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Rethinking Strategic Group Emergence through Genetic Algorithms

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Introduction

The purpose of this thesis is to explore possible applications of complexity to the field of management. In order to narrow the broad range of topics within these two areas of studies, it was decided to focus specifically on the phenomenon of strategic group emergence, which was long debated in the academic literature by the likes of M. Porter and R. Caves. The objective is to analyze and observe this phenomenon from the point of view of complexity sciences and to determine how that can be beneficial in gaining a deeper understanding of the subject.

In order to set the necessary theoretical background to accomplish the objective of this work, the definition of complexity needs to be discussed first. That will be done in the opening chapter, where a general overview about genetic algorithms will be also provided. In fact, different GA-based models, whose concept is strictly linked to the research on complex systems, are going to be employed for describing the dynamics of interactions between firms over the entire work and therefore need to be thoroughly discussed.

After having established the theoretical framework underlying this work, the phenomenon of strategic group emergence will be taken into consideration. The academic literature on the matter will be reviewed and the related lines of research, linked to different theoretical backgrounds, will be pointed out. In particular, the focus will be on the evolutionary framework developed among others by A. Alchian and G. Tintner, which distinguishes itself from the neoclassical one for its struggle to take into account uncertainty and adaptation when describing firms' behavior. This alternative line of research represents the theoretical basis which inspired J. Lee, K. Ree, and S. Rho, three Korean researchers from the Seoul National University and the Korea Advanced Institute of Science and Technology, to develop a GA-based model describing strategic interactions between firms. This model shows an interesting practical application of genetic algorithms and complexity in a management-related topic and it represents the starting point of this work.

The assumptions underlying Lee *et al*'s model will be tested in the third chapter. In order to accomplish that, the model is going to be replicated in Netlogo, a multi-agent programming environment. The original code, developed entirely for the purposes of this work, is made available in the Appendix A. Many simulations will be run in order to validate Lee *et al*'s conclusions and to further understand the phenomenon at issue. The successful replication of the model represents the first important theoretical result of this thesis.

In the fourth and last chapter, the flexibility of Netlogo will be taken advantage of to imagine alternative and equally coherent scenarios describing strategic group emergence. The new models developed in this way allow to further explore and understand the phenomenon of strategic group emergence. In addition to that, they intrinsically show the wide range of possibilities that this tool offers in describing different aspects of reality, according to different needs and premises. Possible future directions of research will be eventually pointed out. The successful results of the cooperation between these two fields of study open up new possibilities of re-interpreting management-related topics using complexity tools

1. Complexity and Genetic Algorithms

In the first chapter of the present work, the notion of complexity and genetic algorithms will be presented. The topic of strategic group emergence will be temporarily abandoned in this part to undertake a slightly longer journey with objective of acquiring a full overview about complexity. This chapter is fundamental to understand the theoretical framework upon which this work is based.

1.1 What is Complexity?

Many attempts to define the notion of complexity have been tried during the brief history of this discipline. However, no definition has been proven to be definitive and stable over time. The reason for this can probably be found in the nature of complexity itself, which tends to elude every struggle to be fixed in a static definition. Such an endeavor is not the objective of the present work. It is nonetheless worthy and necessary to clarify some of its main characteristics and to provide some historical background about the topic, with no presumption of completeness, in order to set the necessary theoretical background characterizing the next chapters.

Complexity arises in any system in which many agents interact and adapt to one another and their environments. […] As individual agents interact and adapt within these systems, evolutionary processes and often surprising "emergent" behaviors arise at the macro level. Complexity science attempts to find common mechanisms that lead to complexity in nominally distinct physical, biological, social, and technological systems.[1]

[1] Santa Fe Institute, viewed 5 January 2020, <https://www.santafe.edu/about>

This definition can currently be found on the website of the Santa Fe Institute, which represents one of the most important research centers on complexity in the world. It was founded by a group of twenty-four scientists and mathematicians in 1984, who understood how the modern challenges in each of their fields of study could not be faced through a static isolation of each discipline. In fact, the objective of the institute is to discuss the "emerging syntheses in science" and "to pursue research on a large number of highly complex and interactive systems which can be properly studied only in an interdisciplinary environment" (Mitchell 2009, p. X).

In the above attempted definition, it is possible to distinguish many keys and recurring features characterizing complex systems, i.e.:

- Multiplicity of agents
- Adaptation, both as a whole system and as a single agent
- Self-organization and emergence, meant as absence of any types of central control and predetermined paths of evolution
- Non-linearity

In order to better understand what these characteristics really mean in practice, let us take a simple and yet profound real-life example of complex systems: ant colonies (Mitchell 2009, p. 4). These large groups gather thousands of little insects, which are among the biologically simplest animals on earth. Yet, ants are able to perform extremely complicated tasks, considering their size and their intelligence as a species. They are, for example, able to build huge and stable nests and other structures, fight enemies jointly, and seek out food. *How is that possible?*

Let us analyze the case of the research for food.[2] Of course, no single ant has any clear perception about the surrounding environment nor any idea about where the food could be. How are ant colonies able to find food and to survive then? It is hardly possible to understand it, if a reductionist approach is employed, in which the actions of every ant are considered separately. Analyzing the system as a whole from the perspective of complexity is the key to reach a deeper comprehension of this phenomenon. If we try to model the ants' behavior when looking out for food, it would be possible to summarize it through two simple rules:

1. Move around randomly in the outside environment ("explore")
2. If food is found, release a chemical signal and bring the food back to the nest ("exploit and communicate")

These simple premises trigger a specific response from the system which leads to complex behavior. In fact, the thousands of ants start to move randomly in the outside environment, without having any idea about where the food could be. At this stage, two characteristics of the complex systems are already observable: multiplicity of agents and absence of central control (there is no one telling anybody where to go). When some lucky ant eventually finds some source of food, it spontaneously releases a chemical trace and takes the food back to the nest. What does this chemical accomplish? Every surrounding ant is naturally attracted by this signal and directed to its source (the food). The process is not so smooth and simple, though. In fact, at the beginning the trace may not be strong enough and just a few ants (or none at all) might be attracted to it. It takes a bit of time until a significant intensity is reached and a considerable number of ants start exploiting

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[2] Many models have been created to simulate ant colonies behavior. For the ants' model, see Wilensky (1997).

the food source. The effect is exponential. In fact, every ant which manages to find the food source will release this chemical trace as well, therefore attracting an exponentially higher number of ants. That is a clear expression of the non-linearity of the process. Because of the higher intensity of the trail itself, it will be easier for every ant in the colony to find the food. In this way, the source is going to be exploited until its exhaustion. The process is then repeated again for another food source. The ants managed to cooperate in a fairly efficient way in order to perpetrate the species, despite the fact that none of them knew exactly what was going on.

Notice that the final outcome of this process, its timing and its dynamic cannot be exactly predicted in advance. It is a gradual result, which depends on many factors that are not entirely controllable or even recognizable (e.g. the probability of one ant to end up finding one food source instead of another, the density of ants in each portion of space, the distance of the food from the nest, etc.). This explains at best what "emergence means": the outcome is generated step by step, without following any type of predetermined path. The colony managed to adapt to the external environment (to find the food and survive), both as a whole and as a single entity.

Complexity is much about an inter- and multi-disciplinary approach. The fascination that comes from this way of seeing things stems from its ability to connect very different types of disciplines. We just used the point of view of complexity to better understand a biological phenomenon. However, complexity is employed to gain deeper insights about other extremely complicated phenomena and "wicked" problems in many fields of study, such as physics (e.g. kinetics), chemistry (e.g. chemical reactions) social sciences (e.g. segregation), finance (e.g. artificial financial markets) and many others (e.g.

climate change). In the present work, the benefits of the employment of complexity tools also in the field of management will be shown.[3]

1.2 What are Genetic Algorithms?

Many GA-based models are going to be employed in the present work as a tool for describing the firms' behavior. For this reason, the concept of genetic algorithm is crucial and it deserves to be treated separately. What distinguishes a genetic algorithm from a simple algorithm?

An algorithm is defined as "a set of mathematical instructions or rules that [...] will help to calculate an answer to a problem".[4] It refers to the instructions (the "recipe") to follow in order to find a solution to a specific issue. The adjective *genetic* refers to its intrinsic possibility to *generate* increasingly better solutions to an optimization problem. The term "genetic algorithms" mixes two very different disciplines together: genetics and mathematics/computer science. This is no chance, since the inspiration for conceiving these types of algorithms came exactly from the studies on the DNA, the natural selection and, in general, the mysteries of adaptation.

John Henry Holland, professor of computer science at the University of Michigan, was the first one to introduce this term. He was extremely interested in the phenomenon of evolution. In particular, he was trying to find an answer to the question: *"How does evolution produce increasingly fit organisms in environments which are highly uncertain for individual organisms?"* (Holland 1992, p.2). In fact, it is observed that living organisms in nature have the capability to increasingly adapt to the external environment and to

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[3] Recently, there have already been some attempts to do it - see Allen, Maguire, McKelvey (2011) for the main reference book about the topic. Nonetheless, management studies were not, so far, one of the disciplines where complexity was employed the most. That was probably due to the difficulty to model in an effective manner this field of study.

[4] Cambridge Dictionary, viewed 5 January 2020,<https://dictionary.cambridge.org/dictionary/english/algorithm>

survive. This fitness with the external environment is made of virtuous behaviors and routines, which intrinsically assume the environment as something static and immutable. However, in reality, the nature of the surrounding environment is not stable at all. Changes can be observed over time and sometimes even in a very sudden way. The organisms in nature cannot predict those changes. They have to adapt quickly to the new conditions, which could also make their previously virtuous behaviors and routines detrimental. There are clearly two conflicting needs coming into play here. On the one hand, there is the need to fix some determined and day-to-day rules to live in the environment and, on the other hand, the opposite demand to be responsive to fast changes of the outside conditions. *How is adaptation possible?* Biology and genetics are very helpful in finding an answer to this question. In fact, in nature, the fittest organisms are more likely to survive and, therefore, more likely to give birth to a new generation of individuals. This new generation will include the genetic legacy of the parents, conveniently mixed through crossing over of the DNA. For this reason, a solid fitness with the external environment is preserved throughout the generations. That is not all. During this process, some random mutations can occur. This fact is very important, since it leaves room for improvement in case of change in the external environment. This explains how living organisms can respond to these two conflicting demands and how adaptation is possible.

Holland was inspired by the natural selection process and realized that the same procedure could be fruitfully employed in the field of computer science and mathematics. It is not a chance that the structure of the genetic algorithms clearly retraces these intuitions. In fact, the complete formal structure of a genetic algorithm generally comprises the following phases:

1. Creation of an initial population of random candidate solutions to a problem
2. Test of the performance of each candidate solution thanks to a fitness function

3. Selection of the best-performing solutions to generate a new population of candidates through crossover
4. Mutation of some genes in the new generation with a low random probability

In other words, a genetic algorithm, as any other type of algorithm, is geared towards finding a solution to a determined problem. In this specific case, it is often employed to solve an optimization problem. In order to accomplish that, it creates random answers to that problem and selects the best among them to generate new solutions. The selection is possible thanks to a "fitness function", which represents an indicator of the candidate ability to solve the problem or, more in general, to "fit" with the external environment (as the name suggests). The higher the value of this indicator, or fitness score, the better the proposed solution to the problem. The best performers, ranked according to their score, have the highest chance to generate new solutions. The newly-born solutions comprise a mix of characteristics of the "parents" and some random mutations. Thanks to these simple operations, the fitness score increases generation after generation, until it reaches optimal results. In the next paragraph, a practical example of genetic algorithm will be discussed.

A genetic algorithm – "Robby the Robot"

"Robby the Robot" represents an interesting practical example of genetic algorithm. It was introduced first by Melanie Mitchell and it gained popularity over time (Mitchell 2009, p.130)[5] Robby is a robot-janitor, whose purpose is to collect the highest quantity of trash (in the simplified form of scattered cans) spread on the ground. The "ground" is simplified as a 10x10 square environment, in which Robby can freely move.

[5] The popularity is testified by many different versions of this model. See for example: Pattis (1981) and Mcleod & Nasrinpour (2018)

Every time Robby picks up a can, it gains 10 points. If it crashes into a wall, it loses 5 points. Finally, if Robby decides to pick up a can in a site where there is none, it loses 1 point. A determined number of moves are available to the robot to achieve the best score. After that, the game resets and new trash cans are created and thrown randomly into the new environment. The score also starts over from zero.

Robby's possible moves are: move-north, move-south, move-east, move-west, move-random, stay-put and collect-a-can. In deciding its next move, Robby takes into consideration its surrounding environment. It is able to perceive just the square it is in at that moment and the five adjacent ones (north, south, west and east).[6] Each of these sites can either contain a can, be a wall, or be empty. This means that the different possible scenarios in which Robby can find itself are 243. In fact, there are three different states combined with 5 different sites. (= 3^5). For each of these 243 circumstances, Robby has a determined response, which is present in his "genetic code". Of course, some decisions will determine a higher score than others. For example, if Robby systematically crashes into walls, its score will most likely be worse than if it decided to avoid them. We define "strategy" here as the sum of every action taken by Robby in response to each of the 243 different states of the world. It would be possible for a human to write down a good strategy for Robby to be a decently efficient janitor. However, let us give a chance to a genetic algorithm and see how it performs.

As formally described in the previous paragraph, a GA will initially generate different random solutions and assign them to a given population of "Robbys", comprised by a determined number of robots. After each run, the algorithm will calculate the performance of each individual using the fitness function described above.[7] After that,

[6] In the model, it is not possible for Robby to sense the other 4 sites located North-West, North-East, South-West and South-East. It could be interesting to modify the code by adding also this possibility and observe the change in the performance.

[7] Fitness score = (10 points * cans collected) – (5 points * crashes on the wall) – (1 point * times that Robby tried to collect a can in an empty site)

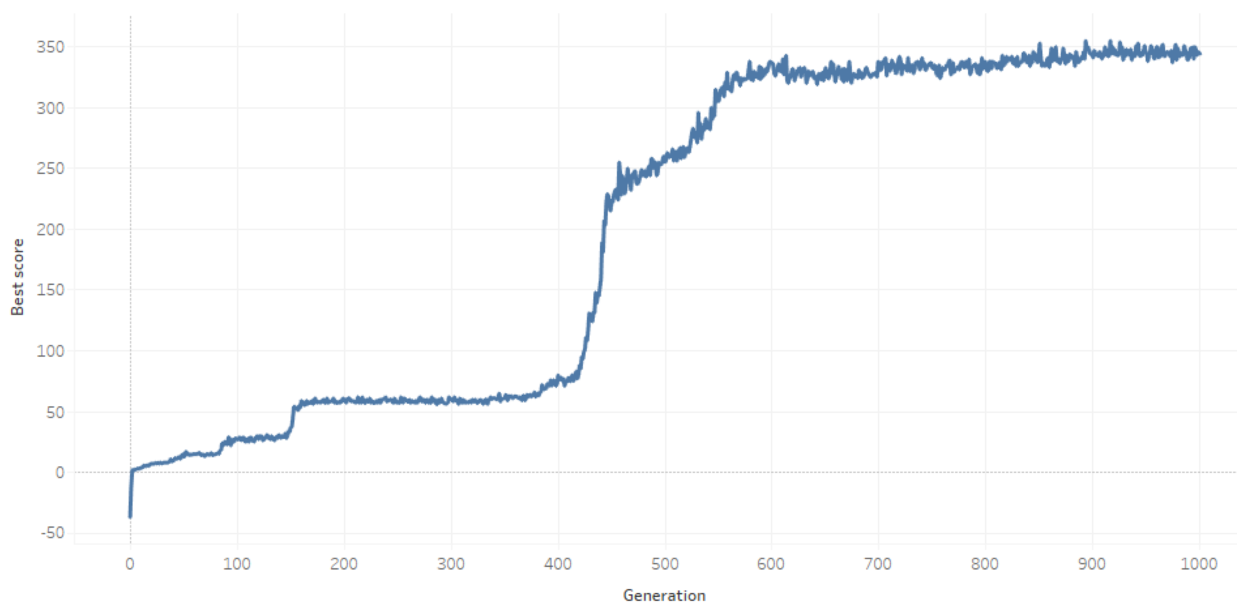
it will rank them accordingly. The best-performing individuals are going to have better chances of being selected as parents and, therefore, to transmit their strategy. As a final step, random mutations modifying the final "gene" of the offspring can occur with a certain probability. In this way, a stochastic component adds some volatility to the model. This grants diversity to the population and avoids an early convergence to a specific chromosome structure. In the model, the original number of individuals are kept unaltered (the population size does not grow or diminish). The different types of parent combinations create a brand-new set of candidate strategies that will be assigned to each individual in the population of robots. The same operations described above are then repeated again and again for every new generation.

The described model was replicated successfully in Netlogo by Mitchell, Tisue, & Wilensky (2012). That makes it possible to easily run some simulations and to discuss the outcomes. In this way, it will be easier to fully grasp the functioning of a genetic algorithm.

Computational results

The Netlogo version of the Robby the Robot model replicates almost exactly the one described above. Few aspects have to be clarified, though. Each Robby has 100 moves available to score the highest number of points. That can be considered its life duration. After that, the game resets and a new generation is created. The selection operator has been modeled to take into account both performance and randomness. To select two parents, 15 potential candidates are first selected randomly over the entire population. The top performer between them is then selected as first parent and will provide the first sequence of "genes" characterizing the child's strategy. The same operation is then repeated to select the second parent to complete the full chromosome. The parent strategies are mixed through crossover: a mix of the two different parent genes occur by exchanging the separate parts of each parents. The mutation operator sets first a determined likelihood for a change in the agent's behavior to take place. When mutation occurs, an action related to a specific state of the world is changed to a random one.

For the current simulation, the population of robots has been set to 100 individuals. That means that every generation, 100 robots are competing for the best result. The mutation rate has been established to 1%. Each single individual action in response to a determined state of the world has 1% of probability to randomly change each generation. Having clarified these premises, it possible to analyze now the computational results, shown in the graph below:



As it clearly emerges, the genetic algorithm managed to develop an increasingly better strategy, generation after generation. The trend of this improvement is nonetheless volatile. Until about the 400th generation, the best score among the population of robots was around 50 points. Suddenly, the performance dramatically improves in a very fast way, until it reaches a value of ca. 250 points. That represents a 500% improvement in a bunch of generations. What happened there? Most likely, a favorable random mutation in a new offspring gene occurred. This has determined the sudden increase in the performance. Thanks to the selection operator and the quality bias, the favorable mutation, generated initially at random, was inherited by the individuals in the following generations and became stably part of the genetic legacy of the robots. That played a crucial role in increasing the average score durably over time. The following increase in the performance, from the ca. the 400th generation to the 600th is way smoother than the previous one. Most likely, this improvement was due to the small and constant progress in the candidate performance thanks to the selection operator. From the 600th generation, the fitness score gets steady again. There is not much room for improvements anymore. However, it is to be underlined that even if the top performer's score does not change much, the average score among the population of robots increases and a convergence between the top scorer and the worst scorer can be observed. The analyzed simulation is very explanatory because it makes it possible to analyze two different types of improvements, equally possible in the model: huge, sudden, and random on the one hand, and slow, planned and constant on the other. If more simulations were run, the average trend would most likely be steadier and more linear, but these aspects would not be observed.

The maximum score reached in this simulation was 355 points. Is it a good result? To answer this question, it must be determined first what the maximum score possible is and compare it to the one obtained here. It is possible to calculate it considering the total number of cans present in the environment each run. Looking at the code of the Netlogo model, it is possible to see that the can's density is about 50%. Given that the environment is a 10x10 board for a total of 100 squares, the total number of cans is 50.[8] The highest score possible is therefore 500 points (=50*10), assuming that Robby never hits a wall or tries to pick up a can where there is none (both actions determine a point penalty). This

[8] The actual number varies a little (from 48 to 52) according to some random variables.

score is just theoretical though, as it does not take into consideration other important factors. Robby's maximum moves per run are 100. In the model, the action "pick a can" is considered a move. If Robby were to pick up all 50 cans, there will be just 50 remaining moves to find the remaining cans. Therefore, for each of the 50 remaining moves Robby should end up on a square that contains a can it can collect. This means that every square with a can should border one another with another square containing a can as well. Assuming that the distribution of cans is random, this would be possible in just few scenarios among the millions of combinations. The reason why the fitness score improves up to a certain point and then remains steady is related to the fact that, generation after generation, the best performers reach a close to optimal score which is increasingly difficult to overcome. For these reasons, Robby's performance of 355 out of 500 (theoretical maximum) is a pretty good result, considering that the original strategy was generated at random. Actually, this strategy is very often better than what a human would rationally conceive in the first place (Mitchell 2009, p.135).[9] In fact, the evolution of the strategies brought to behaviors that might even seem counter-intuitive and that instead revealed themselves to be extremely successful. For example, in some situations Robby deliberately decides not to pick up some cans, even if it could, in order to use them as a marker to guide it in the collection of more cans present in the neighboring cells. Emergence of hardly predictable behavior, typical of complexity and complex systems, is again clearly observable here.

The necessary context for the understanding of genetic algorithms has been now set. It was previously said that genetic algorithms are often used to find a solution to an optimization problem. Interestingly, the use of a GA-based model for the purposes of the present work will completely transcend that. In fact, genetic algorithms can also represent an extremely useful tool in describing the behavior of agents embedded in complex

[9] In this case, the GA beats the human strategy by more than 100 points.

systems. Thanks to them, it is possible to instruct agents to follow simple rules and to observe the outcomes of their interactions, both as a single entity and as a whole. In such an acceptation, GAs are a tool that allows the possibility to observe and study particular types of complex systems from a privileged point of view, as it will be clearly shown in the next chapters. Holland understood that, as he claimed in the preface of the 1992 edition of *Adaptation in Natural and Artificial Systems*:

"Genetic algorithms began to be seen as a theoretical tool for investigating the phenomena generated by complex adaptive systems - a collective designation for nonlinear systems defined by the interaction of large numbers of adaptive agents (economies, political systems, ecologies, immune systems, developing embryos, brains, and the like)" (Holland 1992, p. IX)

2. Strategic Group Emergence, Complexified

In the first part of this chapter, strategic groups will be shortly defined and the background academic literature on the matter will be discussed. In the second part, a GA-based model outlining the phenomenon of strategic group emergence, developed by Lee, Lee & Rho (2002) and inspired by Alchian's and G. Tintner's evolutionary framework, will be thoroughly described. After that, the computational results of the related simulation runs will be presented and analyzed.

