainstream economics of the "new economic geography" on the other, would be very valuable. Not only would it be a first-order academic attainment, but it would also provide policy-makers with invaluable tools for decision-making. However, this would still only bring externalities arising from market imperfections into the picture. Other types of externality, such as knowledge spillovers would remain excluded [Martin and Sunley, 1996].

New contributions are needed to incorporate the latter. In fact, in recent decades, and in response to the new challenges posed by globalization and the knowledge economy, many insights arising in disciplines other than economics have been adopted and applied to the problems of the spatial economy. In the next sub-section we will mention some of them.

2.4. The need for further contributions

The complexity of the modern economy calls for a multidimensional analysis of economic problems. Neoclassical economics has clearly failed to deal with spatio-temporal frictions[1]. The treatment of processes that involve dynamic non-equilibrium situations or in which space plays a role requires a new approach, both from non-mainstream economics as well as from other disciplines. Only from such an approach will a better understanding of spatial economic issues become possible. We will now outline some of these contributions.

Organizational economics contributes the concept of bounded rationality [Simon, 1996] and Institutional economics contributes the transaction costs perspective [Williamson, 1975; Williamson, 1985]. If bounded rationality places limits on the information processing power of economic agents, the transaction costs perspective highlights the economic cost of this information processing. Given the bounded rationality of

[1] Actually, in the opinion of Philip Mirowski, it was not interested at all [Mirowski, 2002].

economic agents, therefore, transaction costs between firms can be mitigated by their spatial proximity to one another and their location strategies will be in part dictated by transaction cost calculations.

Evolutionary economics also contributes to the study of the spatial economy. For instance, Boschma and Lambooy [1999] show how key notions from evolutionary economics, such as selection, path dependence or chance may be applied to the study of how the spatial environment impacts technological change or, conversely, how technological change influences the long-term evolution of the spatial system. The same authors analyze also the links between evolutionary economics and regional policy [Lambooy and Boschma, 2001]. From an organizational ecology perspective [Hannan and Freeman, 1989] one can adopt a populations view of evolution in order to deal with the phenomenon of agglomeration in different geographical settings. From the evolutionary theory of economic change [Nelson and Winter, 1982] comes the concept of routines, which provides an evolutionary treatment of certain types of knowledge in firms.

Finally, within organization theory we find attempts to create a knowledge-based theory of the firm [Spender, 2002], as well as general concern with learning, knowledge spillovers, and knowledge management [Jaffe et al., 1993]. These help us to better understand[Kogut and Zander, 1992] one of the sources of agglomeration economies which had been introduced by Marshall, but then neglected by traditional economics and even by the "new economic geography": the spread of information,

Of course, there are also important contributions from the business literature. Among them, perhaps the most important for the spatial economy is Porter's concept of competitive advantage [Porter, 1990]. The Ricardian concept of comparative advantage describes something that is taken as given: a country's or region's natural endowment of natural resources, climate and population. The Porterian concept of competitive advantage describes something that can be created—and, as the experience of postwar Japan suggests, it can be created out of virtually nothing. Thus if the former concept induces a certain passivity, the latter encourages initiative and imagination, both concepts that turn out to be very relevant in the spatial economy. If there was ever a time when a location with a good endowment of natural resources provided a comparative advantage, today a location is often evaluated for its knowledge-acquisition-and-creation potential and for the competitive advantages this might confer [Porter and Stern, 2001; Porter, 1998]. When it comes to design policies that foster regional development, the implications of the difference between the two approaches are clear.

The contributions to the new spatial economics that have been presented are very diverse. From quite different origins, they contribute to an understanding of the part played by geography in the knowledge economy. All of them in one way or another share a concern with information and knowledge flows. In the neoclassical economic scheme of things, comparative advantage is something that regions either have or do not have, depending on their essential characteristics. Yet through a proper exploitation of knowledge, competitive advantage is something that can be built—hence the importance of Porter's models. It is clear that the concept of knowledge is at the core of theories of learning and knowledge management. The concept of knowledge also informs most of the concepts that are used in evolutionary economics—i.e., innovation, rules, routines, creative destruction, etc. Finally, one of the key concepts underpinning institutional economics is that bounded rationality—again a matter of knowledge and information processing.

The ubiquity of the concept of knowledge in these new contributions suggests that it merits a greater influence in the different approaches to the spatial economy. If our models do not offer a credible treatment of the concept of knowledge, they will find themselves unable to explain the modern economy. In the following section we show that the four approaches we have discussed face this problem.

2.5. Introducing knowledge

If we look closely at the main models of urban economics, of regional science, and of the "new economic geography", we see that there is little attempt to articulate the concepts of data, information or knowledge or to look at how these flow. Yet data, information, and knowledge have become the main inputs and outputs of the information economy. The way in which physical inputs and outputs enter into the analysis is through transportation costs. As transportation costs issues never really threatened the economic discipline's neoclassical core—equilibrium in space could still be achieved—the problem of how inputs and outputs get distributed when they cease to be physical goods was pretty much ignored by the economic community.

But if transportation costs are important when dealing with physical assets, In a global knowledge-based economy, one in which information and knowledge assets have become a major source of wealth creation, the part played by knowledge and information flows must must be given far more prominence in the study of the spatial distribution of economic activity. Knowledge and information can no longer be taken simply as parameters of the system; they have become crucial variables and often objects of economic exchange in their own right [Boisot, 1995]. Any friction in the flow of knowledge and information goods, therefore, challenges the whole concept of a neoclassical economic equilibrium. This is probably why neoclassical analytical tools could not be applied to spatial issues. It lacked a concept for information and knowledge transactions that was equivalent to that of transportation costs in the case of physical goods.

The neoclassical economic model treats knowledge as something exogenous. The aggregate production function, showing constant returns to labor and reproducible capital, take the state of knowledge as given [Mas-Colell et al., 1995], and ignore either knowledge or information flows or changes in their state. Endogenous growth theories go one step further, accepting that new knowledge has to be discovered through a process of innovation. They therefore introduce a variable representing technological knowledge as intellectual capital [Barro and Sala-i-Martin, 2004; Aghion and Howitt, 1998]. But now suddenly, with the introduction of novelty and innovation into their system, the concept of strategy becomes important. It moves us from a fixed endowment model of comparative advantage to a variable endowment model of competitive advantage, one in which firms survive the competitive struggle through innovation rather than by varying prices and quantities [Porter, 1990].

Yet even in the endogenous growth theories, an adequate treatment of data, information and knowledge and how these flow are missing. Indeed, the concepts of space, time, and energy—which in essence define the real world—are all missing from neoclassical economic models and their more recent variants.

In earlier works, two of us have proposed an alternative to the neoclassical production function [Boisot, 1998; Boisot and Canals, 2004] that is aimed at clarifying this problem. The key idea is to clearly distinguish the concepts of data, information, and knowledge from each other. This distinction is consistent with our overall theoretical approach and underlies the research presented here as well as two of the preceding works [Boisot et al., 2004; Canals et al. 2004]. The production function that we propose relates two different types of productive factors: i) purely physical factors, such as space, time, and energy, and ii) data factors, which we take to be discernable differences in the states of the physical factors. In this scheme, information constitutes an intelligent extraction from the data factor that allows an agent to work productively with less data and thus results in factor savings [Boisot and Canals, 2004: 59].

Like mainstream economics, spatial economics has devoted little attention to information and knowledge issues. One of the main problems in the spatial economy, for instance, is the agglomeration of economic activity. If we analyze how Krugman and the "new economic geographers" treat agglomeration, we can see that the "centripetal forces" that favour the clustering of industries come mainly from pecuniary externalities [Martin and Sunley, 1996]. This, to be sure, can explain large-scale agglomerations, but nowadays perhaps smaller scale agglomerations are becoming more important. As Audretsch puts it: "[…] globalization has shifted the comparative advantage of the leading industrialized countries to knowledge-based economic activity, which is a local phenomenon" [Audretsch, 2000: 63]. And in order to understand small-scale agglomeration processes, knowledge and the specific strategies of firms must necessarily be taken into account.

Yet, in contrast to economists who tend to look only at *information*, traditional economic geography has to some extent incorporated *knowledge* in its analysis [Martin, 1999], [Storper, 2000: 57]. Unfortunately, the fruits of its efforts lack the power of more formal and rigorous models that could be integrated with those used in mainstream economics.

Fujita, one of the principal actors in the "new economic geography", recognizes the need for a combination of both views: "…for the development of a truly general theory of human society, we must explore the general theory [of location and space-economy] on self-organization and co-evolution of the dual spaces consisting of the traditional economic space and the knowledge-mind-culture space" [Fujita, 1999: 380].

How this can be done? Two challenges must be solved. First, one must find a methodology that makes possible an integration of the dual spaces mentioned by Fujita. Second, one must introduce knowledge in the resulting models in a satisfactory way. In the next sub-section we present an approach that we believe, will help us meet the challenges.

2.6. Proposing a methodology and a theoretical framework

As stated before, we need also a methodology in spatial economics that makes it possible to combine the formal models of mainstream economics with the more empirical and eclectic point of view of economic geography. As Paul Krugman points out, geographic concentration is clear evidence of the "pervasive influence of some kind of increasing returns" [Krugman, 1991b: 5]. This suggests that spatial economic systems can be explained as complex adaptive systems in the way described, among others, by Brian Arthur [Arthur et al., 1997]. A suitable methodology for the study of complex adaptive systems uses simulation models, and more specifically agent-based simulation models. These should prove useful in the study of spatial economic systems.

In fact, simulation models are already used in the "new economic geography" by Krugman and his colleagues [Krugman, 1996; 1995; 1997; Fujita et al., 1999], but these are used to solve complicated equation systems derived from the underlying mathematical models. In agent-based simulation the approach is different. There are no complex equations; only rules that individual agents follow. Complexity emerges from the behaviour of the group of agents as a whole.

Using agent-based simulation makes it easier to introduce knowledge-related characteristics. We need only to define the rules that agents should follow when dealing with knowledge assets as defined by the chosen theoretical framework. These rules can be combined with others that relate to other aspects of agent behaviour and can be used to simulate a whole economic system. The approach makes it easier to accommodate the idiosyncrasies of economic geography while maintaining some level of formal rigor. Of course, this kind of modeling cannot give us anything comparable to an empirical result, but it can serve as a source of insights for the development of new hypotheses that could be eventually tested empirically [Carley, 1999].

Some simulation models, such as *Sugarscape*, are based on very simple sets of rules [Epstein and Axtell, 1996]. There, the aim is to show how from a very simple set of rules, complex higher-order patterns can emerge. Our goal is slightly different, and perhaps more ambitious. If we want our results to lead us to really fruitful and consequential insights, our simulation must be built on a more solid theoretical base, one that allows for an adequate treatment of information flows and knowledge-related processes in dynamic spatio-temporal settings. We need to derive our simulation model from a theoretical framework that meets these needs. Our theoretical framework must allow us first to introduce knowledge flows as natural phenomena and then permit us to assess how new ICTs might affect them. We have seen that neither the neoclassical economic models nor the more recent exogenous growth models can meet this requirement. Moreover, we need a conceptual framework that can be easily implemented by a simulation model. In some of our previous works, the I-Space framework has proved to be quite useful as a theoretical basis for modeling knowledge-intensive economic scenarios [Boisot et al., 2004] as well as the evolution of knowledge management strategies within populations of firms in different ICT regimes [Canals et al. 2004]. This makes it an appropriate choice for tackling the problem of the interrelationship between knowledge management strategies, spatial location patterns in geographical industrial clusters and the impact of new ICTs development. In the next section we present 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.

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.

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[2] This section draws mainly upon Canals, Boisot, et al. [2004; Boisot et al., 2004].

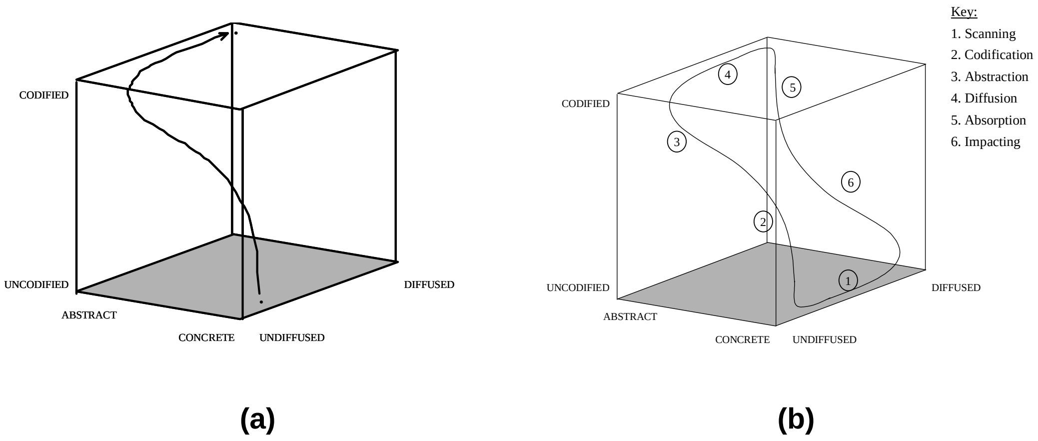

Figure 1 Diffusion curve (a) and Social Learning Cycle (b) in the I-Space.

The relationship between the codification, abstraction and diffusion of knowledge is illustrated by the diffusion curve of **Figure 1**a. 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 1**b 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 **Figure 2**, 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.

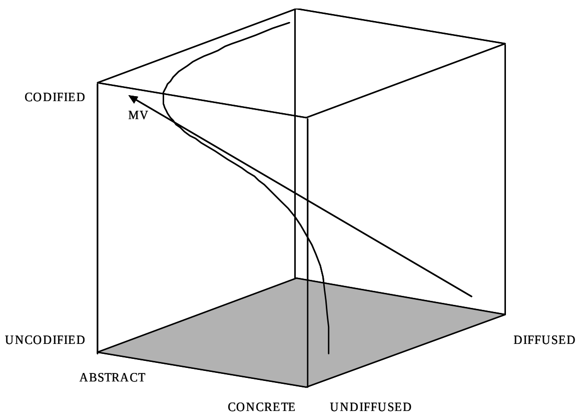

Figure 2 Maximum Value (MV) in the I-Space

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 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 rather of fostering a speeding up of the Social Learning Cycle in order to secure new knowledge assets whose value will compensate for the loss of the old ones. The difference between these two strategies can be illustrated with two examples from the software industry. On the one hand, Microsoft expends huge efforts to prevent the diffusion of its software codes in order to extract the maximum value from them by selling the products in which these codes are embedded - a typical N-learning strategy. On the other hand, the open-source community gives away all the codes that they create free of charge. This drives a Social Learning Cycle into a continuous creation of new knowledge. In a clear example of an S-learning strategy, the generation of value by firms like Red Hat, that earn their money by packaging and selling Linux products, depends on this continuous creation of new knowledge.

The introduction of more developed Information and Communication Technologies (ICTs) has as a consequence the shift of the diffusion curve as is shown in **Figure 3**. This shift has two effects. On the one hand, there is a diffusion effect, represented in the figure by the horizontal arrow shift. For a given degree of codification and abstraction, a higher number of agents can be reached with the same information per unit of time. There is an increase in the population. Electronic mail, for instance, allows us to reach a much higher number of people than a traditional letter. On the other hand, there is a bandwidth effect, which is represented by the more vertical down-pointing arrow. For a given number of agents targeted—i.e., holding the population constant—the bandwidth of the message can be increased. The information transmitted can then be both less structured and more concrete, as, for example, when we use videoconferencing instead of the written word to communicate.

