INVESTIGATING ABSORPTIVE CAPACITY STRATEGIES VIA SIMULATION

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ABSTRACT

Absorptive capacity, defined as the organizational capability to identify, absorb and exploit knowledge, is one of the most discussed topics in the management literature. Yet, its complex nature makes it almost impossible to empirically test it. This paper develops SimAC, an agent-based simulation tool that enables studying and comparing different absorptive capacity strategies, their related financial payoffs, and their knowledge creation potential through time.

INTRODUCTION

Absorptive capacity (Cohen and Levinthal, 1990) – hereafter AC—is one of the most discussed and advanced concepts in management theory, and still one of the less empirically tested (Lane, Koka and Pathak, 2006). Absorptive capacity is traditionally defined as the organizational capability to identify relevant external knowledge, assimilate it and exploit it for commercial ends (Cohen & Levinthal, 1990: 128). Although scholars have advanced complex and detailed theoretical models about organizational skills in knowledge identification, absorption, and exploitation (Lane *et al.*, 2006; Todorova and Durisin, 2007; Zahra and George, 2002), empirical studies that test the entire AC process are rare, partial, and sometimes misleading. The reason is that knowledge acquisition involves several intervening variables that could be frustratingly difficult to retrieve and observe (Lim, 2009). Furthermore, the abstract nature of knowledge does not allow a direct observation of the phenomenon, forcing scholars to identify proxies to measure AC development. Knowledge is an intangible asset, which has distinctive characteristics when compared to physical assets. For this reason, in order to deeply understand the processes underpinning AC, research needs to be grounded in a solid theory of knowledge evolution.

In this paper, we aim to improve the understanding of diverse AC strategies by developing SimAC, a simulation model, which helps scholars to study the effect of diverse approaches to organizational learning on firm performance. Our work is based on *SimISpace2*, an agent-based graphical simulation environment designed to model strategic knowledge management processes, in particular knowledge flows and knowledge-based agent interactions. The simulation is based on Max Boisot's Information Space (or I-Space), a conceptual framework, which helps analyze knowledge flows in populations of agents (Boisot, 1995, 1998). Within the I-Space framework, the Social Learning Cycle provides a process interpretation of the dynamic evolution of knowledge, its structuring, and sharing. The process interpretation of organizational learning and its sub-phases makes the I-Space a suitable framework to advance the understanding of AC strategies (Aversa, 2011).

ABSORPTIVE CAPACITY STRATEGIES

According to the traditional definition of AC by Cohen and Levinthal (1990) and the more recent reconceptualization by Zahra and George (2002), AC can be summarized into a four-step process. In the first phase, the organization *identifies* bundles of external useful knowledge to *acquire*. The knowledge identified is usually very concrete, and embodied in artifacts that belong to other agents, or more in general to the external environment. Once identified and acquired, knowledge must be structured in order to be replicable and exploitable. Firms *transform* the practical and tacit knowledge embodied in the artifacts (e.g. products, technologies, machineries) into abstract and codified knowledge (e.g. formulas, scientific and technical principles etc.): the more structured knowledge is, the easier it becomes to share and exploit (Boisot, 1998; Nonaka, 1994). In the third phase, structured knowledge is diffused among the members of the organization and embedded in concrete practices aimed at develop artifacts, organizational rules, procedures and behavioral patterns (*impact* phase). The organization economically *exploits* the new knowledge, creating and commercializing new products, services, and knowledge assets. Therefore, according to the social learning cycle concept (Boisot, 1998), knowledge completes a full "cycle", since firms obtain it in an unstructured form, they structure it and then exploit it by embedding it in products, processes and artifacts. AC leads to superior performance and competitive advantage. To protect their competitive advantage, organizations can *patent* the knowledge they possess. However, while firms that have superior skills only in knowledge acquisition and transformation (called potential AC) obtain only part of

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the benefits, firms skilled in knowledge development and exploitation (called realized AC) are able to maximize their economic performance and develop, in a complete form, the entire AC potential (Jansen, Van den Bosch and Volberda, 2005; Zahra and George, 2002).