2.1 Strategic groups in the academic literature

The term "strategic groups" was coined first by Hunt (1972) to define different clusters of companies within the same industry, whose survival strategy varies on one or more key dimensions. The strategic choices of firms within the same strategic group regarding key activities, key resources, products, etc. are instead very similar. The concept of strategic groups started to gain popularity in the strategic management field over time, since it provided an effective tool to interpret different industries.

Caves & Porter (1977) further deepened the research on the subject.[10] According to them, the origin of strategic groups can be attributed to random initial differences in the firms' resources, competences and preferences, which eventually leads to the formation of groups of firms adopting the same strategy. However, one of the most important contributions to the discussion pertains the differences in performance between the groups. They introduced the concept of mobility barriers, which negatively affects the

[10] See also Porter (1980)

success probability for a firm to enter a strategic group.[11] They represent different types of structural obstacles (capital costs, economies of scale, legal barriers, learning curve, etc.). In addition to that, Caves & Porter (1977) discussed the tendency to collude in order to hinder the possibility for other companies to enter another strategic group. In this way, firms within the same strategic cluster prevent profits' degradation due to increased competition.

Another line of research about the topic focused specifically on the empirical research. Its purpose was to analyze different industries in order to determine whether commonalities or differences about the emergence of strategic groups were recognizable or not. The empirical research showed different and mixed findings.[12] In some industries, two or more different strategic groups were clearly identifiable, while in others they seemed apparently missing. This fact started to draw criticisms (Barney & Hoskisson, p.1990). The issue was that the research on strategic groups never expressly defined any conditions under which they were more likely to emerge or not. It did not take into consideration the specific case of the absence of strategic groups in certain industries and therefore it fell in the non-falsifiability fallacy.

A different theoretical framework

Lee, Lee, Rho (2002) have exactly the objective to respond to these criticisms. To accomplish that, the authors employ a GA-based model through which they are able to analyze and simulate the dynamics of competition between different firms, while interpreting industries as a complex systems of interactions. It is possible to observe here a successful use-case of a tool employed in the study of complex systems in order to solve

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[11] Mobility barriers are comparable to another famous concept introduced by M. Porter: entry barriers. The latter apply to the new potential entrants into an industry, while the first to new potential entrants into a determined strategic group.
[12] See for example: Zajac & Jones (1989) and Comanor (1964).

a problem related the strategic management field. Before describing the model, it is important to take a step back and underline the important mutation in the conceptual framework underlying the authors' assumptions. Strategic groups were traditionally thought as being structural and static features of each industry. In the seventh chapter of the successful book *Competitive Strategy*, M. Porter refers to competition between strategic groups as a structural feature characterizing an industry, which are statically present. The strategies employed by the companies are the result of an equation which takes into account Porter's famous 5 forces. (Porter 1980, p.4). Lee, Lee & Rho (2002) recognize the historical contribution of this line of research, yet they try to propose a different point of view in which the competition between strategic groups is seen from a process view point. That view was inspired by an "evolutionary" line of research, which recognized how "competition, in the everyday sense of the term, is an active process, not a structural state" (Nelson & Winter 1978, p. 524).[13] This evolutionary perspective, which has much in common with the later developed concept of complexity, will be discussed in the next paragraph.

The evolutionary perspective represents a radically new line of research, which distinguishes itself from the neoclassical economic theory. In fact, it struggles to take into account different factors neglected in the traditional literature on the matter, such as uncertainty, incompleteness of information, and agents' bounded rationality. It proposes a new way of describing the dynamics of interactions between firms through imitation, evolution, and adaptation. The multiplicity of firms is conceived as a complex system of interaction *ante litteram*.

Under the neo-classical hypothesis of perfect competition, the market is assumed to be endowed with perfect information. The supply and demand curve and the prices are known to each agent in the market. The price of the goods itself is set by the market:

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[13] See also Nelson & Winter (1982)

firms are price-takers. The firm's only purpose and guide of action is to maximize profits. How can it do that, without being able to set the prices? The only actual firm's choice concerns the optimal quantity to produce in order to maximize profits. The firm knows exactly the supply and demand curve, as well as the marginal costs and marginal revenues (i.e. the cost/revenues generated by the production of an additional unit). In order to maximize profits, the firm will produce additional units until the marginal revenue equals the marginal cost. The quantity produced under these premises is called profit-maximizing quantity. The described model is still nowadays taught at school and constitutes the foundation of microeconomics. Nonetheless, many of its underlying assumptions have been challenged over time. Some of the criticisms drawn by the neoclassical perspective will be discussed, as they contributed to determine a sharp shift in the theoretical background underlying this work.

Tintner (1942) objections to the assumption of complete information are worth being taken into consideration.[14] According to the neoclassical view, firms are conceived as extremely rational agents, which are able to know precisely and in advance the market conditions and the outcome of their actions. However, this premise is rather unrealistic, as Tintner points out (1942, p. 275). Firms, like human beings, are often incapable of solving complex problems involving different interdependent variables. In addition, their foresight is limited and imperfect. Finally, the behavior of the agents themselves can determine hard-to-predict changes in the outside environment and in the industry conditions. With such constant and unpredictable modifications, it is conceptually very difficult to frame a determined state of things. This aspect of reality is not taken into consideration under the neoclassical premises. It is closer to reality, then, to conceive economic agents as acting according to some *estimates and forecasts* about the different parameters influencing their decisions outcomes (e.g. supply, demand, competition, etc.).

[14] See also Tintner (1941)

As accurate as these estimates may be, they are to some extent *uncertain.* Introducing uncertainty radically changes the way of conceiving the industry dynamic among firms.

In fact, does it still make sense to talk about profit maximization under uncertain conditions? A firm is able to properly "maximize profits", in the classical sense, just when the underlying conditions under which it acts are certain. In this case, the neoclassical model is valid. The firm knows precisely the supply and demand curve, the costs and the prices set by the market: it has just to solve a simple equation determining how many product units to produce. However, if the factors influencing the firm's profits are not certain, the firm will act according to uncertain estimates. Each choice won't be deterministically characterized by just one specific outcome, but rather by a *distribution* of potential outcomes, depending on the different possible scenarios. Each distribution has a mean (μ) and a standard deviation (σ). The outcomes distribution comprises *all* the possible "realized profits" (or any proxy to measure the performance) under *all* the possible scenarios that could occur. By looking at this in such a way, the problem shifts from "profit maximization" to rather choosing the "optimal distribution". The optimal distribution depends heavily on the subjective utility function of each agent. It could be for example the distribution of outcomes with the highest mean. At the same time, though, there could be riskier options with a lower mean but a higher standard deviation, which could guarantee (in the best-case scenarios) higher profits. Finding the optimal distribution depends on a *subjective risk* preference function, "which indicates how the individual in question evaluates his probability distributions of utility under conditions of subjective risk" (Tintner 1942, p. 279). Under the neoclassical premises of perfect competition, profit-maximization was the only guide for action and it was the same for every firm, whereas in Tintner's view that depends on a *subjective* utility function which allows the economic agents to rank the preferred choices according to their individual preferences. The shift in the perspective is clear and sharp.

Tintner's spark was picked up by A. Alchian, which borrowed his criticism and thoughts about uncertainty and developed them further. The author describes the economic system as the arena where a process of natural selection takes place. According to Alchian, the economist's work resembles the biologist's:

"Like the biologist, the economist predicts the effects of environmental changes on the surviving class of living organisms" (Alchian 1950, pp. 220-221).

Firms are conceived as living organisms with a limited capability to understand the environment surrounding them. They fight for limited resources and struggle to survive. The economist observes this process of natural selection and attempts to forecast a firm's behavior. The key factor which determines a firm's survival is the realized profit (Alchian 1950, p. 213). It is meaningless to refer to a theoretical concept like profit maximization. For Alchian, it does not matter whether firms apply a hyper-sophisticated and complex survival strategy or they just act blindly at random and are successful out of pure luck. The outcome is the same: positive realized profits determine a firm's survival likelihood. The author expresses this concept clearly by stating that firms do not always *adapt* to the environment to survive; the environment often just *adopts* some of them as survivors with some random favorable mutations (Alchian 1950, p.214). The role of luck and chance is clearly recognized by the author.[15] Under this perspective, firms are not conceived anymore as perfectly rational agents, acting according to perfect information. Their rationality is highly bounded. This does not undermine in any way

[15] The author points out that the acknowledgment of the importance of luck and chance does not undermine the value of individual motivation and foresight. Alchian describes an unrealistic random-behavior model at the beginning of his paper just to show the perfect coherence of an economic system even under these extreme conditions, whose consistency is an indirect confutation of the neoclassical assumption regarding the hyper-rationality of the economic agents. In conclusion, Alchian's objective is not to nihilistically deny the role and the will of the agents in taking decisions, but to recognize the existence of the variable "luck", which plays an important role and therefore must be taken into account

the existence of markets: *"Even in a world of stupid men, there would still be profits"* (Alchian 1950, p.213)

In the economic arena, a process of natural selection, similar to the one described by C. Darwin, is in play. The fittest individuals are selected as survivors and are more likely to procreate. In this way, the new generations inherit key characteristics for the survival from their parents' genes. Some random mutations can stochastically change some genes of the new-born agents. It is the process of adaptation described in the previous chapter. How does this biological framework translate in the language of economic theory?

As already outlined above, the fittest individuals are the ones that realize the highest positive profits, regardless of how and why they managed to. The worst-performing firms are going to be selected for extinction. Between these two groups (worst- and best-performing firms), it is possible to observe a set of companies in the middle, whose performance is not as bad as the extinguished "species" (they managed somehow to survive) but neither as good as the best ones. What are these firms going to do? Most probably, Alchian says, they will start imitating the firms with a superior performance by replicating their actions. In this way, they try to level down the difference with the competitors and to achieve comparable results. In the pragmatic world shaped by A. Alchian, a good economic performance is not an absolute concept, like in the case of profit maximization. It rather depends on the average performance of the other peers.

The dynamics of interactions between firms change further when the increasing number of imitators determines a performance degradation due to high competition and profit-sharing. At this point, some firms have enough incentives to try changing their "survival strategy" vis-a-vis the external environment. Translated in the business jargon: to innovate. Innovation can be extremely successful in terms of realized payoff. In this case, it will likely trigger a positive feedback mechanism, enacted by chasing imitators. At the same time, if unsuccessful, it can have disastrous effects and determine the extinction of a firm. It is important to notice that innovation is not always something intentional; it can occur even by chance, as a result, for example, of an imperfect or partial imitation of a peer by a firm (Alchian 1950, p. 219)

The just-described view challenges different assumptions underlying the neoclassical economic theory, such as rationality of agents, complete information, determinism, etc. The theoretical background of the described perspective is characterized by many characteristics which can be found also in the study of complex systems. In fact, it is possible to observe a multiplicity of agents (the firms) interacting with each other according to simple rules of behavior (imitation and innovation). In addition, there is no central control and the outcomes of the system are not easy to predict due to uncertainty (will innovative behaviors emerge? how many firms will survive? etc.). These above-described intuitions will constitute the conceptual basis of the GA-based model by Lee *et al.*, as it will be shown in the next paragraph.

2.2 A GA-based model on strategic group emergence

In describing the model, the authors state immediately the propositions whose validity is going to be tested throughout the simulations. These propositions challenge different problems and incontinences of the literature on the phenomenon at issue. Lee *et al*'s objective is to expressly circumscribe the area of the research and to find an answer to these problematic questions, using the perspective of complexity. The below statements concern four different aspects that will be shortly analyzed: Mobility Barriers, Strategic Interactions, Dynamic Capabilities and Boundary of Rivalry.

Let us consider first the mobility barriers. As mentioned above, this concept had already been formulated and described thoroughly by Caves & Porter (1980). They "deter the movement of firms from one strategic position to another" (Caves & Porter 1980, pp. 133-134). There can be many different types of mobility barriers: switching costs, capital requirements, access to distribution, etc. In this paper, J. Lee, K. Ree, and S. Rho choose to define them as the difficulty for a company to develop a high-end product. As it will be later explained, the authors distinguish in their model two different strategic groups: the first targeting the low-end segment (less profitable, less risky) and the second targeting the high-end (more profitable, riskier). The industry paradigm employed in the model is represented by the pharmaceutical industry, where traditionally two different strategic groups can be found: generic drug-maker (low-end) and companies investing heavily in R&D to develop new and exclusive drugs (high-end). This difference will be thoroughly explained in the next paragraphs. It is important to notice now that mobility barriers, however they may be conceived, are *structurally* present in each industry due to some inherent conditions (that can be both generic and industry-specific). That is why they are also called *structural* barriers by the authors. They should not be confused with the barriers voluntarily erected by incumbents to protect their competitive positioning, which will be taken into consideration later. The authors formulate two different propositions related to the structural barriers, which are going to be tested throughout the simulations:

"Proposition 1a: The higher the structural barriers, the larger the performance difference between strategic groups." (Lee, Lee & Rho 2002, p. 732).

The above proposition can be explained in the following way: if the mobility barriers within an industry are high, the success probability for a company trying to enter the high-end segment are going to be low. Mobility barriers and success probability are inversely correlated. Because of the smaller number of firms in the high-end segment, the performance differences between strategic groups will be indirectly higher, since the degree of competition within the same strategic groups will be lower, resulting in a lower degree of performance degradation. The direct consequence of this leads to another statement:

"Proposition 1b: The higher the structural barriers, the less likely a group structure will emerge and persist." (Lee, Lee & Rho 2002, p. 733).

With high mobility barriers, it is difficult for a company within a determined industry to pursue an entirely new strategy with respect to the competitors. For example, if there was no law or regulation protecting intellectual properties and patents, firms in the pharmaceutical industry will hardly choose to invest in the research of new drugs, since they would not have any economic incentive to do so. The group of firms pursuing the strategy of developing new drugs would most likely disappear. That is a clear example of structural barriers preventing strategic groups to emerge.

The second proposition is related to the barriers erected by incumbents in a determined strategic group. The authors call them generically "Strategic interactions". Traditionally, they represent the explicit or implicit collusion among companies which are part of the same group.[16] Their objective is to reduce the success possibility of new entrants to enter the most-profitable high-end segment. By enacting preemptive actions, incumbents manage to increase their performance jointly to the detriment of other firms outside the group:

"Proposition 2: The stronger the preemptive strategic interactions within a high-end group, the larger the performance difference between strategic groups." (Lee, Lee & Rho 2002, p. 734).

[16] See for example: Dranove, Peteraf & Shanley (1998) and Besanko, Dranove & Shanley (2000)

The third premise to be validated by the model takes into consideration the "dynamic capabilities" of the company. They represent an important factor whose purpose is to take into account modifications in the outside environment and in the industry structure. This term was introduced for the first time by Teece, Pisano & Shuen (1997), but the general ability to renew its own competitive advantage had been already generally discussed by M. Porter and R. Cooper in the above-mentioned works. Teece *et al.* define dynamic capabilities as "the firm's ability to integrate, build, reconfigure internal and external competences to address rapidly changing environments" (Teece, Pisano & Shuen 1997, p. 516). This term was inspired mostly by the observation of the dynamics of interactions, evolution and adaptation in high-technology industries, in which the pace of change and the intensity of competition was extremely high (Teece, Pisano & Shuen 1997, p. 515). The dynamic capabilities approach borrows from the resource-based view and its theoretical framework and adaptation to "a world of Schumpeterian competition" (Teece, Pisano & Shuen 1997, p. 515), in which disruptive innovation constantly changes the rules of the game. To be successful, a firm's resources have to be not only valuable, rare, and difficult to imitate, they have also to be *modular*. The most important capability for a company in a fast-changing industry is being able to reconfigure its own resources in order to align to modification in the outside environment. Dynamic capabilities are the key of sustainable advantage especially in extremely fast-changing and hyper-competitive industries. Lee *et al.* recognize the importance of this factor:

"Proposition 3: Given instability of payoff in the high-end segment, the weaker the dynamic capabilities a high-end segment has, the less likely a group structure will emerge and persist." (Lee, Lee & Rho 2002, p. 734).

If a firm does not have a satisfactory level of dynamic capabilities, it will not be able to keep up with the changes in the industry and will eventually be thrown out from the market. In this scenario, it is less likely for different group structure to emerge.

The "Boundary of rivalry" represents the last parameter to be considered in the GA-based model and it clarifies how rivalry and competition are operationalized. For the sake of simplicity, the authors just consider rivalry between horizontal strategic groups, i.e. between firms targeting similar market segments. Do different strategic groups within the same industry compete with each other? The answer is not simple, since it is heavily dependent on the categorization of strategic clusters and on the theoretical framework employed. According to the authors, if companies in different strategic groups were serving similar clients, their strategy would probably gradually converge until it reaches a point where it is not possible to distinguish the two different groups anymore. Therefore, strategic groups would cease to exist. Rivalry is assumed to be limited to companies within the same strategic group. The fourth proposition stems from this assumption:

"Proposition 4: Strategic groups are not likely to emerge and persist if rivalry is extended over firms of dissimilar strategies" (Lee, Lee & Rho 2002, p. 735).

After having defined the propositions that are going to be tested, the model will be discussed first and then the computational results of the simulations will be discussed.

The model - Description and results

Lee *et al*. define precisely the assumptions underlying the model. In doing that, the authors intend to solve the issue of hidden premises, often present in the research about strategic groups, responsible according to them for many inconsistencies and fallacies (Lee, Lee & Rho 2002, p. 728).

In the model, some simplifications have been necessarily made. As mentioned before, Lee *et al.* limits the possible strategic groups to just two types: low-end and high-end. In reality, it would be possible to distinguish many more strategic groups within the same industry (Porter 1980, p. 131). In addition, the firm's strategy is characterized just by the dimension of the product quality: in the model, the only strategic choice for a firm is to select the quality of its products within a determined range. In reality, the dimensions of strategy cannot be entirely attributed to just one dimension. However, these heavy simplifications make it possible to give the model a wide generality. In addition to that, the dynamics of the interaction between companies is the object of the study. This phenomenon can be coherently recreated under these circumstances, however simplified, and its result can be relevant and valid also for more complicated scenarios.

In the next paragraphs, it will be thoroughly explained how mobility barriers, strategic interactions, dynamic capabilities and boundaries of rivalry have been translated in the mathematical language of a model?

The payoff function

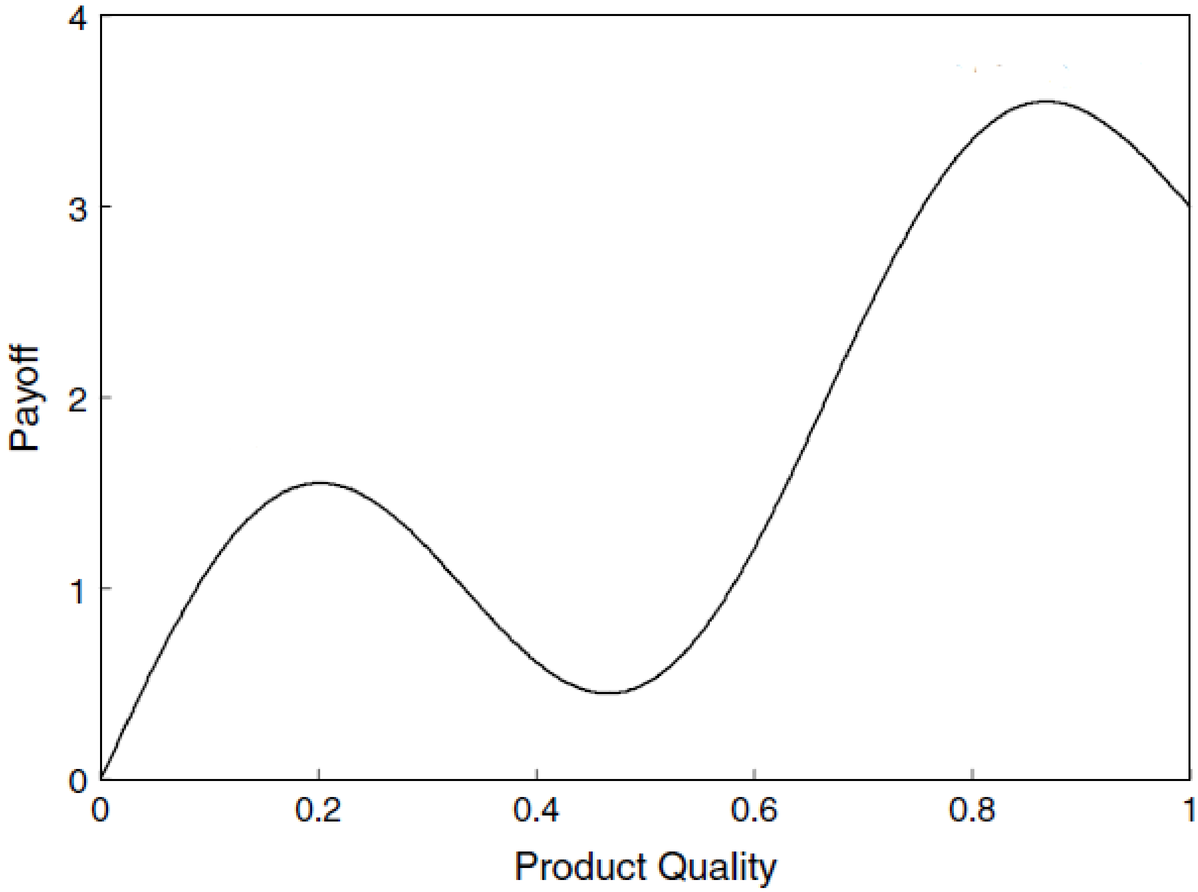
As mentioned above, the two strategic groups have different characteristics: the first one (low-end) has a relatively low performance but its overall profits are safe, while the second (high-end) is characterized by higher volatility in economic performance, which is rewarded by a higher payoff. The authors assume furthermore that:

1. At the birth of each industry (when the first interactions between competing firms start), there is no strategic group in the "high-end market"[17]
2. This group can emerge later *if* some companies find successful ways of entering the high-end market and constitute a higher-performing group (Lee, Lee & Rho 2002, p. 732).

The "if" is not casual. Not in every industry is it possible for some companies to constitute a high-end strategic group. If structural barriers are too high, for example, the success probability for a different strategic group to emerge will be lower. In this scenario, all the companies would be part of the same strategic group, applying similar strategies. It would be meaningless in this case to talk about different strategic groups. In this way, the authors attempt to address the criticisms of the non-falsifiability of the strategic group theory. The circumstances under which no strategic group emerge are now defined and the assumptions beneath them are clearly stated.

