INVESTIGATING ENTREPRENEURIAL STRATEGIES VIA SIMULATION

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KEYWORDS

Agent-based simulation, strategic knowledge management, entrepreneurship, opportunity recognition.

ABSTRACT

This paper presents an agent-based simulation tool that enables researchers to study entrepreneurial strategies, their associated financial payoffs, and their knowledge creation potentials under different environmental conditions. Opportunity recognition processes can be analyzed in detail both on a micro- and macro-level.

INTRODUCTION

The academic field of entrepreneurship aims to develop theories that help us understand entrepreneurial *opportunities* and their formation (Alvarez & Barney, 2008, Alvarez & Barney, 2008). The concept of opportunity is central to the discussion of the entrepreneurial phenomenon (Shane & Venkataraman, 2000). Opportunities are emergent and one of a kind. Opportunity recognition – and the knowledge appropriation and development that underlie it – are complex and non-repeatable processes. This makes simulation modeling an appropriate methodological approach for researching opportunity recognition (Davis, Eisenhardt, & Bingham, 2007, Harrison, Lin, Carroll, & Carley, 2007). The unique simulation tool presented in this paper will help researchers model different entrepreneurial actions and the contexts in which they take place. It thereby allows to conduct innovative research that results in theory driven frameworks and hypotheses that are difficult to obtain from empirical analyses alone. Being able to explore distinct opportunity recognition strategies is the basis for advising entrepreneurs on their paths to success and governments on the right policy actions. Following a short description of the phenomenon under study, we describe the details of the simulation model we have built. We then conduct two virtual experiments that allow us to highlight the distinct simulation and modeling capabilities and to suggest theoretical insights for the field of entrepreneurship.

OPPORTUNITY RECOGNITION STRATEGIES

Reading the literature on opportunity recognition, one might get the impression that we are dealing with only one player: the classical hero of entrepreneurship, the innovator. However, we have good grounds for believing that there are also other valuable strategies for recognizing and realizing opportunities, especially those that involve imitative behavior (Aldrich & Martinez, 2001, Bygrave & Zacharakis, 2004). As the extant literature seems to conflate categories, we are in need of distinctions with a sound theoretical grounding.

Ihrig and zu Knyphausen-Aufseß (2009) put forward a model that differentiates between the *origination* of a new venture idea and its *development*. The Philosophy of Science literature encourages us that this distinction is meaningful. Hans Reichenbach (1938) differentiates between the *context of discovery* and the *context of justification*. The first is close to origination and the second to development. Karl Popper (1968) distinguishes "sharply between the process of conceiving a new idea, and the methods and results of examining it logically". Similarly, we argue that in a first step, entrepreneurs obtain their new venture ideas, and then, in a second step, further develop and refine them. Our theoretical distinction between origination and development lets us build the following two by two matrix (Figure1).

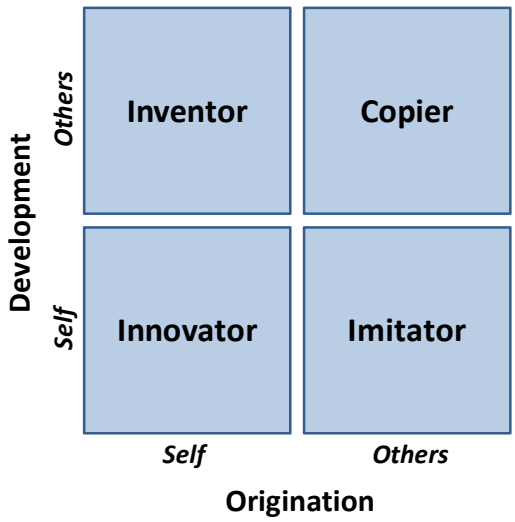

Figure 1: Four different entrepreneurial strategies

Entrepreneurs can either conceive a new venture idea by themselves or obtain the insight from somewhere else. Similarly, the development of a new venture idea can be done either independently or by drawing on others. Our model results in four different entrepreneurial roles or strategies: innovating, inventing, imitating, and copying. By means of simulation, we will be able to explore those strategies, to show that they can be meaningfully distinguished, and to point to theoretical and practical implications. Simulation modeling allows us to operationalize our theoretical concepts and the

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processes behind it, and then to dynamically analyze micro and macro effects. In particular, we are interested in the comparative payoffs of each of the four entrepreneurial strategies in different environments. We expect to see distinctive knowledge progression and financial performance profiles. In addition, we will be able to study societal level effects that arise from competitive agent behavior.

USING *SIMISPACE2* TO MODEL THE OPPORTUNITY RECOGNITION PROCESS

We take a knowledge-based approach when studying how entrepreneurs obtain their new venture ideas and develop them (Ihrig, zu Knyphausen-Aufseß, & O'Gorman, 2006). Based on Austrian economics (Kirzner, 1997), we consider *knowledge*, and in particular its appropriation, development and exploitation, as the basis for new venture creation. *SimISpace2* is an agent-based graphical simulation environment designed to simulate strategic knowledge management processes, in particular knowledge flows and knowledge-based agent interactions. The simulation engine's conceptual foundation is provided by Boisot's (1995, 1998) work on the Information Space or *I-Space*. In what follows, we describe how we have used *SimISpace2* to build an application-specific model – *SimOpp* – that enables us to study opportunity recognition strategies and their outcomes under different environmental conditions.

Basic workings of the *SimISpace2* environment

Ihrig and Abrahams (2007) offer a comprehensive description of the entire *SimISpace2* environment and its technical details. For this particular research project, we only use a limited set of the features the program offers. Below, we briefly review some of the underlying principles of the simulation and explain how knowledge is represented.

