Chapter 1

Hypercompetitive Environments: An Agent-based model approach

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1. Introduction

Information technology (IT) environments are characterized by complex changes and rapid evolution. Globalization and the spread of technological innovation have increased the need for new strategic information resources, both from individual firms and management environments. Improvements in multidisciplinary methods and, particularly, the availability of powerful computational tools, are giving researchers an increasing opportunity to investigate management environments in their true complex nature. The adoption of a complex systems approach allows for modeling business strategies from a bottom-up perspective - understood as resulting from repeated and local interaction of economic agents - without disregarding the consequences of the business strategies themselves to individual behavior of enterprises, emergence of interaction patterns between firms and management environments. Agent-based models are at the leading approach of this attempt.

Agent-based models are increasingly used in different fields of economics and management. Many of these models fall into the field of Finance (S. D. Farmer, 2005; R. Cont, 2001; Stanley, 2002) and a very important part of them deals with Innovation and Diffusion processes (Dawid et al, 2001). Among the later, some of the models encompass the study of strategic behavior. However, those models do not usually account for both strategic behavior and the dynamics of the interactions among agents, in what concerns their interplay in unstable and hypercompetitive domains. Hypercompetitive domains are characterized as complex and adaptive environments, with non-linear behaviors, which emerge from an interdependent set of strategies (Stacey, 1995). Some authors (Eisenhardt and Sull 2001) advocate strategizing by simple rules in high velocity environments, in order to retain sufficient flexibility to make rapid decisions.

Drawing on the biological evolution of ecosystems, research on hypercompetitive environments emphasizes the interdependence of different actors within a system (Eisenhardt and Galunic, 2000), where evolution takes place in a continual process of contradictory forces with positive and negative feedbacks. In those self-organizing environments, the actual most valuable strategy may become a loosing one.

In order to deal with such a complex subject, we adopt an agent-model approach and depart from the usual solutions in this type of models: each agent occupies a given position in the two-dimensional space, being represented by a set of weighted strategies. Strategies are continuously updated and depend on the strategies of the agent nearest neighbors. At each time step, the agent performance is computed through a payoff function. As often happens, improvement of one agent payoff is generally made at the expense of other agents. Typical examples of strategies are differentiation and low cost, innovation and market segmentation.

One may think on the abstract representation of strategies we have adopted in our model as being that of a highly adaptive system where specific tasks are performed without strongly committed configurations. Our model is, therefore, a contribution to interweave two lines of research that have progressed in a separated way: business strategies models to complex environments and the agents based economic literature, with a strong emphasis on spatial interactions.

The rest of this paper is structured as follows. In section two we present the main features of the model. Section three comprises the simulation results and their analysis accordingly to relevant scenarios. Section 4 concludes and outlines future work.

2. An agent-based model of business strategies – the features

2.1. Enterprise and Environment Characteristics

The model comprises a set of N agents witch are randomly placed in the two dimensional space (with periodic boundary conditions). Each agent has K strategies representing its available resources. To ensure the existence of a limited amount of resources, the vector of the strategies (Ei) is convex coupled.

At each time step and based on their neighborhood, the agents are allowed to update their strategies accordingly to the rules presented in section 2.3. The amount of influence of the neighborhood in the agent strategies depends on the value of a local parameter (D), whose specification follows a sigmoid function, as in (1).

$$Vi_k(t) = \sum_{j=1}^{N,\, j \neq i} \frac{1}{1 + e^{-0.15 \cdot (d_{ij} - D)}} \cdot Ej_k(t)) \qquad (1)$$

2.2. Parameters

The model parameters allows for representing the following properties:

- **Agent susceptibility** (F_i) represents the agent propensity to redistribute its strategic resources (a null value represents inertia and the corresponding impossibility of strategic change).
- **Agent Myopia** (M_i) allows for weighting local and global competition asymmetrically.
- **Agent mobility** (S_i) specifies the agent capacity to change its position in the two dimensional space (null values represent static agents and unitary values represent agents with high inertia).
- **Agent concentration** (C_i) allows for the specification of a biased distribution of strategy weights (setting this parameter to one means that the agent invests all its strategic resources in a single strategy).