Literature shows that companies need different types of knowledge to develop innovation and increase performance. In this paper we follow the Lim (2009: 1252) three-type knowledge classification, complementing it with a fourth group we consider important: (1) *Disciplinary knowledge*, such as general scientific knowledge; (2) *Domain Specific Knowledge*, such as solutions specific to technical projects; (3) *Encoded knowledge*, such as knowledge embedded in tools and processes, and (4) *Market knowledge*, such as knowledge about commercial opportunities and market characteristics. Firms can concentrate on acquiring particular types of knowledge assets, for example focusing their investments on one kind, or on a mix of two or more. For this study, we decided to test the impact of five different types of AC strategies on financial performance. We simulated the competitive behavior of five different agent groups, each pursuing one specific AC strategy:

- Agent group 1 - **Research Firm**: These kinds of agents focus their AC strategy on *scanning knowledge*;
- Agent group 2 - **Managerial Firm**: These kinds of agents focus their AC strategy on *abstracting knowledge*;
- Agent group 3 - **Manufacturing Firm**: These kinds of agents focus their AC strategy on *impacting knowledge*;
- Agent group 4 - **Marketing Firm**: These kinds of agents focus their AC strategy on *exploiting knowledge*.
- Agent group 5 – **Balanced Firm**: These kinds of agents focus their AC strategy on pursuing a balanced mix of *all the possible actions.*

In addition, every agent group can protect the knowledge possessed via *patenting*.

According to our theoretical premises, our parameterization will distinguish between the different strategies in the simulation environment, and thus enables us to dynamically analyze micro and macro effects of AC strategies on firm performance. In particular, we are interested in comparing the payoffs of the five AC strategies. We expect to determine distinctive knowledge evolution and financial performance profiles for each firm (agent) type.

USING SIMISPACE2 TO MODEL AC STRATEGIES

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 I-Space (1995, 1998). Recent studies have used the *SimISpace2* simulation suite to investigate knowledge evolution in complex systems (Ihrig, MacMillan, Knyphausen-Aufsess and Boisot, 2010).

Basic Parameterization of SimISpace2

Ihrig and Abrahams (2007) offer a rich and detailed description of the structure and technicalities of the *SimISpace2* simulation environment. Due to the wide set of modeling opportunities that this suite offers, we will limit our description to the set of features that will be used for our purposes. However, for readers that are not familiar with this simulation framework, we will briefly introduce some of the main *SimISpace2* principles, paying attention to the way knowledge is represented and processed by the agents. The following description is adapted from Ihrig (2010):

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 to the individual group members (agents and knowledge items) characteristics in accordance with the group they belong. Knowledge in the simulation environment is represented through *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 agents *structure* knowledge (which only applies to knowledge stores, not to knowledge items). Multiple agents hold knowledge items, and one agent's investment in *structuring knowledge* does not influence the codification and abstraction level of the same knowledge item held by another agent. Agents possess knowledge stores that can have different degrees of structure. If the agent structures its knowledge, the properties of the knowledge item itself – i.e., its *contents* – are not changed, but it gets moved to a new knowledge store with higher degrees of structure – 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 *structure* them beyond user-specified threshold values in order to achieve the required level of integration and abstraction. 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 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.

Specific *SimISpace2* Parameterization to Model AC Strategies

Similar to Ihrig (2010) we decided to keep our model as parsimonious as possible, thus using only six out of the twenty actions available in the *SimISpace2* suite: *1. Scan, 2. Abstract, 3. Impact, 4. Learn, 5. Exploit*, and *6. Patent.* Each agent's goal is to scan knowledge items (either from the *ocean* or from others), *abstracting* the new knowledge (which correspond to structuring it). Once knowledge has reached a certain level of structure, it is diffused in practices and routines among and across the organization (*impact*), and absorbed within the organization (*learn*). Through the commercialization of products and services developed based on the newly acquired knowledge assets, the agent *exploits* the knowledge potential, and thus increases its financial performance. Simply put, superior capabilities in managing this process of knowledge development and exploitation correspond to higher AC. Higher levels of AC lead to superior financial funds. The higher the financial funds obtained following a specific AC strategy, the more successful we will consider that specific AC strategy.