It has already been mentioned that the payoffs between the two groups differ. That means that a particular payoff function is in play, which distinguishes the two groups. The authors employ the following one:

[17] Therefore, each company is assumed to serve just the low-end segment at the beginning of each industry. (Lee, Lee & Rho 2002, p. 732)



[18]

To evaluate the performance of the different strategic groups, the authors design a multi-peaked function defining the payoff correlated to the selected quality. As mentioned, the two possible groups are distinguishable just because of the quality of their products. From the above image, the payoff curve of the two different strategic groups is clearly visible. Firms with a product quality from 0 to 0.5 (excluded) are considered being part of the low-end strategic group. On the contrary, firms with a product quality from 0.5 (included) to 1 join the high-end strategic group.

The payoff (y) corresponding to a choice of product quality (x) is given by the following formula:

$$y = sine\ (3\pi x) + 3x$$

[18] See Lee, Lee & Rho (2002, p. 732)

The payoff related to the first group appears to be lower in comparison to the second. However, the payoff in the high-end segment is riskier. The above-mentioned concepts come into play. In fact, for both incumbents and new entrants, mobility (or structural) barriers can diminish the success likelihood. Preemptive strategic interactions by incumbents, then, can further obstacle new entrants to take advantage of the higher payoffs. Eventually, incumbents need to possess a high degree of dynamic capabilities to keep up with industry mutation and evolution. Therefore, the realization of payoff related to a product quality higher than or equal to 0.5 is not as safe as in the case of the low-end segment[19]. This is expressed in the model as follows:

$$y = sine\,(3\pi x) + 3x \qquad \text{if } 0.5 \le x \le 1 \text{ and } r \le p$$
$$y = 0 \qquad \text{if } 0.5 \le x \le 1 \text{ and } r \ge p$$

This formula basically states that if the firm's strategic choice regarding the product quality is higher than 0.5, it will realize the related payoff just under some circumstances, i.e. $r \le p$, otherwise the realized payoff will be null (0). *What do r and p represent?* r represents a random number between 0 and 1, while p represents the success probability of a firm to enter the high-end segment.

The probability of success (p) is determined by the different factors that come into play depending on the different case: mobility barriers (MB), strategic interactions (SI) and dynamic capabilities (DC). The authors operationalize them in this way:

$$p = MB \qquad \text{if age} = 0 \text{ and n} \le \text{S}$$

[19] For the sake of simplicity, the authors assume that the payoff related to a product quality from 0 to 0.5 (excluded) is certain (Lee, Lee & Rho 2002, p. 736)

$$p = SI \qquad \text{if age} = 0 \text{ and n} \geq \text{S}$$

$$p = DC \qquad \text{if age} > 0$$

The above-mentioned formulas are consistent with the premises. The parameter age determines whether the firm is a new entrant[20] (age = 0) or an incumbent (age > 0). If a firm is a new entrant, two different scenarios can happen. If the number of firms in the high-end segment (n) is lower than S (a threshold for strategic interactions[21]), then the success probability will stem from the mobility barriers (MB). On the contrary, if n is higher than S, p will be the stem from the result of strategic interactions (SI). Notice that SI will be always lower or equal to MB, since it is the result of the mobility barriers itself minus the preemptive effect of strategic interactions. If the firm is an incumbent (age > 0), its success probability[22] stems from the dynamic capabilities (DC), previously defined as the ability for a firm to respond to mutations in the underlying industry structure. The firms act under extremely uncertain conditions. Tintner's influence is clearly recognizable here.

By designing the payoff function in this way, Lee *et al.* managed to take into account all the above-mentioned parameters affecting the agents' behavior and to include them in the model. MB, SI and DC's values can be arbitrarily set on the basis of a qualitative and quantitative industry analysis. These parameters are going to change and

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[20] The term "new entrant" is here used not in the traditional sense of a firm entering a new industry, but rather a new strategic group. The same applies to "incumbent"

[21] S can be thought as the minimum number of firms needed to inflate preemptive effects vis-a-vis new entrants. Intuitively, this threshold establishes that if there are not enough firms already in the high-end segment, no collusion will be enacted and no barriers will be erected by high-end firms. In this scenario, new entrants would be obstructed just by mobility barriers, which are structural to an industry. If the number of firms in the high-end segment is higher than the threshold S, then, in addition to the mobility barriers, some preemptive interactions can further diminish the success probability for new entrants. Therefore, MB will be always higher than SI.

[22] It would be more appropriate to talk about the probability to maintain its competitive positioning, since the incumbent firm is already present in the high-end segment by definition.

influence the industry landscape. In fact, the firms are going to adapt and "play" according to these rules. This fact is crucial since it allows the outcomes to be the closest possible to reality (or, at least, to be a close-enough simplification of it).

There is still a factor that needs to be taken into consideration: boundary of rivalry. It has been previously said that rivalry just pertains companies within the same strategic group. How is that operationalized? It is introduced in the model an arbitrary range of neighbors, called σ_{rivalry}, which share the focal firm's payoff (Lee, Lee & Rho 2002, p. 738). The higher this parameter, the higher the number of firms sharing the payoff (and the lower the individual profits). Given that rivalry is confined to firms within the same strategic group, this parameter should be set accordingly. The individual payoff function of the firm *i* is given by the following formula:

$$f_i = y_i / m_i$$

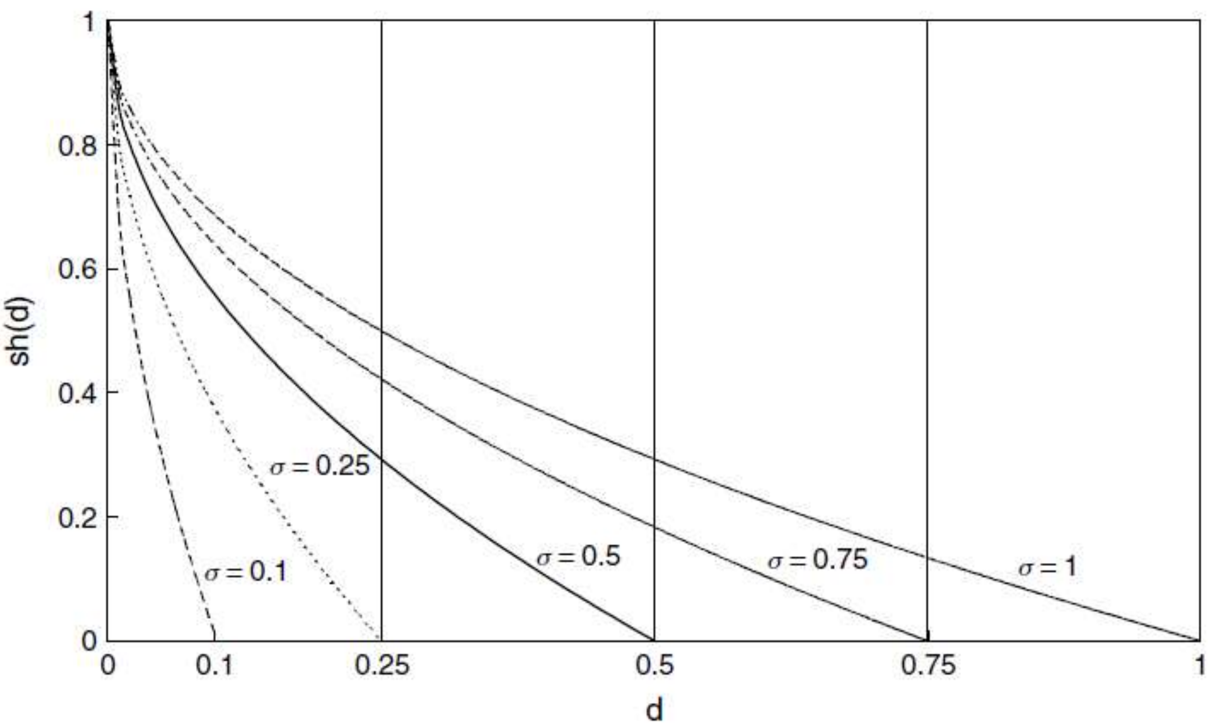
y_i is the payoff related to the product quality x_i. m_i represents the density of neighboring firms. This value is determined by σ_{rivalry} . m_i is formally defined as follows:

$$m_i = \sum_{j=1}^{N} sh\,(d_{ij})$$

N represents the total number of firms; d_{ij} is the distance between firm x_i and x_j. *sh* is the sharing function:

$$sh\,(d) = 1 - (d/\sigma_{\text{rivalry}})^{\alpha} \qquad \text{if } d < \sigma_{\text{rivalry}}$$
$$sh\,(d) = 0 \qquad \text{otherwise}$$

α determines the power law sharing function. In the model it has been set to 0.5. The below image shows graphically the above-mentioned formula.



[23]

It is important to notice that the above described payoff structure represents at the same time the fitness function, which is crucial for the functioning of the selection operator and ultimately of the GA itself. A. Alchian's influence is clearly recognizable here: positive realized profits eventually are the indicator that determines whether a firm is going to be selected for survival or for extinction

Selection, mutation and adaptation

All the propositions expressed in the previous chapter (MB, SI, DC, BR) have been operationalized in the model. It is now time to understand its functioning. The general mechanism for change in the model works in the following way:

[23] See Lee, Lee & Rho (2002, p. 738).

1. The first generation of 50 firms is generated. Due to information incompleteness, the first generation is assumed to start operating randomly within the low-end segment ($0 \leq x < 0.5$).[24]
2. The firms' performance and fitness are ranked according to the above-described payoff function.
3. The five worst performing firms are selected for extinction and have the possibility to reshuffle their strategic choice (product quality x)
4. The five new strategic choices are generated through variation mechanisms, such as crossover and mutation, and substitute the previous ones
5. The steps 2-4 are repeated up to the 2000th generation.

A few words must be spent on the variation mechanisms. As said, the five worst performing firms will change their strategic choice each generation, while the remaining will keep their product quality unaltered (due to information uncertainty). It is possible to assimilate that to unsuccessful companies trying to imitate more successful peers, or new entrants substituting firms that went bankrupt. In fact, in the language of genetics and GA, imitation is the perfect equivalent of reproduction, as already pointed out by Alchian. As per the Robby the Robot model, the performance of a determined agent is positively correlated with the probability of being chosen as a "parent" for the next generations. In this model, the same applies: top performers are most likely to be selected as targets for imitation.[25] Two different parents are chosen and their "genes", represented by the combination of their strategic choice (product quality x) are crossed over. The way

[24] This assumption stems from the consideration that at the beginning firms do not know the industry payoff function. They are going to discover it through trial-and-error and the imitation of the more successful peers. This expedient is also useful to show more clearly the dynamics of the emergence of different strategic groups.
[25] Lee *et al.* do not expressly mention how performance and probability to be selected are correlated.

Lee *et al.* conceive the product quality (x) is a 10-bit string, such as 1000100010. The combination between the two 10-bit strings happens by inheriting one bit from parent 1 and one bit from parent 2, until the end of the string (Lee, Lee & Rho 2002, p. 736).[26] The resulting gene will constitute a new strategic choice.

GA algorithms typically take into consideration also a stochastic component to operationalize random genetic changes that often occur in genetics. Again, like in the Robby the Robot model, this random variation is translated by introducing a mutation probability of the bits in the string representing product quality. In the model, it is assumed to be 0.005% per bit, for a total of 0.05% for a 10-bit string. In the business jargon, this random mutation could be represented by innovation, intended in every form (both intentional or unintentional). Alchian's influence is still very much recognizable.

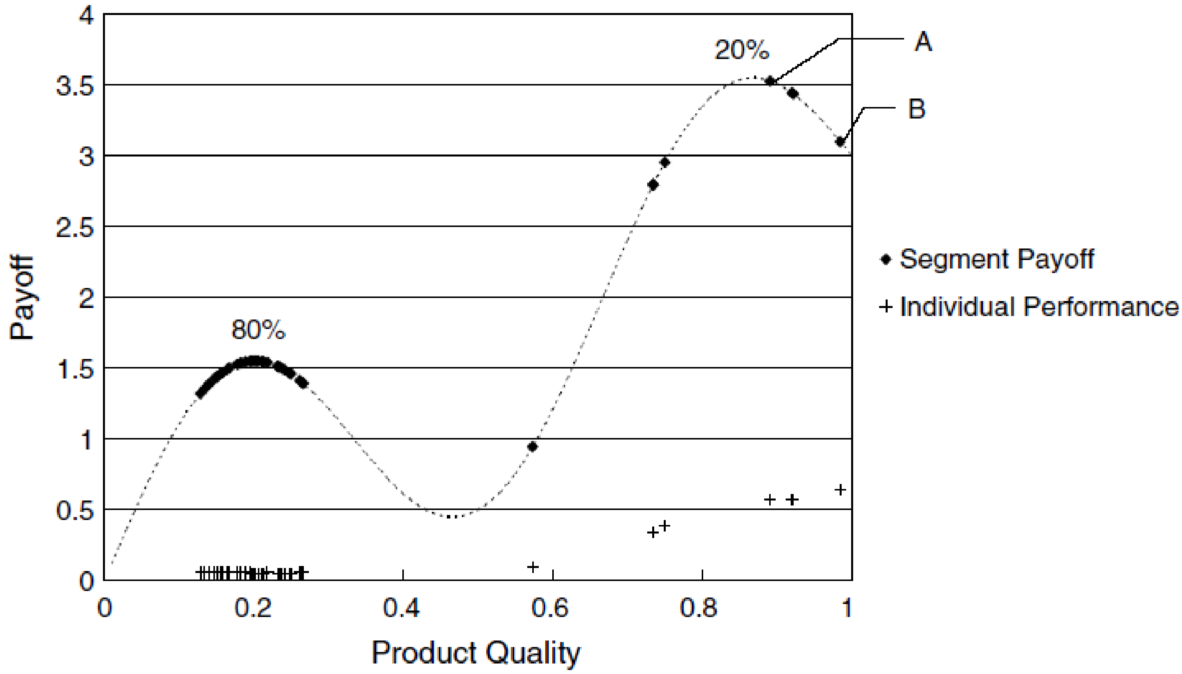
All the instructions needed for a GA to operate are now defined. The authors proceed in running some simulations accordingly and analyze the related results, with the objective of validating the above-mentioned propositions (1-4).

Computational results

Let us see consider first the result of a standard scenario, in which the parameters' values are set as follows:

- MB: 0.10
- SI: 0.10
- DC: 0.96
- σ_{rivalry}: 0.50

[26] As it will be seen later, this represents a huge difference from the way product quality is operationalized in the replication of this model in Netlogo, where a real encoding has been used.

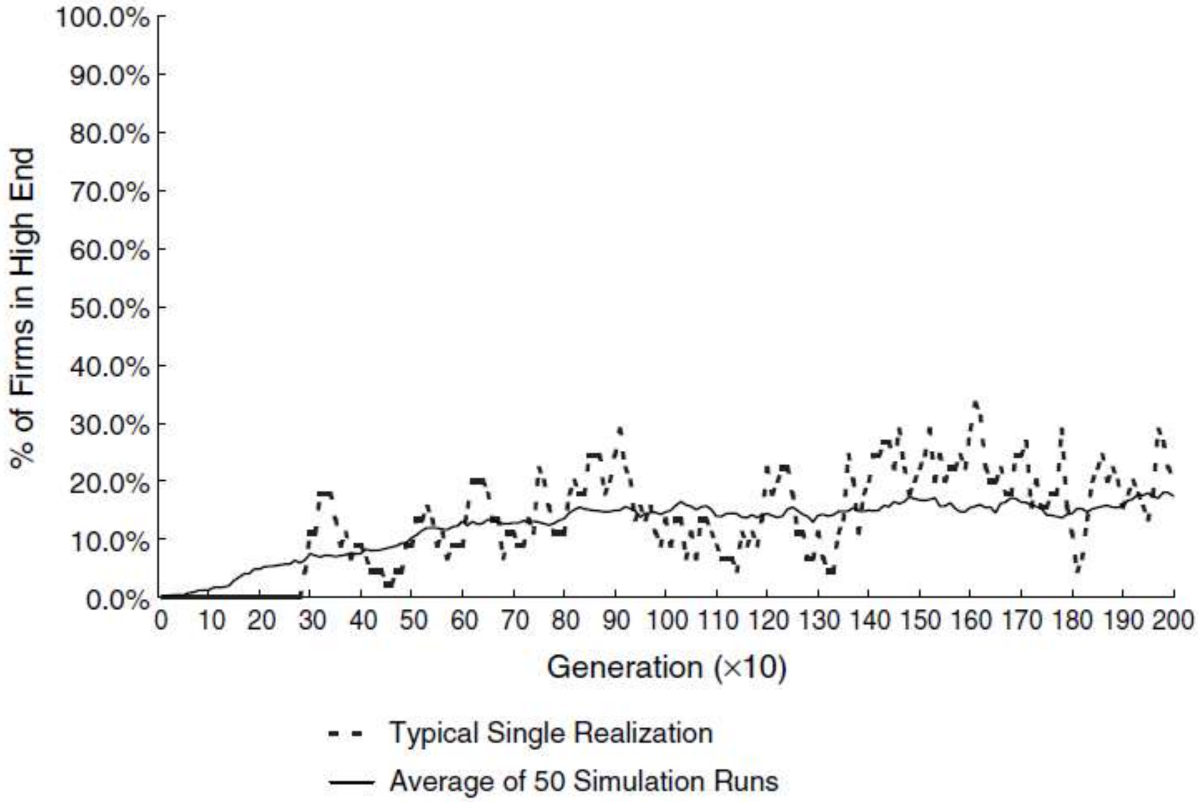


[27]

The above figure shows the distribution of firms between the low- and the high-end segment. The dots along the function represent each firm's individual strategic choice. The cross symbol represents the payoff related to each firm. It is lower than the function would suggest because of the boundary of rivalry.[28]

[27] See Lee, Lee & Rho (2002, p. 739)

[28] In fact, A should have a higher payoff than B. On the contrary, given the lower degree of competition of substitutive products, B has the highest payoff within its industry.



[29]

The above image shows the dynamic of group emergence along all the 2000 generations. The dotted line represents the actual appearance/disappearance of groups in the high-end. The first high-end strategic group emerged ca. at the 280th generation. The solid line represents the average of 50 simulation runs. The line is smoother but the percentage of firms in the high-end appears to be consistently close to 20% of the total. The standard scenario appears to be coherent with the literature con strategic groups.

After that, Lee *et al.* attempts to validate the propositions mentioned in the previous chapter. In order to accomplish that, the values of the parameters MB, SI, DC and BR are modified to observe the effect on the firms' behavior and on the strategic group emergence. That is repeated for 50 simulation runs for each value, in order to

[29] See Lee, Lee & Rho (2002, p. 740).

provide the model outcomes with a high confidence level. By modifying those values, it is possible to see how the final outcomes change and to gain important insights.

Table 1. Variation in mobility barriers

Mobility barriers (*MB*)	% of SG emergence	% of firms in high end	Average duration	Average performance		
				Low end	High end	Difference (*t*)
0.01	0.0%	–	–	–	–	–
0.02	6.0%	3.0%	86	0.044	1.063	1.019 (12.324**)
0.03	18.0%	4.4%	235	0.045	0.558	0.512 (7.186**)
0.04	20.0%	6.2%	143	0.046	0.702	0.656 (8.433**)
0.05	22.0%	6.9%	219	0.046	0.552	0.506 (7.418**)
0.06	36.0%	7.2%	481	0.046	0.509	0.463 (6.673**)
0.07	66.0%	12.2%	684	0.049	0.434	0.385 (4.809**)
0.08	78.0%	14.7%	870	0.051	0.400	0.349 (4.758**)
0.09	80.0%	16.0%	1267	0.051	0.372	0.321 (4.336**)
0.10	*94.0%*	*18.5%*	*1177*	*0.053*	*0.365*	*0.312 (3.802**)*
0.11	100.0%	19.0%	1529	0.053	0.378	0.325 (4.334**)
0.12	96.0%	22.0%	1644	0.055	0.311	0.256 (3.840**)

[30]

The above table shows clearly that by increasing the value of the mobility barriers, the likelihood for strategic groups to emerge is higher.[31] MB represents the *success* probability for a firm to enter the high-end segment. The lower the success probability due to structural barrier, the less likely for strategic groups to emerge (if MB is equal to 0.01, strategic groups do not emerge in over 50 simulation runs). This fact validates the proposition 1b. At the same time, the table shows that the lower the MB value, the higher the performance difference between the groups. That happens due to the sharing function. With a lower probability of success, a lower number of firms will join the high-end group, as shown in the table. If less firms enter the high-end, it indirectly beneficially

[30] See Lee, Lee & Rho (2002, p. 741)

[31] The "% of SG emergence" has been defined by the authors as "the percentage of simulation runs that produce a group structure at period 2000" (Lee, Lee & Rho 2002, p. 746)

affects the individual payoff of each firm in that segment. The results validate the proposition 1a.

Table 2. Variation in strategic interactions

Effect of Strategic interactions (*MB-SI*)	% of SG emergence	% of firms in high end	Average duration	Average performance		
				Low end	High end	Difference (*t*)
0.09	82.0%	10.9%	1032	0.049	0.483	0.435 (5.555**)
0.08	82.0%	10.9%	968	0.048	0.495	0.447 (4.945**)
0.07	84.0%	10.3%	884	0.048	0.466	0.418 (6.154**)
0.06	80.0%	12.4%	1162	0.049	0.467	0.417 (5.785**)
0.05	90.0%	13.7%	1170	0.050	0.431	0.381 (5.698**)
0.04	92.0%	14.0%	1209	0.050	0.408	0.357 (5.408**)
0.03	94.0%	14.0%	1117	0.051	0.418	0.368 (5.116**)
0.02	86.0%	14.6%	1110	0.051	0.403	0.352 (4.565**)
0.01	86.0%	17.4%	1372	0.053	0.373	0.320 (4.507**)
0.00	*94.0%*	*18.5%*	*1177*	*0.053*	*0.365*	*0.312 (3.802**)*

[32]

The above table shows the change in outcomes related to the different intensity in preemptive effects of strategic interactions. The higher the difference between MB and SI, the lower the percentage of firms in the high-end group. This is intuitively clear: when strategic interactions between firms are ignited, the entry probability of new firms in the group is hindered. Therefore, less firms are going to successfully manage to enter the best-performing group. If a lower number of firms is present in this group, the performance difference between the two groups will be higher for the same reasons of the previous case (less firms to share the payoff with). These results validate proposition 2.