2.3. Agents Performance

The algorithm for strategies updating aims to maximize individual payoffs. The payoff specification has two components, the first component accounts for the results of local interactions (between the agent and its nearest neighbors). The second component accounts for the global effects. The computation of local component (PL) is based on the Porter generic strategies theory, where differentiated products and services are intended to lead to higher profits. In this context, the global component (PG), is based on the environmental conditions and depends on the alignment between local and global strategies. The closer are these strategies, the higher is global agent performance. The agent payoff is computed as the sum of expressions (2) and (3).

$$PL_i(t) = \frac{1}{K}\sum_{k=1}^{K} | Ei_k(t) - Vi_k(t) | \qquad (2)$$

$$PG_i(t) = 1 - \frac{1}{K}\sum_{k=1}^{K} | Ei_k(t) - G_k(t) | \qquad (3)$$

2.4. Local and Global Dynamics

Usually, the dynamics of a model represents the conditions that influence its temporal evolution. Its description should consider structural properties and their evolution. As the agent payoff depends on both local and global components, in updating the agent strategies one must account for both local interaction and global environment conditions.

From the local interaction point of view, an agent may choose its worse strategy (Li_k) and set it with the highest possible weight (one).

$$Li_k = \begin{cases} 1 \Leftarrow k = k_1 : Vi_{k_1} = \min(Vi) \\ 0 \Leftarrow k \neq k_1 \end{cases} \qquad (4)$$

At the next time step, the agent strategies are computed as in (5).

$$ELi_k(t+1) = (1 - F_i) \cdot Ei_k(t) + F_i \cdot Li_k(t) \qquad (5)$$

From the global point of view, the condition that determines the influence of the global environment on the agent strategies aims to maximize the alignment between them and the global strategies (G_k). Updating strategies also depends on the agent susceptibility (F), as defined in the expressions (6) and (7).

$$EGi_k(t+1) = (1-F_i)\cdot Ei_k(t) + F_i \cdot G_k(t) \tag{6}$$

$$Ei_k(t+1) = (1-F_i)\cdot Ei_k(t) + F_i \cdot \frac{ELi_k(t) + EG_k(t)}{2} \tag{7}$$

Since our model relies on strategic differentiation, when an agent changes its position in space the euclidian distance to its major competitors is intended to be enlarged. Finding out that competitor, the agent must define an inverse rectilinear trajectory, whose distance dependents on the agent mobility coefficient (S_i). Before each move, the agent must check the boundary conditions to see if it is a valid move. In that case, the new position $x_i^{'}$ is computed as

$$x_i^{'} = x_i + S_i \cdot d_{ij} \tag{8}$$

Finally, there is a population renewal rate (E) representing the lack of economic sustainability of agents operating under unpredictable markets This parameter specifies the percentage of agents that, at each time step, will be replaced by new ones.

3. Simulation Results

The model validation was based on experimental results obtained from the simulations of a baseline and four specific scenarios. The **baseline** fixes the start-up referential, with a set of typical values for each parameter. The remaining four scenarios represent real enterprises environments, and are created by individual variations of each parameter (according table 1). **Scenario 1** corresponds to high instability enterprise domains, with the global environment strategies continuously changing. The asymmetric influence of local and global competition is evaluated in **scenario 2**, which uses the agent myopia coefficient (M_i) to model this behavior. **Scenario 3** allows for investigating the influence of strategic concentration in agents' performance, through the variation of the concentration coefficient (C_i). Finally, **scenario 4**, is tailored to represent, geographic mobility.