Within the *SimISpace2* environment we use specific actions to model the agent groups' focus on a particular set of learning strategies AG1: Research firm (*scanning* from the ocean and from others); AG2: Managerial firm (*abstracting*); AG3: Manufacturing firm (*impacting* and *learning*); AG4: Marketing firm (*exploiting*); AG5: Balanced firm (*an distributed mix of all the actions*). In addition, all the AGs have an equal propensity to protect their knowledge through *patenting*. An agent can patent knowledge for a certain duration and with a specific strength. The agent can patent only the knowledge it possesses, and only if it holds the knowledge in a knowledge store that has an abstraction level above a user set-level. In other words, patenting is valid only if performed after abstraction. Also, when the knowledge is possessed by a user-set number of other agents, it becomes public domain and it cannot be patented. In our simulation, the patent protection lasts for the entire 2,000 rounds, and has a strength of 0.5, which means that the patented knowledge has a likelihood of 50% to be effectively protected. Our patent abstraction threshold has a value of 0, which means that any kind of knowledge can be patented. Finally, when all the 50 agents possess a specific knowledge item, nobody can *patent* it as we consider it "public domain."

In order to compete in the market, each firm needs to have at least a minimum propensity in pursuing each type of these actions, which are mandatory for any kind of innovation development. Yet, as mentioned above, focusing on specific sets of actions corresponds to different AC strategies.

We have also created four groups of knowledge items, corresponding to the classification we previously explained. For each group we assigned a base value of 20 and an abstraction and codification increment of 0.1. Also, for each knowledge group we assigned a starting value of codification and abstraction. The more *structured* knowledge is, the higher will be the codification and abstraction level we assigned.

- Knowledge group 1: *Disciplinary knowledge*
  Codification: 1.0
  Abstraction: 1.0
- Knowledge group 2: *Domain specific knowledge*
  Codification: 0.8
  Abstraction: 0.8
- Knowledge group 3: *Encoded knowledge*
  Codification: 0.5
  Abstraction: 0.5
- Knowledge group 4: *Market knowledge*
  Codification: 0.3
  Abstraction: 0.3

To develop innovations, firms need to acquire all four types of knowledge items. To simulate this knowledge acquisition, development, and exploitation scenario, we have given a fixed budget of 9 "chips" to each agent per round. The nine chips correspond to the different activities that each agent can theoretically pursue in each round, in order to develop innovation. The chips are distributed based on the actions that define their learning strategy. One of these chips is dedicated to patenting their knowledge. For example, overall *research firms* will spend 5 chips out of 9 in *scanning*, because their strategy is focused on that kind of activity. The remaining 3 chips are equally distributed for the other actions, and 1 chip will be used for *patenting*. Table 1 shows the resource distribution for each agent group.

Table 1: Parameterization of the 5 strategies

Action	AG 1. Balanced Firm	AG 2. Research Firm	AG 3. Managerial Firm	AG 4. Manufacturing Firm	AG5. Marketing Firm
1.Scan*	2.0	5.0	1.0	1.0	1.0
2.Abstract	2.0	1.0	5.0	1.0	1.0
3.Impact	1.0	0.5	0.5	2.5	0.5
Learn	1.0	0.5	0.5	2.5	0.5
4.Exploit	2.0	1.0	1.0	1.0	5.0
5.Patent	1.0	1.0	1.0	1.0	1.0
Total	9.0	9.0	9.0	9.0	9.0

*From the ocean and from others.

For each round, the agents perform their actions in knowledge acquisition, transformation, and exploitation. The agents gain a DTI, the knowledge we model innovation with, when they obtain a specific set of knowledge items. Agents increase their financial funds by capitalizing on the knowledge they possess, especially DTIs. The financial funds accumulated by an agent are the measure of its performance and success. Agents with financial funds of zero die.

Following the definition of potential and realized AC (Zahra and George, 2002), we developed two different kinds of DTIs: *scientific DTI* and *technical DTI*. The scientific DTI represents the potential AC (i.e. abstract knowledge, that has no practical application yet), and agents obtain it when they get a scientific knowledge item plus a managerial knowledge item. The technical DTI, which leads to higher financial return than the scientific one, represents the realized AC (i.e. concrete and applied knowledge), and agents obtain it when they get a *scientific DTI* plus a *manufacturing knowledge* item and a *market knowledge* item. Table 2 describes the knowledge items needed for agents to collect DTIs.