Two major forms of entities can be modeled with *SimISpace2*: agents and knowledge items/assets. When setting up the simulation, the user defines agent groups and knowledge groups with distinct properties. Individually definable distributions can be assigned to each property of each group (uniform, normal, triangular, exponential, or constant distribution). The simulation then assigns the individual group members (agents and knowledge items) characteristics in accordance with the distribution specified for the corresponding property for the group of which they are a member.

Knowledge in the simulation environment is defined as a 'global proposition'. The basic entities are *knowledge items*. Based on the *knowledge group* they belong to, those knowledge items have certain characteristics. All knowledge items together make up the *knowledge ocean* – a global pool of knowledge. Agents can access the knowledge ocean, pick up knowledge items, and deposit them in knowledge stores through the *scanning* action. A knowledge store is an agent's personal storage place for a knowledge item. Each knowledge store is local to an agent, i.e. possessed by a single agent. As containers, knowledge stores *hold* knowledge items as their contents. Stores and their items together constitute *knowledge assets*. Examples of knowledge stores include books, files, tools, diskettes, and sections of a person's brain. There is only one knowledge item per knowledge store, i.e. each knowledge item that an agent possesses has its own knowledge store. If an agent gets a new knowledge item (whether directly from the knowledge ocean or from other agents' knowledge stores), a new knowledge store for that item is generated to hold it.

The concept of a knowledge item has been separated from the concept of a knowledge store to render knowledge traceable. If knowledge items are drawn from a common pool and stored in the knowledge stores of different agents, it becomes possible to see when two (or more) agents possess the same knowledge, a useful property for tracking the diffusion of knowledge.

The separation between a global pool of knowledge items and local knowledge stores is particularly important when it comes to codification and abstraction (these only apply to knowledge stores, not to knowledge items). Knowledge items are held by multiple agents, and one agent's investment in codification or abstraction does not influence the codification and abstraction level of the same knowledge item held by another agent. Agents possess knowledge stores at a particular level of codification and abstraction. If the agent codifies its knowledge and makes it more abstract, the properties of the knowledge item itself – i.e., its *content* – are not changed, but it gets moved to a new knowledge store with higher degrees of codification and abstraction – i.e., its *form* changes.

SimISpace2 also features a special kind of knowledge. A DTI (knowledge *Discovered Through Investment*) is a composite knowledge item that is discovered by integrating the knowledge items that make it up into a coherent pattern. DTIs cannot be discovered through scanning from the global pool of knowledge items. The user determines knowledge items to act as the constituent components of a DTI. The only way for an agent to discover a DTI is to successfully scan and appropriate its constituent components and then to codify and/or abstract them beyond user-specified threshold values in order to achieve the required level of integration. Once these values are reached, the agent automatically obtains the DTI (the discover occurrence is triggered in the simulation). Investing in its constituent components – i.e. scanning, codifying and abstracting them – is the primary means of discovering a DTI. By specifying the values of different DTIs, the user can indirectly determine the values of the networks of knowledge items that produce DTIs. Such networks represent more complex forms of knowledge. Once an agent has discovered a DTI item, it is treated like a regular knowledge item, i.e. other agents are then able to scan it from the agent that possesses it.

Important *SimISpace2* processes and occurrence types used for the modeling

To keep our model and the resulting analyses simple, we only use six of twenty actions that the *SimISpace2* environment features, which will be explained below: relocate, scan, codify, discover, learn, exploit. By conducting those actions, our virtual agents try each period to accumulate new knowledge and develop it, and to discover DTIs. Agents increase their financial funds by capitalizing on the knowledge they possess, in particular DTIs. The financial funds property of agents measures entrepreneurial success. The better the knowledge appropriation, development and exploitation strategy, the higher the funds will be. Agents with financial funds of zero die. Based on different agent group behaviors, the increase of the agents' individual financial funds and the increase of their stock of knowledge occur at different rates. Whereas all agents in our simulation will try to *learn* and *exploit* their knowledge (and thereby to grow their financial funds), agents will differ in their approaches to obtaining and developing knowledge. What follows is a concise review of the critical actions we assign for modeling knowledge appropriation and development.

Scanning. An agent can scan for knowledge, randomly picking up knowledge items, either from the knowledge ocean or from other agents' knowledge stores. The probability of picking from the knowledge ocean (vs. from other agents) can be specified on the agent-group-level. While an agent can scan any knowledge item in the knowledge ocean, it can only scan knowledge items in those knowledge stores (of other agents) that fall within its *vision*. *SimISpace2* agents populate a physical, two-dimensional space (called *SimWorld*), and the vision property determines how far the agent can see within a certain spatial radius from its current location. A knowledge item that is successfully scanned is placed in a new knowledge store possessed by the agent. The new knowledge store picks up the level of codification and abstraction either from the knowledge group that the knowledge item belongs to in the knowledge ocean or from the knowledge store where the agent found the item. Agents will only try to scan knowledge items that they do not already possess at that level of codification and abstraction. The ease with which a knowledge item is scanned from another agent's knowledge store is some positive function of the store's degree of codification and abstraction. Knowledge items in knowledge stores with higher codification and abstraction have a higher probability of being scanned. In the case of the knowledge ocean, ease of scanning is determined by the nature of the network a knowledge item is embedded in. Finally, recall that once an agent has scanned all the components that constitute a given DTI and has codified and abstracted them up beyond a certain threshold, it automatically obtains the DTI (*discover* action is triggered).

Relocating. An agent can relocate within a certain distance of its position in the 100 by 100 grid of the *SimWorld*. Relocating implies moving either closer to or further away from other agents or knowledge stores. The distance an agent moves per relocation depends on the *distance* setting for the relocate action of its agent group. Relocation is relevant to scanning as it affects what knowledge stores and other agents an individual can see. As agents can only scan within the radius of their vision, they are only able to pick up knowledge in a different area by moving. When agents relocate, they leave their knowledge stores behind in the original location, but still retain access to them. (N.B.: When a new knowledge store is created, it is always assigned the same location as the agent that possesses it.)