The results obtained rely on four mains aspects: *i)* agent performance distribution, *ii)* influence of agent susceptibility to strategic change, *iii)* local *versus* global competition and *iv)* resources concentration during strategy definition.

Table 1. Scenarios configuration

<table>
<tr><th></th><th>Baseline</th><th>Scenario 1</th><th>Scenario 2</th><th>Scenario 3</th><th>Scenario 4</th></tr>
<tr><td>Number of steps, R</td><td colspan="5">100</td></tr>
<tr><td>Number of agents, N</td><td colspan="5">1000</td></tr>
<tr><td>Number of strategies, K</td><td colspan="5">K = 3</td></tr>
<tr><td>Mobility, S_i</td><td colspan="4">S_i = 0</td><td>S_i random</td></tr>
<tr><td>Renewal Rate, E</td><td colspan="5">E = 0.1</td></tr>
<tr><td>Neighborhood range, D</td><td colspan="5">D = 30</td></tr>
<tr><td>Susceptibility, F_i</td><td colspan="5">F_i random</td></tr>
<tr><td>External Environment $G_k(t)$</td><td>$G_k(t)$ random</td><td>$G_k(t)$ variable</td><td>$G_k(t)$ random</td><td colspan="2">$G_k(t)$ random</td></tr>
<tr><td>Agent myopia</td><td colspan="2">M_i = 0.5</td><td>M_i random</td><td colspan="2">M_i = 0.5</td></tr>
<tr><td>Strategic concentration</td><td colspan="3">C_i = 0</td><td>C_i=1, i=1,.., 100
C_i=0, i=101,., 1000</td><td>C_i = 0</td></tr>
</table>

3.1. Payoff Distribution

An important goal of this work is to characterize self-organizing properties emerging from the agents behavior. To this end, the distribution of the performance of the agents is evaluated, in two different situations: at the beginning of the simulations and after 1000 interactions have been performed

The results show that in the later situation, the distribution of the agents payoff displays a power-law signature, as often happens in several real societies (Pareto, 1897). Moreover, the results also show that the values of the payoff function are significantly higher in stable environments than in unstable ones (scenario 1).

When the role of an asymmetric influence is analysed (scenario 2), one verifies that it leads to higher payoffs, allowing to conclude for the advantage of asymmetric valorization of local and global strategies. Finally, the agents with strategic concentration (scenario 3), are likely to obtain higher payoff values, as advocated by Porter theory.

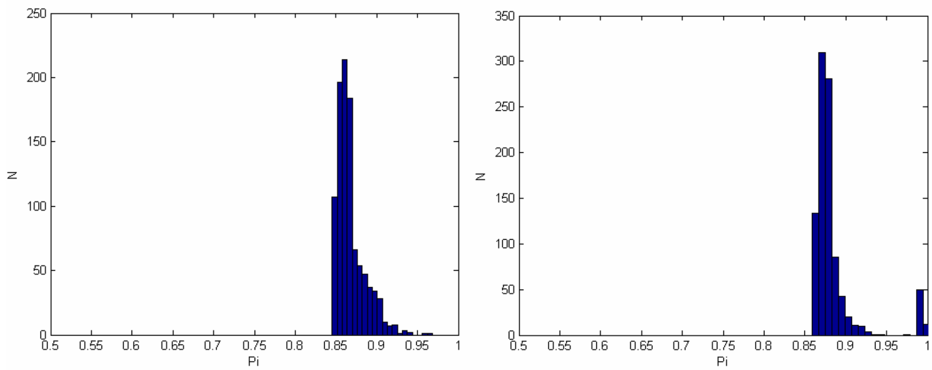

Figure. 1. Payoff distribution: baseline and scenario 3

3.2. Susceptibility to Strategic Change

The ability of the agents to change their strategic resources in order to maximize their profits has assumed a relevant role in strategy theory. Our simulation results show a non-linear relation between the susceptibility (F) of the agents, and their payoff values, in the baseline and in scenarios (1 and 2), Both cases, high inertia leads to high payoff values, while susceptibility superior to ½ leads to lower payoff values. One possible explanation is that the continuous strategic redistribution implies increasing costs.. In the opposite case, agents with reduced susceptibility may reach best performances, since they waste few resources trying to align with the global dynamics.