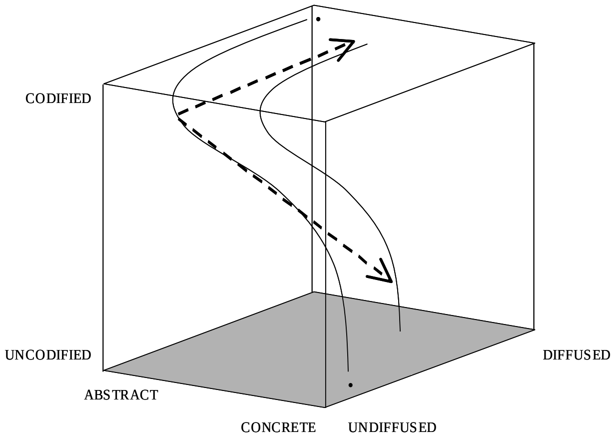

Figure 3 ICTs shift of the diffusion curve in the I-Space

The I-Space framework is especially well-suited to the study of knowledge flows among a group of agents since it allows us to distinguish different degrees of structuring of knowledge assets and of diffusion of those assets among the population of agents. Moreover, it also allows us to assess the impact of ICTs on the diffusion of knowledge. In the I-Space, the development of ICTs results either in a reduction of the need to structure knowledge in order to diffuse it, or, alternatively, in the possibility of diffusing it to a larger population of agents if the level of knowledge structuring remains the same. We will show how these features make it suitable for dealing with the problems of a spatial economy in which the diffusion of knowledge plays a key role.

4. KNOWLEDGE MANAGEMENT STRATEGIES AND LOCATION IN GEOGRAPHICAL INDUSTRIAL CLUSTERS

The topic we choose for implementing our spatial economy simulation model is the interplay between knowledge management strategies and location and agglomeration patterns in geographical industrial clusters. Thus, our aim will be to build a model that constitutes a simplified representation of industrial districts framed in terms of knowledge management strategies and spatial location. With our model, we shall first attempt to reproduce the main features of two different types of high-tech industrial districts or clusters based in two well-known paradigmatic and thoroughly studied examples: Silicon Valley and Boston Route 128. After that, we shall ask a question with implications for the future of such clusters: what impact might future ICT developments have on their evolution? Will they maintain their spatial integrity in the face of the Internet, a technology that makes it possible to transfer much larger volumes of data over longer distances? What will be the effect of ICT developments on the number of firms present in an industrial district and on the knowledge management strategies they adopt? Our hope is that the use of our simulation model will allow us to shed some light on the possible answers to those questions and to formulate insightful and empirically testable hypotheses.

Geographical industrial clusters have attracted a lot of interest because of their role in the generation of economic growth and have been studied from several perspectives. These have given rise to different terms covering the same phenomenon with slightly different shades of meaning: i.e., *industrial districts*, a post-Marshallian term that has been mostly applied in an Italian context [Andriani, 2003]; *clusters*, a term used by Michael Porter in his work on strategy and competitiveness [Porter, 1990; Porter, 1998]; *growth poles*, introduced into the French literature by Perroux [1950]; and *technopoles*, a term proposed by Castells and Hall [1994]. Whatever conceptual differences[3] might distinguish these terms, our model can be applied to all of them.

The use of agent-based simulation is particularly well adapted to the modeling of industrial districts, since it allows them to be viewed as complex adaptive systems evolving over time through processes of variation and selection. Thus, it is possible to observe the dynamics of agents performance and of knowledge assets creation, as well as the distribution of knowledge management strategies and spatial agglomeration patterns across a population of organizational agents.

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[3] Even in the specialized literature, it is not always easy to find the differences among terms like industrial districts or clusters [Belussi, 2004]. We will use both terms interchangeably.

Clearly knowledge plays a key role in modern regional clusters [Castells, 1996; 2001; Castells and Hall, 1994; Dunning, 2000b; Bryson et al., 2000; Acs et al., 2002]. And since, as we have seen before, knowledge spillovers among firms and institutions are one of the main drivers of agglomeration, knowledge diffusion mechanisms become important [Storper, 2000]. It follows, therefore, that knowledge management strategies that aim either to block or slow down the diffusion of knowledge could undermine the drive to agglomerate in industrial districts.

Also important will be knowledge management strategies that express a preference for working either with tacit or with explicit knowledge. As Audretsch puts it, "the theory of knowledge spillovers, derived from the knowledge production function, suggests that the propensity for innovative activity to cluster spatially will be the greatest in industries where tacit knowledge plays an important role" [Audretsch, 2000: 72].

Thus, our simulation efforts will focus on two knowledge management dimensions, one expressing a managerial preference for either blocking or not blocking diffusion, and the other expressing a managerial preference for either tacit or explicit knowledge. Translated into I-Space terms (see section 3), diffusion-blocking strategies will increase the probability of successfully impeding the diffusion of one's knowledge assets to other agents, thus lowering the mean degree of diffusion of knowledge assets in the agent population. This corresponds to what we have described above as an N-learning strategy, one in which an agent aims to confine its knowledge assets as long as possible in an I-Space location from which it can extract a maximum value for them. By contrast, a non-diffusion-blocking strategy corresponds to an S-learning strategy, in which an agent aims to move faster that its competitors around a social learning cycle in the I-Space in order to create new value-adding knowledge.

An agent with a strategic preference for knowledge structuring will invest to increase the degree of codification and abstraction of its knowledge assets—whether it succeeds or not is determined probabilistically. By contrast, an agent with a strategic preference for tacit knowledge will invest in lowering the degree of codification and abstraction. The first option expresses a cognitive preference for the upper regions of the I-Space, where knowledge is highly structured—where, for example, a bond trader operating on the basis of perfectly codified information might want to be. The second option expresses a cognitive preference for the lower regions of the I-Space, where knowledge is more tacit—the region of choice, perhaps for a zen master, whose ineffable wisdom can only be transmitted face-to-face to a few disciples.

The development of the Internet and other ICTs plays an important role in the diffusion of knowledge [Castells, 1996],[Castells, 2001] and particularly so in high-tech clusters [Eng, 2004], In our model we vary the degree of development of ICTs. In this way, we are able to simulate the effect of different ICT regimes on the clustering process. As we have mentioned in the previous section, the evolution of ICTs shifts the diffusion curve to the right along the diffusion dimension of the I-Space and has two discernable effects on the trajectories of knowledge assets in the space: a diffusion effect and a bandwidth effect. In the diffusion effect, for a given level of data structuring (codification and abstraction), more agents can be reached in a given unit of time. In the bandwidth effect a given number of agents can be reached at lower levels of data structuring. We implement the shift in the diffusion curve in our model by making the physical distance over which knowledge can be transferred dependent on the level of knowledge structuring. The latter is then modified by the evolution of ICTs. The evolution of ICTs thus results either in a longer spatial reach for a given level of knowledge structuring or in a lowered requirement for the structuring of knowledge for a given spatial reach.

5. SIMULATING GEOGRAPHICAL INDUSTRIAL CLUSTERS[4]

In this section we present a simulation model that will allow us to reproduce some of the characteristics of two well-known cases of regional clusters: Silicon Valley (SV) and Boston's Route 128 (R128) [Dorfman, 1983; Saxenian, 1994b; Brown and Duguid, 2000]. In order to study the

[4] This section draws mainly upon Canals, Boisot, et al. [2004].

evolution of strategic options within a population of organizations and the influence on this evolution of developments in ICTs, we will use an agent-based simulation. Agent-based simulation, in contrast to equation-based simulation techniques, adopts a bottom-up approach made possible through the use of Distributed Artificial Intelligence (DAI) technologies [Brassel et al. 1997]. Agent-based modeling can directly represent 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. This is typically beyond the reach of 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 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.

5.5.1.1. 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.

5.5.1.2. 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.

5.5.1.3. 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.[5]

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

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 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.

*5.5.2.1. The spatial loca***tion 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. The grid is represented graphically while the simulation is running (see **Figure 4**). At this stage of the model's development, we take the space that agents occupy to be isotropic—that is, without geographical irregularities.

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

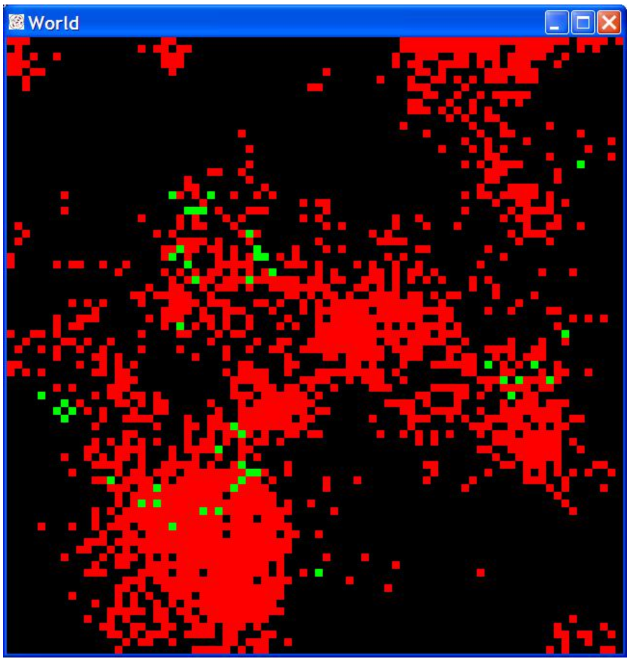

Figure 4 Image of the simulation graphic representation

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, 2000b]. 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.

5.5.2.2. 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].

5.5.2.3. 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[6]. So we have:

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

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 5** 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.

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[6] 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.

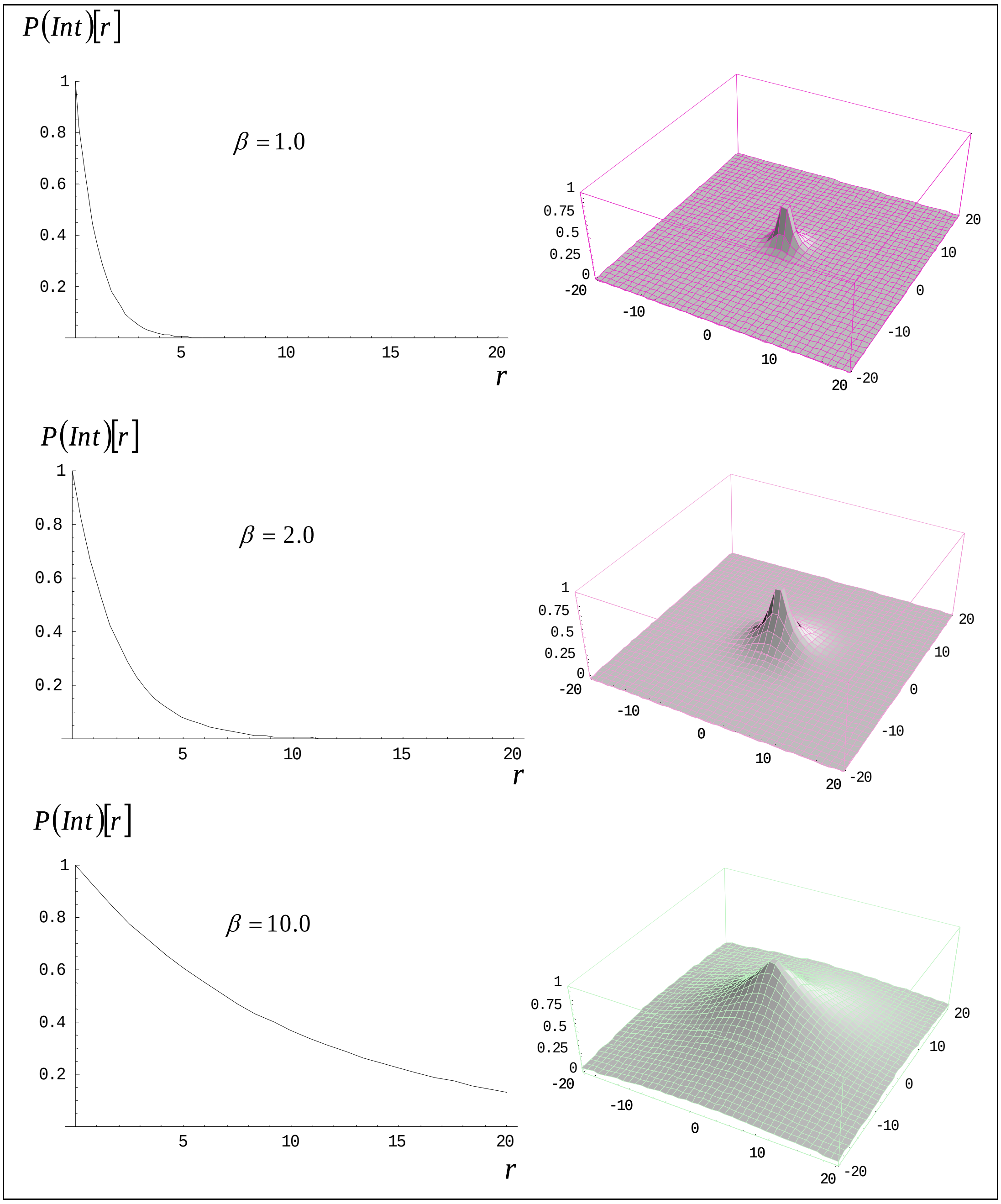

Figure 5 Bandwidth effect: the shape of the probability of interaction $P(Int)[r, \beta]$ for different values of β as a function of the distance *r* between cells.

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.

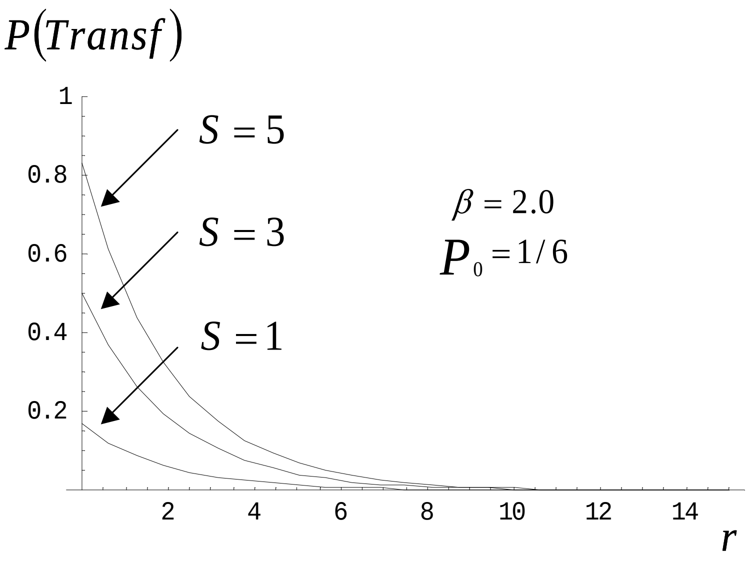

Figure 6 Form of $P(Transf)$

Figure 6 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.

5.3. Using the model for geographical industrial clusters

We will use the model we have described above to simulate the dynamics of knowledge-based geographical industrial clusters. Given the limited focus of our model on knowledge creation and knowledge transfer, it cannot study geographical clusters in all their complexity. The rents earned by our agents, for example, arise solely from the exploitation of knowledge assets, and their investments are limited to matters related to knowledge creation and to agent interactions focused on knowledge-related trades or collaborations. We ignore transportation costs, labor market phenomena, or the price of raw materials. Of course, such factors are important in the development of a geographical industrial cluster, but our simulation model will not take them into account. It is, thus, perhaps better adapted to representing knowledge-based clusters or services sectors, and gains in relevance with the increasing knowledge-intensity of the goods traded. Interpreting our model's results in terms of real-world situations, therefore, we must filter out issues unrelated to knowledge. Our conclusions do not translate directly into real cases, but only provide insights on the dynamics at work in industrial clusters where knowledge is a key issue.

