Analysing industry profitability: a "complexity as cause" perspective.

CALDART, A.A. and OLIVEIRA, F.

2010

Analysing industry profitability. A "complexity as cause" perspective.

Adrian Caldart and Fernando S. Oliveira

We investigate how the competitive complexity of an industrial sector affects its profitability. For that purpose, we developed a set of simulations representing industries as complex systems where different firms co-evolve linked by multiple competitive dimensions. We show that increases in the complexity of an industry, resulting from increases in the number of players and in the number of competitive dimensions linking them, damages industry performance. We also found that the negative impact on performance resulting from a higher number of competitive dimensions decreases as the number of players in the industry increases and that the decrease in industry performance associated to big increases in the number of players is mediated by the number of competitive dimensions linking them.

Keywords: industry structure; competitive strategy; competitive dimensions; agent based simulations; complexity theory; co-evolution.

Introduction

The analysis of the structure of industrial sectors has been at the forefront of the strategic management field during the last three decades (Porter, 1980). This analysis has been mostly based on the Structure-Conduct-Performance (S-C-P) paradigm (Mason, 1939; Bain, 1956) originally developed in Industrial Organization Economics. The S-C-P paradigm suffers, however from some limitations, notably the employment of static analysis focused on equilibrium conditions and the assumption of homogeneity of firms within the industry (McWilliams and Smart, 1993). In this paper we address those two limitations by adopting a systemic and longitudinal perspective to analyze how the dynamics of competitive interaction evolve within an industrial sector. More specifically, we focus on how the structural complexity associated to the number of competitors in the industry and the number of competitive dimensions that characterize their interaction, affect the industry's performance across time. In order to illustrate these ideas we develop

a set of agent-based simulations representing industries characterized by different number of players who interact along different numbers of competitive dimensions.

This paper is organised as follows. We begin with a discussion of industrial sectors as complex systems composed by firms that interact along multiple activities. We then develop an agent-based model that captures the competitive interaction of multiple firms at the level of their activities. Finally, we analyze our results and discuss their implication for the debate on competitive strategy.

Industrial sectors as complex systems

From a systems theory perspective (Forrester, 1968) an industrial sector can be characterized as a *complex system*. A complex system has been usually described as "one made up of a large number of parts that have many interactions" (Simon, 1996, pg 183). Following this definition we can say that the complexity of an industrial sector, as a system composed by firms (the "parts" of the system) that interact with each other, derives from two different but related sources. The first is the *number* of firms competing in such an industry. As this number increases, the ability of each firm to anticipate and even notice their competitors' moves decreases making competitive interaction more complex. The second arises from the number of dimensions that characterize interactions between firms. Operationally, firms do not interact along a single dimension –as institution vs. institution– but along several activities, such as advertising, manufacturing, quality control, customer relations, logistics, customer service, etc, each of which contributing towards the creation of the overall value proposition of the firm. The

activities that are subject to competitive interaction in an industry constitute the *competitive dimensions* (Porter, 1980) within their industry.

The literature on competitive strategy has documented extensively the impact of the relationship between the first of these sources of industry complexity, the number of firms competing within an industry, and its profitability (Porter, 1980; D'Aveni, 1994). This work was rooted on the structure-conduct-performance (S-C-P) paradigm of Industrial Organization (IO) Economics. Its basic tenet is that economic performance of an industry is a function of the conduct of buyers and sellers which, in turn, is a function of industry's structure (Mason, 1939; Bain, 1956). The higher the number of competitors pursuing similar strategies in an industry, the more intense competition becomes as firms improve their value propositions in their attempt to gain customers' favour. Instead, in an oligopoly market, competitive intensity fades as the leader(s) tend to assume a coordinating role in the industry imposing discipline in the market, for instance, through their pricing policy (Tirole, 1988).

Less attention has been paid, however, to the impact on industry's performance associated to the number of competitive dimensions chosen by firms to pursue their value propositions. As firms formulate their strategies around a wider range of competitive dimensions the complexity of competition within such industry increases as the variety of possible changes in firms' value propositions grows exponentially increasing the potential of competitive clashes. Such complexity makes more difficult for firms to plan ahead in the long run, as their competitive landscapes are likely to suffer frequent alterations, damaging the performance associated to their current strategies. This situation

hampers firms' ability to improve performance by exploiting current knowledge incrementally within the boundaries of their current strategy, forcing them to explore alternative strategic directions.

A complete understanding of the structural drivers of industry profitability calls for a specific analysis of how shifts in the path of firms' strategic evolution, as a response to changes in their competitive landscapes derived from decisions from other firms along several different competitive dimensions, affect their profitability –and therefore that of the industry- across time.

Competitive dimensions in practice

Porter (1980) states that firms position themselves strategically within the industries according to some sort of broad "game plan". These game plans have been labelled in the literature, as generic strategies (Porter, 1980), value propositions (Treacy and Wieserma, 1995) or strategic options (Hax and Wilde, 2001). While these generic strategies are usually characterized rhetorically, for example, as "cost leadership" or "customer intimacy", operationally they are the result of a set of specific policy choices and routines followed by the firm. For instance, a "cost leadership" strategic position is the result of a set of consistent policy choices and routines aimed at increasing the firm's cost efficiency such as, for instance, highly standardized manufacturing, narrow product portfolios, a mature technology base and a "lean and mean" organisational culture. Each of these policy choices makes its specific contribution to the overall value of the firm's value proposition. When different firms choose to compete along the same policy choices these

become interdependent, representing the competitive dimensions of that industry. For instance, global leading manufacturers of eyeglasses, such as the two Italy-based firms Luxottica or Safilo, pursue "differentiation" strategies, built around several competitive dimensions such as a strong in-house product design, high profile marketing campaigns and control (through ownership or licensing) of a strong portfolio of sophisticated brands (Box 1).

[Insert Box 1 here]

The number of competitive dimensions characterizing competition may not only vary between different industries or strategic groups within an industry (Porter, 1980; McGee and Thomas, 1986) but also across time within the same industry as we show in Box 2 using the Tier 1 European car components industry as an example.

[Insert Box 2 here]

Box 2 illustrates clearly how the complexity of competition increases with the number of competitive dimensions, as firms need to master more capabilities in order to survive. Car component manufacturing firms competing in the Tier 1 sector in Europe by the mid 1980s could only survive till our days by developing capabilities in product development based on electronics and IT, component assembly engineering, setting and managing multiple technology joint ventures and alliances, market entry in countries outside Europe and adopting global management practices. Finally, if we divide the industry in strategic groups we realize that different strategic groups within the same industry are affected by different competitive dimensions (Porter, 1980). For instance, the capability to coordinate efficiently a global supply chain network constitutes a key competitive dimension in the

strategic group composed by global car component manufacturers supplying assembled car systems and sub-systems for OEMs ("Tier 1"). Therefore improvements made by one firm related to this activity will have a relevant impact on its cost position and will increase its relative competitiveness against its competitors'. However, the same capability would hardly constitute a competitive dimension for the strategic group populated by local Tier 2 (or Tier 3) SMEs firms supplying simple car components to Tier 1 players.

In order to analyze systematically how the performance of an industry is affected by its structural complexity, in the next section we introduce a formal model of competitive interaction in industries with different numbers of competitors and different degrees of competitive complexity.

A model of the evolution of industry performance

In this section we discuss our model of industry evolution. It is rooted on the theoretical tradition of behavioural and evolutionary theories (March and Simon, 1958; Cyert and March, 1963; Nelson and Winter, 1982). Firms in our model engage in problem-solving through path-dependent processes of search and discovery under bounded rationality.

A model capturing the evolution of the performance of firms that compete within an industry must satisfy several requirements:

- It must be, by definition, dynamic. A dynamic model is one where the variables at a given time are a function (at least in part) of the same processes at an earlier time (Koput, 1992).

- We need well-defined instructions on how the firm's search for better strategic positions unfolds as well as a representation of a payoff space or *landscape* in which such adaptive search takes place.