Codifying and Abstracting. An agent can create new knowledge stores at different levels of codification and abstraction with values ranging from 0 to 1. Every new store represents a per period carrying gain or cost for the agent that is added/deducted at the end of each period from the agent's financial funds. Codification and abstraction are separate actions that affect the knowledge stores (form) in which a given knowledge item (content) is held. The agent must first possess a knowledge item in a store before it can perform these actions. The levels of codification or abstraction of a newly created knowledge store are increased incrementally beyond those of existing stores. The knowledge item in the new knowledge store remains always the same; only the level of codification and abstraction of the knowledge store changes. Stores with higher levels of codification and abstraction are more likely to be scanned from and are more valuable when exploited. However, remember that the more diffused knowledge gets the less value the agent can extract from it. In *SimOpp*, we only use the codification action to model the knowledge structuring process.

Learning. Before a knowledge item can be exploited, it has to register with an agent through a learning process. This can only apply to a knowledge item that an agent possesses. Its chances of success increase with the levels of codification of the knowledge store that holds it.

Exploiting. Agents can capitalize on their knowledge, i.e. generate value for themselves. An agent can only exploit knowledge that it has registered and internalized through learning. The financial funds of an exploiting agent are increased by the value of the different exploiting actions that it undertakes. The *exploit amount* is calculated based on the user-set *base value* of the knowledge item involved. This is done according to the level of codification and abstraction of the knowledge store holding the knowledge item, and to the level of diffusion of the knowledge item (percentage of agents that possess the particular piece of knowledge in a period). The user can define an industry-specific table of revenue multipliers based on abstraction and codification levels. In the *I-Space*, the value of knowledge is some positive function of both its utility (the level of codification and abstraction) and its scarcity (the level of diffusion). Therefore, typically, the higher the levels of codification and abstraction, the higher the revenue multiplier, i.e. more codified and

abstract knowledge is worth more. More codified and abstract knowledge, however, is also more likely to be diffused, thus eroding the value of knowledge. Furthermore, the calculations allows for the effects of obsolescence, which, like diffusion, also erodes value: obsolete knowledge is worthless. Whereas revenue multipliers depend on the characteristics of a knowledge *store* (its level of codification and abstraction), obsolescence solely depends on the properties of the knowledge *item* the store contains.

Basic parameterization and set-up: the *SimOpp* model

We can now describe the *SimISpace2* model designed and built for the opportunity recognition context, *SimOpp*, and present the properties of the participating agent and knowledge groups.

Agents

In line with the framework we have developed, we create four *agent groups*. The following matrix (Figure 2) shows the four agent groups and the relevant *SimISpace2* actions that distinguish them from one another.

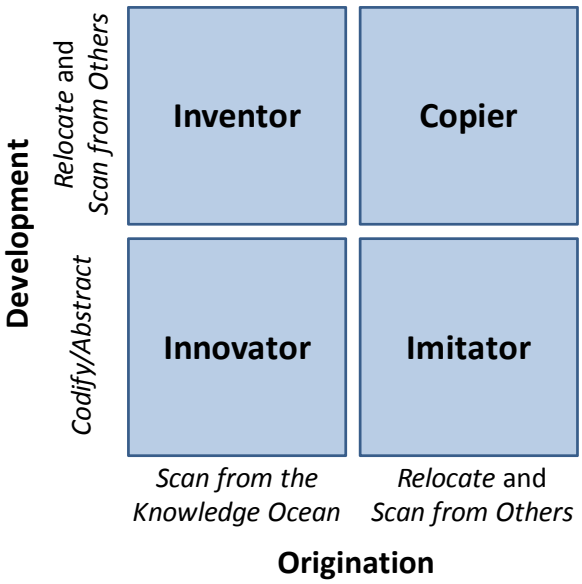

Figure 2: The four entrepreneurial groups in *SimOpp*

The probabilities to chose and perform particular actions vary from group to group based on the conceptual distinctions we have made. In total, agents engage in four activities. There is one activity assigned for implementing *origination* (either *self* or *others*) and one activity assigned for implementing *development* (either *self* or *others*). When it comes to *origination*, the activity of obtaining insights from a third party, as opposed to coming up with it oneself, is implemented with the 'Scan from Others' and the 'Relocate' actions. Agents can move through the *SimWorld* and scan knowledge assets from other agents. The activity of arriving at an insight oneself is implemented with the 'Scan from the Knowledge Ocean' action. When it comes to *development*, the activity of developing by yourself is implemented with the 'Codify' action. The activity of developing by drawing on others is again implemented with the 'Relocate' and 'Scan from Others' actions. To be able to capitalize on their knowledge, all agents can perform the 'Learn' and the 'Exploit' action (activity three and four respectively). Note that the numbering of the activities should not necessarily imply a particular order in which the actions are conducted in the simulation. Knowledge can only be learned once it has been obtained and can only be exploited once it has been learned. However, a random draw each period based on the distributions assigned for the propensities to engage in an action determines which of the possible actions an agent chooses. Looking at each agent group in turn, we can see what actions and properties agents have in common and, based on the description above, what distinguishes them (constant distributions assigned for propensities to engage in a particular action in brackets).

Innovator. Innovators perform four actions; they *scan* (1) and they *codify* (1), and as all the other groups, they *learn* (1) and *exploit* (1). When it comes to scanning though, they can only scan from the knowledge ocean.

Imitator. Imitators can perform five actions; they *scan* (0.5), *relocate* (0.5), *codify* (1), *learn* (1) and *exploit* (1). In contrast to the Innovators, Imitators only scan from the agents surrounding them; they do not scan from the knowledge ocean.