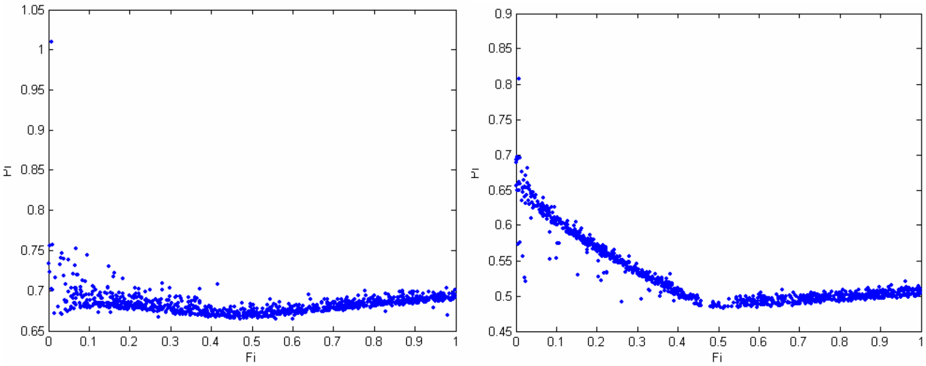

Figure. 2. Correlation between susceptibility and payoff: baseline and scenario 1

3.3. Strategic Concentration

According to Porter theory, concentrating investment in one of the four generic strategies is fundamental to enlarge performances. As Figure 1 and Figure 3 show, the agents with concentrated behavior obtain higher payoffs. We can see in Figure 3 that those agents have their payoff around three main values: $P_i = 1.42$, $P_i = 0.88$ e $P_i = 0.71$. Although we do not find any reason for these three different types of distribution, we must highlight the low variance of the payoff function of such agents.

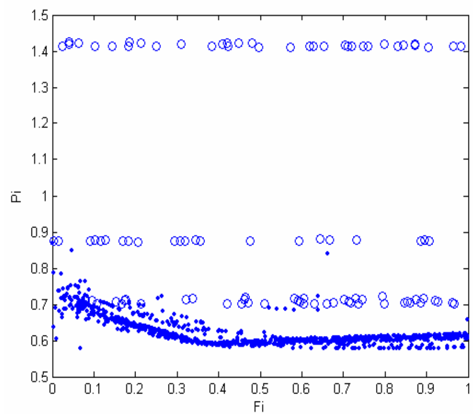

Figure. 3. Payoff versus susceptibility, in strategic concentration scenario

3.4. Local Competition versus Global Influence

The valorization of local competition *versus* global influence is evaluated from the values of the myopia coefficient. This coefficient allows the agents to asymmetrically weight local and global components. Figure 3 shows the correlation between payoff values and the agent myopia coefficient (M_i), in the baseline and in the instability scenarios. Baseline results show a non-linear correlation which tends to benefit extreme values of M_i. In the instability scenario results are interesting and unexpected: there is no apparent correlation. The specification of a major influence factor (local competition or global influence) seems to depend on the environmental conditions: under high doubtful environments, the agents should pay more attention to local competition, since competitive advantages come mainly from differentiation to direct competitors. Otherwise, both factors should be equally considered.