Table 2: Knowledge items and DTIs in *SimAC*

Disciplinary Knowledge	Scientific DTI (First order DTI)	Technical DTI (Second order DTI)
Domain-Specific Knowledge		
Encoded Knowledge		
Market Knowledge		

SIMULATION AND RESULTS WITH *SIMAC*

We have conducted *SimISpace2* virtual experiments with the *SimAC model,* aimed at exploring the impact of different AC strategies on firm performance. We ran the simulation 20 times, and each run lasted 2000 periods. We created 10 participants for each of the five agent groups (50 agents in total) and 10 knowledge items per type (40 knowledge times in total). All graphs show the average across all runs.

Simulating Financial Performance with SimAC

The first graph we present (Figure 1) shows the different financial performance profiles measured in funds accumulation, derived from the five different strategies. Based on distinct AC strategies of the five firm types, we can clearly distinguish five different groups.

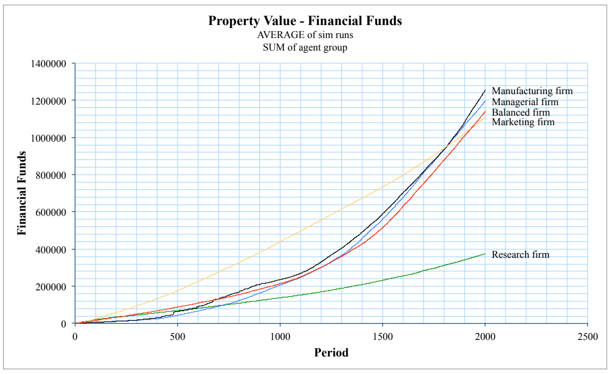

Figure 1: Financial Funds (Longitudinal Report)

Insight 1: The financial performance of the five AC strategies – *research, managerial, manufacturing, marketing,* and *balanced* – will have distinct profiles, as a result of the differences in their knowledge appropriation and knowledge development behaviors.

The *SimAC* results are consistent with management theory. Research firms are strongly dedicated to knowledge identification and *scanning*, and therefore are not able to exploit the commercial value of their knowledge. *Marketing firms*, on the contrary, are mainly dedicated to knowledge *exploitation* (*exploit* activity set to five), but do not widely develop the first phases of AC processes. As a result in the long run they perform as the second worst, despite being the best performing AG for the first 1750 periods. At the end, the manufacturing firms, which focus on *impacting* and *learning*, are the best performers of all the groups.

All of this highlights distinct simulation and modeling capabilities of *SimAC*, which can be summarized as follows.

Simulation & Modeling Capability 1: *SimAC* enables simulating the different AC strategies and their respective financial payoffs for different agent groups.

Simulating Potential AC with SimAC

The first insight shed light on the impact of strategies on financial performance. However, money is not the only way to measure the outcomes of organizational learning. Innovation is also an important aspect that we have to take into consideration in this context. Innovation performance in *SimAC* is measured via the accumulation of DTIs. The first type of DTI is the *scientific DTI,* which stands for the *potential AC* (Zahra and George, 2002). This kind of DTI corresponds to possessing and combining *disciplinary* and *domain specific knowledge.* The agent groups have access to a maximum of 100 DTIs in the simulation environment. Figure 2 represents the appropriation of scientific DTI across the agent population (maximum 100 DTIs – 10 DTIs, 10 agents in a group). In Figure 2, we can distinguish how different AC strategies require different timing to obtain the 100 scientific DTIs.

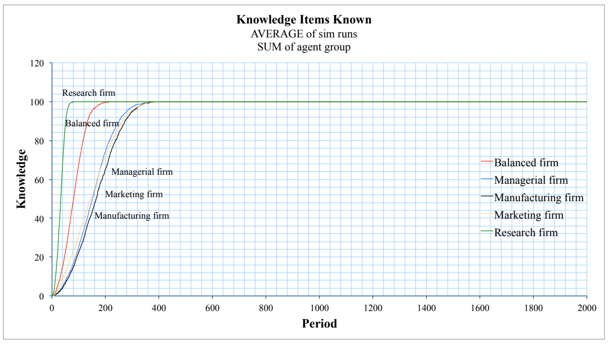

Figure 2: Scientific DTIs (Longitudinal Report)

Insight 2: The five AC strategies – *research, managerial, manufacturing, marketing,* and *balanced* – lead to distinct results *in potential AC*, due to the agents' knowledge appropriation and knowledge development behaviors.