Inventor. Inventors do not codify, they only *scan* (1.5), *relocate* (0.5), *learn* (1) and *exploit* (1). They can scan from both the knowledge ocean and from other agents.

Copier. Copiers also do not codify and only *scan* (1), *relocate* (1), *learn* (1) and *exploit* (1). They only scan from other agents and not from the knowledge ocean.

There are ten agents in each agent group. All agents start with financial funds of 100. The *relocate distance* and *vision* property are the same for all groups, but they change with each scenario (case) under study. Imitators, Inventors, and Copiers are randomly spread out in the *SimWorld* (uniform distribution 0-100 for x and y location); Innovators are clustered together at the center (uniform distribution 45-55 for x and y location) as can be seen in Figure 3 further down.

Knowledge

We use both basic knowledge and the higher-level DTI knowledge in *SimOpp*. We have three distinct basic knowledge groups: *Local*, *Entrepreneurial*, and *New Venture Idea Knowledge*.

Local Knowledge. Local Knowledge represents an understanding of the local market and its culture. It starts at a high level of codification and abstraction (0.7) and has a base value of 5. Remember that the intrinsic *base value* of a knowledge item is the starting point for calculating the *exploit amount*, which represents the increase in financial funds after an exploit action has been performed on a knowledge asset. As in the *I-Space* the value of knowledge is some positive function of its utility and its scarcity, both the level of codification and

abstraction and the level of diffusion are included in the calculation.

Entrepreneurial Knowledge Entrepreneurial Knowledge represents the 'Know-How' (Ryle, 1949). Abilities like to "sell, bargain, lead, plan, make decisions, solve problems, organize a firm and communicate" (Shane, 2003: 94) are examples for knowledge items in this group. To this we would add skills like writing business plans, initiating sales, creating initial products and services, securing initial stakeholders and finances – creating the initial transactions set (Venkataraman & Van de Ven, 1998). Knowledge from this knowledge group starts at a medium level of codification and abstraction (0.5) and has a base value of 10.

New Venture Idea Knowledge. New Venture Idea Knowledge represents the 'Know-What'. Knowledge items in this group are insights about a particular potential service or product offering. Knowledge from this knowledge group starts at a low level of codification and abstraction (0.3) and has a base value of 20.

There are ten knowledge items in each knowledge group. All basic knowledge groups have an *obsolescence rate* of zero, a *codification* and *abstraction increment* of 0.1, and no *per period carrying gain or cost*. All agent groups are endowed with Local Knowledge and Entrepreneurial Knowledge, but they do not possess New Venture Idea Knowledge.

Opportunities

We use DTI knowledge to model opportunities. Once an agent possesses a knowledge item each from the Local Knowledge, Entrepreneurial Knowledge and New Venture Idea Knowledge groups, in knowledge stores with a codification level that is equal or greater than 0.6, it obtains the corresponding DTI, i.e. the agent 'discovers' an opportunity. There are ten DTIs, each being based on a combination of the nth item of each basic knowledge group (e.g., the underlying knowledge items for DTI 1, are knowledge item 1 of Local Knowledge, knowledge item 1 of Entrepreneurial Knowledge, and knowledge item 1 of New Venture Idea Knowledge). DTI knowledge items have a high *starting level of codification* and *abstraction* (0.8), a high (compared to base knowledge) *base value* of 2500, an *obsolescence rate* of zero, a *codification* and *abstraction increment* of 0.1, and no *per period carrying gain or cost*.

Agents obtain opportunities in different ways. Based on the dynamics of the simulation, we can identify the following three.

Opportunity Construction. The classical way is to construct an opportunity. An agent obtains all underlying knowledge items, structures them up to the specified codification threshold, and is then rewarded by obtaining the DTI, i.e. the opportunity (the *discovery* occurrence in the simulation is triggered). As prior stock of knowledge, agents already possess Local Knowledge and Entrepreneurial Knowledge from period one on. Agents can obtain the missing New Venture Idea Knowledge item either directly from the knowledge ocean (*self*) or from a knowledge store of somebody else (*others*). Agents can then reach the required threshold by either codifying the knowledge themselves or by scanning it from another agent (or, in the case of the imitator, by a combination of both).

Opportunity Acquisition. Not only can agents scan from others basic knowledge items, but also can they scan DTIs. This means, in addition to constructing opportunities themselves, agents are able to directly acquire the knowledge about an opportunity by scanning from a knowledge store of another agent that carries a DTI.

Opportunity Amplification. Agents can also further develop and structure their opportunities. They do so, either by codifying their DTIs directly or by scanning from other agents that possess higher codified stores of that DTI.

PUTTING *SIMOPP* TO USE: TWO VIRTUAL EXPERIMENTS

To highlight the distinct modeling capabilities of our simulation tool, we now conduct two virtual experiments. Each scenario is run 60 times, and each run has 1000 periods. All graphs show the average across all runs and some display the standard deviation to indicate the significant difference between the lines. Virtual Experiment 1 models an environment with low access to competitors' knowledge, Virtual Experiment 2 one with moderate access to competitors' knowledge.

Virtual Experiment 1: Access to competitors' knowledge is low

We model low access to competitors' knowledge by setting the vision property and the relocate distance to five (out of 100). Agents can – within a limited radius – see other agents and can move away from their original positions – in little steps – through the 100 by 100 grid of the *SimWorld*. As an example, Figure 3 depicts the area (black) that one (random) agent covers throughout the 1000 periods.