[32] See Lee, Lee & Rho 2002, p. 741

Table 3. Variation in dynamic capabilities

Dynamic capabilities (DC)	% of SG emergence	% of firms in high end	Average duration	Average performance		
				Low end	High end	Difference (t)
0.80	8.0%	6.1%	47	0.046	0.621	0.576 (5.375**)
0.82	12.0%	5.9%	27	0.046	0.757	0.711 (8.937**)
0.84	14.0%	3.5%	53	0.044	0.642	0.598 (24.831**)
0.86	10.0%	7.6%	98	0.046	0.478	0.432 (8.472**)
0.88	20.0%	5.3%	224	0.046	0.493	0.447 (7.073**)
0.90	38.0%	10.3%	248	0.048	0.427	0.379 (4.610**)
0.92	70.0%	13.4%	780	0.049	0.398	0.349 (3.693**)
0.94	*94.0%*	*18.5%*	*1177*	*0.053*	*0.365*	*0.312 (3.802**)*
0.96	98.0%	31.1%	1701	0.062	0.268	0.207 (3.201**)
0.98	100.0%	57.7%	1782	0.097	0.171	0.074 (2.258*)
1.00	100.0%	72.0%	1768	0.147	0.151	0.005 (0.494)

[33]

Dynamic capabilities affect the likelihood of strategic group emergence and the overall number of firms in the high-end segment, as shown in the above table. If the DC are low, it is impossible for companies to keep up with changes in the industry and they will eventually lose their favorable competitive positioning. Not surprisingly, the outcomes in the model are very sensitive to modifications of this parameter. The outcomes shown in the above table testify the proposition 3. Interestingly, if DC capabilities were 1.00, strategic groups would theoretically cease to exist. Each firm entering the high-end group will have 100% likelihood to persist operating there. This would imply a high-performance degradation due to the sharing function. The performance difference between the two groups would be under these circumstances close to 0.

[33] See Lee, Lee & Rho (2002, p. 742).

Table 4. Variation in boundary of rivalry

Boundary of rivalry ($\sigma_{rivalry}$)	% of SG emergence	% of firms in high end	Average duration	Average performance		
				Low end	High end	Difference (t)
0.10	96.0%	23.8%	1420	0.188	0.828	0.640 (2.734*)
0.25	96.0%	21.8%	1634	0.085	0.519	0.434 (4.014**)
0.50	*94.0%*	*18.5%*	*1177*	*0.053*	*0.365*	*0.312 (3.802**)*
0.75	64.0%	13.1%	734	0.044	0.250	0.206 (4.703**)
1.00	36.0%	8.5%	451	0.039	0.143	0.104 (8.435**)

[34]

Finally, the boundary of rivalry is taken into consideration. If the parameter σ_{rivalry} is increased, the percentage of strategic group emergence falls dramatically. Due to the sharing function, the high-end firms become less attractive and less targeted for imitation. In fact, they are heavily subject to a performance degradation. When the parameter reaches values close to one, it becomes almost meaningless to talk about strategic groups, since every company competes with each other regardless of their strategic choice. This is well reflected also by the performance difference, which becomes increasingly irrelevant.

Lee *et al.'s* GA-based model on strategic interactions has been thoroughly analyzed. The parameters and factors affecting the relationship between firms and strategic group have been first qualitatively discussed by taking into account the most meaningful contributions to the strategic group research in the past years. After that, it has been described and explained how these parameters have been operationalized in the model presented in the paper. The results of the simulations have validated the author's premises. In this model, G. Tinter's and A. Alchian's evolutionary framework has been successfully translated into a consistent model. Realized profits under uncertain conditions determine winners and losers in the economic arena, while imitation (the

[34] See Lee, Lee & Rho (2002, p. 743)

quality bias in the selection operator) and innovation (mutation) guide the evolutive behavior of the firms, struggling to adapt to the external environment. In the next chapter, the present model will be replicated using Netlogo.

3. Replicating the Model in Netlogo

Premise to the model - Netlogo

In the present chapter, the GA-based model by Lee *et al.* will be replicated using Netlogo (Wilensky 1999). Netlogo is a multi-agent modeling environment employed to simulate natural, social and economic phenomena. It was created by Uri Wilensky, professor of Computer Science at Northwestern University, and further developed thanks to the support of the Center for Connected Learning and Computer-Based Modeling of the same university. It employs as programming language, mostly Scala and secondarily Java. Netlogo is an extremely useful tool to simulate the dynamics of complex systems. In fact, it makes it possible to create an environment where a multiplicity of agents acts and interacts according to established rules. In this way, the emergence of complex behavior can be observed and its outcomes can be analyzed. In addition to that, modifications of all the variables in play can be easily performed and the related changes in the agents' behavior can be detected and studied. Thanks to that, it is possible, for example, to test the assumptions of a specific model, to perform sensitivity analyses, to run what-if scenarios under different circumstances, etc. Netlogo can be interestingly employed also in the managerial studies. Its pragmatism and simplicity make the programming of *agent-based models* (ABM) very handy. Management-related issues often pertain decision-making under uncertain conditions and bounded rationality. In Netlogo, both these limitations can be taken into consideration when defining the interacting agents in the model. Thanks to this approach, firms can be described in a more realistic way than in other theoretical frameworks, such as the neoclassical one. In conclusion, it is believed that Netlogo represents potentially an extremely useful tool both for the understanding of complex systems and for the research about strategic group emergence.

3.1 Description of the model

Replicating Lee *et al.*'s model using Netlogo serves the purpose of testing the consistency of the aforementioned theoretical assumptions, observing the similarities and discussing the differences with the current model. Replicating successfully a model is an important theoretical achievement, since it provides great validity to the findings. The program is available in Appendix A. The way in which the features of Lee's model have been translated in Netlogo will be shortly analyzed.

In Netlogo, it is necessary to first define the agents at issue (which are called here "turtles") and their attributes. The first attribute of the turtles (the firms in this case) is the product quality[35], which has been defined as the variable x linked to the following payoff function:

$$y = sine\ (3\pi x) + 3x$$

The product quality of the first generation of agents is randomly generated. It is assumed, as Lee *et al.* does, that all the firms start operating in the low-end segment ($x < 0.5$).

In addition to that, each firm owns a probability (p), which represents the probability to either access or maintain the competitive positioning in the high-end segment, depending on the case:

p = MB	if age = 0 and n < S
p = SI	if age = 0 and n ≥ S
p = DC	if age > 0

[35] The product quality represents here the only strategic choice of the firm, as in Lee *et al*'s view.

As in Lee *et al.*, if the firm is a potential new entrant in the high-end, then the success probability is either going to be provided by the mobility barriers (MB), if the number of incumbents is less than S (a threshold value for strategic interactions), or by the strategic interactions (SI) otherwise. Dynamic Capabilities (DC) are going to apply just for incumbents. It is possible to distinguish incumbents by new entrants in Netlogo by introducing another feature characterizing the firms: their age. For every generation in which a firm manages to survive in the high-end segment, the age value is increased by one. Therefore, each firm with an age higher than 0 is going to be incumbent, while new entrants' age is going to be 0.

In addition to p, the turtles own r, a casual number from 0 to 1, drawn at the beginning of each new period. This number is necessary to randomly determine whether the firm is going to be successful or not in joining the high-end segment, according to the related probability. In fact, as seen in the previous chapter:

$$
\begin{aligned}
y &= sine\,(3\pi x) + 3x && \text{if } 0 \le x < 0.5 \\
y &= sine\,(3\pi x) + 3x && \text{if } 0.5 \le x \le 1 \text{ and } r \le p \\
y &= 0 && \text{if } 0.5 \le x \le 1 \text{ and } r > p
\end{aligned}
$$

By substituting p respectively with MB, SI and DC, depending on the case, Lee *et al.*'s payoff function is exactly replicated. The sharing function is similarly replicated by dividing the payoff y by m, a parameter that takes into account the neighboring firms to share the payoff with. To summarize, the firms ("turtles") own the following characteristics:

- Product quality (x). It represents a number from 0 to 1, related to the determination of the payoff (y)

- Payoff (y). It represents the payoff related to a determined choice in product quality. The final payoff is affected by the presence of neighboring firms (m)
- p. It represents the probability for a firm to be successful in joining the high-end segment. It is described alternatively by the mobility barriers, strategic interactions or dynamic capabilities, depending on the case.
- r. It represents a random number drawn each turn for each firm. It determines whether the firm is going to be successful ($r \leq p$) or not ($r > p$)
- age. It represents the age of a firm, conceived as the number of consecutive generations in the high-end segment. It distinguishes incumbents and potential new entrants (in the high-end segment)

To function in Netlogo, some changes to the original model had to be done. An important modification pertains the way the numbers representing the product quality have been encoded. In fact, as mentioned above, Lee *et al*. conceived a number as a 10-bit string representative of a value between 0 and 1 (Lee, Lee & Rho 2002, p. 736). To perform the crossover, the offspring string was composed by one bit coming alternatively from parent 1 and one bit from parent 2, until the tenth and last bit of the string. Mutation was translated in the model language by setting a determined likelihood for each bit to change, as thoroughly described in the previous chapter. Encoding a real number as a binary string was really popular some decades ago, because of the limited technical possibilities available. Nowadays, thanks to innovation in the computer systems and in the softwares, it is possible to instruct the model using a simple real encoding.

For the present model, a simple real number from 0 to 1 has been employed to describe x. Crossover is just a weighted average of the two parents' product quality:

$$x_{ab} = \lambda\, x_a + (1 - \lambda)\, x_b$$

λ is generated randomly each generation. x_a and x_b represent respectively the product quality of parent 1 and parent 2. In this way, it is possible to determine in a much easier way the offspring product quality by calculating the weighted average between the selected parents. In addition to that, the fact that λ floats between a random value range (from 0 to 1) adds a stochastic component which makes crossover more dynamic. Mutation is operationalized similarly by adding a random value, which is a normally distributed floating-point number (z). The mean (μ) of the related distribution is 0 and the standard deviation (σ) is 0.2:

$$x1 = x0 + z$$

In Lee's model, only the 5 new firms mutate each period.[36] This assumption has been kept unaltered also in our model in order to be the closest to the original.

The selection operator requires to be further discussed as well. In fact, in the original model the potential parent candidates' payoff was positively correlated with their chances to be selected for reproduction. Lee *et al.* does not specifically mention the function determining the relation between probability to be selected and the performance.[37] In order to translate the selection process in our model, a mechanism similar to the one described previously in "Robby the Robot" was employed. Five parent candidates are selected at random. Among them, the top performer is selected to be the first parent. The same operation is repeated to select the second one. In this way, both a stochastic and a performance-based way for capturing natural selection in the model is granted.

---

[36] "In our model, the 45 highest performers will not change their choices, given incomplete information", (Lee, Lee & Rho 2002, p. 736).

[37] The authors just generically state that "In the language of GAs, this intuition is captured in the following selection rule: a probability for any firm to become a target of crossover in the next generation is proportional to its performance." (Lee, Lee & Rho 2002, p. 736)

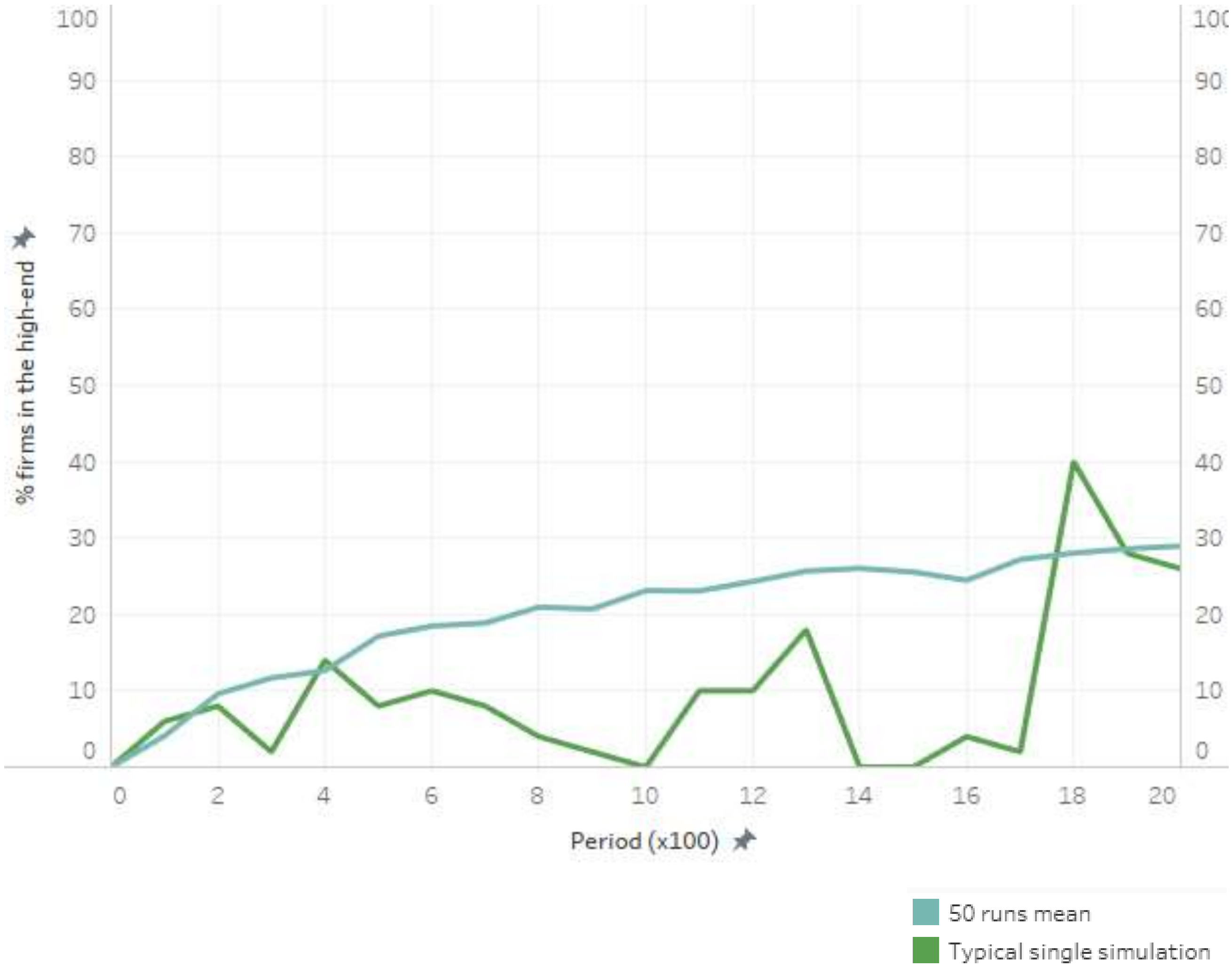
The most important features of the model have been analyzed. Further information is going to be provided when necessary in explaining the computational results of the simulation runs, which will be presented in the next paragraph.

3.2 Computational results

In order to make the comparability between the two models easier, the same structure in presenting the results will be kept. Therefore, the outcomes related to a "standard" scenario will be presented first. Lee *et al.* defines as standard the scenario with the following parameters:

- MB: 0.10
- SI: 0.10
- DC: 0.96
- σ_{rivalry}: 0.50

The here reported graph represents the emergence of strategic groups in terms of percentage of firms in the high-end segment:



The green line represents a typical single realization. The volatility is high and strategic groups appear and disappear at a fast pace. The solid line shows the mean of 50 simulation runs. Here it is easier to observe the overall trend. The percentage of firms in the high-end segments steadily increases until it reaches a value of ca. 30%. The below table recaps the most important parameters values:

Measures	*Lee* et al*'s model*	*Netlogo replication*
% of strategic group emergence	94%	88%
% of firms in the high-end segment	18,5%	28,96%

The percentage of firms in the high-end segment is slightly higher than the one obtained by Lee *et al.* This happens most likely because of the difference in the selection operator and in the real encoding. This matter will be further discussed in the next paragraphs. Nonetheless, it is clearly observable how the outcomes of the current model over 50 simulation runs are consistent and comparable to the one reported in the previous chapter.

In the following paragraphs, the key parameter of the model (MB, SI, DC, σ) will be modified to measure on which extent the final results are affected by this variation. Before doing that, some premises about the measures for detecting strategic groups are believed to be necessary.

Measuring strategic group emergence

The measures considered in the present chapter will be mostly these:

- *Percentage of Strategic Group emergence*
- *Percentage of Firms in the high-end segment*

The first one had been conceived by Lee, Lee & Rho (2002, p. 746). as the percentage of the simulation runs that produced a strategic group at period 2000 (the last one). The second one, strictly related to the first, reports the average number of firms in the high-end segment when the afore-mentioned strategic group existed at period 2000. For the sake of simplicity, the measures of "Duration" and "Difference" (Lee, Lee & Rho 2002, p. 746) are not going to be taken into consideration here unless necessary to further explain the results or validate Lee *et al*'s propositions, since they did not offer useful insights in most of the cases and provided redundant results.

Some modifications to the way group structures are detected have been attempted in the present work. In fact, according to current view, strategic groups are considered as existing if and only if they are present at the 2000th period. That arguably fails to fully represent the phenomenon of strategic group emergence and poses a serious threat of invalidating the computational results. In fact, the period number in which a strategic group randomly appears or disappears should not affect the results on such a high extent. According to the current definition, for example, if a high-end strategic group emerged at period 2 and disappeared at period 1999, it would not be reported. The program would just consider the 2000th period, in which the group structure was not present anymore. The percentage of strategic group emergence would be 0 for that simulation run. To take similar cases into account, an alternative definition to the two measures have been proposed:

- *Percentage of Strategic Group Emergence:* It represents the percentage of periods, within the entire simulation run, in which a group structure was present
- *Percentage of Firms in the high-end segment:* It represents the percentage of firms in the high-end segment over all the periods, within the entire simulation run

When many simulation runs are analyzed, these two measures will be represented by the mean of the above values. According to this new way of measuring strategic groups, the "Percentage of Strategic Group Emergence" in the above-mentioned example would be 99.9%, instead of 0% as in the previous case. Of course, that was an extreme example and the difference is usually not so high. However, it is believed that these definitions can better capture the considered phenomenon. In the following part of this chapter, both the two definitions are kept in order to make the model comparable with Lee *et al*'s.

After having clarified these premises, the computational results related to the variation of each one of the key parameters (MB, SI, DC, σ) will be now reported. To accomplish that, the Netlogo functionality "Behavior Space" has been employed. Behavior Space is an extremely useful tool for such a purpose. In fact, it allows the user to run a model many times, systematically varying the model's settings and recording the results of each model run. In this way, it is possible to explore the model further and observe which combination of parameters causes the behaviors of interest.

Mobility Barriers

In the below table the computational results of 10 simulation runs for each MB value from 0.01 to 0.10 are reported, while the other parameters are kept unaltered as in the standard scenario.[38]

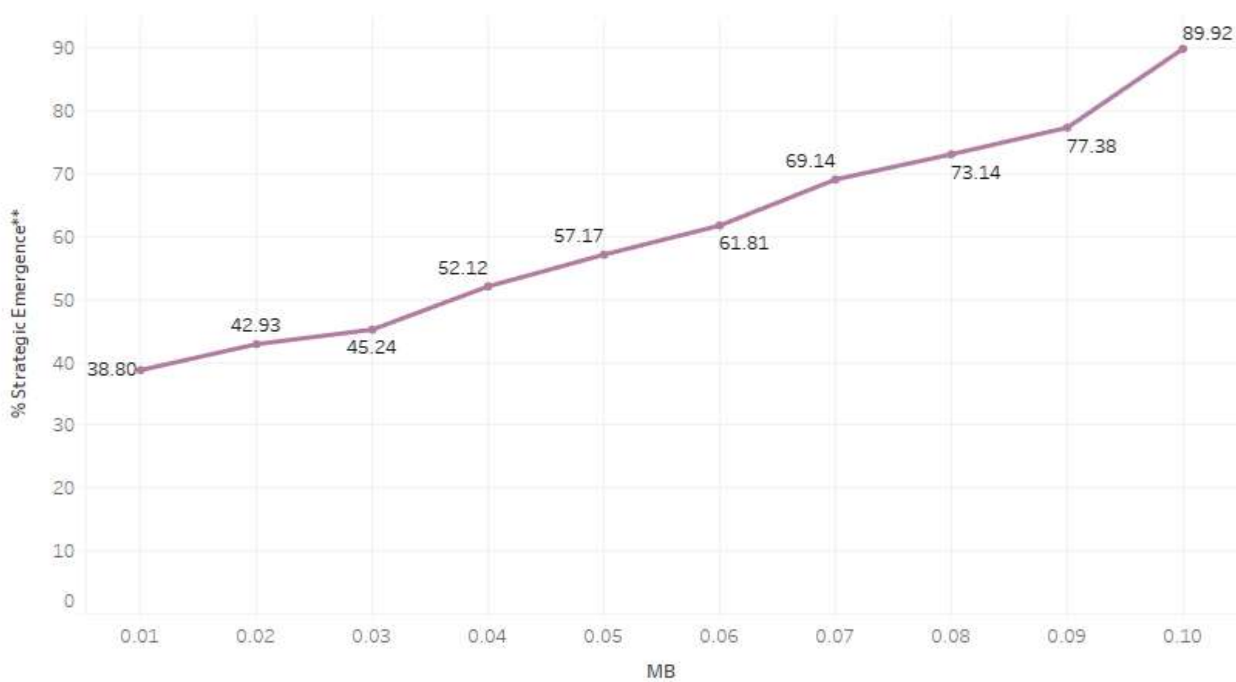
MB	%firms in high-end*	% Strategic Emergence*	% firms in high-end **	% Strategic Emergence**
0,01	2,00	20,00	2,65	38,80
0,02	3,67	60,00	2,82	42,93
0,03	2,00	60,00	3,03	45,24
0,04	11,00	20,00	3,48	52,12
0,05	3,00	40,00	3,84	57,17
0,06	3,60	50,00	4,33	61,81
0,07	5,14	70,00	6,01	69,14
0,08	5,33	90,00	6,34	73,14
0,09	15,75	80,00	8,66	77,38
0,1	40,00	80,00	27,30	89,92

The table presents the percentage of strategic group emergence and firms in the high-end segment in two alternative ways: the first one (*) as conceived by Lee *et al.* and the second one (**) according to the new definition provided in the previous paragraph. The two values reported are similar, but the second way of detecting strategic emergence seems to capture better the phenomenon and to exclude outliers. That is clearly visible for

[38] I.e. MB-SI = 0, $\sigma = 0$, DC = 96

example for low MB values. The percentage of strategic group emergence is equal to 60% for MB = 0.03 and to 20% for MB = 0.04. This result is not consistent with the general Lee *et al*'s proposition stating that the emergence of a group structure is positively correlated with the increase in MB. In this case, instead, a higher MB value presents a lower percentage of group emergence. That was most probably just due to pure chance. It is possible to prove that by analyzing all the 2000 periods of the simulation run and not just the last one. As shown in the table, the results of MB 0.04, according to the new definition of group emergence, are perfectly consistent with Lee's own proposition and in line with the overall trend. That proves that the units of measures, as defined in the previous paragraph, are more effective in describing the phenomenon. However, both of them are going to be kept in order to keep consistency and comparability with Lee *et al*'s results.