It is also important to note that time frame within which simulation runs is not much aligned with that of real systems but it is one that allows evolutionary processes to manifest themselves. In fact, it would be very difficult trying to match the evolution of the simulation with that of a real system since at this stage of our model's development it would be impossible to introduce the kinds of environment changes that occur in the real world during a run.

In our representation of geographical industrial clusters, the spatial grid on which agents of the simulation are located represent a geographical area more or less comparable in size to Santa Clara Valley or Boston's Route 128. We are focusing on the dynamics of evolution within already existing industrial clusters, not on the formation of new clusters within a larger geographical area. At the start of the simulation, therefore, we populate the grid with a number of agents representing the firms in a given cluster and set the parameters in such a way as to make the agents behave and interact in a manner consistent with what we know about that particular cluster.

After running the simulation we look for emergent patterns. If these are consistent with what has been observed in the cases on which the simulation is modeled, we have a measure of validation of the model. Furthermore, we can use the intermediate data generated by the simulation runs to shed light on the underlying mechanisms that led to those patterns. And even if we cannot readily assess whether the observed patterns are consistent with empirical reality, they can nevertheless provide us with useful insights for the formulation of fruitful hypotheses. In the next sections we apply our simulation model to two cases of geographical industrial clusters: Silicon Valley and Boston's Route 128.

6. MODELING GEOGRAPHICAL INDUSTRIAL CLUSTERS: SILICON VALLEY AND ROUTE 128

In order to build differentiated representations of Silicon Valley and Route 128, we will parametrize our model, taking into account the culture and industrial differences between these high-tech industrial districts. To identify those differences we rely mainly on the analysis by Saxenian [1994a; 1994b; 1996] and by Castells and Hall [1994], but also on the large number of studies of the subject that we can find in the literature [Dorfman, 1983; Florida and Kenney, 1990; Brown and Duguid, 2000; Kenney, 2000; Best, 2000].

As stated before, the aim of our model is not to fully and realistically replicate the economic features of Silicon Valley and Route 128, but to achieve a simplified—and hence more useful—representation of these two industrial districts. To do that, we introduce into our model some of the more salient features that distinguish the two cases that we now respectively label SV and R128. We want to keep the differences between the two cases to a minimum in order to obtain differential patterns consistent with the observation of real cases. If we can achieve this by varying just a few key parameters, it will help to interpret the results and to confirm the usefulness of the model.

From our review of the literature we have selected the following features that we believe distinguish SV from R128:

1) A larger number of firms are located in Silicon Valley than in Route 128.

   In the 1980s there were about 3,000 manufacturing electronic firms in the Silicon Valley geographical area[7]. An additional 3,000 firms provided them with services and 2,000 more were pursuing other high-technology activities [Castells and Hall, 1994: 12]. Thus we find a total of about 8,000 firms in the cluster. Along Boston's Route 128, by contrast, we find about 900 high-technology manufacturing establishments in 1980 and another 700 firms engaged in related consulting and technological services, making a total of 1,600 firms [Castells and Hall, 1994: 29]. Taking more restrictive technological criteria[8], Saxenian [1994b: 207-208] identifies around 4,000 establishments in Silicon Valley in the early 1990s and over 2,500 around Route 128. Since our model focuses on high-technology firms in general, we will take a ratio of four SV firms to one R128 firm.

2) Along Route 128, firms tend to be larger than in Silicon Valley, and to each use a greater number of technologies.

   Measured in terms of employees, the size of firms is quite different in the two cases. While in Silicon Valley 3,000 manufacturing electronic firms employed around 200,000 workers in the 1980s, Along Boston's Route 128 over 250,000 employees

[7] The data come from the Bureau of the Census and correspond to the following sectors: computers, other office machines, communications, semiconductors, other electronic components, missiles/parts, instruments, drugs, software/data processing, IC labs, electronic wholesale, and computer wholesale.

[8] She considers only the establishments devoted to the following activities: computing and office equipment, communications equipment, electronic components, guided missiles and space vehicles, instruments, and software and data processing.

were employed by 900 high-technology manufacturing establishments [Castells and Hall, 1994: 12, 29]. This translates into an average workforce of less than 70 employees per firm in Silicon Valley—in fact, it turns out that 85% of the firms in the Valley had less than 50 workers [Castells and Hall, 1994: 12]—compared to an average of more than 275 workers per establishment along Route 128.

This difference in firm size is partly explained by the fact that firms in Silicon Valley firms tend to be more specialized than their counterparts along Route 128, and show a higher degree of integration. As Saxenian puts it, "The industrial structure that emerged in this environment was highly fragmented. Silicon Valley's start-ups exploited the apparently limitless opportunities offered by electronics technology to differentiate their products, processes, and applications. Products and services became increasingly specialized as each firm sought to define and dominate a particular niche of a broader industry" [Saxenian, 1994b: 43], while "The Route 128 region, in contrast, is dominated by a small number of relatively integrated corporations. Its industrial system is based on independent firms that internalize a wide range of productive activities" [Saxenian, 1994b: 3].

In our model we express this difference in through the maximum number of knowledge assets that a firm can possess. While each agent in the SV case will only be able to possess a maximum of 7 knowledge assets of which only 5 can be actively exploited at any given time, in the R128 case, each agent will be allowed to possess 28 knowledge assets, 20 of which may be active.

3) Interaction between firms in Silicon Valley, of both the informal and the formal kind, is much more frequent in Silicon Valley than along Route 128.

The technical-professional culture of Silicon Valley's pioneers, drawn by their commitment to innovation and the sense that they are building a new industry, contrasts with the far more classical corporate culture dominating the firms along Route 128. In the Californian region this results in the formation of a dense personal network structure fostering informal interactions among professionals of different firms that ultimately also contributes to the formation of more formal ties between companies. In Saxenian's words: "The habits of informal cooperation among Silicon Valley engineers predate the semiconductor industry. […] The informal socializing that grew out of these quasi-familial relationships supported the ubiquitous practices of collaboration and sharing of information among local producers. […] A variety of more and less formal gatherings—from trade association meetings and industry conferences to trade shows and hobbyists' clubs—also served as specialized forums for information exchange." [Saxenian, 1994b: 32-34]. Contrarily, in the East Coast even the formal relationships between different firms were much more scarce. "As Silicon Valley's entrepreneurs created an industrial system based on the region and its social and technical networks, their counterparts along Boston's Route 128 inherited and reproduced an industrial order based on independent firms. Route 128's technology enterprises adopted the autarkic practices and structures of an earlier generation of East Coast businesses." [Saxenian, 1994b: 59].

These differences show up in our simulation model as allowing a higher number of random meetings to take place between firms in each period in the SV case and as increasing the probability of those meetings. We also introduce a higher propensity to participate in planned meetings in the SV case.

4) The Silicon Valley's culture is more prone to collaboration

As a consequence both of the previously described differences in the interaction propensities of firms and of the fact that the Californian firms are more specialized, there is a much higher degree of collaboration between firms in Silicon Valley than along Route 128. While in the Santa Clara Valley region cooperation is as fundamental as competition [Saxenian, 1994b: 37], along Boston's Route 128 "Secrecy and territoriality ruled relations between individuals and firms, traditional hierarchies prevailed within firms, and relations with local institutions were distant—even

> antagonistic. The regional economy remained a collection of autonomous enterprises, lacking social or commercial interdependencies" [Saxenian, 1994b: 59]. In our model this difference shows up as a higher propensity to collaborate in the SV case.

In order to give distinctive profiles to SV and to R128, we introduce these differentiating characteristics through the initial parametrization of our model. **Table 2** summarizes the different values we have chosen. They are based on the above discussion. For the remaining parameters, we keep to the values that we have used elsewhere [Boisot et al., 2004; Canals et al. 2004] to represent a Schumpeterian economic system. In appendix 1 we present the complete list of the model parameters together with the values chosen to build the SV and R128 cases. A more detailed description of the parameters can be found in [Boisot et al., 2003a].

Differences between the SV and R128 cases in the initial parametrization		
Characteristic	**SV**	**R128**
Initial number of agents in the simulation	20	5
Maximum number of active knowledge assets per agent	5	20
Maximum number of passive knowledge assets per agent	2	8
Probability of occurrence of random meetings between agents	40%	10%
Maximum number of random meetings per period	6	2
Positive propensity to meet other agents	20%	5%
Negative propensity to meet other agents	5%	40%
High propensity to establish collaboration with other agents	30%	10%

Table 2 Differences in initial parametrization between R128 and SV

7. Results

In this section we present the main results that we obtained after running the simulation model for the two cases mentioned: R128 and SV. In sub-section 7.1 we compare the time evolution of the two models. Our overall results turn out to be quite consistent with the real cases modeled and will thus contribute to the validation of the model. Sub-section 7.2 will be devoted to an examination of the results obtained when for both cases—i.e., R128 and SV—we extend our study by introducing different stages of ICT evolution in our model.

Except for those occasions where we show results for a specific representative run at a given moment in time, we will show our results in the form of charts representing the mean values of the 50 runs we perform for each case and tables with the mean values and standard deviations of the representative variables.

As described elsewhere [Boisot et al., 2003a; 2003b; Boisot et al., 2004], the basic simulation model has been verified and validated following established procedures [Gilbert and Troitzsch, 1999]. The set of results presented in sub-section 7.1 contribute to the validation of the extended model we are presenting here. The results reported in this section correspond to a set of simulation experiments that we have performed with the model.

For each case that we examine, the run is repeated 50 times so as to obtain statistically meaningful results. We analyze the results of several different cases using ANOVA to ensure that differences among performance means are statistically significant at $p < 0.001$. In this way we can be reasonably confident that any differences encountered 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.

Our aim in this paper is not to prove the generality of any specific result but rather to use any qualitative patterns that emerge as a basis for generating insights into 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.

7.1. Silicon Valley vs. Route 128: time evolution

In order to analyze the different time evolution of the two cases, R128 and SV, we will look at the results obtained running the simulation for a medium level of ICT development—i.e., a medium bandwidth ($\beta = 2$). **Figure 7** represents the evolution of the number of agents in the simulation.

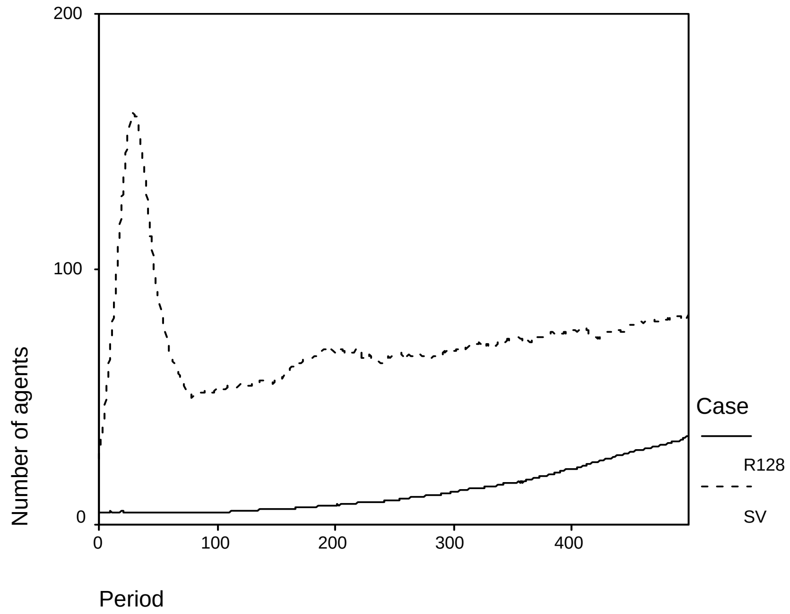

Figure 7 Evolution of the number of agents for the two cases modeled

The SV case shows a type of behavior in the evolution of the number of agents that we have observed in other models [Boisot et al., 2004; Canals et al. 2004]. A sudden increase is followed by a rapid decrease, all within the 100 first periods, followed by a more stable and ordered regime that is characterized by a steady if modest increase. As we have noted in previous works [Canals et al. 2004], such a pattern could correspond to the emergence of order after an explosive phase in the first periods. The R128 case shows a completely different behavior, especially in the first periods. The number of agents in the simulation R128 grows progressively, with no initial oscillation. The difference in the behavior of the two cases could be due to the fact that in the SV case, a "creative destruction" dynamic of a Schumpeterian nature is operative, whereas in the R128 case, owing to the smaller number of agents and the lower degree of interaction between them, such a dynamic is absent.

After the initial periods, however, both cases follow a similar evolution, but with a much higher total number of agents in the SV case. The initial difference in the number of agents between the two cases is maintained throughout the runs, as can be seen in **Figure 8**, which shows the final spatial distribution of agents in representative runs for each case. In the R128 case, we observe a separate nucleus of activity, while in the SV case the activity is more spread out in space.

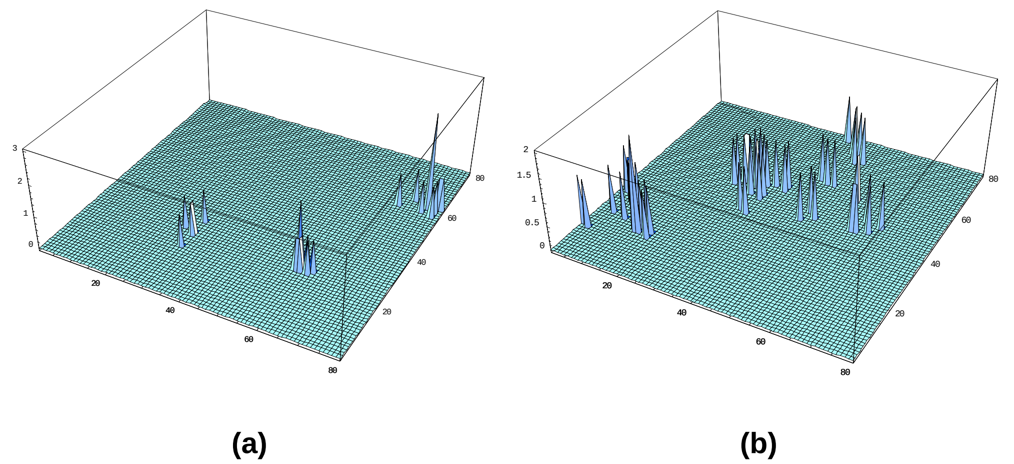

Figure 8 Location of agents in the last period of the simulation for two representative runs (a) R128 (b) SV

The evolution in time of the number of knowledge assets in the simulation and the amount of rents generated each period shows a similar behavior to that of the total number of agents for both the R128 and the SV cases, as shown in **Figure 9**. The data given in **Table 3** corresponds to that presented graphically in **Figure 7** and **Figure 9**. It gives the numerical values of the mean and standard deviation of the number of agents, number of knowledge assets and rents generated at different points in the time evolution of the simulation.

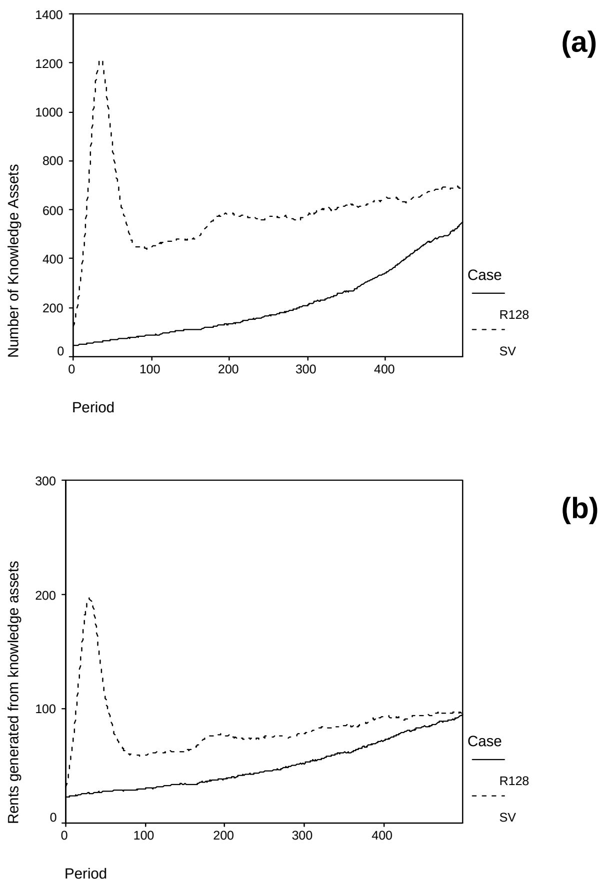

Figure 9 Evolution of the amount of knowledge in the simulation (a) and the rents generated by this knowledge (b).