- Firms must be considered as heterogeneous entities, as during their co-evolution processes they evolve and learn about the existence of better strategic positions in different and path dependent ways (Nelson and Winter, 1982).

- We need the ability to track the performance associated to the different strategic positions that the firms may adopt during their evolutionary process in order to compare the relative merits of different strategies across different time horizons.

We decided to create a model of firms' co-evolution using agent-based simulation as this modelling strategy enables to address all the requirements stated above. In an agent-based model, individual agents, in our case firms, autonomously adapt making decisions based on internal rules and local information. Not being constrained by the imposition of equilibrium conditions, these models offer a degree of flexibility that permit to accommodate out-of-equilibrium behaviour such as the evolution of a firm's strategy over time (Arthur, 2006).

The advantages of the agent-based approach have been highlighted within the social sciences literature. Axelrod (1997) explains agent-based modelling as being a 'third way of doing science' differing from induction, the discovery of patterns within empirical data, and deduction, the proof of consequences that can be derived from a set of specified axioms. Davis *et al.* (2007) state that these models are particularly effective for research

questions involving fundamental organizational tensions or trade offs. Tensions often result in nonlinear relationships that are difficult to discover through inductive cases and difficult to explore using traditional statistical techniques.. Furthermore, Davis *et al.* (2007) state that the use of simulation enables the development of logically precise and comprehensive theory especially when the theoretical focus is longitudinal, nonlinear or processual. Table 1 summarizes the main advantages and shortcomings of agent based models, inductive and deductive methods at the time of analyzing strategic and organisational problems.

[Insert Table 1 here]

Agent-based models have been applied, to the modelling of organisations (March, 1991; Prietula et al. 1998), to the analysis of the formation of economic networks (Albin and Foley, 1992) and to the analysis of strategic decisions (Rivkin, 2000; Siggelkow and Levinthal, 2005). In this paper we build directly from Kauffman's NKC model (Kauffman, 1993). This model has been used in the context of organisation theory and strategy (Levitan, Lobo, Schuler and Kauffman, 2002; Ganco and Agarwal, 2008) as it is particularly versatile for analyses focused on the speed and effectiveness of a set of firms' interacting along a variable number of dimensions.

In the NKC model (Kauffman, 1993) firms are characterized as N dimensional vectors of binary variables. The value of each of those variables either 0 or 1, represents organisational policy choices (Nelson and Winter, 1982; Rivkin, 2000). These choices refer to the activities constituting the firm's business process, such as, for instance, purchasing, manufacturing, marketing, sales or customer service. As each policy choice

can only have two possible values, the modelled firm can pursue 2^N possible different configurations or strategies (Rivkin, 2000). The set of possible strategies and their associated performances constitute the problem space or "performance landscape" of the firm. In other words, the performance landscape of each firm consists of a multidimensional space in which each policy choice of the firm is represented by a dimension of the space and a final dimension indicates the performance level of the firm. In the model, firms adapt by modifying their existing policy choices through small changes involving local search in an attempt to enhance their performance in their performance landscape. The overall behaviour of the firm characterized by the vector $X\{X_1, X_2,...,X_N\}$ where each X_i takes on the value of 0 or 1.

The second parameter of the model, K, represents the number of elements of N with which a given policy choice interacts. When K=0, there are no interactions between the different policy choices. In the absence of interaction effects. global improvement is a sum total of local improvements. As seen in Figure 1, when there are no interdependencies between policy choices, the topography of this landscape is smooth, as neighbouring points in the landscape have nearly the same performance value. In this situation the performance landscape would show a clear maximum associated to the best possible strategy.

[Insert Figure 1 here]

However, in real life policy choices within a firm are hardly independent but show certain degrees of interdependence. For instance, policy choices related to the Market Development activity will affect also policy choices related to Product Development and

Manufacturing. This interdependence between policy choices within the firm is captured in the model by assuming that K>0. In this way, the contribution of a policy choice to the organisation's overall performance is affected by K other policy choices. The existence of interdependences between policy choices unable the firm to find a clear single optimal strategy as such policy choices tend to present complex trade-offs between them, leading to compromised decisions. These trade-offs make the performance landscape a more complex and less correlated one showing several local maxima or "peaks" (Figure 2).

[Insert Figure 2 here]

The third parameter of the model, C, measures the number of a firm' policy choices that are interdependent with those of other firms. In the model, those interdependent policy choices constitute the competitive dimensions that characterize competition in the industry. By enabling to connect the individual performance landscapes of the different firms at the level of their policy choices the parameter C adds two important features to the model:

- First, it makes the performance landscapes co-evolutionary (Figure 3). In this way, the performance associated to a particular strategy chosen by a firm may change as a consequence its competitors' strategic moves. Each firm's payoff surface of performance landscape "deforms" as a consequence of other firms' choices, making their evolutionary process more difficult.

- Second, it tracks competition at the level of the firms' policy choices. This enables us to analyze how changes in the number of competitive dimensions affect the performance of the industry.

The higher the number of interactive policy choices the more complex the firms' strategies become. For example, if C = 1 we say that the competitive complexity of that industry is low, as rivalry is based on a single competitive dimension, for instance, manufacturing cost. If C = 4 the industry has a higher competitive complexity as the incumbent firms compete along four different competitive dimensions, opening the door for a higher number of possible value propositions. The increase in the complexity of firms' strategies associated to higher numbers of interdependent competitive dimensions is analyzed in Figure 4, in which we represent the number of evaluations related to each strategy for an industry with five firms with N=10. This figure looks at two specific cases with C equal to 2 and K equal to 3. It shows that the complexity of an industry is an exponential function of the interdependencies between policy decisions within each firm (parameter K) and between different firms (parameter C).

At this point it is worth emphasizing that the model makes abstraction of the specific competitive context of a particular industry. Its power lies on its ability to analyze industries as complex systems in order to determine how complexity is, *per se*, a driver of industry performance. The model does not include any assumption relative to firm's competitive behaviour as it is the case, for instance, in the Cournot model (Tirole, 1988). Our model just assumes that firms observe the performance of their current strategy and "move" to a better position through local search, as they can only assess the expected performance of incremental moves due to bounded rationality. In this way, only the complexity associated to improving performance through local search, derived from their

interaction with other firms affects their individual performance and that of the industry as a whole.

[Insert Figure 4 here]

The model

The computational model was developed in Matlab. In our model all firms have the same number of routines, $N=12$, this number is big enough to illustrate the typical behaviour in complex industries, but small enough to be analyzed using simulation. There is no limit on N, it can be has big as required by the problem in analysis, however, the bigger Ns lead to complex environments and slower simulations. Firms are modelled in industries of different degrees of competitive intensity. As discussed above and summarized in Table 2, competitive intensity is characterized in our model by two dimensions: the number of firms competing in the industry (P) and the number of policy decisions that constitute interdependent competitive dimensions in such industry (C). Regarding the number of firms, we modelled duopoly (P=2), oligopoly (P=3) and fragmented competition (P=10). We represented situations of no interdependence between firms (C=0) as well as situations of variable levels of interdependence that we labelled as low interdependence (C=1), moderate interdependence (C=2) and high interdependence (C=4). For all the experiments, the degree of interdependence between policy decisions within firms was the same (K=5; See Appendix 1). As the model is dynamic and probabilistic, each simulation experiment is run 100 times in order to ensure the robustness of our results (as shown in Figure 6). This number is enough as the distribution for the means follows a normal distribution and the standard errors are small

12

enough to guarantee a robust result, as illustrated in Figure 6. Further detail on the robustness and the architecture of the simulation is provided in Appendixes 1 and 2, respectively.

Analysis of the simulations' results

The results from our experiments are summarized in Figures 5 to 9. Figure 5 represents the evolution of the average industry's performances for the cases of two, three and ten competitors. Average industry performance is a strong indicator of the industry's competitive intensity, indicating its relative attractiveness both for incumbents and potential entrants (Porter, 1980). Industry performance is computed as the mean of the performance values of all the firms included in the model. Firm performance is computed as the average of the performance values of the firm's policy choices.