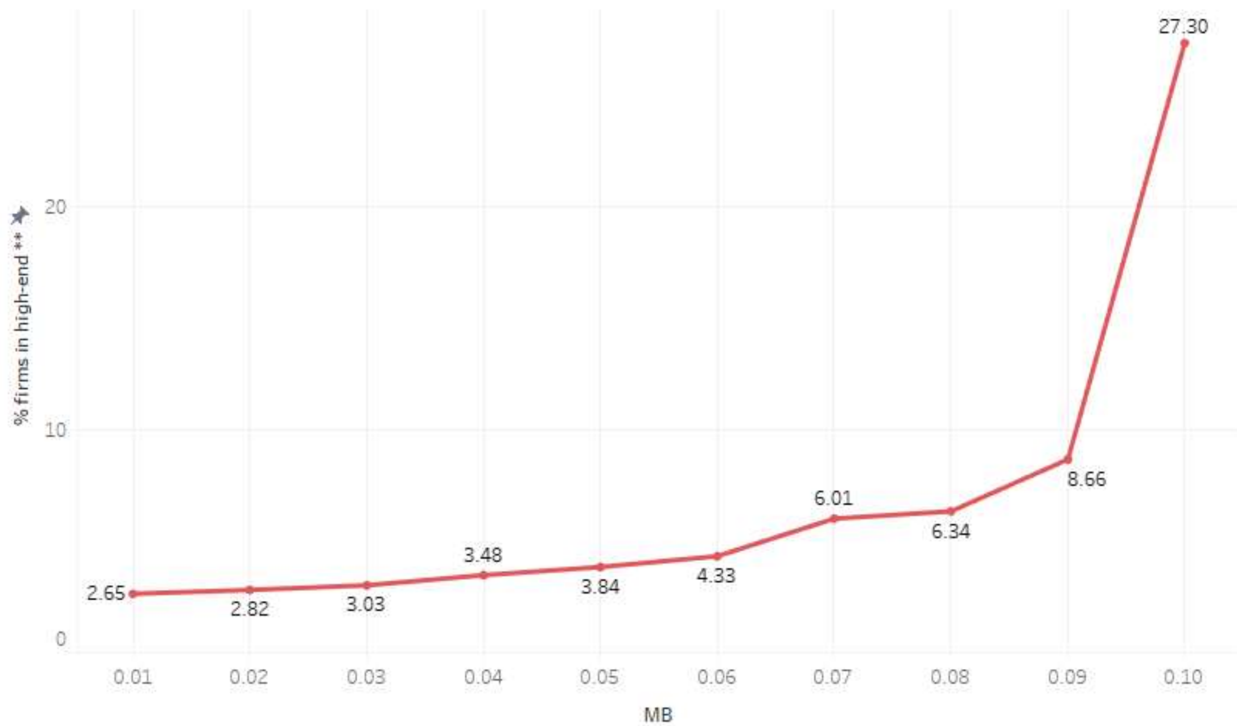
The below line graph sums up the results of the simulation runs in a clearer way:



The trend describing the emergence of a group structure is consistent with Lee *et al*'s findings (Lee, Lee & Rho 2002, p. 741). It is clearly positively correlated with MB. A slight difference in the results can be observed in percentage of group appearance for low

MB values. In fact, despite the similar trend, the emergence of strategic groups is in that case higher. Two possible reasons can explain that difference. The first one is the already thoroughly discussed difference in conceiving the measures, which can be observed thanks to the above table. The second one is probably attributable to the mutation operator. In the present model, as said above, the newly-born firm mutates according a normally distributed random floating number. The mean of that distribution is 0 and the standard deviation is 0.20. These values were necessary in order for the model to work. In fact, with the assumption of all the firms beginning operating in the low-end segment, a sizeable mutation was necessary to let some firms enter the high-end and trigger the strategic interactions. As mentioned in the previous chapter, the authors conceive the strategic choice (the product quality) as a 10-bit string, whose percentage to mutate is 0.005% per bit (for a total of 0.05% for the entire string). In the current model, which employs a real encoding, such a low degree of mutation was not sufficient for igniting interaction dynamics between firms.[39] Therefore, a higher range and likelihood of mutation has been provided to the agents. Firms, by mutating more and more often, have more chances to reach the high-end segment. However, it must be noticed that this fact does not undermine the consistency of the model. In fact, the percentage of firms in the high-end segment for low MB values is perfectly consistent with Lee's results. Even if lucky firms manage to enter the high-end segment thanks to mutation, they are too few to grant a long-lasting survival due to the adverse circumstances (high mobility barriers). The high-end group is likely extinguished after few generations. That is why the percentages of firms in the high-end segment for low MB values is around 2%, which is very similar to Lee *et al's* findings for the same scenario.

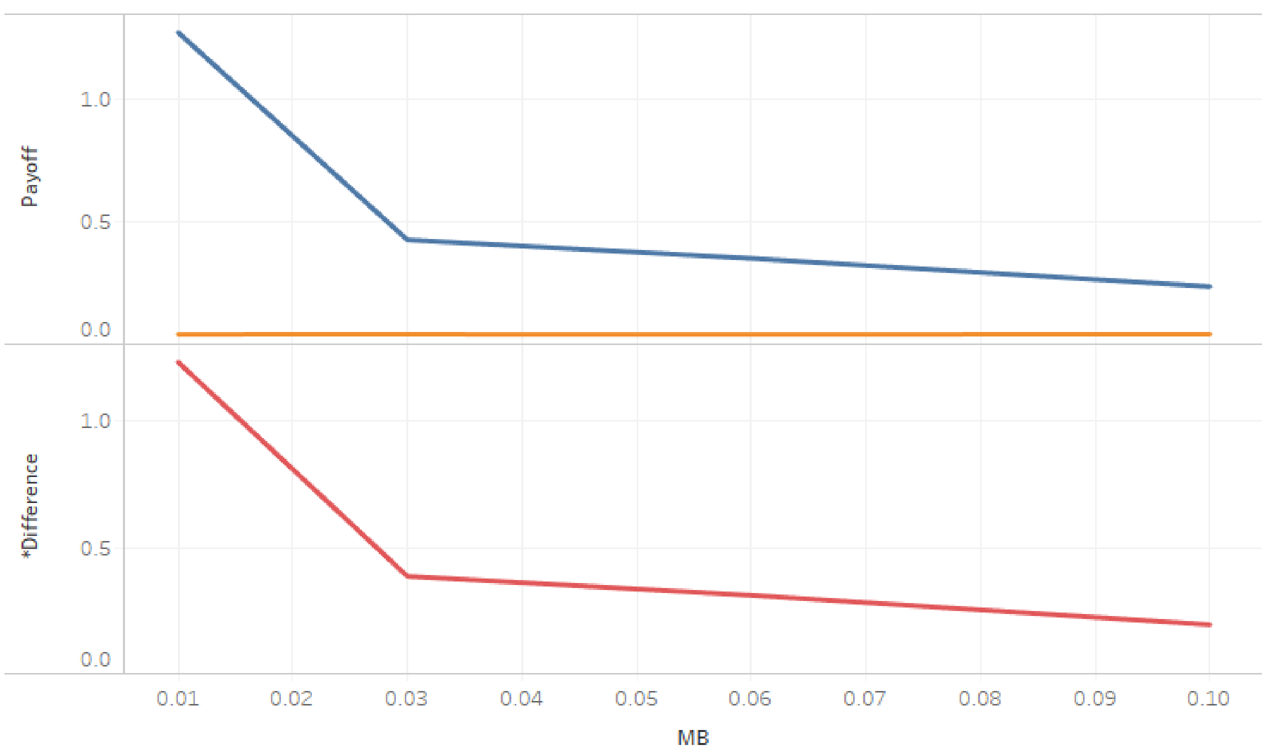
[39] Using a binary encoding, it is possible to obtain huge mutations if the initial bits change. The potential mutation range is way higher, even though the likelihood for mutation is lower than in the Netlogo replication

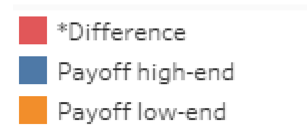


The overall trend of the percentage of firms in the high-end segment is, again, comparable to results of the previous model. The only difference can here be observed with high MB values. The percentage of firms in the high-end segment for MB = 10 is higher than the one reported by Lee, Lee & Rho (2002, p. 741), which was 18,5%. This difference has already been underlined when presenting the results of the standard scenario above. As mentioned before, the reason for that can be attributed to the selection operator. The authors do not explicitly explain how the parents are selected. It is just said that the higher the performance, the higher the probability to be selected as a parent. The function describing this probability is not reported. The selection process in the present model, described above, was conceived to take into account both chance (the selection of the 5 candidates is done randomly) and performance (the best one among them is picked), in absence of more precise information about the way in which was done in the model by Lee *et al*. By comparing the results, it can be concluded that the top performer's likelihood to be selected as a parent must be higher in the current model than in the previous one.

In fact, the percentage of firms in the high-end ends up being slightly higher, even if the overall results are comparable anyway.

The proposition 1b stated that the higher the mobility barriers, the higher the performance difference between the two groups (Lee, Lee & Rho 2002, p. 732). The performance difference is strictly linked with the percentage of firms in each of the two groups. In fact, the final payoff is dependent on the sharing function, which in turn is dependent on the number of neighboring firms. After it has been proved that the number of firms in the high-end is higher for low mobility barriers, it may be redundant to state that the performance is higher for high mobility barriers, since they are inversely correlated. However, in order to provide a full overview and comparison between the two models, the performance difference between the two groups was tested also here. That was done by analyzing the performance of sample groups representing each of the two strategic choices for different MB values:





As shown in the line graph, the values of the two different payoffs tend to converge as MB increases. This data further confirms Lee *et al*'s proposition 1b.

In conclusion, it can be said that the above results corroborate overall Lee *et al's.* findings about mobility barriers: the higher the success probability for firms trying to join the high-end segment (MB), the more likely for a strategic group to emerge and, at the same time, the lower the performance difference between the two groups.

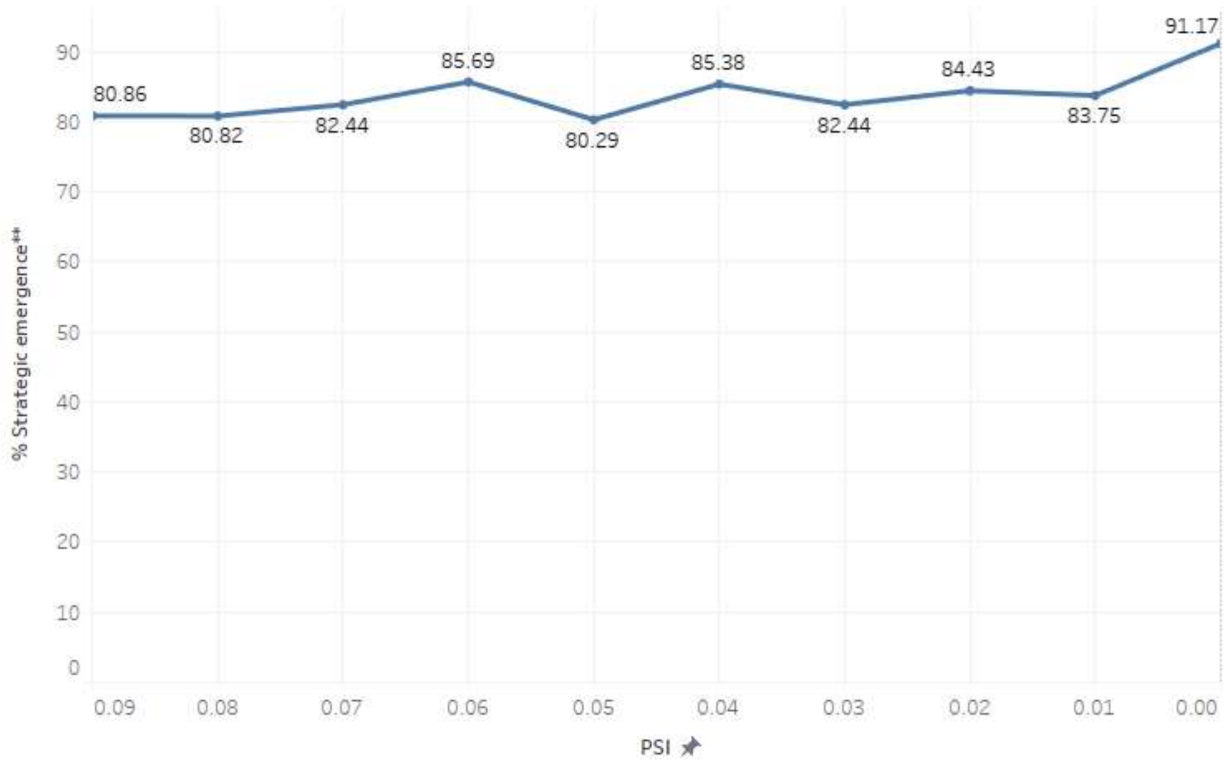
Strategic Interactions

In the below table, the computational results of 10 simulation runs are reported for each PSI value from 0.00 to 0.10, with all the other parameters being equal to the standard scenario above described:

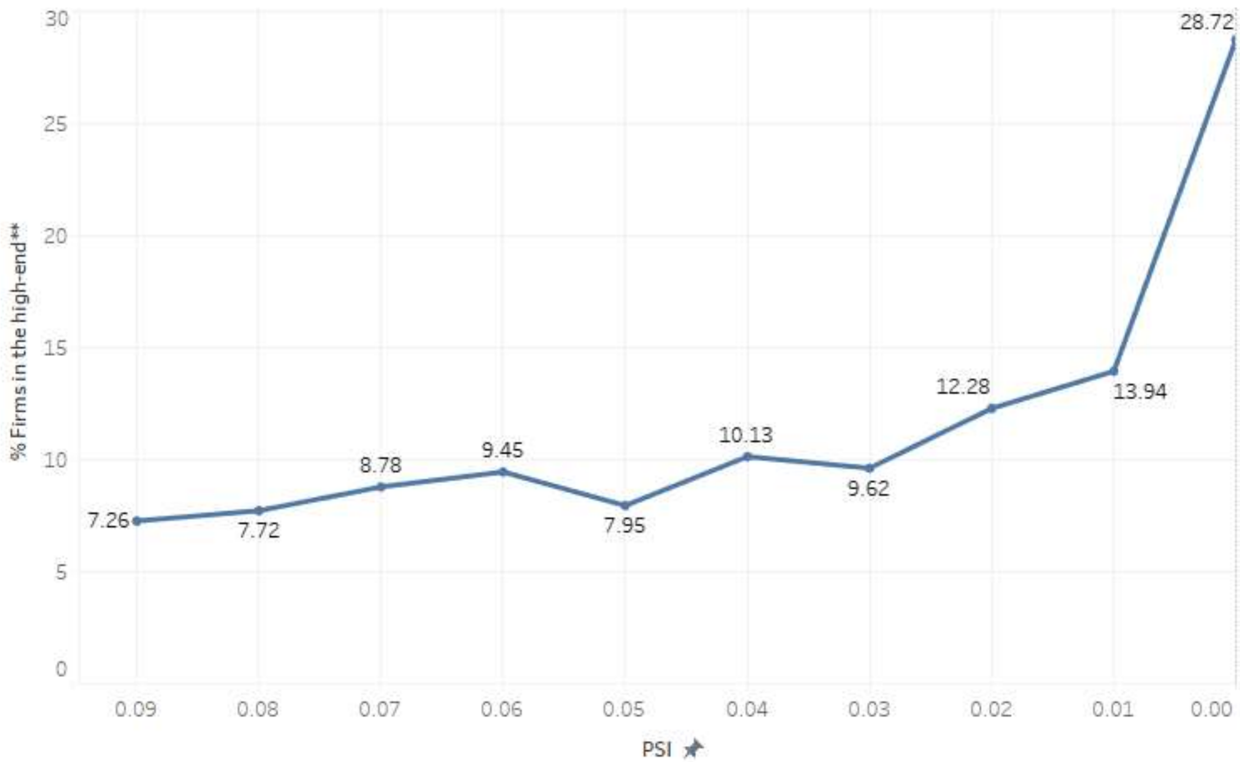
PSI	% Firms in the high-end*	% Strategic emergence*	% Firms in the high-end**	% Strategic emergence**
0	30.60	100.00	28.72	91.17
0.01	12.67	90.00	13.94	83.75
0.02	9.60	100.00	12.28	84.43
0.03	9.50	80.00	9.62	82.44
0.04	14.00	90.00	10.13	85.38
0.05	6.67	90.00	7.95	80.29
0.06	9.33	90.00	9.45	85.69
0.07	10.89	90.00	8.78	82.44
0.08	7.40	100.00	7.72	80.82
0.09	12.33	60.00	7.26	80.86

PSI is a variable conceived for modeling purposes, which represents the preemptive effect of strategic interactions. Strategic interactions (SI) are equal to MB – PSI. Given that SI must be always higher or equal to MB, PSI value has to be comprised between 0 and MB. When PSI is 0, SI and MB have the same value. That means that no preemptive effects from firms in the high-end segment come into play. As before, the two different units of measures are both reported (* for the original one and ** for the other).

Let us analyze now the computational results and compare them with the ones presented in the previous chapter:

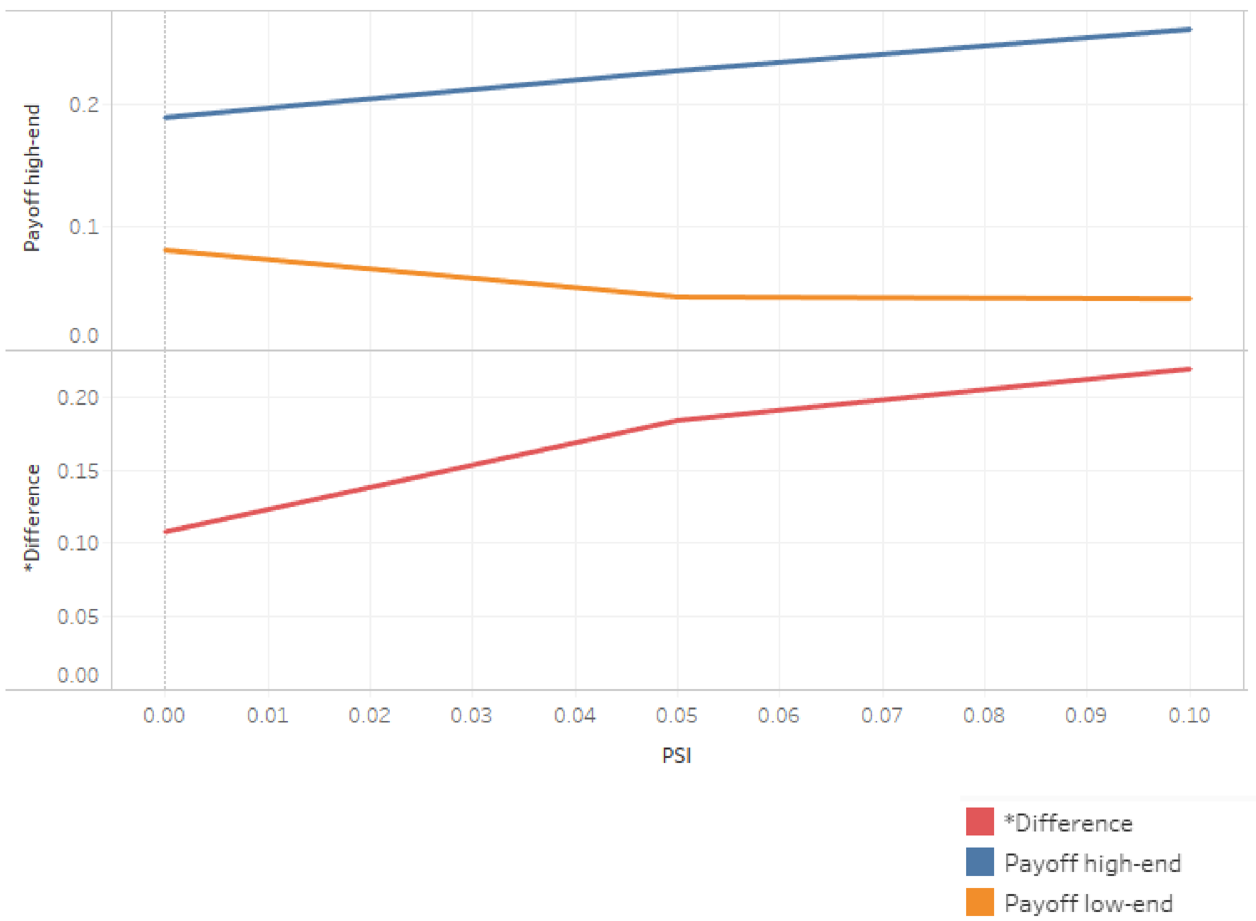


The line graph shows a net increase in the percentage of strategic group emergence from PSI 0.09 to PSI 0.00. The trend nonetheless is not easy to identify and is surprisingly fragmented: the likelihood of a strategic group structure increases from PSI 0.09 to PSI 0.06, but then a deflection is observable in PSI 0.05, PSI 0.03 and PSI 0.01, with some peaks reached at PSI 0.04, PSI 0.02 and finally PSI 0.0. These results are similar to the ones obtained by Lee, Lee & Rho (2002, p. 741). A possible explanation to this interesting phenomenon may be found in the asymmetrical effect of SI, which affects just potential new entrants when a threshold for triggering strategic interactions (S) is reached. Before that threshold value is reached (in the current model 5 firms are needed), the probability to join the high-end segment is equal to MB. SI is therefore irrelevant. That is why results oscillate in this way and a lower SI run might end up reporting a higher percentage of strategic emergence. This is confirmed also by the percentage of firms in the high-end segment, which is almost the same regardless of the SI values, except for high PSI values, as shown in the graph below:



The above graph shows how the percentage of firms in the high-end segment is positively correlated to the increase in SI. The difference with Lee's *et al's* results is yet again related to the lower PSI values (SI = 10), similar to the previously described scenario, which represents its equivalent. The reasons for that are most likely attributable to the same causes as the one described above: real encoding and selection operator.