Variable		**Period**					
	Case	**0**	**100**	**200**	**300**	**400**	**499**
Number of agents	*R128*	5,00 *(0,00)*	4,90 *(1,07)*	7,64 *(3,64)*	12,74 *(8,35)*	21,74 *(23,15)*	35,00 *(40,72)*
	SV	25,56 *(2,17)*	53,06 *(15,83)*	67,52 *(30,52)*	68,36 *(26,48)*	75,34 *(32,43)*	82,06 *(40,81)*
Number of knowledge assets	*R128*	44,90 *(3,58)*	87,82 *(23,31)*	133,04 *(55,10)*	209,22 *(122,64)*	342,04 *(335,97)*	550,96 *(627,09)*
	SV	125,00 *(8,86)*	446,58 *(127,68)*	583,02 *(248,97)*	577,38 *(223,98)*	648,42 *(265,08)*	688,46 *(341,50)*
Rents generated from knowledge assets	*R128*	22,73 *(3,16)*	30,07 *(9,34)*	39,00 *(17,86)*	51,87 *(26,21)*	72,34 *(41,12)*	95,24 *(54,67)*
	SV	32,08	59,12	77,12	78,38	93,76	96,71

		(4,97)	*(17,42)*	*(31,86)*	*(34,11)*	*(46,31)*	*(59,21)*

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

As stated above, our simulation model incorporates evolutionary features. This means that through a process of variation and selective retention of strategic options, the system will evolve towards some optimal state for the population. In **Figure 10** we present for the two cases modeled the evolution of two key variables in our simulation: the mean degree of structuring of knowledge assets (**Figure 10**a) and the mean degree of diffusion of those assets (**Figure 10**b).

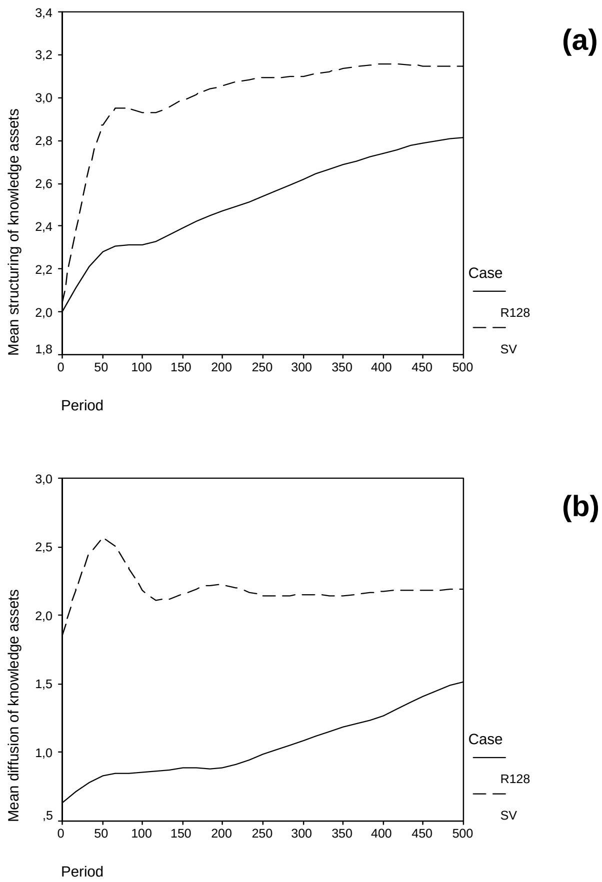

Figure 10 Evolution of the mean degree of structuring (a) and the mean degree of diffusion (b) of the knowledge assets within the population

Examining the SV case we see a clear tendency to evolve towards a more or less stable values for the mean degree of structuring (between the values of 3.0 and 3.2) and the mean degree of diffusion (between 2.0 and 2.3). This hints that there could be some optimal values of those magnitudes for the population and that the system evolves in their direction. In the R128 case the tendency is not so clear, but the evolution of the system is clearly consistent with such an orientation. Both values point to a future evolution in the direction of the values already reached in the SV case. The only difference is that, in the R128 case, the system lacks the capacity to reach the optimal values as quickly as in the SV case. This might be attributed to the fact that, as we have already seen, the lower number of agents and the lower degree of interaction prevent the system from engaging in the type of "creative destruction" in which evolution is speeded up. In the SV case there is an initial phase characterized by a high rate of agent entry and exit—the hallmark of a Schumpeterian scenario. Such a scenario accelerates the pace of evolution and thus the speed at which a fitter type of population can be achieved. This happens earlier in the SV case than in the case of R128, the latter being somewhat closer to a Neoclassical environment.

What is the mechanism by which the populations of agents achieve this evolution towards an optimal state? As in every evolutionary process, the mechanism consists of the variation and selective retention of some elements that act as genes. In our model, two kinds of items can play that role. One is the knowledge management strategies that our agents possess and inherit through a mechanism similar to genetic algorithms. The other is spatial location. Agents that are the product of mergers, joint ventures or the creation of subsidiaries are located in the vicinity of one of their parent agents. Location is therefore in some sense inherited. As the transfer of knowledge is dependent on the spatial distance between agents, location patterns play an important role in the evolution of the system. In order to understand this evolutionary dynamic, we will now examine it at work in the knowledge management strategies and location patterns of agents.

Figure 11 shows the evolution of both the fraction of agents with a strategic preference for structuring knowledge (KSS = 1) and that with a strategic preference for applying a diffusion blocking mechanisms (BDS = 1).

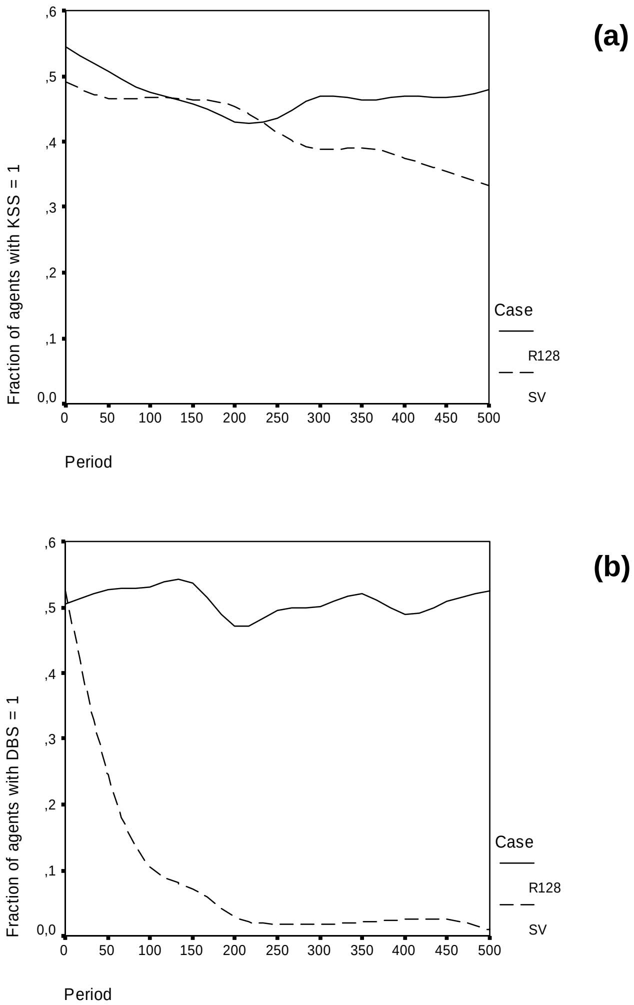

Figure 11 Evolution of the knowledge-structuring-strategy (KSS) (a) and diffusion-blocking-strategy (DBS) (b) within the population

In the R128 case, the proportion of agents that have a propensity to structure knowledge seems to fluctuate around 50% throughout the simulation This means that in the system the number of agents with KSS = 1 remain more or less the same as the number of those with KSS = 0. As can be seen from **Figure 10**a, the SV case behaves differently. It shows a steady decline in the percentage of knowledge structuring strategies (KSS = 1) in the population; These go from 50% to around 35%.

An analysis of the distribution of diffusion-blocking-strategies points to another important difference in the behavior of the two cases (see **Figure 10**b). The R128 case does not show any suppression of the strategic preferences for blocking diffusion (DBS=1) that are observed in SV, and that have been detected in previous models [Boisot et al. 2003]. As already mentioned, this is probably due to the absence of any "creative destruction" in the environment that would accelerate the evolution process.

Yet, does this particular distribution of knowledge management strategies within the population have any effect on knowledge assets? Contrarily to what one would expect from the data in **Figure 11**, the R128 case generally shows a lower degree of structuring of knowledge assets even though the number of agents with a KSS = 1 strategy is larger. On the other hand, the strong decline of diffusion blocking strategies in the SV case that are observed in **Figure 11**b is consistent with the data of **Figure 10**b, where the SV case shows a higher degree of diffusion for knowledge assets.

The discrepancies observed between the knowledge management strategies adopted by the agent population and the actual characteristics of their knowledge assets suggests that we should look at location. Although the different locations of economic agents in space generate complex patterns that are hard to understand without recourse to the analytical techniques used by statisticians and economic geographers [Haining, 1990; Bailey and Gatrell, 1995; McCann, 2002; Diggle, 1983], in our case—bear in mind that our data are not real data but are derived from a simulation model—a good enough approximation to such techniques can be obtained from simple clustering algorithms. We will make use of one to examine the agglomeration patterns of agents in physical space. In **Figure 12** we represent two different measures of the degree of clustering of a population. **Figure 12**a shows the Index of Cluster Size or ICS [Bailey and Gatrell, 1995]. To calculate this index, a spatial region is first divided up into regions of equal area called *quadrats*.[9] Then,

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[9] The name *quadrat* comes from the historical use of square sampling frames in field sampling [Bailey and Gatrell, 1995: 84].

the number of events (agents) found inside each quadrat is then counted. If $\{x_1, \dots, x_m\}$ gives a counts of the number of events in m quadrats, the expression for the Index of Cluster Size is:

$$ICS = \left(\frac{s^2}{\bar{x}} \right) - 1$$

where $\bar{x}$ is the mean of the observed counts and s^2 is their observed variance.

The higher the value of ICS, the more important the degree of clustering is. As can be seen from the figure, clustering is more important in the SV case, although in the last phases of the simulation the R128 case shows a slight increase in the degree of agglomeration.

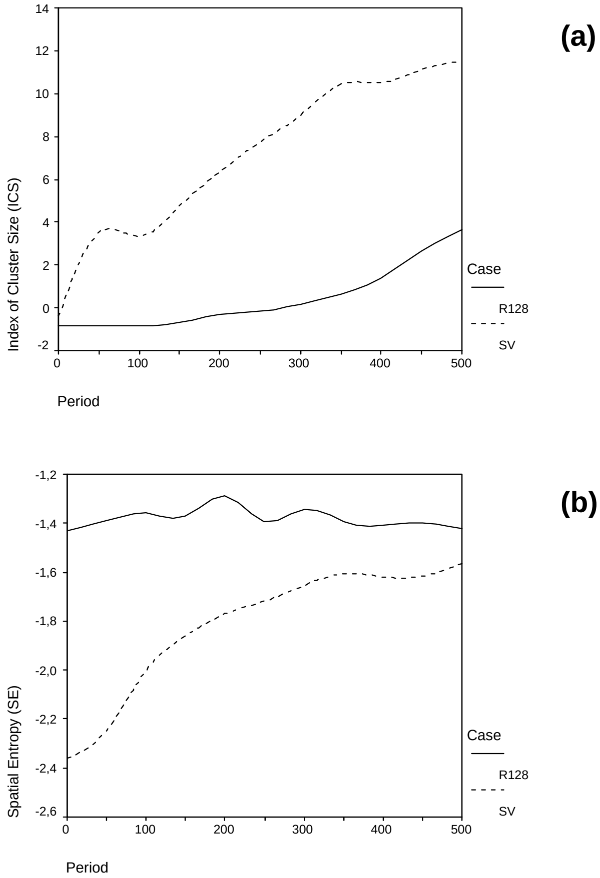


Figure 12 Two measures of clustering: (a) Index of Cluster Size (ICS) (b) Spatial Entropy (SE)

An alternative clustering coefficient is given by the Spatial Entropy (SE) [Bonabeau et al., 1999: 154]. This is calculated at a given spatial scale s (for example, *s = 4*, the scale that we use, means that we adopt 4x4 patches—called *s*-patches—to cover the area). The spatial entropy E_s at scale *s* is defined by:

$$E_s = \sum_{I \in \{s-patches\}} P_I \log P_I$$

where P_I stands for the fraction of all agents on the lattice that are found in s-patch *I*. For our simulations, E_4 is shown in **Figure 12**b. In this case, the coefficient is negative. Lower values of SE now correspond to higher degrees of clustering. Both measures, however, show a higher degree of clustering for the SV case, although the difference between both cases is reduced in the last phases of the simulation. In our analysis we will use the ICS index.

Our results point to the possibility that changes in the degree of clustering have a higher impact on the mean degrees of structuring and diffusion of knowledge assets than changes in knowledge management strategies. This strongly suggests that, in the systems being modeled, knowledge management strategies and locations co-evolve in the population of agents.

Table 4 gives the figures for the temporal evolution of the mean values of the variables discussed above: average degrees of structuring and diffusion, knowledge management strategies, and clustering coefficients.

Variable		Period					
	Case	0	100	200	300	400	499
Mean degree of structuring of knowledge assets	*R128*	2,00 *(0,19)*	2,31 *(0,18)*	2,47 *(0,18)*	2,62 *(0,19)*	2,74 *(0,18)*	2,81 *(0,17)*
	SV	2,05 *(0,23)*	2,93 *(0,18)*	3,06 *(0,19)*	3,10 *(0,15)*	3,16 *(0,15)*	3,15 *(0,19)*
Mean degree of diffusion of knowledge assets	*R128*	0,63 *(0,11)*	0,85 *(0,22)*	0,89 *(0,24)*	1,09 *(0,27)*	1,27 *(0,36)*	1,52 *(0,41)*
	SV	1,85 *(0,10)*	2,18 *(0,21)*	2,22 *(0,24)*	2,15 *(0,26)*	2,18 *(0,26)*	2,19 *(0,24)*
Fraction of agents with KSS = 1	*R128*	0,54 *(0,25)*	0,48 *(0,26)*	0,43 *(0,28)*	0,47 *(0,28)*	0,47 *(0,26)*	0,48 *(0,30)*
	SV	0,49 *(0,13)*	0,47 *(0,20)*	0,45 *(0,22)*	0,39 *(0,22)*	0,37 *(0,23)*	0,33 *(0,24)*
Fraction of agents with DBS = 1	*R128*	0,50 *(0,24)*	0,53 *(0,25)*	0,47 *(0,27)*	0,50 *(0,25)*	0,49 *(0,25)*	0,52 *(0,27)*
	SV	0,53 *(0,12)*	0,10 *(0,13)*	0,03 *(0,04)*	0,02 *(0,04)*	0,03 *(0,04)*	0,01 *(0,02)*
Index of Cluster Size (ICS)	*R128*	-0,85 *(0,22)*	-0,85 *(0,24)*	-0,31 *(0,90)*	0,18 *(1,26)*	1,39 *(3,97)*	3,64 *(7,00)*
	SV	-0,39 *(0,22)*	3,30 *(2,97)*	6,36 *(5,13)*	8,99 *(8,07)*	10,49 *(7,40)*	11,54 *(8,06)*
Spatial Entropy (SE)	*R128*	-1,43 *(0,21)*	-1,36 *(0,25)*	-1,29 *(0,33)*	-1,34 *(0,26)*	-1,41 *(0,28)*	-1,42 *(0,29)*
	SV	-2,36 *(0,11)*	-2,00 *(0,20)*	-1,77 *(0,30)*	-1,65 *(0,35)*	-1,62 *(0,29)*	-1,57 *(0,36)*

Table 4 Evolution of the degrees of structuring and diffusion of knowledge assets, knowledge management strategies and clustering coefficients (standard deviation in brackets).