[Insert Figure 5 here]

Overall, the results show that the performance of the industry is lower as the number of competitors increases and as competitive interdependence increases. In a 2 firms scenario with C=0 (no interdependencies) firms obtain the highest performance. Such performance is matched in the long term also by firms competing in a duopoly situation with low degrees of interdependence (C=1). Even markets with 3 firms and C=1 achieve similar levels of performance. The reason for this is that when competitive interdependence is low (only one competitive dimension), competitors' moves only alter minimally the competitive landscapes of each firm. In this competitive scenario, the performances

associated to the different strategies (or peaks in the landscape) are relatively stationary enabling firms to benefit from their incremental efforts to learn and improve their strategies. The situation is different when competitive complexity is higher (C=4). As the number of interdependent competitive dimensions increases, the firm's landscapes become more dynamic as there are now many decisions from each firm that affect the performance contribution of decisions from the others. Firms efforts to improve their strategies incrementally (peak climbing) are less effective as it is more likely that such peaks will shift. In other words, the attractiveness of a particular strategy is likely to be affected by the "emergent" changes derived from competitors' actions. These emergent changes destroy previous learning preventing firms from pursuing their intended strategies through a learning process based on the incremental refinement of a certain generic strategy.

Each experiment was repeated 100 times in order to ensure the robustness of the results. The t-statistics for the null hypothesis that the number of firms and the degree of complexity has no impact on performance is presented in Figure 6.

[Insert Figure 6 here]

Figure 6 shows that only in the case of two firms with C=1 the decrease in profit due to the increase in the number of interdependencies is not statistically significant. For all other cases the increase in the number of firms and in the number of interdependencies has a significant impact on performance. Moreover, the higher the number of interdependences and firms the lower the performance.

Figure 7 represents the differences in performance between the different cases versus the C=0 "happy world" of evolution in isolation from competition. When a low number of competitors (2 and 3) and low competitive complexity (C=1) are combined, we notice that firms can benefit from learning through time, improving their profitability and that of the industry. This is reflected by the notable narrowing of the gap between the profitability of the "no competition" case (C=0) and that of the cases mentioned above. In the case of 2 firms and C=1 the performance by iteration 100 is not significantly different from the one from the experiment with C=0.

In contrast, differences in profitability become substantial for cases with C=2 arriving to a maximum for industries with ten players and higher competitive complexity (C=4). In these cases the gap in profitability vs. the C=0 case widens and stabilizes in the long run. As the number of interdependent dimensions multiply, firms cannot, even in the long run, take advantage of their learning as their competitive game changes too frequently for them to improve gradually their strategic positioning through incremental search.

[Insert Figure 7 here]

Partial effects. Figures 8 and 9 analyze separately the impact of the number of competitors and of competitive complexity on industry's performance, respectively. Figure 8 illustrates the differences in industry profitability between industries with two players vs. those with three and ten for the same level of competitive complexity. Results show that increases in the number of competitors, keeping competitive complexity

15

constant, reduces industry profitability. Interestingly, differences in performance between industries with 2 and 10 players are lower for the highest level of complexity. The reason for this is the already low performance of the 2 players industry with C=4. This suggests that increases in the number of competitors in an industry with high competitive complexity are not as harmful as increases in markets with a lower number of interdependent competitive dimensions. The widest differences are noted in the cases with C=2.

[Insert Figure 8 here]

Figure 9 analyzes the differences in profitability due to differences in the number of competitive dimensions for the same number of players. We notice that in all the cases industries with a higher level of competitive complexity shows lower performance than those with a lower complexity, for a constant number of players. Moreover, the magnitude of the difference in performance due to the number of competitive dimensions is similar to that due to differences in the number of players. Interestingly the magnitude of this reduction is lower the higher the number of players in the industry. In industries with 10 firms, increases from low to high competitive complexity only decrease performance in a range between 3-7% throughout the simulation. Instead, industries with more competitive dimensions (C=4) perform much poorer than low complexity ones (C=1) for concentrated industries, duopolies and oligopolies, with differences reaching between 12-14%. A summary of the findings discussed above can be found in Table 3.

[Insert Figure 9 here]

[Insert Table 3 here]

Discussion

16

Our application of the NKC model to the analysis of whether complexity can be deemed a cause of differences in industry performance led us to develop three theoretical propositions.

Proposition 1: The higher the number of competitive dimensions within an industry the lower its profitability.

Our simulations' results showed that decreases in performance associated to increases in the number of competitive dimensions are comparable to those associated to increasing the number of competitors. This evidence has important implications at the time of assessing the intensity of rivalry within an industry. The number of competitive dimensions constituting bases of competition within an industry is as important as the number of firms competing in such industry at the time of explaining the impact of complexity on industry profitability. As the number of interdependent competitive dimensions multiply, firms interact along more activities, making their strategic choices vulnerable to a higher number of competitors' moves. This exponential growth in the number of potential emergent changes derived from competitors' moves makes more difficult for firms to pursue their intended strategies and make strategic management more a dialectic process than a long term plan or pattern. In this way, these results help to shed new light on the debate on deliberateness vs. emergence (Ansoff, 1990; Mintzberg, 1994; Porter, 1996). Our findings suggest that in industries with low competitive intensity, Porter's (1996, p. 77) advice to top managers to resist "constant pressures to

compromise, relax trade-offs and emulate rivals" is sound. Given the relative stability of their performance landscapes due to the small number of competitors and the low competitive intensity, these firms can learn incrementally how to make their strategies more efficient and eventually achieve high performance, as shown in Figure 4. This situation is consistent with the rational tradition of strategic planning embedded in the design, planning and positioning schools of strategy (Mintzberg, 1994).

As the environment becomes more dynamic (due a higher number of players and a higher number of competitive dimensions linking them), the competitive situation changes dramatically. The multiplication of the possible competitive responses along several different competitive dimensions makes each of the firm's decisions more subject to uncertainty, as shown in Figure 4. High competitive dynamism limits managers' ability to build incrementally on their current strategy, therefore, obliging managers to alter their initial plans and explore new strategic directions as a response to these emergent changes. Given the widespread agreement among academics and practitioners that business environments are becoming increasingly dynamic and complex (D'Aveni, 1994; Brown and Eisenhardt, 1998), these conclusions are especially relevant. What we have labelled as "landscapes with high competitive intensity" represent the kind of environments that we find in an increasing number of industries.

Proposition 2a: The higher the number of players, the lower the negative impact of the number of competitive dimensions on performance.

Despite the fact that a decrease in performance associated to an increased number of competitive dimensions was observed "across the board" in our simulation experiments, it is worth reminding the reader that these effects were smaller as the number of competitors increased. In our model, duopolies and oligopolies showed higher damage in their profitability from the increase in the number of competitive dimensions than their counterparties operating in fragmented industries with 10 players. Fragmented industries were already less profitable due to the impact of intense competition, being therefore relatively less affected by increases in the number of competitive dimensions. Therefore, firms willing to alter their value propositions by improving their offering around new competitive dimensions, should be more worried about the potential backlash derived from competitive responses if they compete in a concentrated industry than if they do in a more fragmented one.

Proposition 2b: The higher the number of competitive dimensions, the lower the negative impact of big increases in the number of players on industry performance.

An observation complementary to Proposition 2a is that in our experiments big differences in the number of players tend to have less impact on industry performance in complex industries than in industries with less competitive dimensions. For instance, Figure 8 shows that the impact on industry performance resulting from increasing the number of players from 2 to 10 is higher in industries with a low C than in those with a high C. This outcome of the simulations shows that a hypothetical increase of the number of firms due to the entry of several new players in a market, for instance due a

"competitive shock" in a particular country due to its entrance in a market block such as the EU, might have a milder impact on industry performance when the number of competitive dimensions linking the current firms is already very high. This finding implies that, at the time of making market entry decisions, managers should consider the number of dimensions characterizing competition in that industry as an important driver of the downside risk of industry performance. Ceteris paribus, an industry with a smaller number of dimensions is more prone to decrease its attractiveness as a result of an increase in the number of players than one with a higher number of competitive dimensions.