The performance difference between the two segments has been analyzed also in this case, in order to corroborate Lee, Lee & Rho's proposition 2, which stated that the higher the preemptive effects of incumbents in the high-end, the higher the performance difference (2002, p. 734):



The above graph shows clearly that the payoff of the high-end segment increases as the preemptive effects increases.[40] The difference between the performance of the two groups is higher for high PSI values as well.

From the above data, it is possible to conclude that our model is able to replicate closely Lee *et al*'s also with respect to strategic interactions and validates their related proposition. In the next paragraph, the dynamic capabilities will be taken into consideration.

[40] PSI is equal to MB-SI. When PSI is 10, it means that the preemptive effect is at is maximum (PSI = MB).

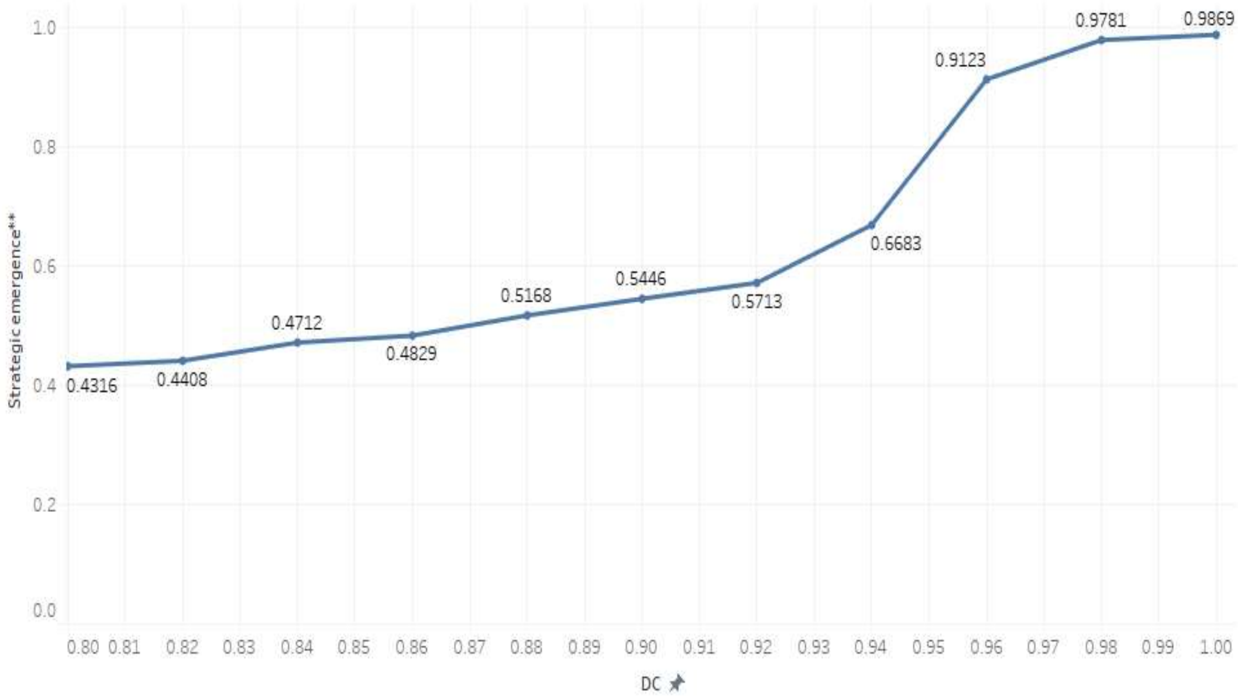
Dynamic Capabilities

The below table reports the results over 10 simulation runs for each DC value from 0.8 to 1, with 0.02 intervals:

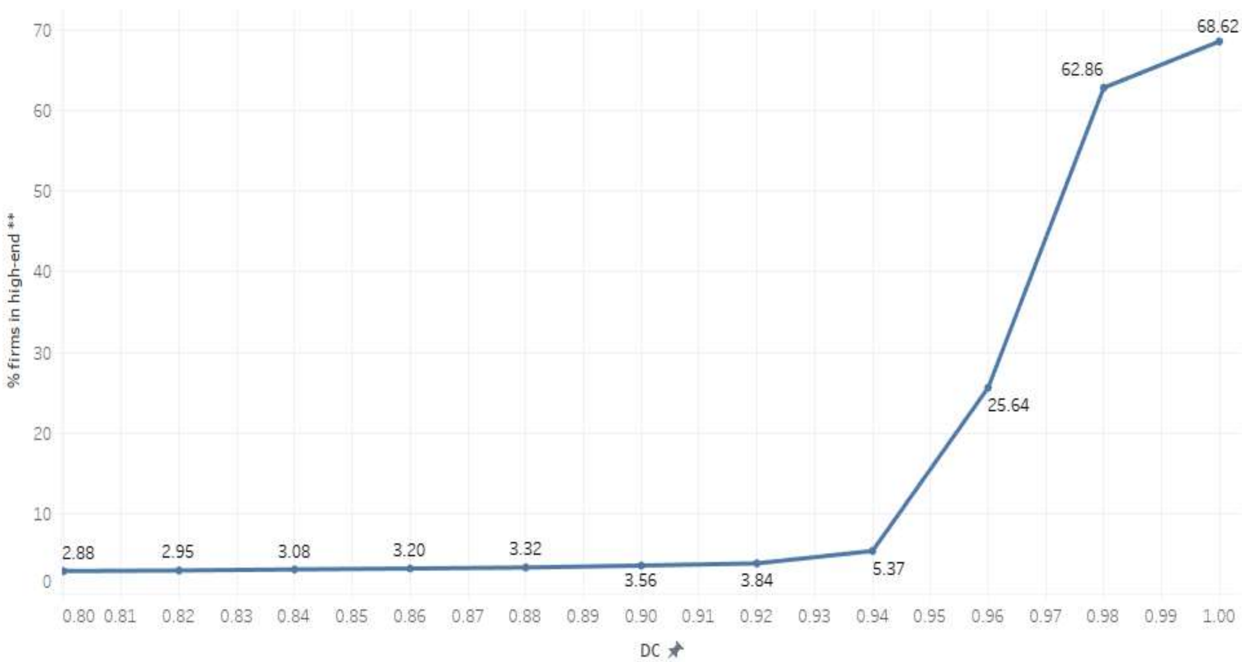
DC	%firms in high-end*	% Strategic Emergence*	% firms in high-end **	% Strategic Emergence**
0.8	3.00	40.00	2.88	43.16
0.82	2.40	50.00	2.95	44.08
0.84	3.60	50.00	3.08	47.12
0.86	3.60	50.00	3.20	48.29
0.88	2.57	70.00	3.32	51.68
0.9	4.80	50.00	3.56	54.46
0.92	4.00	50.00	3.84	57.13
0.94	6.86	70.00	5.37	66.83
0.96	37.40	100.00	25.64	91.23
0.98	70.60	100.00	62.86	97.81
1	72.00	100.00	68.62	98.69

The data confirms Lee *et al*'s proposition 3 about dynamic capabilities: the higher the firm's ability to adapt to changes in the environment, the more likely it is going to survive in the high-end segment. The percentage of strategic group emergence and percentage of firms in the high-end segment steadily grow as DC increases.

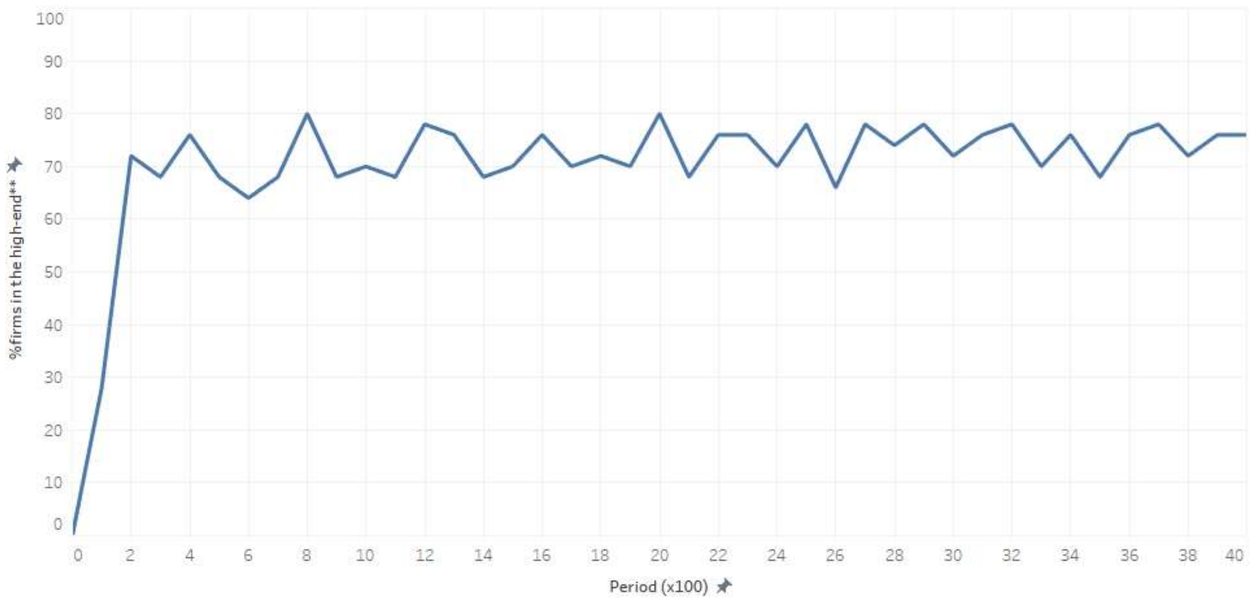
Let us analyze in more depth the data related to strategic group emergence:



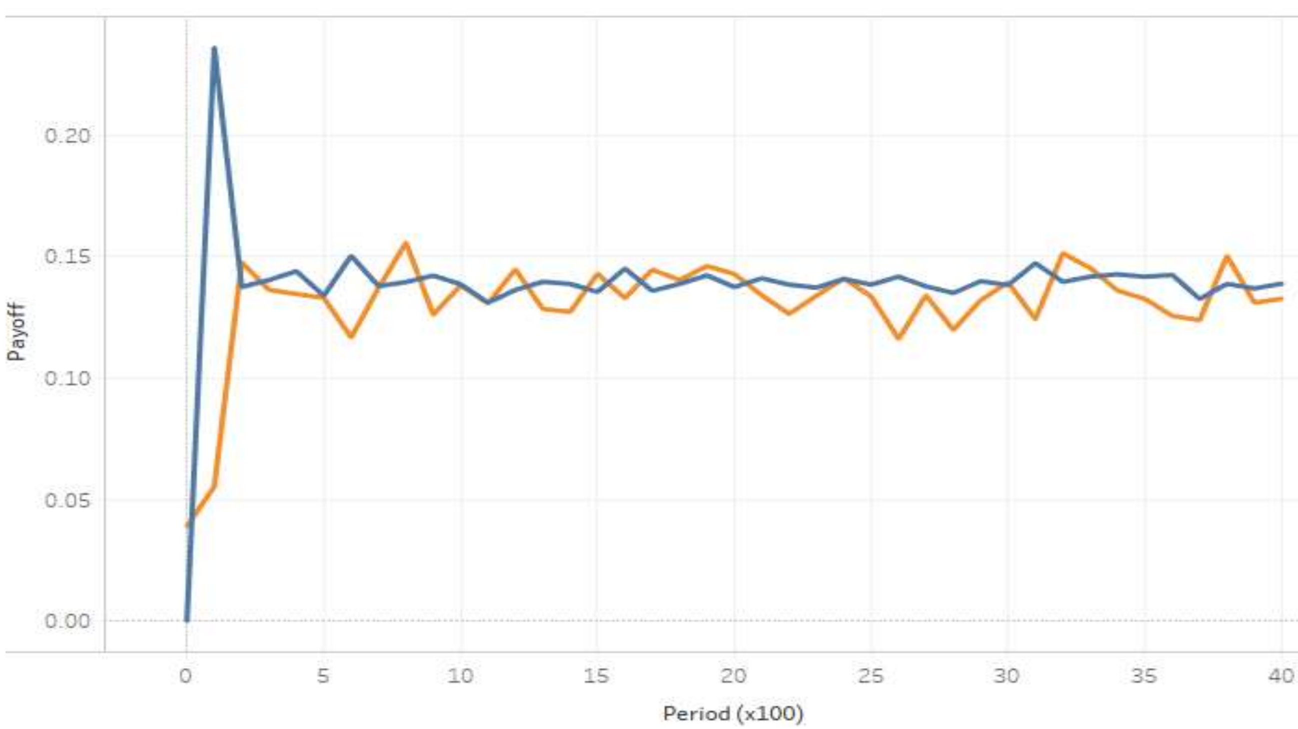
The results in this case are almost the same as the ones obtained by Lee *et al'*. Strategic group emergence is positively correlated with the increase in DC. The data about the firms with a high product quality are worth discussing in more depth:

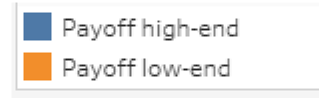


A small minority of firms is present in the high-end segment for low DC. In fact, the absence of the ability to adapt to changes in the outside environment do not let them exploit their competitive positioning for a long time. The high-end strategic group starts increasing until it reaches a value of about 70% when DC is equal to 1. It is worth considering why the high-end group stops at that percentage and does not grow until including every firm in the industry. In fact, if every firm that manages to enter the high-end segment has a 100% probability to maintain its competitive positioning (DC = 1), shouldn't all the firms, reshuffling their strategic choice, eventually end up there? The answer is negative. In fact, a firm's objective is not to enter the high-end segment per se, but rather to have the highest payoff possible. Because of the sharing function, the more firms are present in a determined group, the lower the individual profits are going to be. When about 70% of the firms are in the high-end strategic group, the payoff related to the high-end group starts to be balanced with the one provided by joining the low-end segment, until the last ends up being more profitable than the other. At this point, the new entrants are likely to start imitating firms in the low-end, until the high-end will be again the most profitable between the two. That will trigger again the imitation of high-end firms, and so on. The market reaches a dynamic equilibrium, regardless of the number of generations. Hereby is reported a graph, which replicates the exact same scenario (DC = 1), but the length of the run is 4000 periods (instead of 2000):



The results oscillate between the same values potentially forever. Firms enter and exit the high-end depending on which one is the most profitable between the two. The payoff difference between the two strategic groups clearly reflects these dynamics:





The payoff reaches an equilibrium around the 250th period, which lasts until the end of the simulation. Similar results on the matter are achieved also by Lee, Lee & Rho (2002, p. 742).

In conclusion, it can be stated that the dynamics generated by the variation of DC values replicate satisfactorily Lee *et al*'s once again.

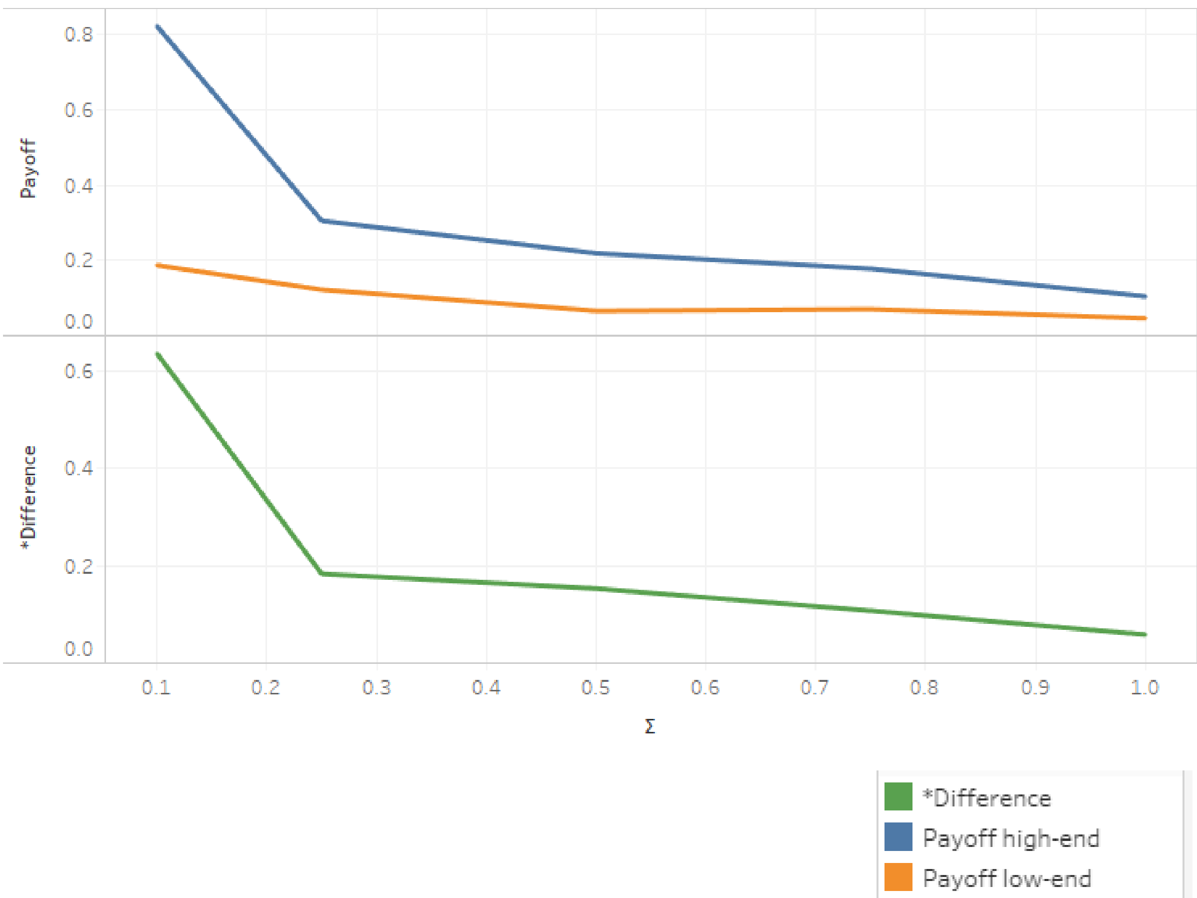
Boundary of Rivalry

The data shows that the higher the boundary of rivalry, the lower the probability for a strategic group to emerge:

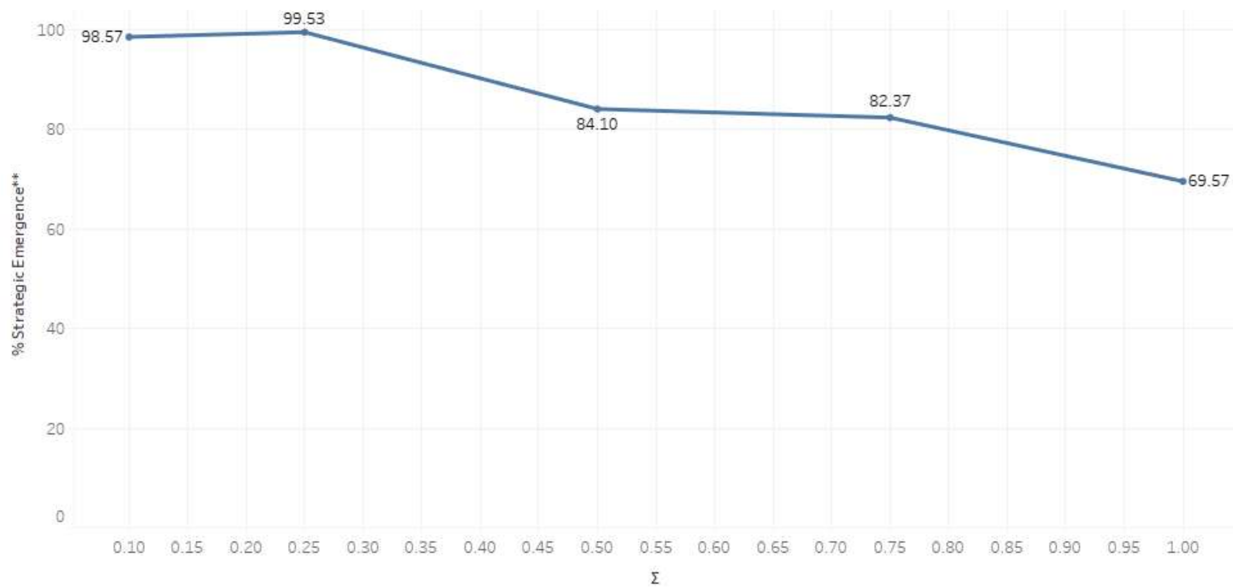
Σ	%firms in high-end*	% Strategic Emergence*	% firms in high-end **	% Strategic Emergence**
0.1	27.78	90.00	24.39	98.57
0.25	46.00	100.00	42.78	99.53
0.5	11.78	90.00	11.34	84.10
0.75	30.44	90.00	20.37	82.37
1	11.50	80.00	8.17	69.57

Strategic emergence diminishes as σ increases, because the payoff degradation of the high-end firms makes them a less appealing target for imitation. In fact, the sharing function, applied to all the firms in the industry ($\sigma = 1$), determines an overall worse performance. That is clearly shown by the below table, which compares the performance between the two groups over all the σ values considered:

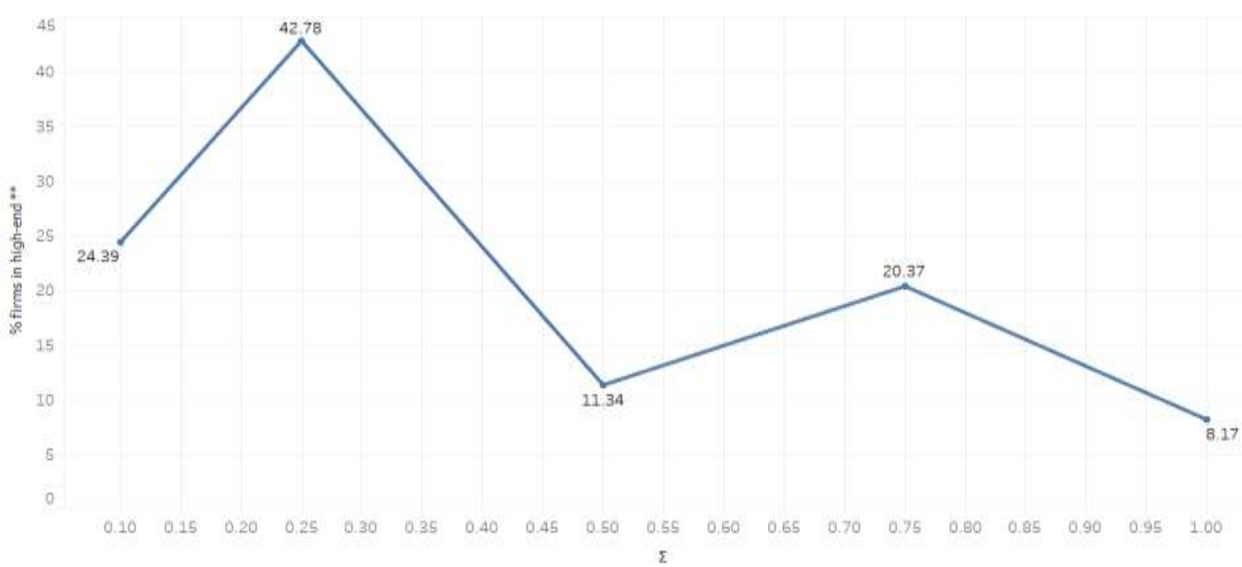
Σ	Payoff low-end	Payoff high-end	*Difference
0.1	0.1869	0.8222	0.6353
0.25	0.1221	0.3051	0.1830
0.5	0.0658	0.2188	0.1530
0.75	0.0702	0.1777	0.1075
1	0.0462	0.1046	0.0584



The difference between the two payoff tends to 0 as σ tends to 1. That is why the percentage of strategic group emergence diminishes for higher boundaries of rivalry:



However, the results slightly differ from the one by Lee *et al.* in that the percentage of strategic group emergence is higher in our model for high σ values.[41] This is probably attributable once again to the higher degree of mutation. In fact, the percentage of firms in the high-end segment for σ = 1 is exactly the same as in Lee *et al*'s findings (8.17% vs 8.15%):



[41] The authors report a 36% percentage of strategic emergence for σ = 1 (Lee, Lee & Rho 2002, p. 743).