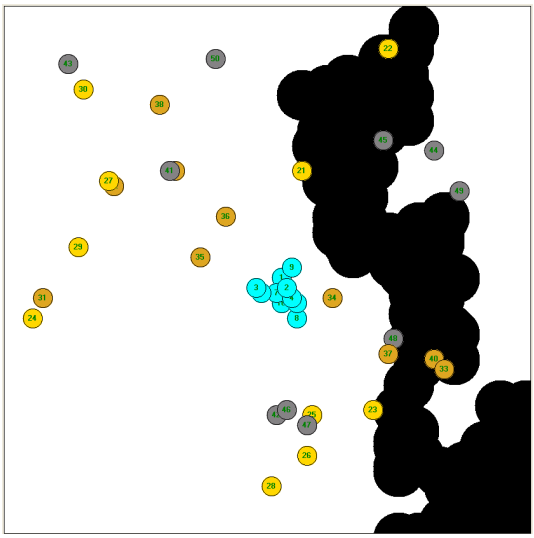

Figure 3: *SimWorld* Report Period 1000

We expect all agent groups to obtain at least some DTIs, because knowledge scanning is possible, even if limited. However, we cannot predict the specific effects this will have on the financial funds. Based on the distributions we have assigned to specify the properties of the four agent groups, we know the different general knowledge appropriation and development behaviors. How those different behaviors or strategies will play out in a population of agents in a knowledge environment, we do not know. We need the simulation to dynamically model the complex relationships among knowledge and agents across time to see how successful or not the different agent groups are in terms of growing their financial funds and knowledge portfolios. Figure 4 shows us the financial profiles for each group.

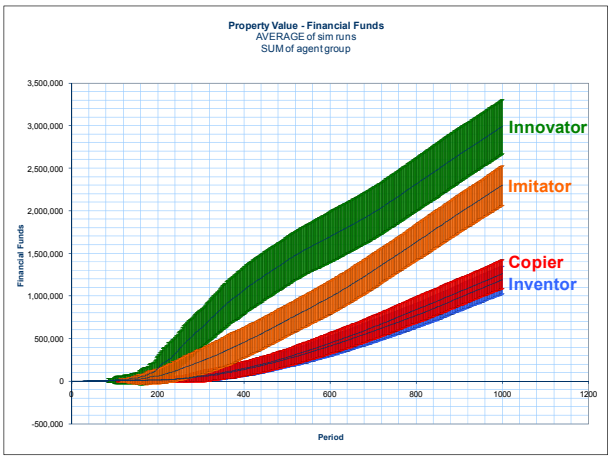

Figure 4: Longitudinal Report Graph Financial Funds

Based on distinct opportunity recognition strategies of the four entrepreneurial types, we can clearly distinguish four different groups. With vision and relocate distance set to five, Innovators perform better than Imitators, and they both outperform Copiers and Inventors, whose financial profiles overlap.

Insight 1a: The financial performance and performance volatility of the four entrepreneurial strategies – innovating, inventing, imitating, copying – will have distinct profiles, as a result of the differences in their knowledge appropriation and knowledge development behaviors.

Compared to a scenario where there is no access to competitors' knowledge (vision and relocate distance set to zero, not illustrated in this paper), we see that the Innovator group loses financial funds, which are picked up by the other three groups we proposed in our conceptual model. This is an example of the inner workings of the simulation. In both scenarios, Innovators follow the same pattern of actions (in particular, the number of exploit actions does not change), but their financial funds in the scenario without access to competitors' knowledge are almost three times higher than in the scenario with low access, demonstrating that rents are competed away. It is a result of what we call the 'diffusion discount effect'. In the former scenario, fewer agents obtain the DTIs and therefore, the ones that do secure them get higher rents. As more diffused knowledge is worth less, innovators in the latter scenario earn less (rent dissipation), because rent is appropriated by other types of entrepreneurs. All of this highlights distinct simulation and modeling capabilities of *SimOpp*, which can be summarized as follows.

Simulation & Modeling Capability 1: *SimOpp* enables researchers to simulate the opportunity recognition process and its respective financial payoffs for different entrepreneurial strategies.

Simulation & Modeling Capability 2: *SimOpp* allows one to simulate competitive agent behavior resulting from different entrepreneurial strategies.

Looking at the relative performance of the four agent groups and their distinctive entrepreneurial strategies, we can sum up the results as follows, giving tentative examples in the context of economic history. These historical stereotypical facts can be seen as a kind of face validation, showing that "the critical characteristics of the process being explored are adequately modeled and that the model is able to generate results that capture known canonical behavior" (Carley, 2002: 262). A pure R&D game (Inventor), originating but not being able to further develop, is not enough. Companies in the UK, for example, have had a long and good track record in invention that goes back to the industrial revolution. However, in recent decades they have had a relatively poor record in turning inventions into commercial products – i.e., in further development. Similarly, a copycat approach (Copier), of not originating and simply copying but not developing, is not sufficient to outperform other strategies. Until recently, many Chinese companies have behaved like this, producing identical copies of foreign products without adding anything to them (copying products without adding ingenuity). Most still do this. Interestingly, both strategies – copying and inventing – result in about the same financial payoffs. Combining pure and applied R&D (Innovator), being able to do both originating and developing, is the most rewarding strategy. Good examples for this are US firms that come up with innovative technologies and know how to develop them to their fullest market potential. Creative imitation (Imitator), by not originating but copying with further development, also represents a highly rewarding path to success. A case in point here is 1970's Japan with companies generating high revenues and profits by the improvement (particularly in production processes) of foreign inventions.