Proposition 3: As the number of competitive dimensions increases, it is less likely that industry profitability will stabilize in equilibrium.

The game theory literature has devoted great attention to the analysis of the competitive equilibrium. A competitive situation is deemed to show a Nash equilibrium when in a given state of the game no player can improve his reward by unilaterally changing his actions, (Fudenberg and Tirole, 1991). In our simulation models, we can define a Nash equilibrium as a situation in which no player in the industry can improve its performance by unilaterally changing one of the policy choices that compose its strategy. In such a situation, industry profitability would achieve stability. In our simulations we found that the higher the number of firms in the environment, the longer it takes until Nash equilibrium is reached. Moreover, competitive complexity also influences the long-term dynamics of a network of firms. In these cases coordination is harder to achieve; the

higher the value of C the less likely is that the firms' performance will converge to equilibrium.

Conclusion

This paper proposes a "complexity as cause" approach for the analysis of industry profitability. In doing so we developed a model of an industry as a complex system composed by firms showing different levels of interaction to analyze how such interaction affected industry's performance across time. Our approach proved to be a relevant one as we found that the two sources of industry systemic complexity analyzed, number of firms and the number of competitive dimensions, had a significant impact on industry profitability. More specifically, we brought to the forefront of the analysis the study of how the number of competitive dimensions characterizing competition within industries affects its performance, an issue that has been rather neglected in the competitive strategy literature. This paper contributes to the literature on competitive strategy in two ways. First, by showing that complexity is a major driver of industry profitability. Second, by using a novel methodology rooted in complexity theory that enables to model industrial sectors as complex systems and competitive interaction between firms as a dynamic phenomenon.

Longitudinal studies tracking the relationship between the evolution in the number of competitive dimensions of a sample of industries and their average profitability across time might contribute to reinforce the insights derived from this study.

References

Albin, P., and Foley, D. (1992). Decentralized, dispersed exchange without an auctioneer: A simulation study. *Journal of Economic Behavior and Organization*, **18,** 27-51.

Ansoff, I. (1991). Critique of Henry Mintzberg's The design school: Reconsidering the basic premises of strategic management. *Strategic Management Journal*, **12,** 449-461.

Arthur, B. (2006). Out-of-equilibrium economics and agent-based modeling. In: K. Judd and L. Tesfatsion (eds.) *Handbook of Computational Economics.* Elsevier/North Holland.

Axelrod, R. (1997). *The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration*. Princeton, New Jersey: Princeton University Press.

Bain, J. (1956). *Barriers to new competition.* Cambridge. Harvard University Press.

Brown, S. and Eisenhardt, K. 1998. *Competing on the edge: strategy as structured chaos*. Boston MA: Harvard Business School Press.

Cyert, R., and March, J. 1963. A behavioral theory of the firm. New Jersey: Prentice Hall.

D'Aveni, R. (1994). *Hypercompetition. Managing the Dynamics of Strategic Maneuvering*. New York; The Free Press.

Davis, J., K. Eisenhardt and C. Bingham (2007). 'Developing Theory Through Simulation Methods.' *Academy of Management Review*, **32**, 480-499.

Forrester J. (1968). *Principles of Systems*. Cambridge: MA: MIT Press.

Fudenberg, D., and J. Tirole (1991). *Game Theory*. Cambridge: The MIT Press.

Ganco, M. and R. Agarwal (2008) Performance Differentials between Diversifying Entrants and Entrepreneurial Start-Ups: A Complexity Approach. Forthcoming Academy of Management Review.

Hax, A. and Wilde, D. (2001). The Delta Project. Discovering new sources of profitability in a networked economy. New York: Palgrave.

Kauffman, S. (1993). *The Origins of Order*. New York: Oxford University Press.

Koput, K. (1992). Dynamics of New Idea Generation in Organizations: Randomness and Chaos in the Development of a New Medical Device. Ann Arbour, MI: UMI Press.

March, J. (1991). Exploration and Exploitation in Organizational Learning. *Organization Science*, **2**, 71-87.

March, J., and Simon, H. 1958. Organizations. New York: John Wiley & Sons.

Mason, E. (1939). Price and production policies of large-scale entreprise. American Economic Review, Supplement 29.

McGee, J. and Thomas, H. (1986) Strategic Groups: Theory, Research and Taxonomy. *Strategic Management Journal*, **7**, 141-160.

McWilliams, A. and Smart, D. (1993). Efficiency v. Structure-conduct-Performance: Implications for Strategy Research and Practice. *Journal of Management*, **19**, 63-78.

Mintzberg, H. (1994) The fall and rise of strategic planning. *Harvard Business Review*, **72**(1), 107-114.

Nelson, R., and Winter, S. (1982), 'An Evolutionary Theory of Economic Change', Bellknap Press, Cambridge.

Porter, M (1980). *Competitive Strategy. Techniques for Analyzing Industries and Competitors*. New York: The Free Press.

Porter, M. (1996). What is strategy? *Harvard Business Review*, **74**(6), 61-78.

Prietula, M. J., Carley, K. M., and Glasser, L. (1998). Simulating organizations: Computational models of institutions and groups. Cambridge, MA: The MIT Press.

Rivkin, J. (2000), 'Imitation of complex strategies', *Management Science,* **46**, 824-844.

Siggelkow, N., and D. Levinthal (2005). Escaping real (non-benign) competency traps: linking the dynamics of organisational structure to the dynamics of search. *Strategic Organization*, **3**, 85-115.

Simon, H. (1996), 'The Sciences of the Artificial', The MIT Press, Cambridge.

Tesfatsion, L. (1997). A trade network game with endogenous partner selection. In Amman, H., Rustem, B., and Whinston, A. B., eds., *Computational approaches to economic problems*. Dordrecht, The Netherlands: Kluwer Academic Publishers.

Tirole, J. (1988). *The Theory of Industrial Organization*. Cambridge, Mass.: MIT Press.

Treacy, M. and Wieserma, F. (1995). *The Discipline of Market Leaders. Choose your customers, narrow your focus, dominate your market.* Reading: Addison-Wesley Publishing Company.

Box 1.- Competitive dimensions in premium sunglasses frames.

The market of frames for prescription and sunglasses had polarized into two sharply differentiated segments in the last years: high-end products and low-end products. By 2005 the global leaders at the high end of the market, based on brand name and design, were two firms of Italian origin: Luxottica and Safilo. These two, besides their own brands, owned licenses to use some the world's most prestigious names. Luxottica sold frames by Bulgari, Chanel, Emanuel Ungaro, Ray-Ban, Versace, Dona Karan and Vogue. And Safilo had the Gucci, Polo Ralph Lauren, Giorgio Armani, Dior, Pierre Cardin, Burberry and Max-Mara brands. Controlling those brands gave the two firms access to other distribution channels apart from opticians, mainly stores selling products of the same brands.

The tendency for manufacturers to purchase licenses for well-known, medium-high to high-end brands had increased notably in recent years. Luxottica was the only manufacturer in the world that still based a substantial part of its business on its own brands, such as Ray-Ban and Vogue, and even so it had also been very active in acquiring licenses for other brands. The frame manufacturers paid the brand owners a royalty that usually consisted of a fixed component and a variable component based on sales. *Licenses had become so important that there was even competitive bidding for certain brands.* For example, Safilo had succeeded in wresting the Armani brand away from Luxottica, while Luxottica had snapped up the Dona Karan brand, previously linked to the U.S. manufacturer Marchon.

The marketing mix of premium manufacturers was completed by high profile advertising based on the endorsement of the firms' brands by worldwide well known celebrities such as top models, movie stars and figures from sport.