In conclusion, it can be said that the above data validates Lee, Lee & Rho's proposition 4 (2002, p. 735), which states the negative relation between σ and strategic group emergence.

Conclusions

In the present chapter, the model by Lee, Lee and Rho has been replicated from scratch. From the above data, it is possible to conclude that the current Netlogo model is able to replicate closely Lee *et al.* This represents the first important result of the present work. The slight differences with the past model can be attributed to modeling differences and incomplete information, such as the different way of encoding product quality (binary, in the case of the original model, real in our case) and in the way the selection and mutation of the agents are operationalized. Nonetheless, Lee *et al*'s propositions, delineated in the previous chapter, have been validated by the data reported.

In the following chapter, some of the assumptions underlying the current model are going to be challenged and some attempts to modify the model accordingly will be tried. Comparing the related changes in the firms' behavior is believed to be extremely useful in gaining a deeper understanding about the phenomenon of strategic group emergence.

4. Rethinking Strategic Group Emergence

In the previous paragraphs, J. Lee, K. Ree, S. Rho's GA-based model on strategic group emergence was thoroughly discussed and then successfully replicated using Netlogo. In the last chapter of the present research, some of the assumptions underlying that model will be challenged and the code will be modified accordingly. Thanks to that, it will be possible to observe and study how the related changes affect the behavior of the firms and draw some more general conclusions about the phenomenon of strategic group emergence. Moreover, modifying the context of interactions without compromising the overall consistency of the results further validates the significance of the strategic group theory. In the following paragraphs, the magnitude of the modifications to the model will gradually increase. At the beginning, just slight changes and fine-tuning alterations will be enacted. Later on, the underlying assumptions will be radically challenged, with a dramatic impact on the model itself.

4.1 Population

The first modification to the original model pertains the size of the firms' population. In fact, one of the unaltered assumptions throughout all the analyzed scenarios so far was that the number of firms within the considered industry was always 50. This number was believed by Lee *et al.* to make it possible to observe the agents' behavior and draw some consistent conclusions, while at the same time preventing the dataset to grow to a difficult-to-handle size. However, it is not clear in which way, if any, the number of firms in an industry affects the final outcomes of the system. Theoretically, the results should be the same in percentage regardless of the size. In the current paragraph, this proposition is going to be tested.

From a modeling point of view, finding an answer to this issue is more difficult than it may seem at a first glance. In fact, it is not sufficient to just vary the number of firms and observe what the outcomes are. If it were the case, Lee *et al.* would have probably already done that. In the code there are actually many parameters whose values are strictly linked to a determined quantity of firms. For example, it has been assumed that the original number of individuals is always stable: the number of agents "dying" each period is the equal to the one of the new-entrants. With the current setup, 5 new firms, or 10% of the firms (with a population of 50 agents), are replaced each generation. If the firms were 200, that number would represent just the 2.5% of the total. How does that affect the final outcomes? Consider also the selection operator. To generate the new individuals, 5 firms are selected at random[42] over the entire population and the best performer among them is selected to be the first parent. What would change if the firms were 200?

The answer to these questions highly depends on the way the parameters related to the population size are conceived. In fact, the way these parameters change with the population size has to be established first. To perform the first simulation, the following assumptions have been made:

- S (the threshold for strategic interactions) has been set to 5 regardless of the number of firms. In fact, there is no reason why the number of firms triggering cooperation among incumbents should depend on the total number of firms within an industry
- The new-entrants every period represent the 10% of the total population
- The number of potential parent candidates (the "tournament-size") represents the 10% of the population

[42] In the model, this 5-firms sample has been operationalized with a parameter called "tournament size".

50 simulations were respectively run for a population size of 50, 100, 150 and 200 firms. The parameters were set to the values used in the standard scenario, i.e.:

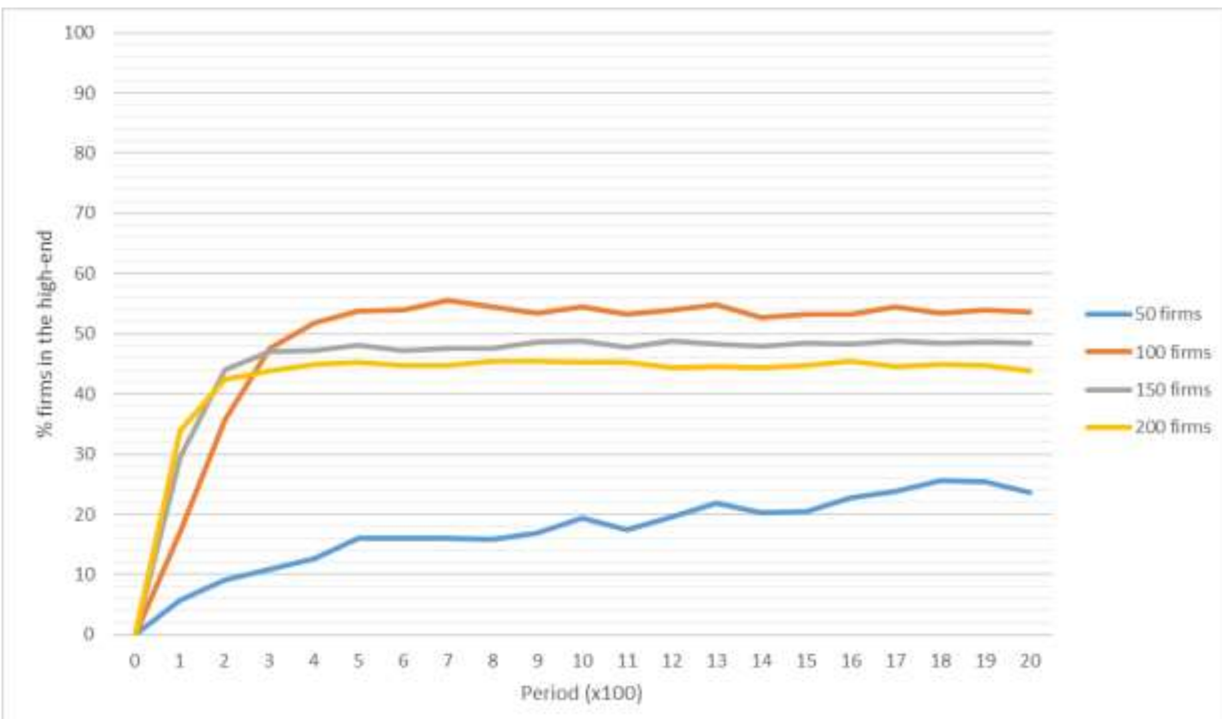
MB: 0.10

SI: 0.10

DC: 0.96

σ_{rivalry}: 0.50

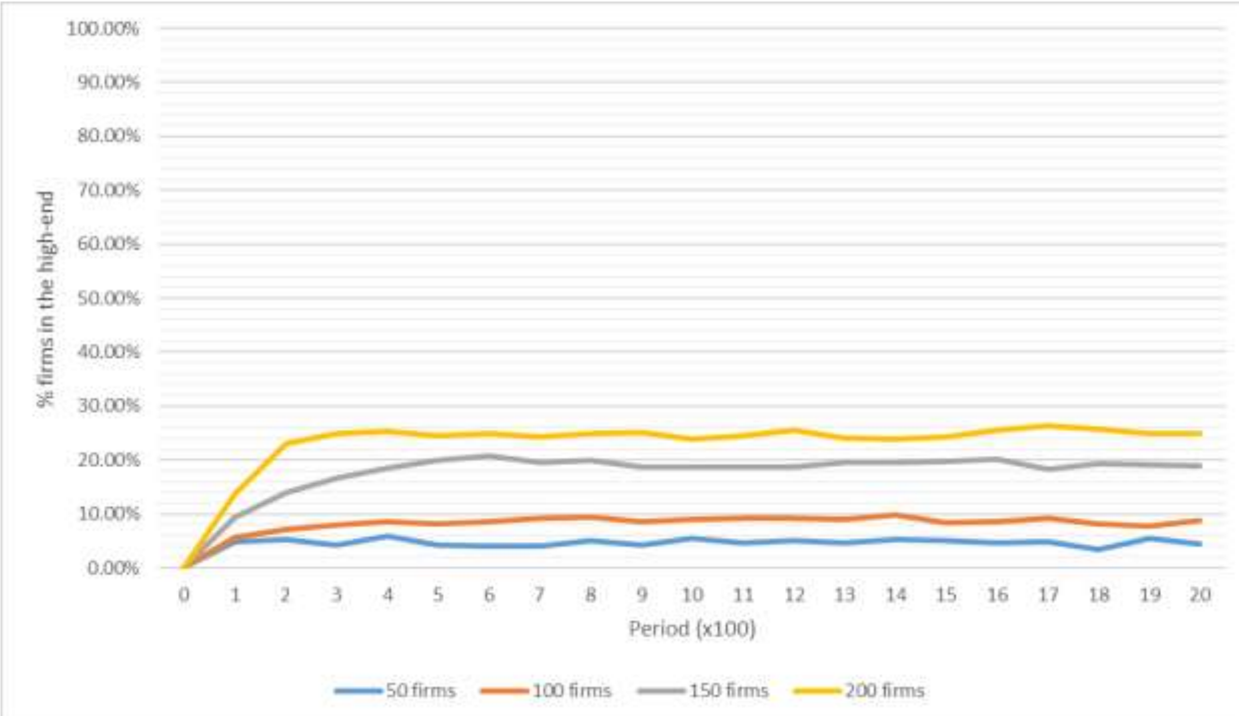
The results are depicted in the following graph:



From the above graph, it seems that the population size is positively correlated with the percentage of firms in the high-end segment. At a closer look, though, it seems that the most evident gap is between the 50-firms size and the others. In fact, it is possible to observe a more than ten percentage points gap with the other scenarios. However, the correlation between number of firms and strategic group emergence is not so straightforward. In fact, the highest percentage of high-end firms has been reported by the 100-firms scenario, followed by the 150 one and then by the 200. This result is surprising and unexpected. It is unlikely to be the result of pure luck, since 50 simulations are enough to soften volatility. In the following table, it is possible to examine the difference in the average percentage of high-end firms for every scenario:

50 Firms	19.40
100 Firms	49.41
150 Firms	45.85
200 Firms	43.11

Notice that in the current scenario there is no collusion operated by incumbents: the preemptive effect of strategic interactions was 0. The parameter S was therefore irrelevant. This premise was modified in order to observe how firms' reactions differ depending on the industry population, when strategic interactions come into play. In this scenario, PSI (the preemptive effects of strategic interactions) was therefore set to 0.05 (SI is therefore 0.05 as well). The other values have been kept unaltered. The below graph shows the related results:

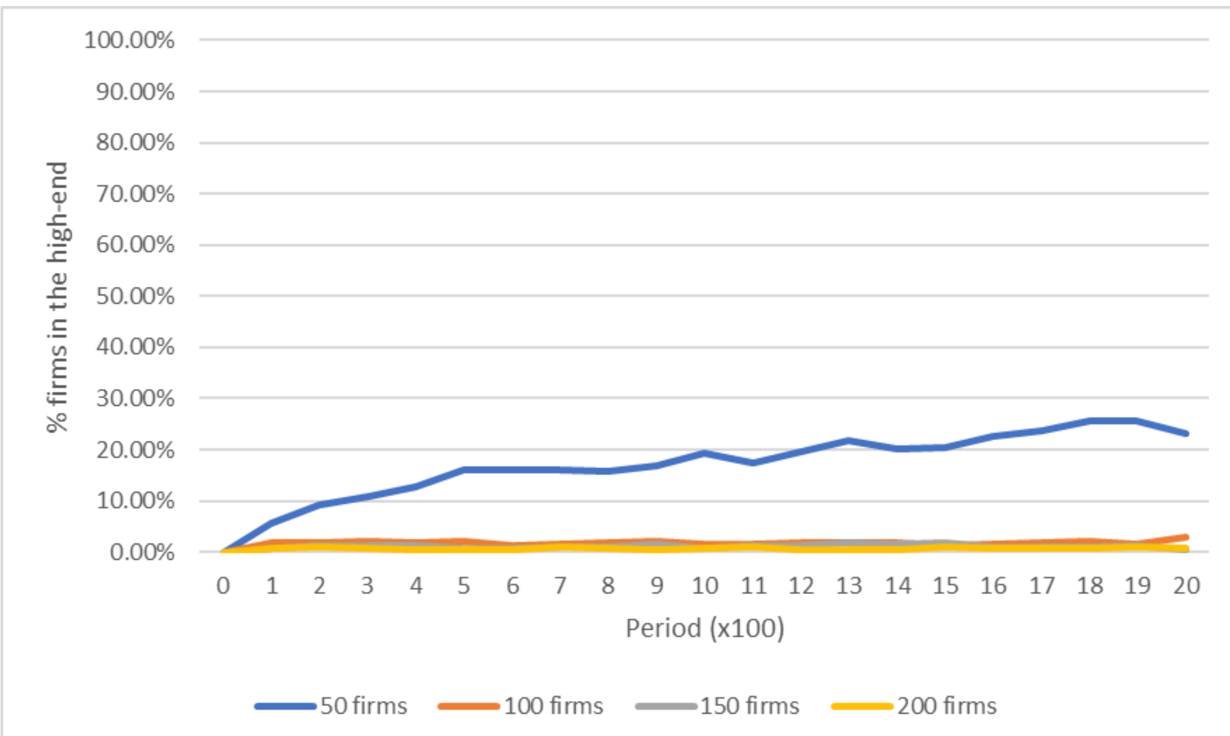


Under these circumstances, the population size seems to be actually a factor in determining the percentage of firms in the high-end segment. The trend can be now recognized easily:

50 Firms	4.72%
100 Firms	8.34%
150 Firms	17.94%
200 Firms	23.63%

With the performed modifications to the model, it can be concluded that the number of individuals is positively correlated with the emergence of more numerous strategic groups. These results can be most likely attributed to the increasingly higher "tournament-size" and to the higher number of new-entrants for each generation. In fact, even if those numbers are equal in relative terms (the percentage on the total is the same), in absolute terms it is of course higher. That contributes in triggering a faster, positive feedback from the system and in diluting the stochastic component, given the higher number of interacting agents.

To test this proposition, a final experiment was conducted. In the last scenario, the code has been kept unaltered with respect to the previous setup. The number of firms drawn during the selection process ("tournament-size") is always 5, regardless of the number of individuals in the population. The same applies as well to the number of new entrants every period (always 5). The parameters have been set again to the values of the standard scenario. The below graph shows the related results:



In this case, it seems that the number of firms is negatively correlated to the percentage of strategic group emergence. That can be explained because of the higher relative weight of the stochastic component. In fact, if a firm manages to enter the high-end segment successfully, it will be hardly selected as possible parent if the population of agents is too numerous. The parent candidates are just 5, which, in the 200-firms case, represents only

2.5% of likelihood (5% for both the parents). The best performer is going to be selected just 1 time out of 20. In the 50-firms scenario, instead, the probability is 20% considering both the parents. These findings are further validated in the table below, representing the average number of firms in the high-end over the entire simulation periods:

50 Firms	17.48%
100 Firms	1.83%
150 Firms	1.17%
200 Firms	0.74%

Modifying the population of firms brought to inconclusive results: depending on the cases and on the way the code was modified, the model reported different and often conflicting outcomes. Probably, that shows only that the model in question must be interpreted as a mere testing environment or a proof of concept which allows the researcher to observe the dynamics of strategic groups from a privileged point of view. However, its nature should not be misinterpreted by pushing this mock-up too far and by trying to operationalize overcomplicated aspects typical of the real-world conditions, among which the number of firms in a determined industry.

4.2 Selection

Excluding organicist biases

Another necessary modification to the original assumption pertains the selection operator. J. Lee, K. Ree, and S. Rho translated in their model A. Alchian's intuitions on strategic interactions between economic agents. The organicist theoretical framework influenced the way in which the different operators in the model have been conceived. As seen in the previous chapters, innovation and entrepreneurial activity, for example, were associated with the random mutations which living organisms are subject to. The generation of new firms, then, was considered as the equivalent of the generation of new individuals from two different parents in nature and modeled through the selection operator.

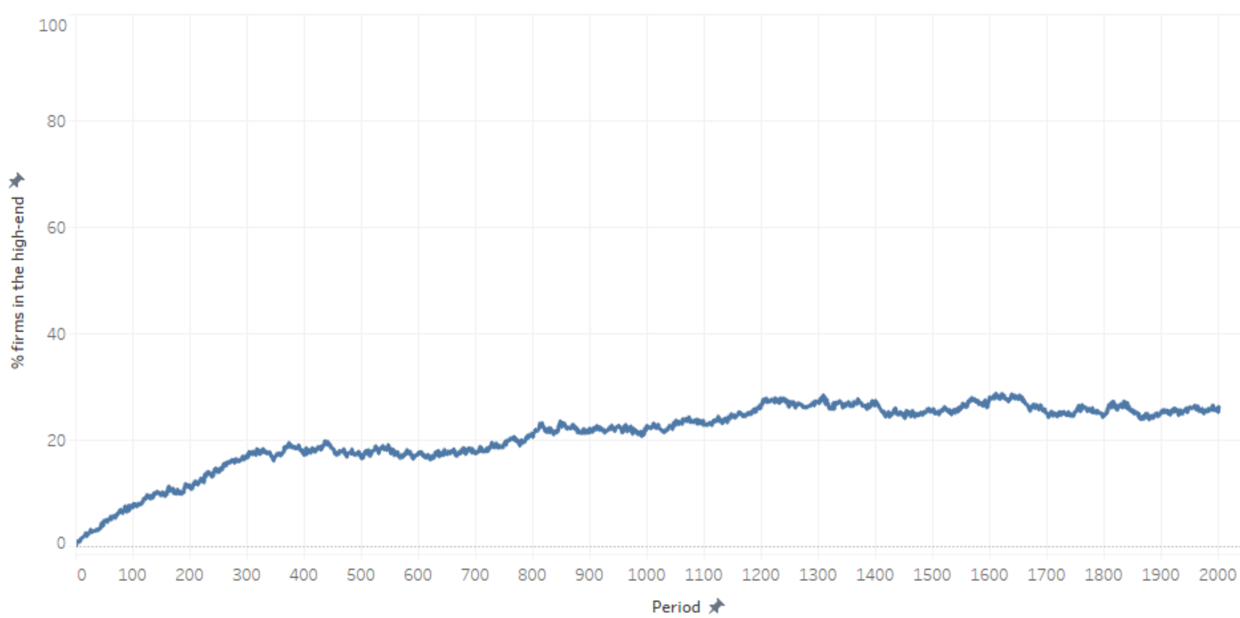
Such an evolutionary approach contributed fruitfully in gaining a different perspective and a deeper understanding of firms' behavior, freeing the economic doctrine by an excessive mechanism and determinism. Nonetheless, it is necessary to be cautious when using metaphors in a scientific field like this one. In fact, interpreting the firm *literally* as a living being might contribute to deceptive results. One of the possible misunderstandings has been identified in the selection operator. In fact, why should a new firm need two "parents" to be generated and enter the market? It could be rather the case in which the target for imitation is just a single successful firm. The rational motivation behind the generation of two firms by *exactly* two parents is not clear and Lee *et al.* does not expressly explain the reason for this choice (besides the fact that it replicates the natural reproduction). The consistency of the selection operator is not called into question here. In fact, thanks to the numerous simulations done in the previous chapters, the fact that the model works is beyond any doubts. Nonetheless, it must be proved that also different and equally coherent ways of conceiving the selection operator provide similar results. Otherwise, the model would highly depend on an entirely conjectural hypothesis, based not on rational assumptions but rather on a specific human tendency to interpret reality using metaphors. The overall results of the previous simulations would be deeply biased.

In order to prove that the model works also with a different selection operator, this last one was modified. The procedure replicates closely the previous one: the only difference consists in the fact that just one "parent" is selected now:

$$x_b = \lambda x_a$$

λ has been modified as well. In the previous versions of the model, it represented a random number between 0 and 1, which changed each period. Thanks to it, it was possible to randomly calculate a weighted average between the two parents. At the present state, with just one parent, it did not make sense to keep the previous definition for λ. Therefore, in the present model λ represent a random number, drawn following a normal distribution of probability having mean (μ) = 1 and standard deviation (σ) = 0.5. The model requires no further modifications and everything else in the code has been kept unaltered.