For the development of entrepreneurship theory, an important observation to make is that there is a significant difference between the Copier and the Imitator. Biology makes the distinction between replication (Copier) and reproduction (Imitator). Sexual *reproduction* is the biological process by which new individual organisms are produced through a combination of genetic material contributed from two (usually) different members of a species, thereby giving rise to variety and ultimately to evolution. In contrast,

replication is the biological process resulting in an exact duplicate of the parent organism (Dawkins, 1976).
Extant entrepreneurship theory has neglected this distinction and thereby largely ignored a viable opportunity recognition strategy. For other authors, copying, imitating, emulating are seen as the same behavior. They miss the crucial difference between appropriating a business idea and implementing it one-to-one (copying), and being inspired by certain preexisting ideas and further developing them (creative imitation). The simulation results show that there is a meaningful distinction, based on both financial performance and knowledge acquisition trajectories.

Insight 1b: In terms of their financial profiles, Innovators will differ from Imitators, and they both will be different from Copiers and Inventors.

Insight 2: In particular, imitation and copying are not the same. The different opportunity recognition strategies of Imitators and Copiers will result in fundamentally different performance profiles. Financially, Imitators will consistently outperform Copiers.

Opportunity Construction, Acquisition, and Amplification

The simulation allows us to look behind the financial funds profiles and to explore the accumulation of DTIs (opportunities). Figure 5 shows the paths each group follows to obtain the ten DTIs (as there are ten agents in each group, the maximum is 100). The graph features S-shaped curves that are characteristic for diffusion processes (Mahajan & Peterson, 1985). Note that research on diffusion of innovations (Rogers, 2003) looks at the process of an innovation's adoption and implementation by a *user*. The focus is on the market for and of an innovation. In contrast, we are looking at the knowledge dynamics that help *entrepreneurial agents* construct and attain opportunities. Looking at Figure 5, it is the initial 600 periods that are most interesting to interpret.

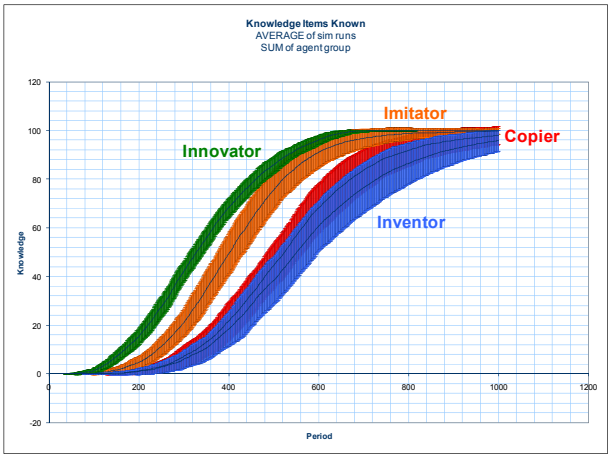

Figure 5: Longitudinal Report Graph DTIs Obtained

The DTIs, with which we model opportunities, have a starting level of codification of 0.8. Remember, that the maximum level of codification is 1 and that the codification increment is set to 0.1. This means that there are up to three knowledge stores per DTI per agent obtainable (with codification levels of 0.8, 0.9, 1.0), or 300 per agent group (Figure 6). As these DTI knowledge stores are the basis for the exploit action, the more stores an agent possesses the better.

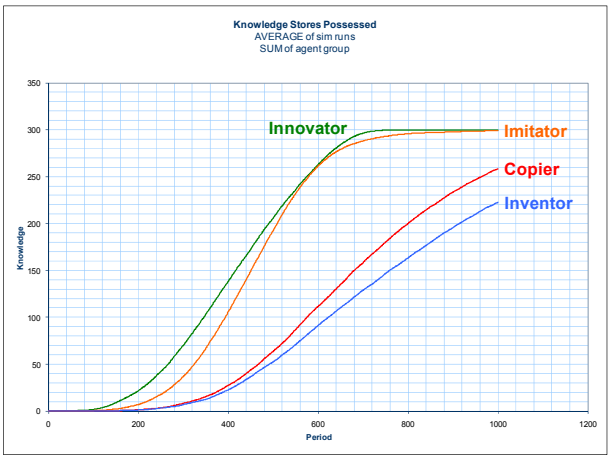

Figure 6: Longitudinal Report Graph DTIs *Knowledge Stores*

Three different occurrences let agents attain DTI knowledge stores. This means, Figure 6 is explained by three distinct actions or ways with which the entrepreneur obtains and develops opportunities. Figure 7 shows the first one, the 'discovery' occurrence.

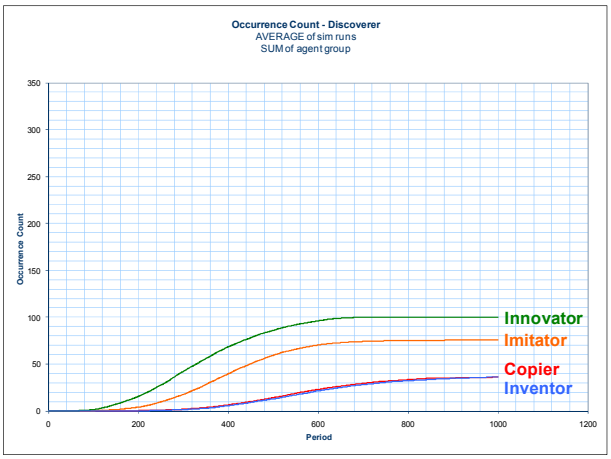

Figure 7: Longitudinal Report Graph DTIs *Discoverer*

The graph depicts the outcome of the *Opportunity Construction* process described earlier. For a 'discovery' to happen, the underlying basic knowledge items have to be assembled and brought to the required threshold. We see that Innovators lead the process with Imitators in second place. The 'discovery' occurrence represents the classical entrepreneurial route of constructing one's opportunity step by step with the help of one's idiosyncratic stock of knowledge (Shane, 2000). The micro processes behind it are as follows. The missing basic knowledge group – new venture idea knowledge – can be obtained directly (innovator, inventor – 'scan from the knowledge ocean') or from someone else (imitator, copier – 'scan from others').