Box 2.- Competitive dimensions in the Tier 1 European Car Components industry.

The Tier 1 European Car Component industry experience substantial changes in its business model between the 1980s and the first decade of this century. These changes led to a substantial increase in the competitive dimensions or prerequisites for success of the industry.

By the mid 1980s European car component manufacturers's business was characterized by the following features:

Technological base: mostly mechanical engineering
Market scope: Western Europe for EU countries or national market in non-EU countries.
Products: car components, to be assembled in systems by manufacturers
Contracting practices: spot sales
Client: local plants who made decisions on sourcing usually relying in geographically close suppliers. This made logistics quite a straightfoward activity.
Competition: EU firms for firms operating within the EU landscape and local firms for firms operating in national protected markets such as Spain or Portugal.

The key competitive dimensions at this time were having a competitive manufacturing cost, competence in mechanical engineering for new product development and developing close links with the car manufacturing plants close to the operations of the component manufacturer.

By 2008, the same business is characterized by quite different features, leading to an increased number of competitive dimensions:

Technological base: mechanical engineering, electronic engineering and IT.
Market scope: Global.
Products: car systems, based on the assembly of components by the manufacturer.
Contracting practices: long term "technology partnerships" with OEMs lasting the whole life of the model for which the systems are manufactured.
Client: Global or regional headquarters of the car manufacturers.
Competition: firms from all over the world

In addition to the competitive dimensions cited above, the industry now has new ones such as having a competitive global system of plants, managing efficiently capacity allocation per project, assembly engineering, R&D increasingly based on electronics and IT and coordinated with the client, global sourcing and logistics, working in partnership with OEMs, dealing with increasingly demanding environmental and safety standards.

Appendix 1
Analysis of the robustness of the simulations

Despite our focus of study is competitive intensity, understood as a function of the number of players in the industry and the number of interdependent competitive dimensions between them, we are aware that the NKC model is also sensitive to the parameter K, measuring the degree of internal complexity of the firm. The results computed above assumed a value of K=5 equivalent to a mid/high level of internal complexity. In order to test the robustness of those results we reproduced all the simulations experiments for a value of K=1, a low level of structural complexity. We found that results for K=1 are consistent with those of K=5 along all the lines of analysis reported. Still, it is worth remarking that for the K=1 case, variance in industry performance is higher for all the cases versus that of K=5. The explanation for this is that while a higher level of internal complexity makes more difficult for firms to "fine-tune" its performance due to the impact of interdependences between its decisions, it mitigates the impact of bad decisions through the connection to other good ones. In the K=1 case instead, firms can adapt more easily due to their low level of interdependence between its decisions but suffers mistakes more intensively as an individual bad move cannot be as easily "averaged" with good ones.

Appendix 2
Architecture of the simulation

We now describe the architecture of the model and the settings used in the simulations of the NKC model. Each set of experiments is repeated 100 times so that we have robust results (this number of repetitions ensures that the distribution of the means is normal and that the standard deviations are small enough to ensure that all the t-tests for our results are statistically significant). The model follows the following architecture, for any given experiment:

1. Randomly generate the decision vector of binary variables $X\{X_1, X_2,...,X_N\}$, which represents the competitive dimensions of the industry.

2. For each player, evaluate the initial state, i.e., compute the value of the performance of the firm, given the decisions of all the players.

3. Start the simulation. While the maximum number of iterations is not reached, for each player:

   a. Generate the current state's neighbour states, assuming the decisions of the other players as given. This is done by swapping 1 and 0 (and vice versa) for each variable in the decision vector. (This corresponds to generate the neighbouring states that are a Hamming distance of 1 from the current state.)

   b. Evaluate the neighbouring states.

   c. Move to a new state if its value is higher than the current one, otherwise stay in the current state.

Evaluate a given state: The performance associated with each strategy is given an index between 0 and 1 (1 being the highest possible performance). The firm's performance is equal to the average of the contributions to performance of each of the N policy decisions, which depend on the level of complexity and interdependencies between the different players, controlled by the parameters K and C. The evaluation procedure works as follows:

1. For every variable X_i in the decision vector $[X_1,...,X_N]$:

   a. Identify the K neighbouring decisions $[d_1, d_2,...,d_K]$

   b. Identify the C decisions of the other players, for the corresponding decision variable $[d_{1,1}, ..., d_{1,C}, ..., d_{p-1,1}, ...,d_{p-1,C}]$, in which $d_{P,C}$ represents the choice C of player P. This is a vector with $(P-1)C$ elements.

   c. Append all the decisions identified in 1.b to the decisions identified in 1.a., in order to generate the state of the world: $[d_1, d_2,...,d_K| d_{1,1}, ..., d_{1,C}, ..., d_{p-1,1}, ...,d_{p-1,C}]$. This new vector has $(P-1)C+K$ elements and fully describes the state of the world conditioning each decision of the player.

   d. Generate a random number (r_i) between 0 and 1 to be assigned to the state of the world computed in 1.c, for variable X_i:

   e. $[d_1, d_2,...,d_K| d_{1,1}, ..., d_{1,C}, ..., d_{p-1,1}, ...,d_{p-1,C}] \rightarrow$ performance(X_i)=r_i.

2. Compute the performance of the player P as the average performance of each variable in the decision vector, as computed in 1.d:

$$\text{Performance } (P) = \frac{\sum_{i=1}^{N} performance(X_i)}{N}$$

In Figure 10 we present an example illustrating the interconnections between the choices of different firms. In this example we have 3 firms, N equals 4, C equals 1 and K equals 2. The connection between the different firms is through each one of their choices (in this case we illustrate only choice 2). If C equals two then each choice will depend on two choices of all the other firms, these would be for the corresponding choice and its right (down) neighbour.

Table 1

Comparison between research methods

|	Inductive (Case Studies)	Agent-based models	Deductive (Closed form models)
Agents' behaviour	Bounded rationality	Bounded rationality	Strict view of rationality prevalent
Heterogeneity of agents	Yes	Yes	No
Depth of analysis	Very high at firm level High (if possible) at industry level	Low at firm level High at industry level	Very low at firm level Low at industry level
Research paradigm	Interpretative	Positive	Positive
Captures behaviour out of equilibrium	Yes	Yes	No
Path Dependence	Yes, for longitudinal designs	Yes	No
External validity	Very low Sample size not representative	High, under the assumptions of the model	High, under the assumptions (stronger than those of ABMs)

Table 2
Simulation parameters

Parameter	Values
Number of policy decisions for each firm (*N*)	N=12
Interdependences between decisions within firm (K)	K=5
Number of players (*P*)	
Duopoly	P=2
Oligopoly	P=3
Fragmented industry	P=10
Interdependent competitive dimensions (*C*)	
No interdependence	C=0
Low interdependence	C=1
Moderate interdependence	C=2
High Interdependence	C=4

Table 3

Summary of findings

| Competitive situation	Impact
Increase in number of competitors	**Decrease in industry performance** *Decrease less pronounced when number of competitive dimensions is higher*
Increase in number of competitive dimensions	**Decrease in industry performance** *Decrease less pronounced when number of competing firms is higher* **Decrease in firms' ability to improve their position** **Increase in the variance of industry performance**