Again, *SimAC* demonstrates results that are consistent with management theory. *Research firms*, whose main intent is focused on scanning new knowledge, are the first ones to obtain the totality of 100 *scientific DTIs,* followed by *balanced firms*. *Managerial, marketing and manufacturing firms*, whose main attempt is not collecting new knowledge, but maximizing the processing and exploitation of the available knowledge, are the slowest in reaching the 100 *scientific DTIs.* Specifically they are more than 4 times slower than the best performers since they obtain the 100 DTIs at around period 400, while *research firms*—the best in class—get them at around period 70. This evidence leads us to define the second *SimAC* capability.

Simulation & Modeling Capability 2*: *SimAC enables simulating the different AC strategies and their respective innovation payoffs of *potential AC*, for different agent groups.

Simulating Realized AC with SimAC

The second type of DTI is the *technical DTI,* which in our scenario corresponds to the *realized AC* (Zahra and George, 2002). This kind of DTI is obtained when an agent gets a *scientific DTI* plus an *encoded* and *marketing knowledge item.* The agent groups can access a maximum of 100 DTIs in the simulation environment. The *technical DTIs* represent knowledge that is more structured and easy to exploit, thus leading to superior financial performance for the agents that obtain them. Figure 3 depicts the distribution of scientific DTIs across the agent population. We can distinguish how different AC strategies lead to different timings to obtain the 100 scientific DTIs.

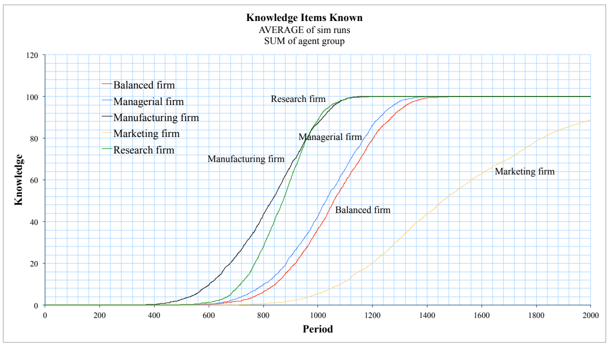

Figure 3: Technical DTIs (Longitudinal Report)

Insight 3: The five AC strategies – *research, managerial, manufacturing, marketing,* and *balanced* – lead to distinct results in *realized AC*, due to the agents' knowledge appropriation and knowledge development behaviors.

The *SimAC* report shows how *research firms* are still the first to obtain the 10 technical DTIs, leveraging their time advantage in reaching the *scientific DTIs,* which are a mandatory requirement to get to the second order DTIs. In fact, in the real world firms need to develop general structured knowledge before developing it in innovative products and services, thus being able to exploit them. *Manufacturing firms*, due to their focus on the *impact/learn* activities, manage to be first together with the *research firm*, despite being the slowest at obtaining the *scientific DTIs*. *Managerial firms* and *balanced firms* follow the same curve, but the *managerial firm* is slightly faster than the *balanced one*. The slowest is the marketing firm, which at the end of the 2000 run is not able to obtain all the 100 *technical DTIs.* This said, we can advance another possibility offered by *SimAC*.

Simulation & Modeling Capability 3*: *SimAC enables simulating the different AC strategies and their respective innovation payoffs of *realized AC*, for different agent groups.

Simulating Knowledge Storage with SimAC

Another way to measure knowledge outcomes, is considering in how many "locations" knowledge is stored. Firms embed innovations into documents, objects, artifacts, and locations. For example, the same technical innovation can be contained in a patent, in two types of products, and in the personal knowledge of the five engineers. Thus, we can affirm that the same knowledge is contained into eight *knowledge stores.* Knowledge stores allow us to trace the diffusion of knowledge among diverse agents, which can hold the same knowledge item in different stores at the same time. Accordingly, literature has underlined how knowledge is an asset that can be shared without implying ownership (Boisot, 1998). For example, while a physical object is either in one place or in another, several people can share the exact same knowledge without affecting its structure or nature.