Bringing all the knowledge up to the required threshold can also either be done directly (innovators, imitators – 'codify') or by getting knowledge stores with higher codification levels from someone else (copiers, inventors – 'scan from others').

Doing everything directly, i.e. getting the idea and developing it yourself, the Innovator group comes first at opportunity construction. A combination of obtaining the insights from other agents but developing them oneself helps the Imitator group come second. The other groups lag behind in terms of being able to construct their opportunities. Those groups, however, come first in the next graph that co-explains the total number of DTI knowledge stores: DTI scanning occurrences (Figure 8).

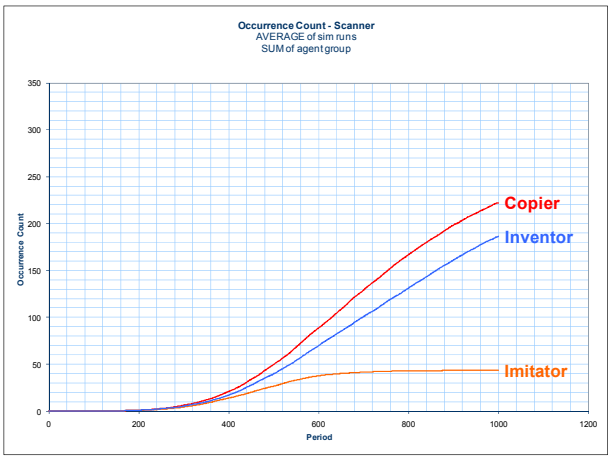

Figure 8: Longitudinal Report Graph DTIs *Scanner*

This graph shows what we described earlier as *Opportunity Acquisition*. The agents scan DTI knowledge stores from other agents. By doing this, they are not only able to obtain the basic knowledge about an opportunity, but also the further developed knowledge items – DTI knowledge stores with higher levels of codification. The 'production' of those can be observed in the last graph that explains the number of DTI knowledge stores: DTI codification occurrences (Figure 9).

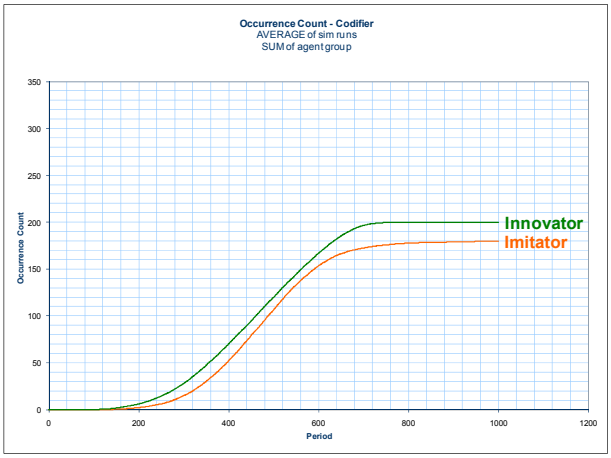

Figure 9: Longitudinal Report Graph DTIs *Codifier*

Figure 9 shows what we have called earlier *Opportunity Amplification*. The Innovator group and the Imitator group are able to further structure their knowledge about opportunities. Again, Innovators lead, building on their first mover advantage of having started to 'discover' DTIs before everybody else; Imitators follow very closely.

Opportunity Construction, *Opportunity Acquisition*, and *Opportunity Amplification* are distinct processes that, taken together, also with the actions behind them, give a more complete and fine-grained picture of what opportunity recognition means. The simulation model enables us to operationalize different entrepreneurial actions and processes, and to later analyze the effects they have on financial performance and knowledge built up. *SimOpp*'s distinct features can be summarized as follows.

Simulation & Modeling Capability 3: *SimOpp* allows one to dissect the opportunity recognition process and to arrive at a more discriminating picture of entrepreneurial strategies. In particular, it lets us distinguish between *Opportunity Construction*, *Opportunity Acquisition*, and *Opportunity Amplification.*

Virtual Experiment 2: Access to competitors' knowledge is moderate

In the previous scenario, we set the vision property and the relocate distance to 5. Five out of 100 is quite a small increment and the question arises what will happen if we increase both vision and relocate distance by another 5. A vision property and relocate distance of 10 is still far from universal sight and hence from total and immediate access to all the knowledge of other agents. Figure 10 shows us the financial profile of all four groups with vision and relocate distance set to 10 – moderate access to competitors' knowledge.

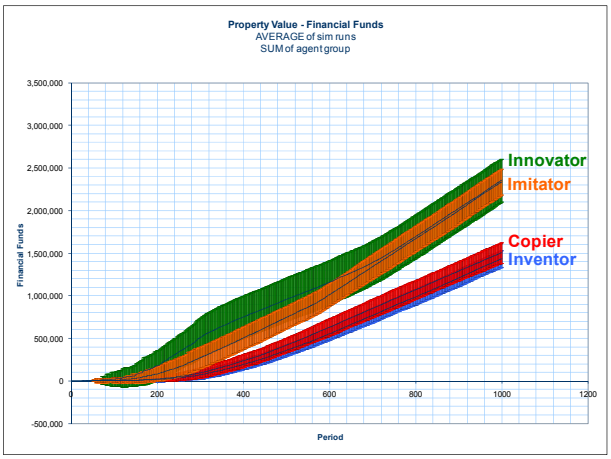

Figure 10: Longitudinal Report Graph Financial Funds

Total output – GDP – is the same as in the previous scenario (total financial funds). Note that as a basic measure of the population's performance, we treat the total financial funds per period (the sum of all agent groups) as a proxy for GDP. Conceptually, it can be viewed as the market value of all final goods and

services made within the *SimWorld* based on the exploitation of the agents' knowledge assets. The financial funds of the Innovator group drop (same amount of exploit actions, but diffusion discount effect), the funds of the Copier and Inventor groups increase, and the funds of the Imitator group stay approximately the same. An intriguing outcome is that now the Innovator group does not do any better than the Imitator group. Imitators can capitalize on their knowledge about opportunities as well as Innovators do, and with a lower standard deviation, meaning with lower instability. This means, not only has our experiment revealed that there is a significant difference between Copiers and Imitators (Insight 1b), but also can it prove that under certain conditions imitating behavior can be as profitable as innovating behavior.