Figure 1
A smooth performance landscape
(K=0)
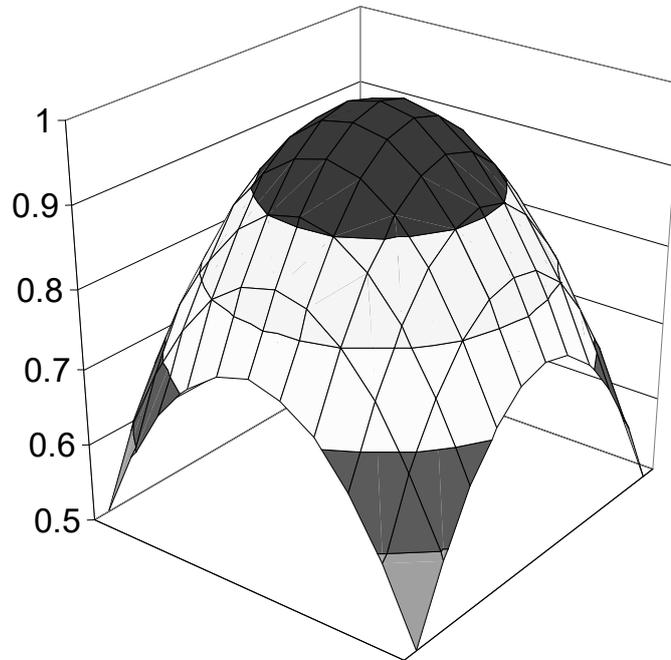
Figure 2.
A rugged performance landscape
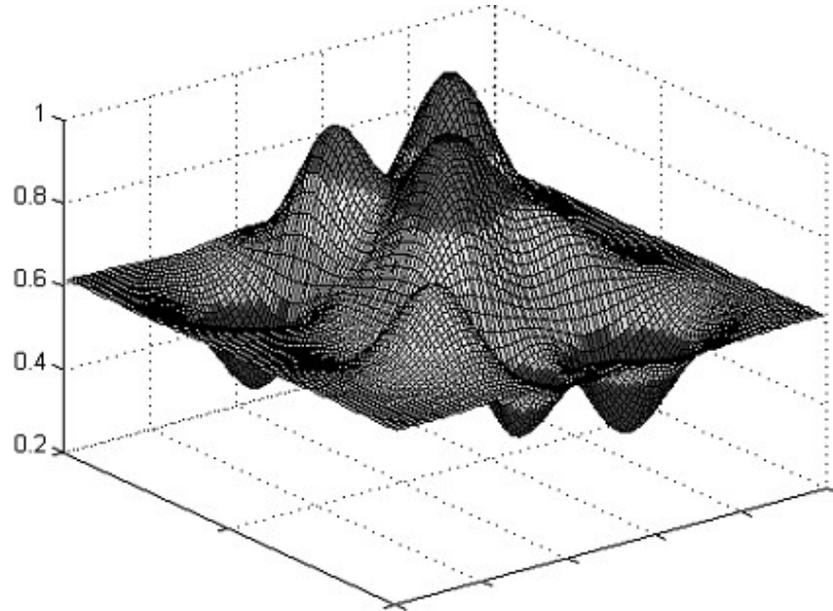
Figure 3
Co-evolving performance landscapes
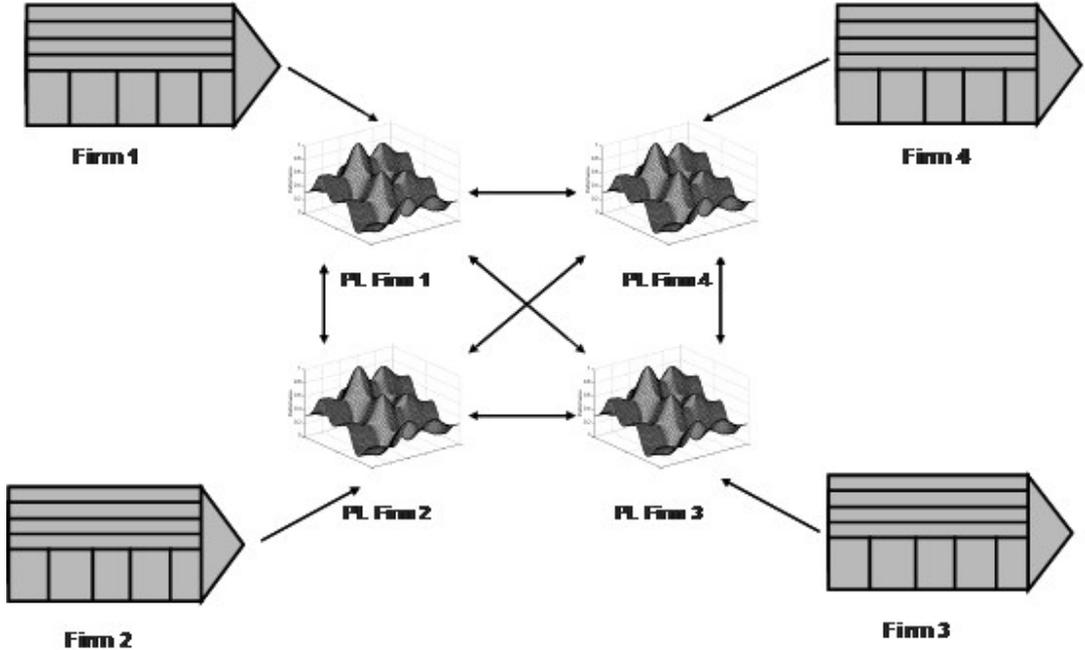
Figure 4.
Number of Computations required for N=10; P=5; K = 3 and C =2
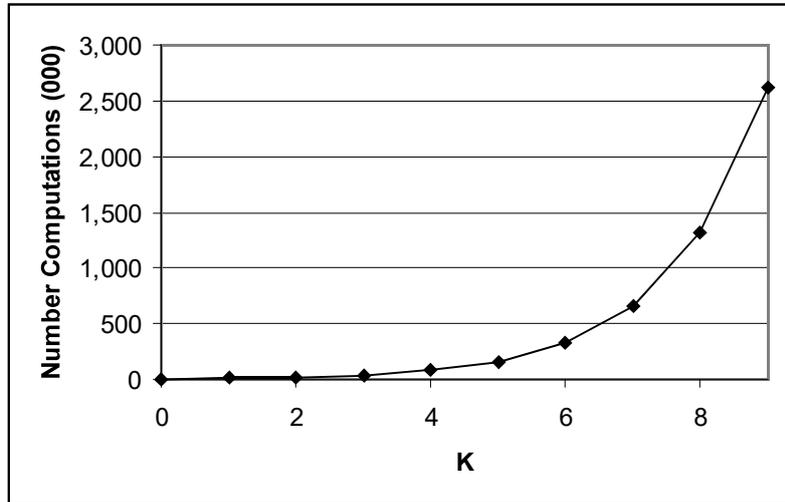
4.a) Number of Computations (000) for N=10, P=5 and C=2
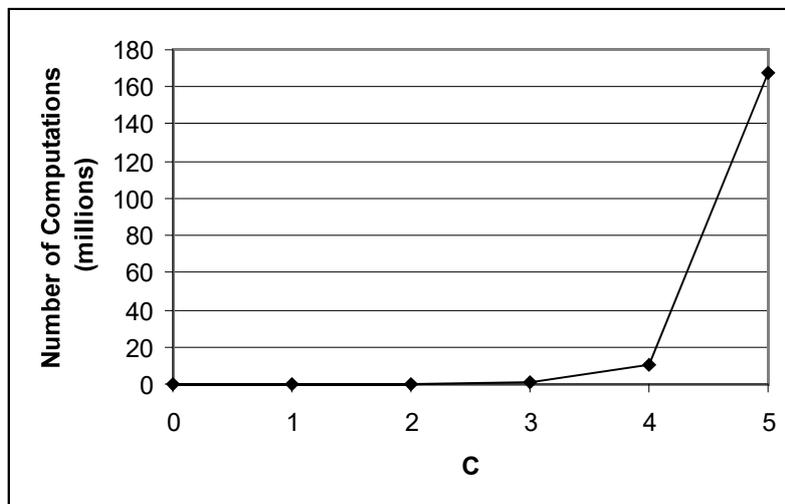
4.b) Number of Computations (in millions) for N=10, P=5 and K=3

Figure 5

Industry performance
2; 3 and 10 players
C=0; 1; 2; 4

Figure 6
t-statistics for the null hypothesis that the number of firms and complexity have no impact on performance