7.2. Silicon Valley vs. Route 128: ICT regimes

In this sub-section we present the results we obtain when simulating the two cases R128 and SV for different levels of development of information and communication technologies (ICTs). Different ICT regimes will be introduced in our model by varying the β parameter. Recall that this parameter makes the probability of interaction between any two agents dependent on the spatial distance between them. We consider three different regimes that we will associate with narrow (β = 0.10), medium (β = 2.00) and broad (β = 10.00) communication bandwidth.

These will serve as good proxy measures for the level of ICT development. In **Table 5** we present values for the number of agents, the number of knowledge assets, and the rents obtained from knowledge assets at different bandwidths. We do this for selected periods of the simulation.

Variable			Period					
	Case	Band-width	0	100	200	300	400	499
Number of agents	*R128*	*Broad*	5,00 *(0,00)*	5,20 *(1,49)*	7,78 *(3,09)*	13,56 *(6,41)*	19,12 *(11,27)*	30,68 *(33,25)*
		Medium	5,00 *(0,00)*	4,90 *(1,07)*	7,64 *(3,64)*	12,74 *(8,35)*	21,74 *(23,15)*	35,00 *(40,72)*
		Narrow	5,00 *(0,00)*	6,56 *(2,11)*	12,12 *(5,57)*	20,66 *(9,73)*	32,08 *(19,36)*	50,38 *(34,87)*
	SV	*Broad*	25,26 *(1,81)*	33,12 *(5,82)*	34,68 *(9,11)*	36,42 *(9,95)*	35,94 *(8,51)*	36,22 *(9,01)*
		Medium	25,56 *(2,17)*	53,06 *(15,83)*	67,52 *(30,52)*	68,36 *(26,48)*	75,34 *(32,43)*	82,06 *(40,81)*
		Narrow	25,42 *(1,74)*	72,04 *(23,57)*	103,78 *(39,29)*	120,38 *(44,95)*	129,00 *(50,19)*	147,74 *(54,96)*
Number of knowledge assets	*R128*	*Broad*	30,16 *(0,37)*	60,68 *(14,64)*	106,16 *(37,19)*	175,06 *(69,94)*	267,18 *(111,57)*	384,24 *(187,89)*
		Medium	30,20 *(0,45)*	58,50 *(11,64)*	98,70 *(29,25)*	155,84 *(57,99)*	231,44 *(89,55)*	341,82 *(176,32)*
		Narrow	30,18 *(0,39)*	64,64 *(16,76)*	116,26 *(42,79)*	188,70 *(70,78)*	273,20 *(101,11)*	383,66 *(151,39)*
	SV	*Broad*	30,52 *(0,74)*	128,84 *(19,88)*	235,16 *(35,62)*	351,38 *(45,66)*	466,22 *(53,81)*	587,76 *(62,68)*
		Medium	30,44 *(0,54)*	225,14 *(40,20)*	365,00 *(75,09)*	517,30 *(108,76)*	683,74 *(160,54)*	859,12 *(223,88)*
		Narrow	30,42 *(0,58)*	265,20 *(45,07)*	450,26 *(112,95)*	681,02 *(200,37)*	955,10 *(288,04)*	1265,82 *(398,21)*
Rents generated from knowledge assets	*R128*	*Broad*	22,88 *(3,71)*	31,44 *(12,82)*	43,97 *(19,96)*	61,61 *(29,95)*	71,93 *(34,49)*	93,78 *(60,23)*
		Medium	22,73 *(3,16)*	30,35 *(9,63)*	39,78 *(18,77)*	52,90 *(26,77)*	73,77 *(41,82)*	97,57 *(55,99)*
		Narrow	22,66 *(3,11)*	37,59 *(15,28)*	52,85 *(25,67)*	77,33 *(32,46)*	96,27 *(43,74)*	122,45 *(61,93)*
	SV	*Broad*	39,47 *(7,68)*	48,84 *(9,46)*	53,46 *(18,32)*	57,38 *(20,66)*	59,41 *(18,30)*	66,84 *(26,42)*
		Medium	40,99 *(7,47)*	61,08 *(17,89)*	79,74 *(33,77)*	81,19 *(35,99)*	96,64 *(47,56)*	99,42 *(60,65)*
		Narrow	41,94 *(6,51)*	70,09 *(23,10)*	95,81 *(36,33)*	111,47 *(45,63)*	121,91 *(52,33)*	141,35 *(57,81)*

Table 5 Evolution of mean values for the number of agents, number of knowledge assets and amount of rents generated (standard deviation in brackets).

Figure 13 shows the complete evolution of the number of agents under the three different ICT regimes and for the two cases R128 and SV. In both cases we observe that the number of agents decreases when the bandwidth increases. Varying the bandwidth does not actually change the shape of the curves significantly except for the case of broad bandwidth in the SV case. Here, the peak observed in the first phase disappears. Probably the low number of agents does not favor the sudden explosion and subsequent implosion observed under medium and narrow bandwidth regimes. In both cases, the evolution of the number of knowledge assets present in the simulation and the total rents obtained from those assets show a similar qualitative evolution.

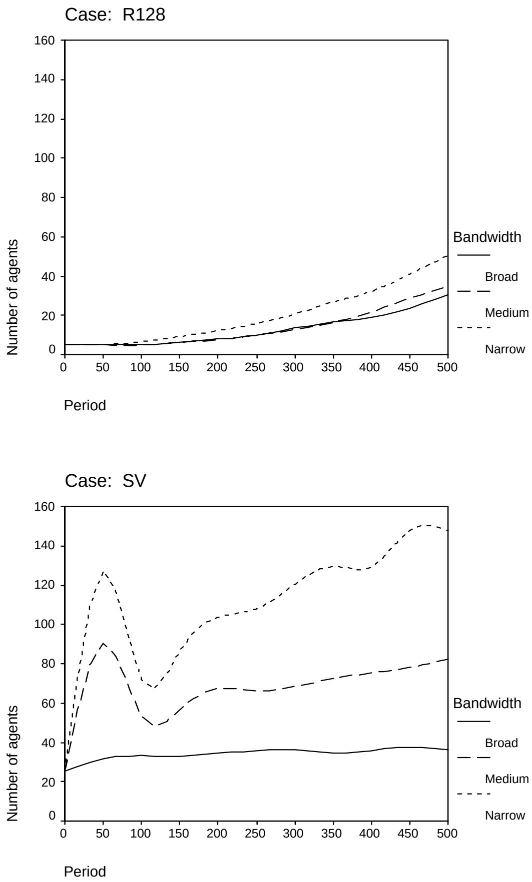


Figure 13 Evolution of the number of agents in the R128 and SV simulations for three different ICT regimes

When we look at values for the mean structuring (**Figure 14**) and mean diffusion (**Figure 15**) of knowledge assets, we see that in the R128 case they are quite similar except under a narrow bandwidth ICT regime. Here, the mean degree of structuring remains more or less constant in the second part of the simulation with a value slightly above 2.4 while for the other regimes the value continues to increase. In the SV case the evolutionary trajectory is quite similar, but with one interesting feature: while a lower bandwidth regime implies a lower degree of knowledge structuring, it turns out that a higher degree of structuring is actually achieved for the medium bandwidth regime. We will return to this non-linearity later on.

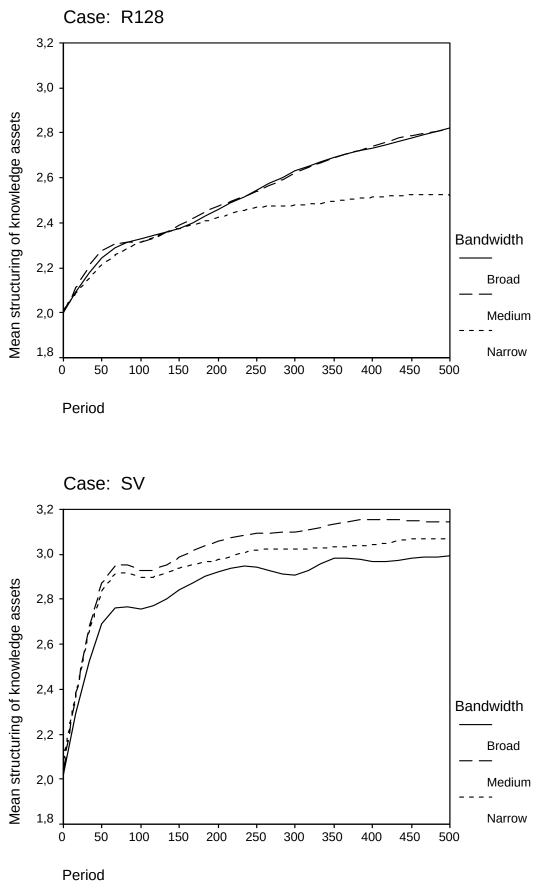


Figure 14 Evolution of the mean structuring of knowledge assets at several ICT regimes

As can be seen from **Figure 15**, the mean degree of diffusion of knowledge assets does not exhibit a similar non-linearity. Broader bandwidth regimes correspond to lower values for the mean degree of diffusion of knowledge assets both in the R128 and in the SV case.

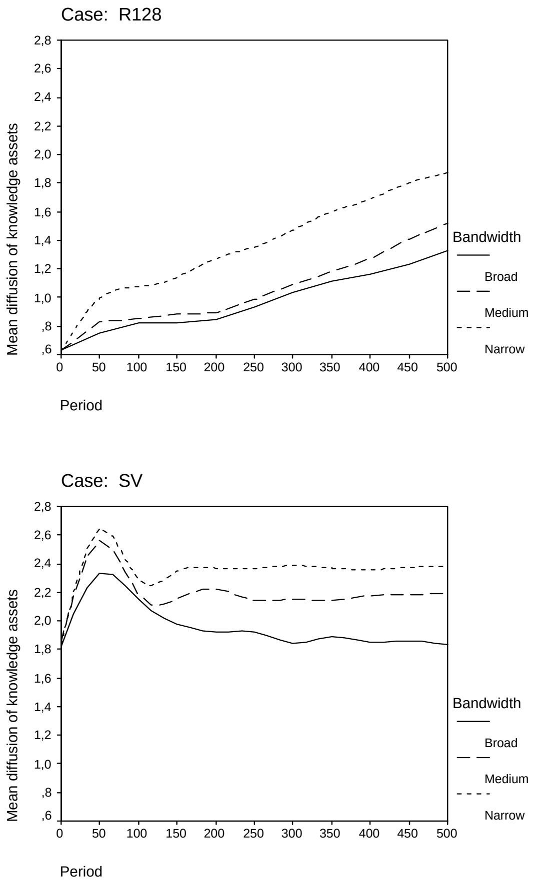


Figure 15 Evolution of the mean diffusion of knowledge assets at several ICT regimes

As in the previous sub-section, the values for the mean structuring and mean diffusion of knowledge assets can only be explained by looking at agglomeration patterns as well as knowledge management strategies.

Figure 16 shows the evolution of the fraction of agents in the simulation having, a strategic preference for structuring knowledge (KSS = 1). Although the values of standard deviation are important (see **Table 6**), the observed differences in the curves corresponding to the different ICT regimes for the two cases are still significant. The first noticeable feature is that there is not a linear correlation between the degree of development of ICTs and the presence of specific knowledge management strategies in the population. In the R128 case, the medium bandwidth regime presents the highest proportion of agents with a preference for structuring knowledge (around 50%), while for both narrow and broad bandwidths the proportion is lower (around 40%). In the SV case, by contrast, we observe that the medium bandwidth regime gives us the lowest proportion of agents with a KSS = 1 strategy—less than 35% of all agents—while for broad and narrow bandwidth the percentage is more than 40%.

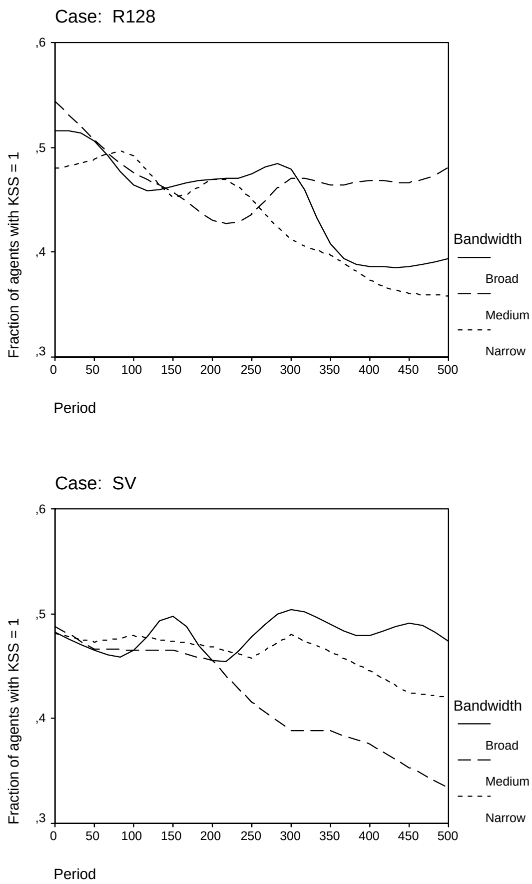


Figure 16 Evolution of the fraction of agents with a KSS = 1 strategy

The non-linear relationship between ICTs development and knowledge-structuring strategies is not repeated in the case of diffusion blocking strategies. In **Figure 17** it can be seen that in each case the behavior is quite similar for all ICT regimes within each case, except for a visibly higher proportion of agents with a preference for a diffusion-blocking strategy under the broad bandwidth regime of the SV case—although the proportion remains below 20%. In the R128 case, there is also a slight deviation in the last periods under the narrow bandwidth regime: here more than 60% of agents opt for a DBS = 1.

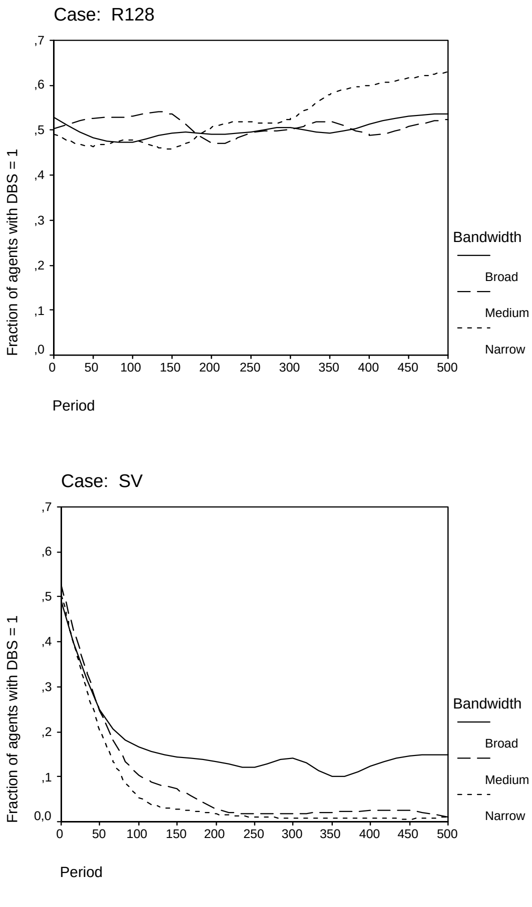


Figure 17 Evolution of the fraction of agents with a DBS = 1 strategy

Table 6 gives numerical values for the mean degree of structuring and diffusion of knowledge assets, the fractions of agents having the different knowledge management strategies, and the clustering coefficient ICS at selected periods for the two cases studied.