Insight 3: In environments where there is moderate access by other entrepreneurial agents to Innovators and their knowledge, there will be no distinguishable difference in the financial performance of Imitators compared to Innovators. So when access by Imitators to Innovators' knowledge is moderate or greater than moderate, creative imitation will be an equally rewarding alternative to innovation.

Macro effects

In addition to doing analyses on a more micro level – looking at individual agents and agent group behavior – we can also explore effects on a macro level. This is a distinct advantage of simulation methods. Not only are we able to assess the financial performance of different groups of entrepreneurial agents, but also can we see what the societal (population) effects of the agents' actions are.

As we have noted above, GDP stays the same and the financial performance of Innovators is lower after the general increase in vision and relocate distance. Why should society find such a scenario beneficial? One thing society is interested in is the 'outgrowth of entrepreneurial opportunities', products or services that are new to the market. The earlier that entrepreneurs perceive and exploit opportunities, the earlier new products, services, or processes – in short, innovations – reach the economy. So the question is whether – apart from maybe being more realistic – the increase in vision and relocate distance is worth it for society in terms of knowledge diffusion. Our simulation results give evidence that it indeed is valuable! Society gains, because as Figure 11 shows, opportunities and the new products or services that come with it are obtained much earlier than before.

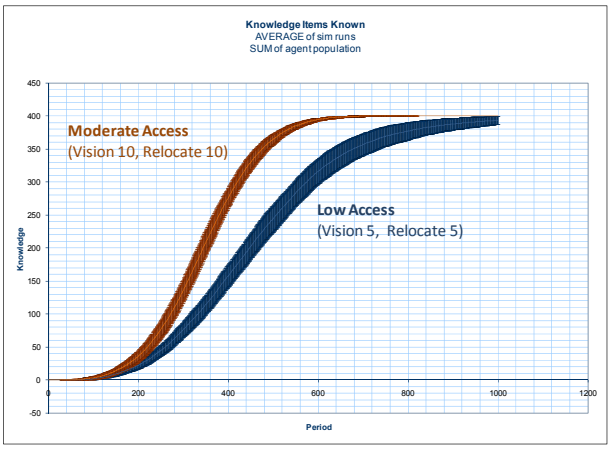

Figure 11: Total Number of DTIs Known (population level) for low access and moderate access scenarios

Looking at the sum of agent groups, this result might have been expected: if the agents have greater access to the knowledge that is out there, the diffusion curve shifts to the left. What is interesting, however, is that the lead group – the group whose agents first obtain *all* DTIs (100%) – changes from Innovators in the low access scenario to Imitators in the moderate access scenario, and they do so *200 periods earlier* as can be seen in Figure 12 (note the two markers, indicating when the respective agent group fully reaches the 100 DTI-knowledge item threshold).

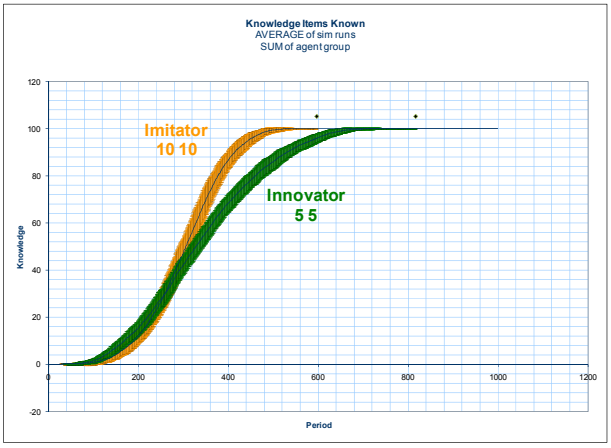

Figure 12: Number of DTIs Known for lead groups in low access and moderate access scenarios

This means that innovations, which are the basis for societal wealth generation, will actually be 'brought to market' earlier, by the creative imitator, not by the classical innovator. This is the foundation of growth and continuing wealth for both a society as a whole and future entrepreneurs. In a virtuous cycle, those entrepreneurs can build on the new insights obtained to discover new sets of opportunities through continuous Schumpeterian-Learning of all participants (Boisot, 1998).

Insight 4: Moderate access to innovators and their knowledge will be accompanied by acceleration in the introduction of innovations, which will thereby also accelerate societal welfare effects.

What does moderate access to innovators mean? It certainly depends on the particular context. Our results can for example be applied to the discussion on property rights (Boisot, MacMillan, & Han, 2007). They do not suggest to abolish property rights, but to establish a system that allows entrepreneurs of different kind to co-evolve opportunities. As we have seen above, society and entrepreneurs will benefit from faster knowledge creation and development based on continuous social learning (Boisot, 1998).

CONCLUSION

In this paper, we have explained how to parameterize and use *SimISpace2* to develop a unique simulation model that lets entrepreneurship researchers study the opportunity recognition process under different environmental conditions. It helps them get a deeper understanding of the nature of opportunities both on a micro and macro level. The practical outcomes are strategy recommendations for both individual entrepreneurs and policy makers. In future research, additional virtual experiments can be conducted that exploit the full range of *SimISpace2*'s parameters.

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