Figure 7
Differences in profitability between different types of industries

Figure 8

Differences in Industry Performance due to different number of players

% variation for 3 firms vs. 2 firms
% variation for 10 firms vs. 2 firms

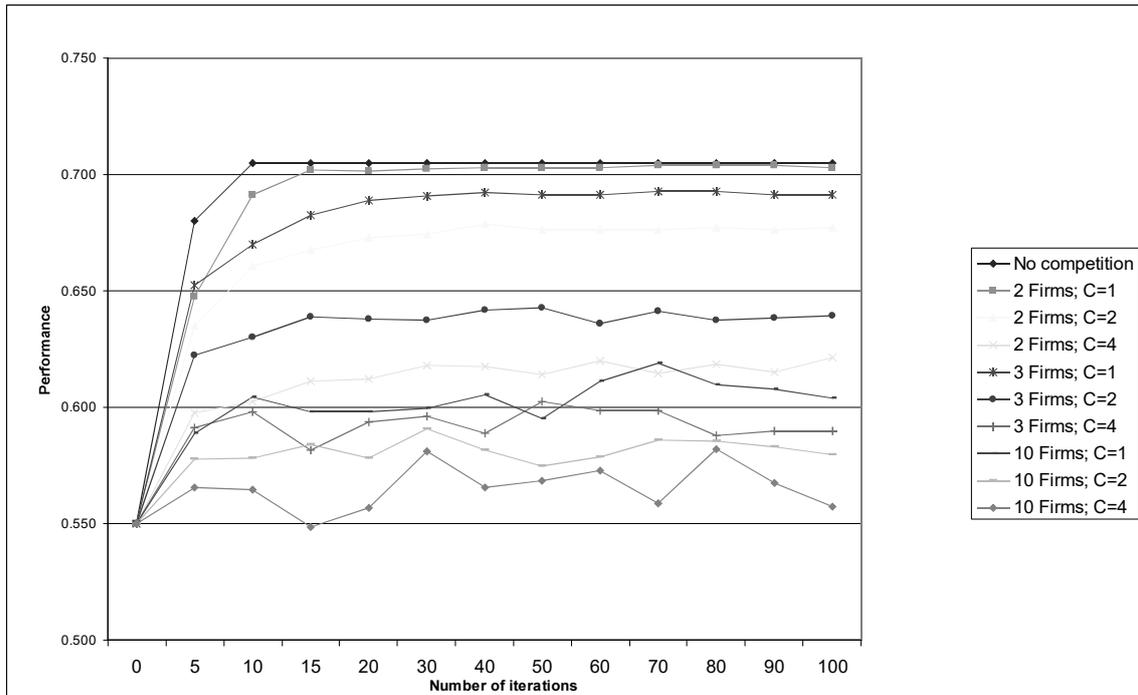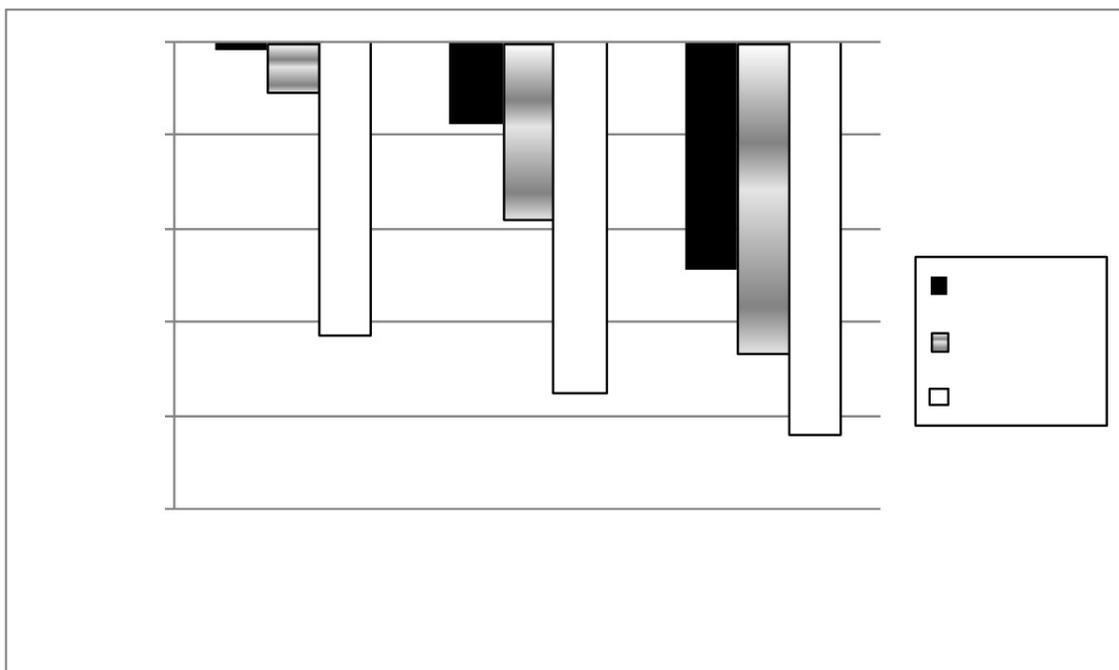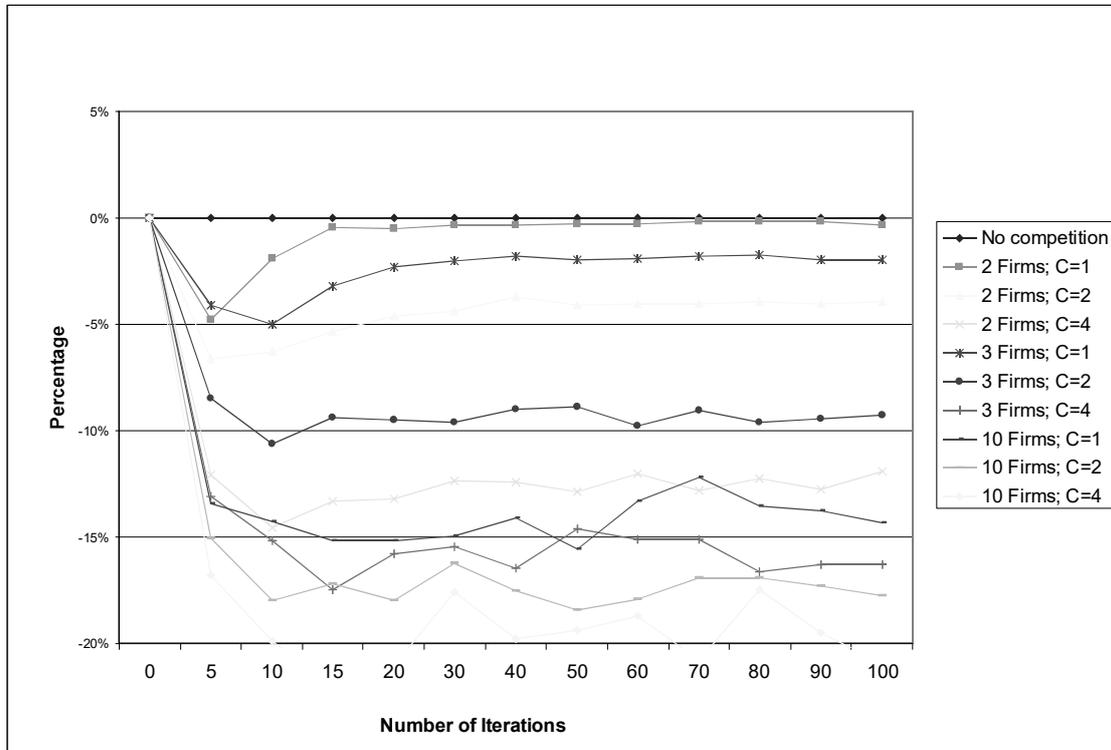|	0	5	10	15	20	30	40	50	60	70	80	90	100
3 vs 2 Firms; C=1	0.0%	0.7%	-3.1%	-2.8%	-1.8%	-1.7%	-1.5%	-1.7%	-1.6%	-1.6%	-1.6%	-1.8%	-1.6%
3 vs 2 Firms; C=2	0.0%	-2.0%	-4.6%	-4.3%	-5.2%	-5.5%	-5.5%	-5.0%	-5.9%	-5.2%	-5.9%	-5.6%	-5.6%
3 vs 2 Firms; C=4	0.0%	-1.1%	-0.8%	-4.8%	-3.0%	-3.6%	-4.6%	-2.0%	-3.5%	-2.6%	-5.0%	-4.1%	-5.0%
10 vs 2 Firms; C=1	0.0%	-9.1%	-12.6%	-14.8%	-14.7%	-14.7%	-13.8%	-15.3%	-13.0%	-12.0%	-13.4%	-13.6%	-14.1%
10 vs 2 Firms; C=2	0.0%	-9.0%	-12.5%	-12.5%	-14.1%	-12.4%	-14.3%	-15.0%	-14.4%	-13.4%	-13.5%	-13.8%	-14.4%
10 vs 2 Firms; C=4	0.0%	-5.4%	-6.3%	-10.2%	-9.0%	-6.0%	-8.4%	-7.5%	-7.6%	-9.1%	-5.9%	-7.7%	-10.3%