Variable			Period					
	Case	Band-width	0	100	200	300	400	499
Mean degree of structuring of knowledge assets	*R128*	*Broad*	2,00 *(0,25)*	2,33 *(0,22)*	2,46 *(0,27)*	2,63 *(0,25)*	2,73 *(0,22)*	2,82 *(0,23)*
		Medium	2,00 *(0,19)*	2,31 *(0,18)*	2,47 *(0,18)*	2,62 *(0,19)*	2,74 *(0,18)*	2,81 *(0,17)*
		Narrow	2,01 *(0,22)*	2,31 *(0,23)*	2,42 *(0,21)*	2,48 *(0,18)*	2,51 *(0,16)*	2,52 *(0,19)*
	SV	*Broad*	2,02 *(0,25)*	2,76 *(0,18)*	2,92 *(0,17)*	2,91 *(0,17)*	2,97 *(0,19)*	2,99 *(0,14)*
		Medium	2,05 *(0,23)*	2,93 *(0,18)*	3,06 *(0,19)*	3,10 *(0,15)*	3,16 *(0,15)*	3,15 *(0,19)*
		Narrow	2,09 *(0,18)*	2,90 *(0,14)*	2,98 *(0,16)*	3,02 *(0,21)*	3,04 *(0,25)*	3,07 *(0,24)*
Mean degree of diffusion of knowledge	*R128*	*Broad*	0,63 *(0,10)*	0,82 *(0,20)*	0,84 *(0,24)*	1,04 *(0,25)*	1,17 *(0,31)*	1,32 *(0,43)*
		Medium	0,63 *(0,11)*	0,85 *(0,22)*	0,89 *(0,24)*	1,09 *(0,27)*	1,27 *(0,36)*	1,52 *(0,41)*
		Narrow	0,62 *(0,12)*	1,07 *(0,24)*	1,27 *(0,26)*	1,47 *(0,30)*	1,69 *(0,34)*	1,87 *(0,39)*
	SV	*Broad*	1,82 *(0,10)*	2,15 *(0,17)*	1,92 *(0,22)*	1,84 *(0,27)*	1,85 *(0,27)*	1,83 *(0,30)*
		Medium	1,85 *(0,10)*	2,18 *(0,21)*	2,22 *(0,24)*	2,15 *(0,26)*	2,18 *(0,26)*	2,19 *(0,24)*
		Narrow	1,83 *(0,10)*	2,28 *(0,20)*	2,37 *(0,18)*	2,39 *(0,12)*	2,36 *(0,16)*	2,38 *(0,16)*
Fraction of agents with KSS = 1	*R128*	*Broad*	0,52 *(0,21)*	0,46 *(0,22)*	0,47 *(0,23)*	0,48 *(0,24)*	0,39 *(0,29)*	0,39 *(0,30)*
		Medium	0,54 *(0,25)*	0,48 *(0,26)*	0,43 *(0,28)*	0,47 *(0,28)*	0,47 *(0,26)*	0,48 *(0,30)*
		Narrow	0,48 *(0,25)*	0,49 *(0,24)*	0,47 *(0,25)*	0,41 *(0,31)*	0,37 *(0,32)*	0,36 *(0,32)*
	SV	*Broad*	0,49 *(0,12)*	0,46 *(0,19)*	0,45 *(0,24)*	0,50 *(0,24)*	0,48 *(0,25)*	0,47 *(0,26)*
		Medium	0,49 *(0,13)*	0,47 *(0,20)*	0,45 *(0,22)*	0,39 *(0,22)*	0,37 *(0,23)*	0,33 *(0,24)*
		Narrow	0,48 *(0,12)*	0,48 *(0,19)*	0,47 *(0,23)*	0,48 *(0,26)*	0,44 *(0,25)*	0,42 *(0,24)*
Fraction of agents with DBS = 1	*R128*	*Broad*	0,53 *(0,23)*	0,47 *(0,24)*	0,49 *(0,26)*	0,51 *(0,24)*	0,51 *(0,28)*	0,54 *(0,27)*
		Medium	0,50 *(0,24)*	0,53 *(0,25)*	0,47 *(0,27)*	0,50 *(0,25)*	0,49 *(0,25)*	0,52 *(0,27)*

		Narrow	0,49 *(0,24)*	0,48 *(0,29)*	0,51 *(0,30)*	0,53 *(0,28)*	0,60 *(0,30)*	0,63 *(0,31)*
	SV	*Broad*	0,49 *(0,10)*	0,16 *(0,13)*	0,13 *(0,13)*	0,14 *(0,10)*	0,12 *(0,11)*	0,15 *(0,12)*
		Medium	0,53 *(0,12)*	0,10 *(0,13)*	0,03 *(0,04)*	0,02 *(0,04)*	0,03 *(0,04)*	0,01 *(0,02)*
		Narrow	0,50 *(0,10)*	0,05 *(0,05)*	0,02 *(0,03)*	0,01 *(0,02)*	0,01 *(0,02)*	0,01 *(0,04)*
Index of Cluster Size (ICS)	*R128*	*Broad*	-0,86 (0,14)	-0,74 (0,42)	-0,42 (0,86)	0,24 (0,92)	1,37 (3,01)	2,99 (7,58)
		Medium	-0,85 (0,22)	-0,85 (0,24)	-0,31 (0,90)	0,18 (1,26)	1,39 (3,97)	3,64 (7,00)
		Narrow	-0,83 (0,21)	-0,65 (0,34)	-0,04 (0,96)	1,43 (2,75)	3,95 (4,95)	7,03 (7,77)
	SV	*Broad*	-0,22 (0,37)	1,97 (2,10)	2,91 (3,25)	2,95 (4,73)	3,10 (3,37)	2,83 (3,09)
		Medium	-0,39 (0,22)	3,30 (2,97)	6,36 (5,13)	8,99 (8,07)	10,49 (7,40)	11,54 (8,06)
		Narrow	-0,20 (0,41)	4,34 (3,25)	9,97 (7,99)	15,14 (11,12)	16,82 (13,30)	20,23 (15,61)

Table 6 Evolution of the degrees of structuring and diffusion of knowledge assets, knowledge management strategies, and clustering coefficient (standard deviation in brackets).

Figure 18 graphically describes the evolution of the Index of Cluster Size (ICS). We can see that the broader the bandwidth, the lower the degree of clustering. This offers some insights into the effects of increasing bandwidth in the development of ICTs. In the R128 case, for instance, the lower value for the mean structuring of knowledge assets, and the higher value for the mean diffusion of knowledge assets under the narrow bandwidth regime, can perhaps be related to the higher degree of clustering in that regime as indicated by the ICS measure. This is precisely what I-Space theories would predict. For the SV case, the non-linearities observed, point to a more complex possible explanation that we develop in the next section.

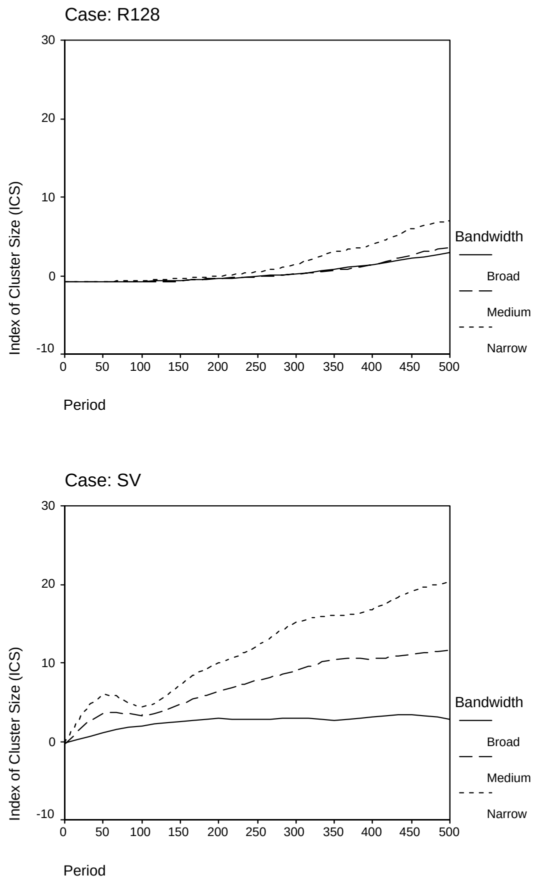


Figure 18 Evolution of the agglomeration measure ICS for several ICT regimes

Working with mean values helps to secure significant results when working with simulation models. However, in order to understand the detailed mechanisms that underlay the aggregate features, it is useful to look at the behavior of specific runs that are selected as representative of the whole class. For selected runs of the simulation, **Figure 19**, **Figure 20** and **Figure 21** respectively give the final spatial distribution of the number of agents, the number of knowledge assets and the generation of rents from knowledge assets[10]. From these figures we see that the two cases

[10] Representative runs for this graphical representations have been selected attending the criteria of choosing for each case and regime the run that presents the values of number of agents, knowledge assets generation and rents generation as close as possible to the mean values of all runs.

differ significantly under the narrow bandwidth regime, but that the difference attenuates as bandwidth increases. If we look at the knowledge and rents generated in the run representing the R128 case, we see that, under the broad bandwidth regime, they are higher than in the run representing the SV case.

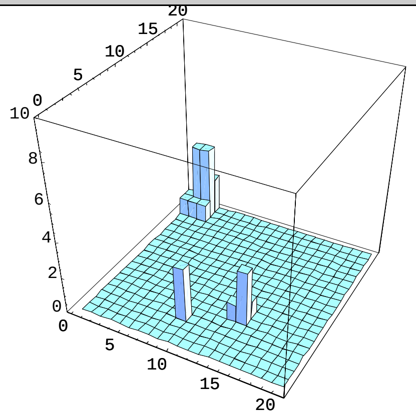
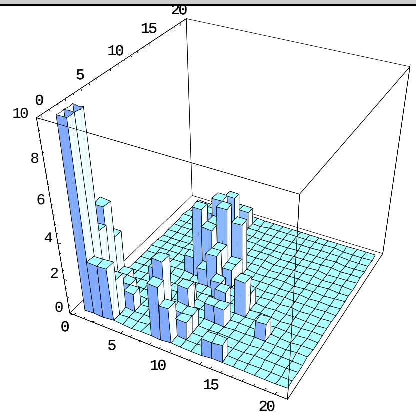
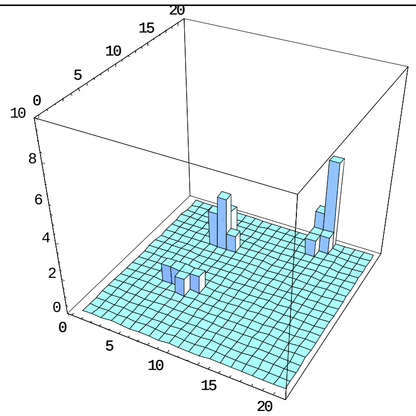
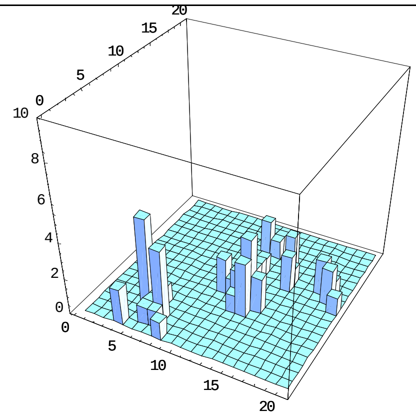
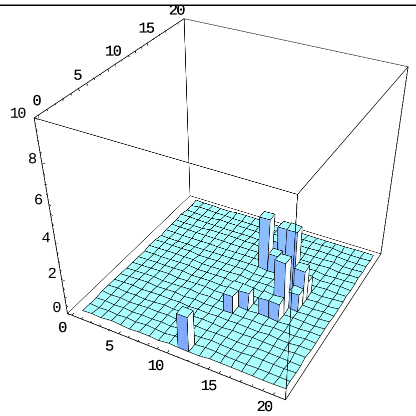
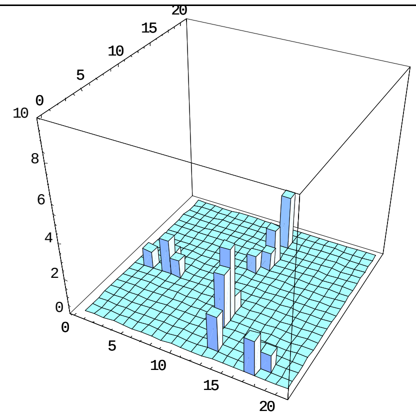
Band-width	Case R128	Case SV
Narrow		
Medium		
Broad		

Figure 19 Spatial distribution of the number of agents for selected representative runs

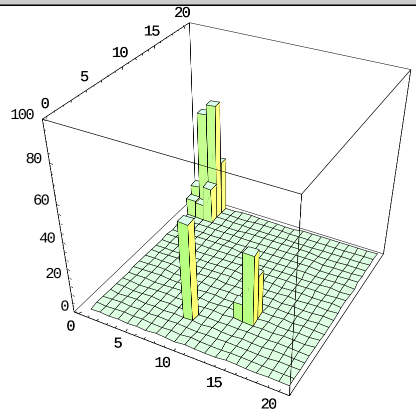
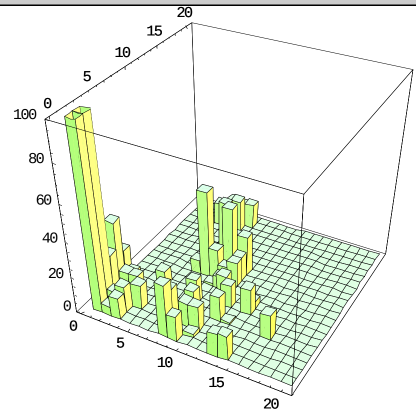
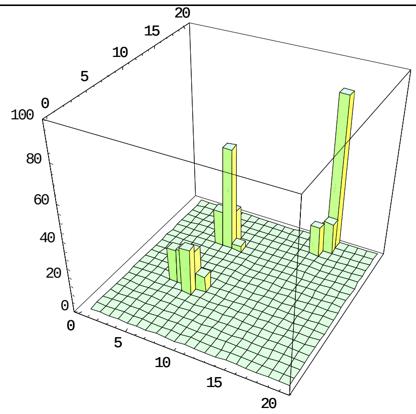
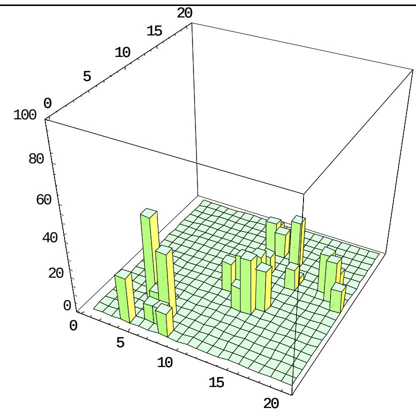
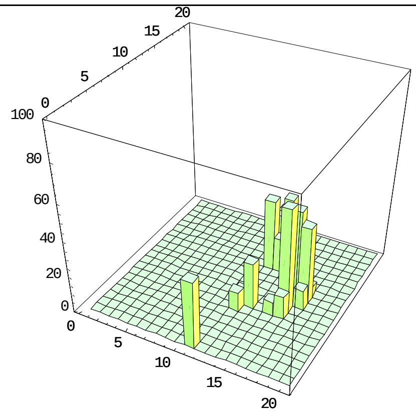
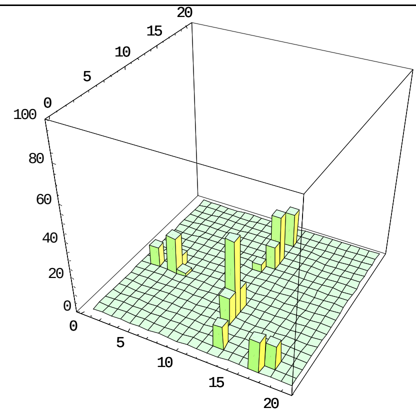
Band-width	**Case R128**	**Case SV**
Narrow		
Medium		
Broad		