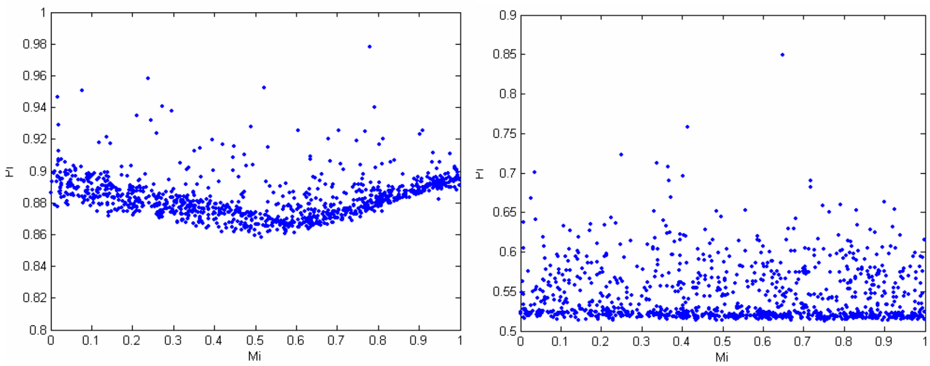

Figure. 4. Correlation between payoff and agent myopia: baseline and scenario 1

3.5. Agents Mobility

The final results concern the spatial (and self-organizing) patterns, as those observed in Figure 5. Departing from a random disposition, we come to a final distribution formed by three main clusters. Based on the agent properties, as susceptibility or mobility, and on performance indicators as the payoff function, we try to identify possible cause-effect relations that could help to understand the emerging patterns. However, it seems to be no apparent correlation between those properties and the agent coordinates

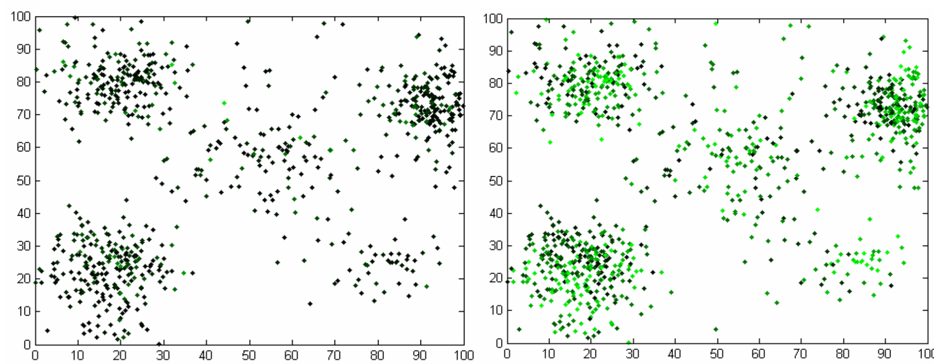

Figure. 5. Final spatial disposition depending on agent payoff and agent mobility

4. Conclusions

Complexity sciences and agent-based modeling have proved to efficiently deal with interdependent, non-linear and emergent factors of hypercompetitive environments.

The results obtained from simulations confirm the emergence of a power law distribution of the payoff of the agents. As the deterministic component of the model is reduced, such distribution has a particular interest since it follows the typical rule of distribution of wealth in real economies. Moreover, as this characteristic is absent at the initial setting, depending only on the dynamics of the agents. Regarding asymmetric valorization of local and global competition, results advise high weight of local interaction under high uncertainty and random environments, i.e., major competitive advantages result from differentiation capability with respect to closest competitors. The third main finding, concerns to the non-linear relation between susceptibility and individual payoffs, namely, the best performance of lower susceptibility enterprises, suggesting an organizational penalization caused by continuous strategic adaptation. Finally, concentration of strategic investments on a single strategy appeared to be a crucial factor to maximize performances, in line with Porter theory.

The abstract model herein presented provides enough freedom to interpret and recognize strategies as specific properties of the model. The availability of experimental (raw) data on enterprise real information may provide less abstract instantiations focused on a specific and concrete reality. Another possible improvement is related to enterprises operations such as fusions, partnership or direct acquisitions, since all these phenomena represent strategic actions on hypercompetitive environments. In this context, complexity sciences issues plus their increasing application in social and economical areas, are envisioned to improve the present approach.

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