Number of Iterations
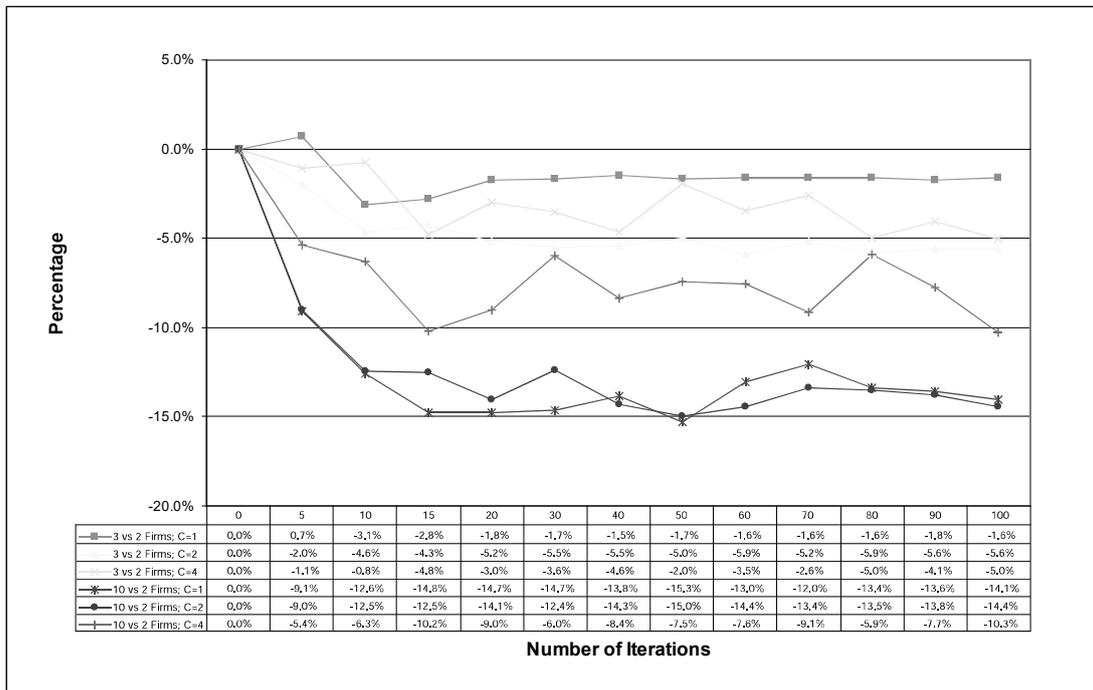
Figure 9

Differences in industry performance due to different number of competitive dimensions

% variation 2 competitive dimensions vs. 1
% variation 4 compretitive dimensions vs. 1

	0	5	10	15	20	30	40	50	60	70	80	90	100
2 Firms; C=2 vs C=1	0.0%	-2.0%	-4.5%	-4.9%	-4.1%	-4.0%	-3.4%	-3.8%	-3.8%	-3.9%	-3.8%	-3.9%	-3.6%
2 Firms; C=4 vs C=1	0.0%	-7.7%	-12.8%	-13.0%	-12.7%	-12.0%	-12.1%	-12.6%	-11.8%	-12.7%	-12.1%	-12.6%	-11.6%
3 Firms; C=2 vs C=1	0.0%	-4.6%	-5.9%	-6.4%	-7.4%	-7.8%	-7.3%	-7.0%	-8.0%	-7.4%	-8.0%	-7.7%	-7.5%
3 Firms; C=4 vs C=1	0.0%	-9.4%	-10.7%	-14.8%	-13.8%	-13.7%	-14.9%	-12.9%	-13.4%	-13.6%	-15.1%	-14.7%	-14.7%
10 Firms; C=2 vs C=1	0.0%	-1.9%	-4.3%	-2.4%	-3.3%	-1.5%	-4.0%	-3.4%	-5.3%	-5.4%	-3.9%	-4.1%	-4.0%
10 Firms; C=4 vs C=1	0.0%	-3.9%	-6.6%	-8.3%	-6.9%	-3.1%	-6.6%	-4.5%	-6.3%	-9.8%	-4.5%	-6.7%	-7.7%

Number of iterations
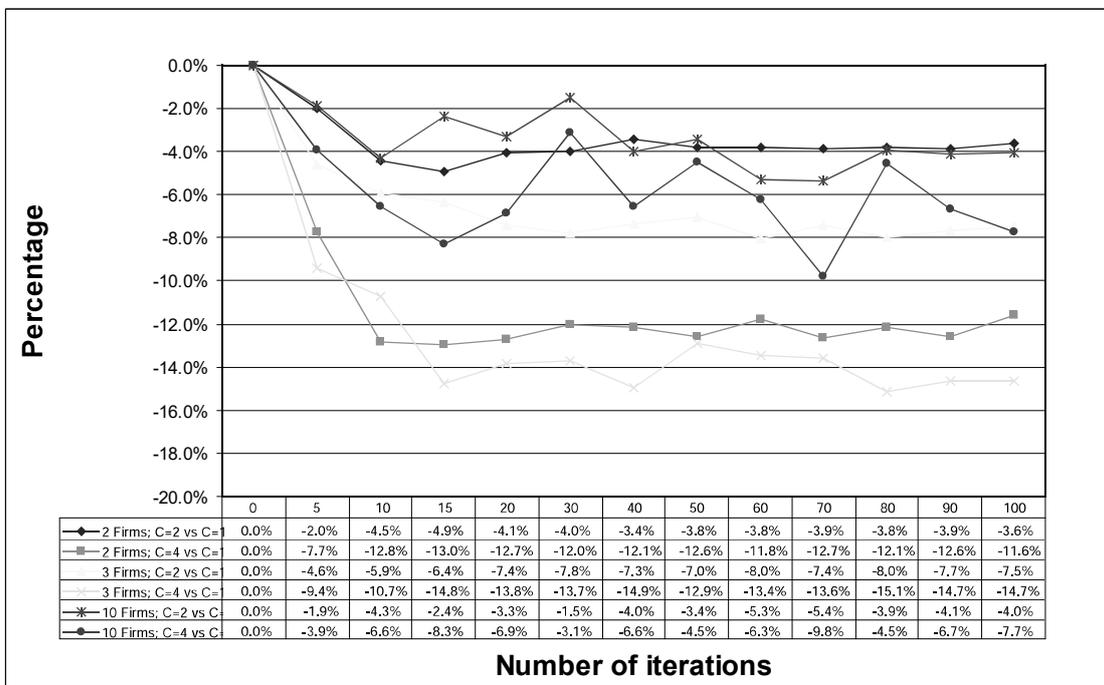
Figure 10

Representation of the connections between the strategic choices of 3 firms
This representation is for choice 2 only