Figure 20 Spatial distribution of the number of knowledge assets for selected representative runs

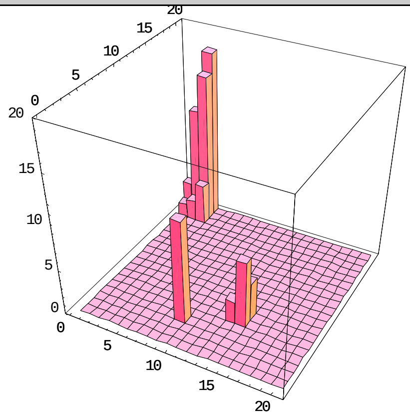
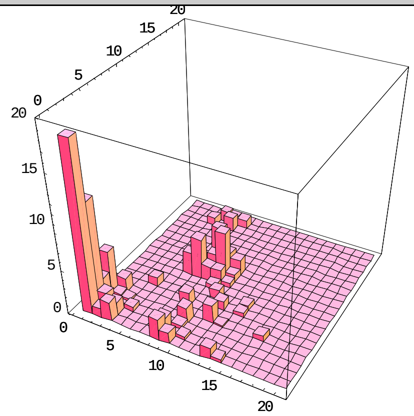
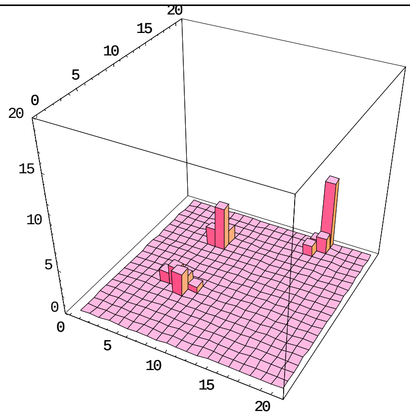
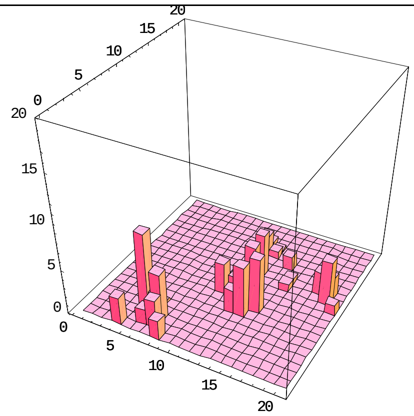
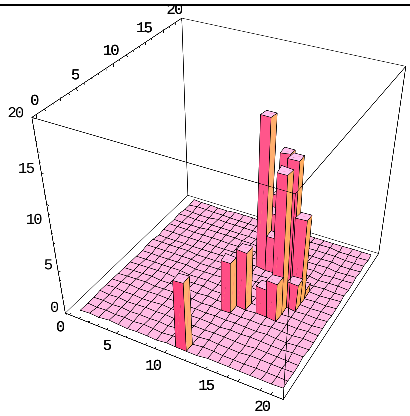
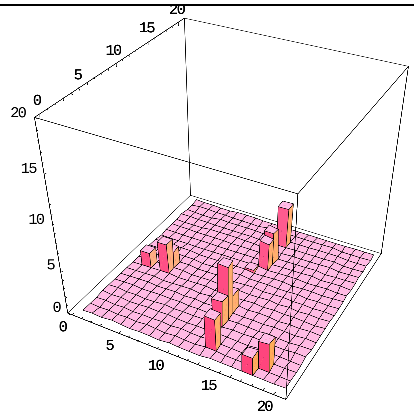
Band-width	Case R128	Case SV
Narrow		
Medium		
Broad		

Figure 21 Spatial distribution of the rents obtained from knowledge assets for selected representative runs

8. DISCUSSION

As stated before, the purpose of this research is to derive, by use of a simulation model, insightful hypotheses concerning knowledge and information flows and their influence on spatial location in industrial clusters. Specifically, we look at the relationship between the knowledge management strategies adopted by firms and their agglomeration patterns. To relate our results to real cases, we initially set model parameters at different values to build two cases that we label R128 and SV. They constitute an attempt to model the main features—in terms of knowledge flows—of the kinds of industrial districts represented by Boston's Route 128 and Silicon Valley. This provides our discussion of the simulation results with real world referents.

In our analysis of the results we will go beyond the results described above and attempt to derive empirically testable hypotheses. In doing so, we are using the simulation as a heuristic tool. Unlike the aggregated statistical data available in business databases or through other kinds of simulation models, agent-based simulations not only provide us with output, but also at large amounts of intermediate data generated in specific runs. Such data allows one to go in depth into the causal mechanisms underlying the behavior of the system. Such data is very helpful to the derivation of empirically testable hypotheses.

In the first part of this section, we compare the results obtained from the two cases modeled, namely, R128 and SV. If our findings are consistent with those to be found in the abundant literature on Route 128 and Silicon Valley, we have, in effect, a first validation of our model. Further examining the underlying mechanisms leading to those results can then provide some hints—framed as hypotheses—as to the mechanisms at work in the real world cases. In the second part of the section we look at the behavior of the model under different ICT regimes for the two cases. Recall that we associate different levels of development of ICTs with different bandwidths, and that these affect the transfer of knowledge at distance. Hypotheses derived from our results will focus on the possible effects of ICT development on the spatial evolution of industrial clusters.

8.1. Silicon Valley vs. Route 128: Validation of the model

The initial number of agents is higher in the SV case (20) than in the R128 case (5). In **Figure 7** we see that this difference in the number of agents increases during the simulation and that the two cases exhibit qualitatively different behaviors. The SV case strongly peaks at over 150 agents in the first 50 periods and then declines and stabilizes, showing a slight and steady increase beyond the first 100 periods. The R128 case, by contrast, shows more stability, the curve being more or less flat during the 100 first periods and progressively rising thereafter.

The initial difference in agent numbers between the R128 and SV cases is not only maintained but it actually shows a net overall increase across the whole simulation (see **Figure 7**). This result is consistent with the empirical fact that the number of firms goes up more rapidly in Silicon Valley than along Boston's Route 128. Relying on the data gathered by Saxenian [Saxenian, 1994b: 208] we see that the rate of increase of firms in Silicon Valley was of 762% between 1959 and 1975, of 389% between 1975 and 1990, and of 126% between 1990 and 1992 while for the same periods along Route 128 it was respectively 313%, 258%, and 116%.

The qualitative differences in agent numbers suggests that, while the SV case displays a pattern attributable to Schumpeterian effects similar to those found in ecological populations subject to evolutionary forces [Boisot et al., 2004; Hannan and Freeman, 1989], the R128 case models a much more stable system. The same qualitative differences are observed when analyzing the number of knowledge assets (**Figure 9**a) and the amount of rents generated from these assets (**Figure 9**b). This is consistent with the findings of the literature, which makes several references to the effects of Schumpeterian "creative destruction" - whether applied to firms or to knowledge—in Silicon Valley. As Bahrami and Evans point out "Paradoxically, while high-technology firms experience a high failure rate, Silicon Valley continues to thrive and prosper. In this domain, the demise of one firm invariably leads to the formation of others, directly and indirectly" [Bahrami and Evans, 2000: 166]. Castells and Hall see creative destruction at work in the creation of knowledge when competition drives firms up the skill-learning curve "into more sophisticated products made in more sophisticated ways" [Castells and Hall, 1994: 223].

When looking at the data in **Table 3**, it is interesting to notice that if we look at the amount of rents generated per knowledge asset across the simulation as a whole, the values are always lower for the SV case than for the R128 one. This would suggest that firms in a Silicon Valley-type system extract less value from their knowledge assets. From an industry perspective, this would be considered a negative, but from a social welfare perspective the result is thoroughly positive: there is a higher rate of knowledge creation benefiting society as a whole, and the latter pays less to the knowledge-creating firms for this benefit in form of rents.

If we pay examine the causes of the evolution of the three magnitudes analyzed above, we can obtain a number of insights. In the R128 case, the absence of a critical mass of agents as well as a lower propensity for these to collaborate and transfer knowledge yields a system with a much lower turnover (around 1%; the SV case is around 10%). This could be consequential: while evolutionary forces are at work in the SV case, their influence in the R128 case is very weak—at least in the first half of the simulation runs. In the absence of enough variation and selection, the population is unable to evolve towards a higher level of fitness. Evolvability has been identified as constituting one of the advantages of the Silicon Valley model [Kenney, 2000].

Evolvability might explain the fact that, while in the SV case the composition of knowledge management strategies held by agents radically changes over time, it stays more or less stable in R128 case (see **Figure 11**a and **Figure 11**b). For the SV case, the proportion of agents pursuing a KSS = 1 strategy goes from the initial value around 50% of the agent population to a final value around 35%. The proportion of agents pursuing a DBS = 1 strategy drops dramatically during the simulation and stays at a very low level after period 200. By contrast, in the R128 case, the proportion of agents pursuing either strategy stays at around 50% throughout the simulation.

This result supports the idea that one of the advantages of the Silicon Valley model over the Route 128 model is that the turbulent environment of the former, characterized by higher levels of creation and destruction, has the effect of speeding up the evolutionary process and thus of improving the fitness of surviving firms. If this argument holds, it should be reflected in the compared performance of the two clusters. The data collected by Saxenian [1996] confirm this fact. For instance, while the total high technology employment in 1959 was in Silicon Valley of about 20,000 employees and in Route 128 of more than 60,000, after a steady increase in 1990 the Californian area advantaged the East Coast one with more than 260,000 employees compared to barely 150,000.[11] In terms of the number of fastest growing electronic firms the advantage of Silicon Valley over Route 128 increased from 22 to 14 in 1985 until a surprising 39 to 4 in 1990.[12] Also the venture capital investment shows this supremacy of Silicon Valley: while the investment in Northern California was in 1989 of nearly $2,000 million, in Massachusetts was of less than $500 million.[13] In 1990 Silicon Valley-based firms exported more than $11 billion in electronics products compared with Route 128's $4.6 billion.[14] The supremacy the Silicon Valley model should be also noticed in knowledge creating activities and, by implication, in the number of patents generated. It turns out that this is indeed the case. For example, an analysis of patent citation data for the U.S. semiconductor industry shows that in 1985 the number of citations of patents produced in the Massachusetts-Connecticut region was of 156 while in the North California area was of 468 [Almeida and Kogut, 1999: 911].

Another noteworthy result is that there is no obvious correlation between the distribution of knowledge structuring and diffusion blocking strategies within the agent population (**Figure 11**) and the degree of structuring and diffusion of knowledge assets actually achieved (**Figure 10**). Clearly, there are many more factors that come into play in a real economy that can impede the direct translation of a strategic choice into the actual behavior of firms or institutions. Our model, of course, cannot

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[11] See Saxenian [1996: 43]. Data source: Country Business Patterns.

[12] See Saxenian [1996: 44]. Data source: *Electronic Business*, "The Top 100 Exporters," pp. 4-42. March 16, 1992.

[13] See Saxenian [1996: 48]. Data source: *Venture Capital Journal*. 1980-92. Selected issues. Wellesley, MA: Venture Economics.

[14] See Saxenian [1996: 43]. Data source: *Electronic Business*, "The Top 100 Exporters," pp. 4-42. March 16, 1992.

include all such factors, but it does introduce a dependency of knowledge transfers on spatial distance—since Marshall, knowledge spillovers have been identified as important drivers of agglomeration economies. Our results in Figure 11 and Figure 12 and Table 4 show that the degree of agglomeration—a consequence of the spatial location of each firm with respect to the others—does effectively influence the distribution of a given knowledge management strategy within the agent population, and vice-versa.

Moreover, in our model, decisions concerning spatial location and knowledge management strategies turn to be complementary and co-evolving within the agent population. From an organizational ecology perspective, this suggests that organizations with the right mix of location and knowledge management strategies will better fit their environment thus improving their survival prospects.

In the light of these considerations, one possible interpretation of the results of the SV case that we present in section 7.1 could be as follows. Initially, the mean level of structuring of knowledge assets is much lower than the optimal one and it starts increasing in order to keep knowledge assets profitable. This is achieved in spite of a decrease in the proportion of agents pursuing a KSS = 1 strategy because the spatial effects of clustering act to counterbalance the effects of their strategic preferences. At the same time, blocking unintended diffusion is not a particularly effective option since it proves to be too expensive to maintain, especially with the degree of knowledge structuring actually rising. Thus, the diffusion-blocking strategy DBS = 1 gets selected out. When, after the initial 100 periods, the number of agents and assets more or less stabilizes (see **Figure 7**), so does the mean degree of diffusion, which remains slightly above 2.0 (see **Figure 10**b).

If this interpretation is correct, it is aligned with four of the main characteristics of the Silicon Valley environment. First, the Valley exhibits a moderate degree of knowledge structuring. The informal sharing of tacit knowledge, to be sure, is common in the valley, but one needs a certain minimum level of explicit technical knowledge to engage in that activity [Saxenian, 1994b: 30]. Second, the Valley's culture is one of knowledge sharing rather diffusion blocking [Saxenian, 1994b: 32-37]. Third, clustering behavior in the Valley facilitates knowledge sharing even when this is supported by only a moderate degree of knowledge structuring [Brown and Duguid, 2000]. Fourth, all of the above take place in the Valley's climate of "creative destruction", one that has the effect of speeding up evolutionary processes [Bahrami and Evans, 2000: 166].

In the R128 case, as stated before, rapid evolution is more difficult and the proportion of agents with different knowledge management strategies remains roughly stable around the initial value of 50%. Only once the degree of spatial clustering starts to increase significantly—in matters of spatial location, evolutionary processes are indeed at work—and once, though the system's natural tendencies, the mean degree of knowledge structuring also rises, does the mean degree of diffusion of knowledge assets starts to increase. It is worth noting that along Route 128 clustering alone is not as effective as the combination of clustering and other factors—cultural and systemic—that are present in Silicon Valley. Brown and Duguid [2000] remark the importance of local social and professional networks in Silicon Valley. Through citation analysis, Almeida and Kogut [1997] show how they play an important role in the creation and diffusion of knowledge. In the Boston area, "the networks of computer firms were weak in comparison to those in Silicon Valley" [Malecki, 2000: 117].

The above discussion has interesting implications for strategic management, especially if we adopt an adaptationist rather than an organizational ecology perspective. Cyert and March [1963] and Nelson and Winter [1982], for example, see organizations adapting to their environments through the strategic decisions made by their managers. To illustrate: while firms located inside industrial districts can rely on tacit knowledge because proximity makes it easy to transfer to and from partners, suppliers or clients, spatially isolated firms need to operate at a much higher degree of knowledge structuring to achieve similar levels of knowledge transfer. Knowledge management strategies can thus compensate for spatial disadvantages and vice-versa. This is what we observe when comparing the knowledge transfer practices within Silicon Valley with those between establishments that are spatially distant from each other [Saxenian, 1994b; Castells and Hall, 1994; Kenney, 2000; Brown and Duguid, 2000].