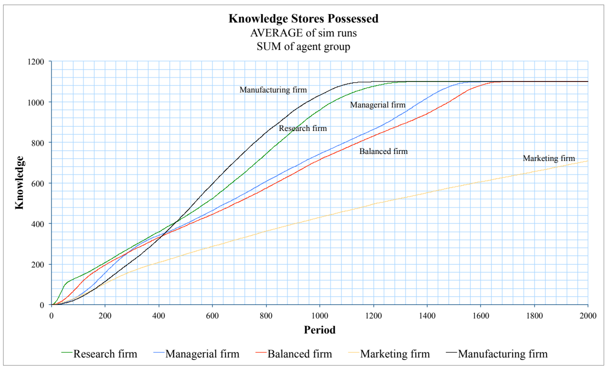

Figure 4: Scientific DTI Knowledge Stores

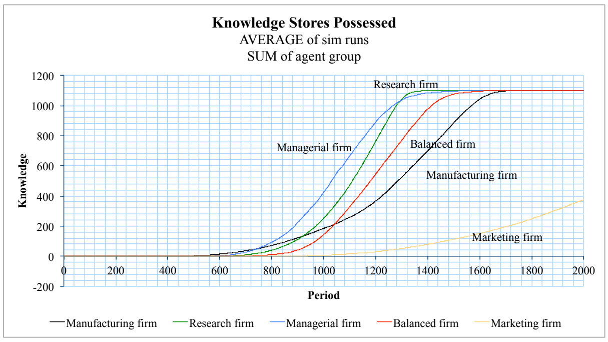

Figure 5: Technical DTI Knowledge Stores

Insight 4: The five knowledge AC strategies – *research, managerial, manufacturing, marketing,* and *balanced* – lead to different knowledge store trajectories, as a result of the differences in the agents' knowledge appropriation and knowledge development behaviors.

SimAC consistently reflects the nature of knowledge by allowing knowledge stores to be more numerous than knowledge items. Figure 4 shows the development of knowledge stores for scientific DTIs among the five agent groups, while figure 5 shows the development of knowledge stores for technical DTIs. The vertical axis shows that the number of knowledge stores is higher than the DTIs obtained. For example, the *manufacturing firms* present around 1100 knowledge stores for *scientific and technical DTIs*. Yet, while manufacturing firms are the fastest at obtaining knowledge stores for *scientific DTIs,* they are the second slowest to obtain the knowledge store for *technical DTIs.* This confirms that the skills in knowledge allocation are independent from knowledge creation, and develop clearly different outcomes depending on the strategy adopted. This leads us to the last reflection on the *SimAC* tool capability.

Simulation & Modeling Capability 4: *SimAC* enables simulating the different AC strategies and their respective innovation payoffs related to knowledge storage, for different agent groups.

CONCLUSION

SimAC is a powerful tool to conduct virtual experiments for exploring the effects of different AC strategies on financial and innovation performance. Being based on the I-Space framework (Boisot, 1995, 1998), the tool offers a consistent integration of AC theory with fine-grained insights about knowledge evolution in populations of agents. Processes of knowledge identification, acquisition, transformation and exploitation can be observed in detail. In this paper we displayed only a limited set of the several reports that the suite *SimISpace2* offers. However, the results we presented in this article already offer opportunities to develop new research questions that can be addressed using the *SimAC* application. For example, in our simulation we have explored a possible scenario where an arbitrary set of 50 firms compete. In our new experiments, we are taking care of simulating environments with significantly higher number of competitors. Also, to compare the outcome of basic AC approaches, this first SimAC simulation models the competition between four strategies focused on one single objective (i.e. AG2, AG3, AG4, AG5) and one strategy that engages in a balanced tradeoff between all the other possible strategies (i.e. AG1). We are aware that in real life firm strategies might be more complex than in our experiments, but our parameterization of SimISpace2 shows that it is possible to simulate competitive situations with more diverse and realistic characteristics, and it is in our future plans providing analysis of these kinds of environments.

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