Although the above analysis should not cause too much surprise—most of them are in line with empirical observations—they have here been derived through a different approach: a theory-driven agent-based simulation. They thus constitute, to some extent, a validation of our model and of the theoretical framework—the I-Space—that underpins. In combination, the model and the framework could be developed into a useful tool for the study knowledge-based industrial districts. In the following sub-section we will make further use of our simulation results to derive hypotheses concerning the effect of ICT developments on these kinds of system.

8.2. Effects of ICT development

In our model we are assuming that the probability of transferring or diffusing knowledge between any two organizations is affected by the spatial distance between them. This is because, beyond what is possible in face-to-face situation—the zero-distance condition—the level of ICT development imposes constraints on such diffusion. Furthermore, following the theoretical tenets of I-Space, we assume that the probability of diffusion is higher if the knowledge to be diffused is more structured—codified and abstract—than if it is more tacit.

Based on such assumptions, we can imagine that any change in the level of development of ICTs is likely to have an impact in the evolution of the sort of organizational populations we are studying. As we saw in section 3, the development of ICTs has the effect of shifting diffusion curve in the I-Space to the right along the diffusion dimension, thus generating a diffusion effect and a bandwidth effect. In this sub-section we analyze what happens when we run our model for the R128 and SV cases at different levels of ICT development. From this analysis we expect to derive empirically testable hypotheses on the evolution of knowledge-based industrial clusters under different ICT regimes.

The data presented in **Figure 13** clearly shows that the development of ICTs in the form of increases of bandwidth have the effect of reducing the number of agents present in the simulation. We can infer from this that the "carrying capacity" of knowledge-based industrial clusters could reduce as ICTs evolve. A detailed examination of our simulation data leads us to think that, as we had already noticed in our previous work [Canals et al. 2004], the drop in agent numbers is largely accounted for by the significant reduction in the number of joint venture agents that occurs when ICT regimes reach the higher bandwidths. Agents created through joint ventures make up approximately 66% of the total number of agents under the narrow bandwidth regime, but this number goes down to 55% for the broad bandwidth regime. Joint ventures are useful as a way of covering a region if knowledge transfer is difficult, but when ICTs develop, firms may no longer need them so that a lower number of establishments, each receiving a higher payoff, will suffice to cover a given territory.

The same effect is observed with respect to the total number of knowledge assets and the total rents generated by those knowledge assets. The broader the bandwidth, the fewer knowledge assets produced and the fewer rents generated. This is so for both the SV and the R128 cases, but the effect is much more important in the SV case. What is interesting is that for the broad bandwidth regime, the total number of knowledge assets and the rents generated are bigger in the R128 case than in the SV one, contrast to the case of the narrow bandwidth regime and even to that of the medium bandwidth regime. Thus, we imagine a process in which the development of ICTs would, by degrees, erode the advantage of the Silicon Valley model industrial districts over that offered by Route 128.

In both cases, an increase in bandwidth triggers an increase both in the amount of rent generated per knowledge asset as well as in the amount of rent generated per agent. This points to a progressive increase in the profitability of a firm's knowledge assets, but to a lower productivity of the agents when it comes to generating knowledge assets. From a social welfare perspective, the results are ambiguous. On the one hand more value would be captured by firms in the form of rents paid by the rest of the society. This could be a source of local development and employment, and hence of benefit to a regional cluster. On the other hand less knowledge would be created and would be paid for at a higher price by society as a whole—i.e., other regions. In effect, what we are dealing with is the impact of ICT development on knowledge-based inter-regional competition.

Focusing on the mean degree of diffusion of knowledge assets within the agent population (Figure 15), we see that in both cases diffusion is higher under narrower bandwidth regimes. This is apparently in contradiction with the I-Space tenets, which claims that, by the diffusion effect, a broader bandwidth should carry as a consequence a major diffusion. In the SV case this paradox could be partly attributable to the noticeable increase in the number of agents with diffusion blocking preferences as bandwidth increases (see Figure 17b), but this should be counter-balanced by the increase in the proportion of knowledge structuring strategies (Figure 16b). In any case, this would not apply in the R128 case. Perhaps we can find an alternative explanation in the phenomenon of agglomeration. If we look at ICS measure[15] (Figure 18), we can see that agglomeration increases under narrow bandwidth regimes and decreases under broad bandwidth regimes. Here the effects of agglomeration seem to overcome the adoption of diffusion blocking and knowledge structuring strategies. Obviously, if mean distances between agents increase diffusion will be more difficult, even though there is an increase in the structuring of knowledge, which is consistent with I-Space theory. We can derive from this the idea that clearly location decisions are complementary to knowledge management strategies and both together influence knowledge diffusion. Of course, the evolution of the system is a consequence of the co-evolution of those two factors.

In the R128 case, and in line with the strategic choices of the population (**Figure 16**), the degree to which knowledge assets are structured is clearly lower under the narrow bandwidth regime (see **Figure 14**). But this is no longer so under either the medium or the broad bandwidth regimes (**Figure 16**) even though the strategies of their agent populations are different from each other (**Figure 14**). There also seems to be an agglomeration effect in the structuring of knowledge, since the behavior of the R128 case under a narrow bandwidth regime differs from that under the other regimes with respect to agglomeration (**Figure 18**).

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[15] Here we are choosing to use ICS instead of SE because, as we pointed out before, ICS is in some way biased by the total number of agents present in the simulation. In this case, we welcome this bias, since diffusion is favoured for “pure” agglomeration, but also for the total number of agents.

Once more, consistent with I-Space theorizing, higher degree of agglomeration seems to require less structuring of knowledge.

In the SV case, as we have seen, when the level of development of ICTs increase, the structuring of knowledge assets at first undergoes an increase and then later a decrease[16]. It could be that two causal factors are at play. One would be associated with the degree of spatial agglomeration; this decreases with the evolution of ICTs. Another one would be associated with the increase in bandwidth itself—i.e., the factor that defines the evolution of ICTs. A possible interpretation of the observed results could be that the early stages of ICT call for spatial agglomeration since the transfer of tacit knowledge requires spatial proximity. However, as the degree of clustering diminishes, the degree of knowledge structuring needs to increase in order to make transacting at a distance possible at all. But then there comes a time when further increases in bandwidth relax the requirement for knowledge structuring. Transferring knowledge at a distance even at low levels of structuring—i.e., codification and abstraction—has become much easier. Under this new ICT regime, although the degree of spatial agglomeration continues to decrease, the degree of knowledge structuring can reduce once more.

It is probably impossible to find a single straightforward causal relationship between the strategic preferences of the agent population for the structuring of knowledge and for spatial agglomeration on the one hand, and the levels of knowledge structuring actually achieved in the simulation on the other. But it seems clear that knowledge structuring and spatial agglomeration influence each other and that they co-evolve.

We complete our analysis with the following four hypotheses:

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[16] The causes of this interesting non-linearity in the fraction of agents with a KSS =1 has already been analysed in another paper of ours [Canals et al. 2004]. However, what is remarkable here is that the same non-linearity appears for the actual mean degree of structuring, but in opposite terms.

HYPOTHESIS 1. The development of ICTs will result in a reduction in the number of firms present in knowledge-based geographical clusters.

HYPOTHESIS 2. Future ICT developments will reduce the advantages of Silicon Valley's cultural model over those of Boston's Route 128.

HYPOTHESIS 3. Future ICT developments will decrease the proportion of knowledge created by firms inside geographical industrial clusters relative to that produced by firms outside such clusters.

HYPOTHESIS 4. Future ICTs developments will lead Industrial clusters of the Silicon Valley type to evolve in two phases. In the first phase, the degree of spatial agglomeration will increase and there will be a decrease in the number of firms adopting knowledge structuring strategies. In the second phase, the degree of spatial agglomeration will decrease and the level of adoption of knowledge structuring strategies by firms will go up again. But it will do so in line with an increase in the number of firms adopting diffusion blocking strategies.

9. CONCLUSIONS

Our research puts forward a new way of conceptualizing and modeling knowledge-related economic processes in which location in space matters. On the one hand, we draw on a theoretical framework, the I-Space, which introduces into our model a theoretically grounded perspective on knowledge flows in an economy. On the other hand, our choice of an agent-based simulation approach allows us to reproduce some of the emergent patterns that characterize complex economic systems. Our results indicate that these kinds of model can replicate some of the characteristics of real-world systems and can be a source of fruitful hypotheses. We therefore believe that this type of research is worth pursuing.

Applying our model to the specific the knowledge-based challenges facing high-tech industrial districts, represented in our research by the two paradigmatic cases of Boston's Route 128 and Silicon Valley, has provided us with interesting insights. One of these, for example, suggests that spatial location and knowledge management strategies are strongly interrelated and co-evolve. Also, a few distinct cultural propensities, for example, related to knowledge sharing, can generate quite different clustering dynamics.

The introduction of different ICT regimes representing different capacities to transfer knowledge at a distance, raises interesting questions on the future evolution of industrial districts. Will the number of firms in high-tech industrial districts decrease in the future? Will the "Silicon Valley model" be still valid when the Internet makes it possible to effortlessly transfer high bandwidth—i.e., uncodified and concrete—knowledge? Will the social welfare gains derived from generating knowledge in industrial clusters decrease? And if so, will public policies aimed at reproducing this model of regional economic growth still retain their validity? How will ICT developments affect the spatial agglomeration patterns observed in industrial clusters? Our results identify some directions in which answers to these questions will be found.

Naturally, our approach has limitations. Simulations must be viewed as tool that we can use to improve our understanding of reality. Any simulation results, therefore, especially when these are generated in the social sciences, cannot be taken as faithful representations of what happens in the real world. Our own model deals with particularly complex problems, in which a large number of factors come into play and interact. We chose to focus on only two of these: the management of knowledge and of spatial location. But many other factors are needed to build a complete picture—industry specificities, economic constraints, logistics, business and country cultures, etc. Even within our chosen approach, there are obvious limitations associated with the range of strategic preferences available to our agents as well as with our representation of space—this is completely flat and isotropic and quite different from the rich and varied spaces that we encounter in the real world. The use of physical distance as the only variable affecting the probability of knowledge transfers is also manifestly too simple.

The above limitations suggest possible avenues for further research and for improving our model. For instance, one could imagine using landscapes with more varied topographies that could modify the effective spatial distance between industrial locations - mountains, valleys, lakes or oceans, etc. Indeed, through the use of geographic information systems (GIS), one could even imagine using the topographies of real landscapes. Another possibility would be to develop some kind of "cultural space" in which the distance between firms would represent their degree of cultural proximity—a key factor in determining the effectiveness of knowledge transfers. Also, we could think of applying the model at a different scale. Instead of representing a region, it could represent a larger economic area such as a nation state or a collection of these. The model could be then used to study the location decisions of either international or global firms and how these impact on the competitive advantage of nations [Porter, 1990].

Finally, further research could attempt to model other knowledge-related economic activities in ways that would be complementary to the one presented. These would, of course, also have to lead to empirically testable hypotheses. All the above would help to make the simulation more robust and extend its scope.

It is clear that, on their own, simulations will not guarantee progress in knowledge management, spatial economics or in economic geography. But we believe they have an important contribution to make to all of these fields.

10. APPENDIX 1: PARAMETER SETTINGS FOR THE SV AND R128 CASES

In the following table we show the values of the simulation parameters we have chosen for the SV and R128 cases whose results we present in section 7.1. The results presented in section 7.2 are obtained with the same set of parameters except for BETA, which takes three different values: 0.10, 2.00 and 10.00.

Parameter settings for the SV and R128 cases runs			
Parameter group	**Parameter**	**SV**	**R128**
Global switches	ASSET_MANAGEMENT	0	0
	MOD_DISCOVERY	0	0
	MOD_RESEARCH	0	0
	AGENT_INTERACTION	0	0
	MOD_OBSOLESCENCE	0	0
	MOD_DIFFUSION	0	0
Main variables	INIT_AGENT_NUM*	20	5
	INIT_NODE_NUM	20	20
	INIT_LINK_NUM	10	10
	MODEL_PERIODS	500	500
	MAX_AGENT_NUM	300	300
	MAX_NODE_NUM	10000	10000
	MAX_LINK_NUM	7000	7000
Asset variables	MAX_COMPLEXITY	7	7
	COMPLEXITY_COST	0.001	0.001
	NEW_LINK_PROB	0.15	0.15
	MOVE_POSSIBILITIES	2	2
	PASSIVE_CARRY_MULT	0.50	0.50
I-Space world variables	BASE_REV_MULT	10	10
	ASSET_SHARE_PROB	0.20	0.20
	OBSOLESCENCE_DECAY	0.005	0.005
	DIFFUSION_DECAY	0.001	0.001
	DIFFBLOCK_COST_MULT	0.001	0.001
	AGENT_ENTRY_THRESHOLD	0.15	0.15
	AGENT_ENTRY_RATE	0.10	0.10
	AGENT_EXIT_THRESHOLD	45	45
	AGENT_EXIT_RATIO	-0.005	-0.005
	MAX_AGENT_ENTRIES	5	5
	AGENT_ENTRY_NODES	2	2
	AGENT_ENTRY_LINKS	1	1

I-Space matrix variables	ABSTRACT_DIM_SIZE	5	5
	CODIFY_DIM_SIZE	5	5
	DIFFUSE_DIM_SIZE	4	4
	DIFFUSE_FACTOR	2	2
Linkage probability variables	ABS_NONZERO_VAL	0.20	0.20
	COD_INCREASE_VAL	0.20	0.20
	ABS_NONZERO_PROB	0.05	0.05
	NEW_ASSET_THRESHOLD	1.40	1.40
Agent variables	INIT_FINANCIAL_FUNDS	20	20
	INIT_EXPERIENCE_FUNDS	20	20
	FINANCIAL_ALLOCATION	0.80	0.80
	ACTIVE_SET*	5	20
	PASSIVE_SET*	2	8
	ISPACE_MOVE_PROB	0.03	0.03
	ISPACE_MOVE_COST	0.03	0.03
	JOINT_VENTURE_RETURN	0.10	0.10
	SUBSIDIARY_RETURN	0.20	0.20
	PAR_FUND_THRESHOLD	15	15
	PAR_ASSET_THRESHOLD	0.50	0.50
Agent meeting	MEETING_ARRANGE_COST	0.005	0.005
	MEETING_FIXED_COST	0.005	0.005
	PRESENT_COST_MULT	0.005	0.005
	EXAMINE_COST_MULT	0.005	0.005
	TRADE_VALUE_MULT	1.75	1.75
	LICENSE_VALUE_MULT	0.25	0.25
Meetingspace variables	PROB_RANDOM_MEETING*	0.40	0.10
	MAX_RANDOM_MEETINGS*	6	2
	TRADING_SET_RATIO	2	2
DM variables	MIN_PREFERENCE_LEVEL	0	0
	MAX_PREFERENCE_LEVEL	1	1
Research DM variables	PROB_MOVE	0.10	0.10
Meeting DM variables	PROB_POSITIVE*	0.20	0.05
	PROB_NEGATIVE*	0.05	0.40
	HIGH_COOP_MULT*	0.30	0.10
	JOINT_VENTURE_INVEST	0.25	0.25
	SUBSIDIARY_INVEST	0.25	0.25
Physical space variables	WORLD_X_SIZE	80	80
	WORLD_ Y_SIZE	80	80
	BETA	2.00	2.00

Notes: (*) Parameters taking a different value for the two cases.

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