To prove the consistency of the results also under these circumstances, 50 simulations have been run, setting the parameters to the standard scenario values. The results for these simulations are the following:



As shown by the graph, the data is clearly comparable to the ones obtained in the previous model under the same circumstances. In fact, the final percentage of high-end firms is almost equal (26,28% vs 28,96%). Thanks to this data, it is possible to conclude that the model results do not depend on biased assumptions guided by an organicist approach and is perfectly coherent also with different hypothesis about the selection operator.

The role of randomness

One of Lee *et al*'s fundamental assumptions originally was that the best performing firms had a higher probability to be selected as targets for imitation. In our previous model, that was taken into account by adding a stochastic component: the top performer was chosen among 5 parent candidates that were selected at random. Both performance and chance were involved in the process.

However, it could be argued that this partially contradicts the premise of information incompleteness, set by A. Alchian and in principle followed by Lee *et al.* themselves. Economic agents cannot precisely know which firm is performing better according to the specific payoff function in play (which they do not know either). The question therefore is: what would it happen if the assumption of information incompleteness were brought to its extreme consequences and firms would choose the target for imitation completely at random? Would strategic groups still emerge? Such questions may seem to refer to a scenario which is very far from reality, since it is dominated by randomness. Yet, finding an answer could help in gaining a deeper understanding about the role of chance in the strategic groups' dynamics. In fact, comparing the results under these new conditions with the previous ones could help in understanding to which extent the quality bias in the selection operator contributes to the development of specific strategic groups dynamics.

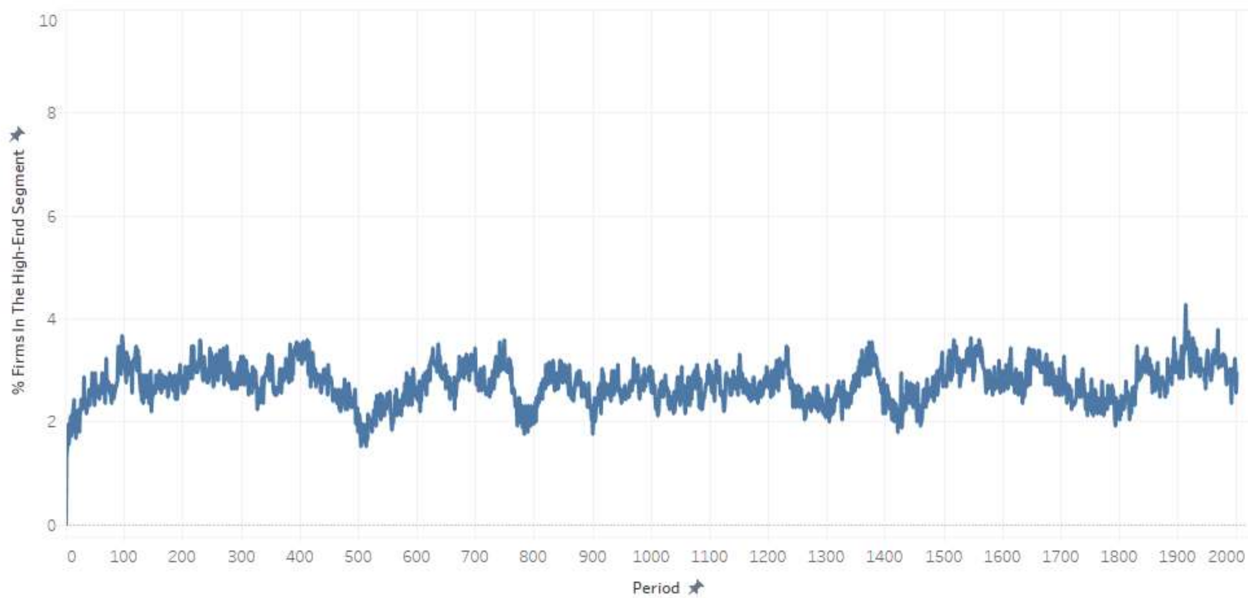
Moreover, finding reasonable motives to challenge the fact that firms are selected according to their economic performance is not too difficult. It could be even argued that a world dominated by randomness is closer to reality than Lee *et al*'s scenario. In fact, the motivation to imitate a specific target may be highly subjective and not necessarily related to economic performance per se. Moreover, the motivations of each economic agent may vary: one firm could favor the economic performance, another the simplicity of imitation, and another one again the fitness with future forecasts or expectations. Theoretically, it would be possible to determine for each agent the weights assigned to each dimension of value and program the model to take that into account in the choice. However, that would be almost equal, in terms of results, of establishing that every firm selects its targets at random. In conclusion, a strictly performance-based guide of action for economic agents may even oversimplify the reality more than a totally random choice of targets for imitation.

To take those considerations into account, the selection operator has been modified in the Netlogo model so that the 5 new firms choose their parents completely at random. The new offspring now just selects by chance one among the 45 surviving firms each period as first parent and then it does the same for the second one. The resulting strategic choice of the new firm is again the weighted average of the two parents:

$$x_{ab} = \lambda * x_a + (1 - \lambda)\, x_b$$

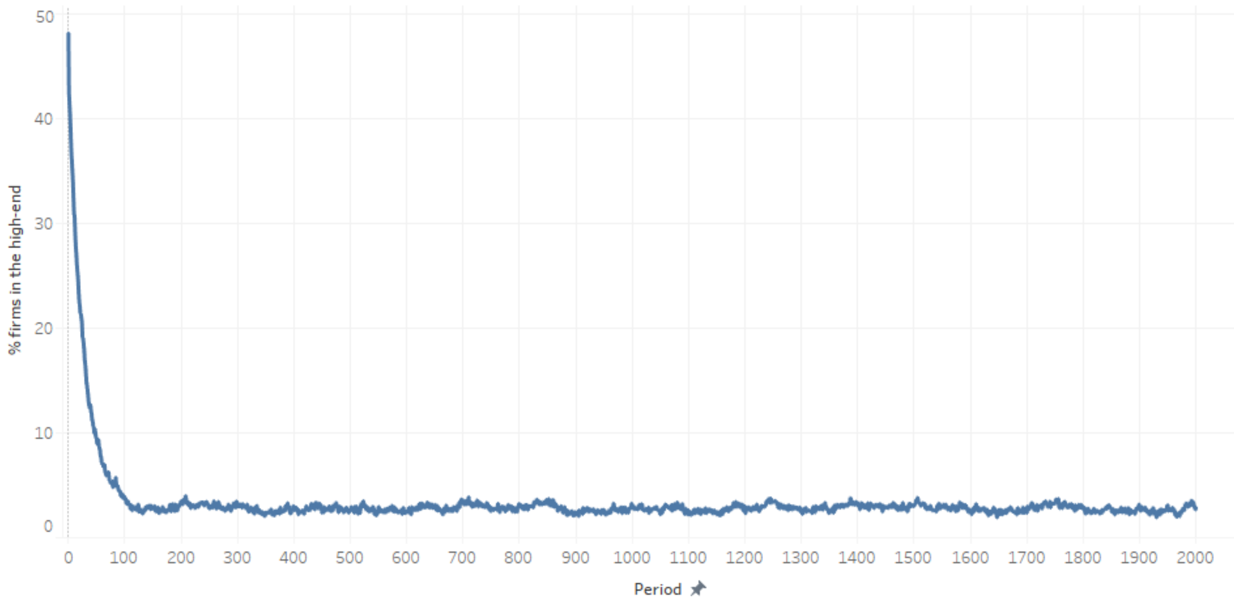
The procedure replicates exactly the one proposed in the previous chapter. The difference pertains just the way the parents (x_a, x_b) are selected.

In order to be able to observe the firms' behavior under these new conditions, 50 simulations have been run. The parameters values are the same of the aforementioned standard scenario, with all the firms starting in the low-end segment ($x < 0.5$):



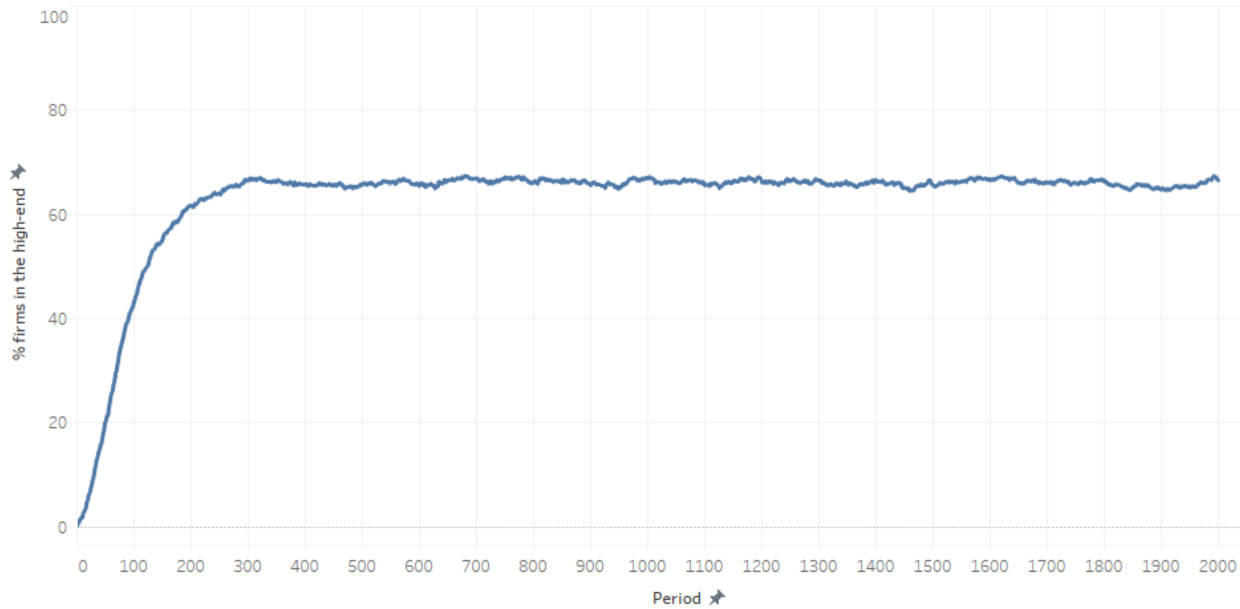
From the above graph, it can be concluded that no strategic group emerges in the long term if targets for imitation are selected completely at random. No clear trend is identifiable, the firms in the high-end group oscillate between a range of 2-4%, which means 1-2 firms on average. This number is steady over all the 2000 periods. The few firms that manage to enter the high-end segment are the ones subjected to extremely favorable mutation. That does not trigger any response by the other firms, though: targets are randomly selected. Because of the limited dynamic capabilities, those lucky firms are not able to maintain their competitive positioning long enough to trigger high-end strategic interactions.

In the present model, it has been assumed that firms start operating in the low-end segment. It is interesting to modify this assumption, in order to verify whether that affects the dynamic of emergence of strategic groups. In the below graph, the firms start initially with a random x value (product quality) comprised between the entire product space (0-1). 50 simulation runs under the same circumstances have reported the following data:



The firms operating in the high-end segment rapidly disappear throughout the periods because of the limited dynamic capabilities. The firms are not able to keep their competitive positioning on the long run because of the random selection of the firms to imitate. The final results are equal to the ones of the previous graph, where all the agents started operating in the low-end. The data clearly show that the initial strategic choice does not affect at all the dynamics of strategic group emergence under these circumstances.

One last simple modification to the model, which could be useful in better understanding the role of chance, consists in the complete removal of randomness in the parents' selection process. What would it happen if just the best firms among all the firms' population are picked to generate the new offspring? To implement that in Netlogo, the code has been changed so that the new entrants pick up the top performers among all the firms (and not anymore among a random sample of 5 firms). In this way, the stochastic component of the selection operator is completely removed. 50 simulation runs, with all the parameters equal to the standard scenario, have reported the following data:



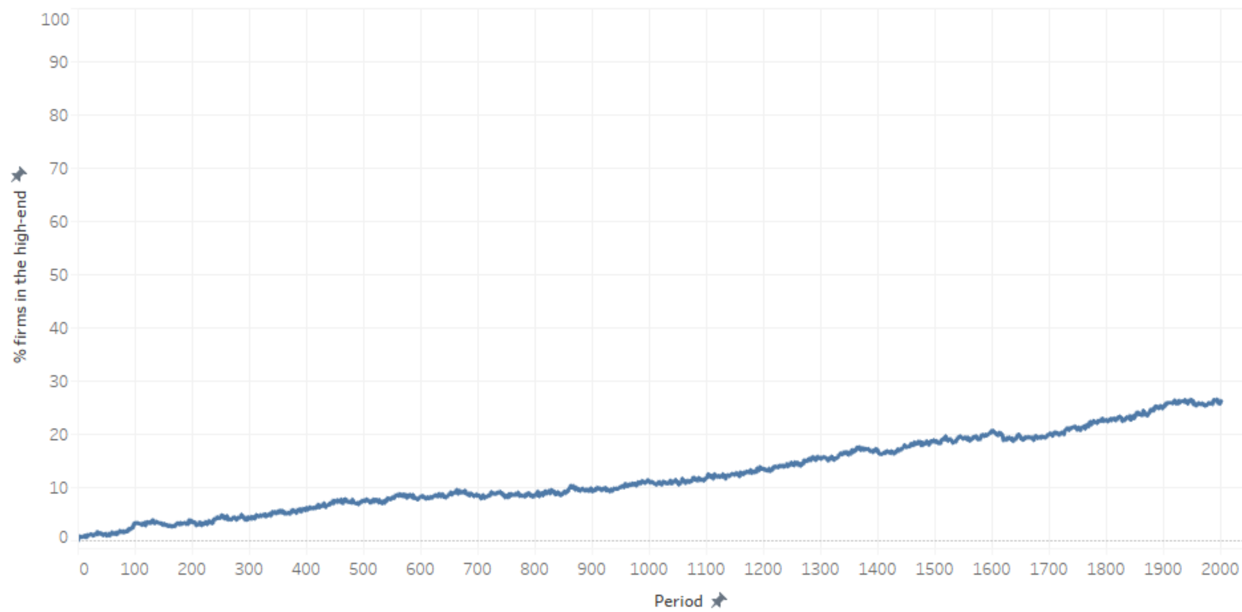
As shown in the graph, if the new entrants select only the best performers, the system reaches soon (in about 300 periods), a situation of dynamic equilibrium between the payoff of the high- and low-end segment, with the percentage of firms in the high-end slightly below than 70%. This condition is similar to the one described in the previous chapter, when the dynamic capabilities were equal to 1. Despite being a quite unrealistic scenario, it helps in further understanding the role of chance. It can be concluded that mobility barriers, preemptive interactions by incumbents and limited dynamic capabilities do not explain alone the fact that usually just a minority of firms operate in the high-end segment. In fact, if firms were able to imitate successfully the best performers every time, the strategic group dynamics would be described by the above graph, even for low success probabilities to enter the most profitable segment. In the real world, though, it is never possible to imitate another firm so easily and exactly as in the current model. That is why the strategic group dynamic emerging in the original model seems to be much more familiar than these ones.

4.3 Mutation

In this paragraph, the mutation operator is going to be deeply analyzed and modified according to different assumptions. In the original model, mutation affected just the 5 new firms that were created each generation, substituting the worst performers. This premise will be challenged here. In fact, it is indeed believed to be very unrealistic. Lee *et al*. refer to "mutation" as the correlative of an "exploratory or entrepreneurial-type activity" or "innovative search" (Lee, Lee & Rho 2002, p. 736). Why should incumbents not be affected by that and why should that possibility be prerogative just of the new entrants? In reality, incumbents in a determined industry are hardly willing to give up the opportunity to innovate and explore new possible and profitable strategies. The R&D departments of firms can be as innovative as entirely new ventures. It is rather unrealistic not to take into account innovation for incumbents, be it intentional or the mere product of chance.

Therefore, the model was modified in order to observe the impact of a wider concept of mutation on the behavior of the agents. It was assumed that each firm has a 5% probability to mutate. When a firm undergoes such a change, a random number is added (or subtracted) to the original value representing the strategic choice of the firm (in our case, x, the product quality). A normal probability distribution with mean (μ) = 0 and standard deviation (σ) = 0.15 determines the likelihood of a determined number to be picked and, therefore, establishes the magnitude of the mutation. A firm may both increase and diminish its product quality (x) when it mutates. Notice that the increase in the product quality does not automatically represent an increase in performance (and the other way around), because of the sharing function.

With the standard parameters' values, 50 different simulation runs gave back the following results:

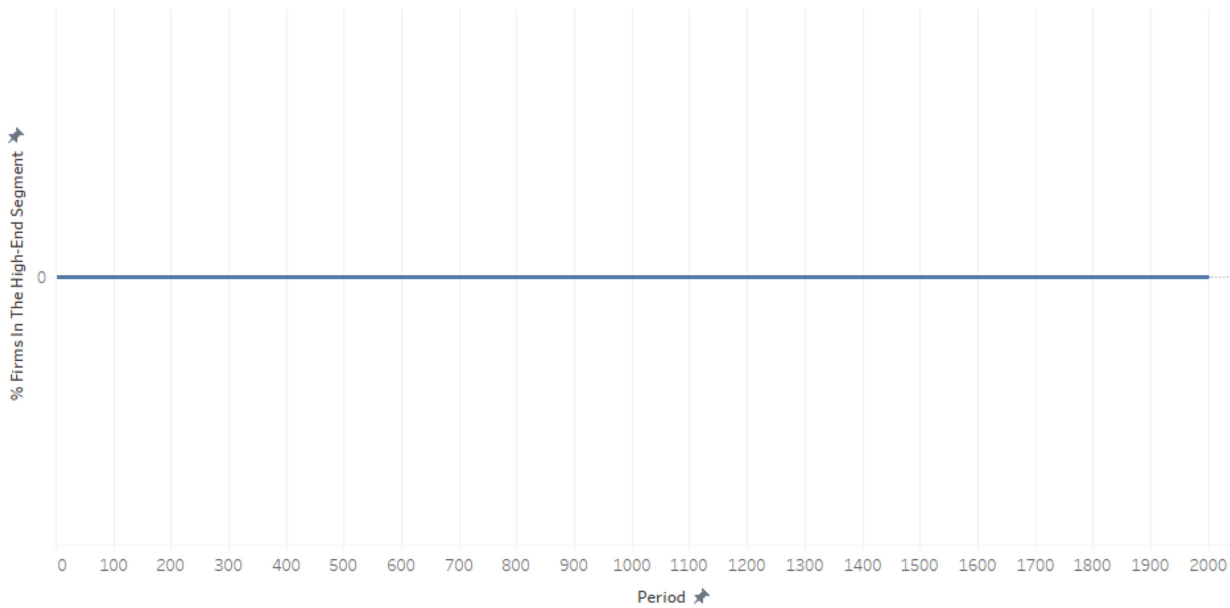


The line graph shows a dynamic of strategic interactions which is similar to the one replicating Lee *et al.* The percentage of firms in the high-end segment after 2000 periods is very similar to the previous one (28.88% vs 25.88%). The percentage of strategic emergence is, instead, lower:

Measures	*Current model*	*Previous model*
Percentage of strategic group emergence	56,36%	88%
Percentage firms in the high-end segment	25,88%	28,96%

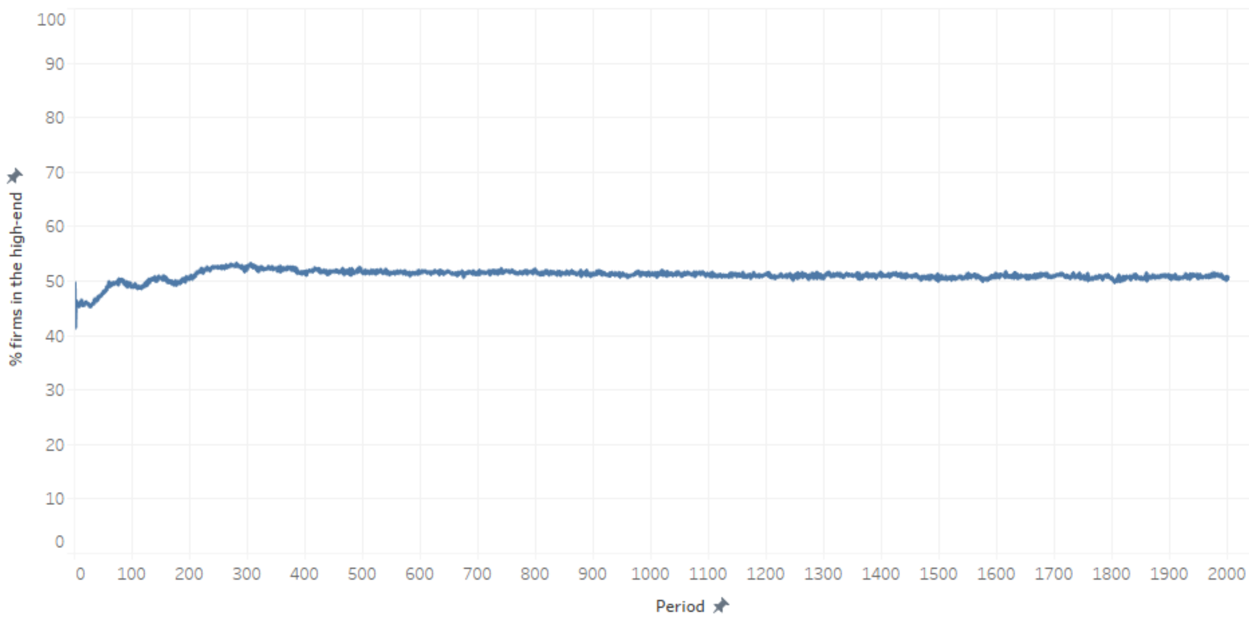
That is probably explainable with the relatively lower magnitude and likelihood of mutation. Previously, just the 5 new firms were assumed to mutate every period, following Lee *et al*'s assumptions. In the present scenario, it has been assumed that, on average, just 5% of firms mutate. That means that on average 2,5 firms mutate each time (and with a lower standard deviation). Strategic groups are therefore slightly less likely to emerge.

Despite that difference, the dynamic of interaction is entirely comparable, especially in the cases in which strategic groups do emerge. It is interesting to notice how mutation - which, as defined above, is here meant to be innovative and entrepreneurial research, is fundamental to unlock new and profitable opportunities. In fact, if firms were not able to innovate, it would not be possible in any way to access the high-end segment, assuming that no firm starts operating there from the beginning:



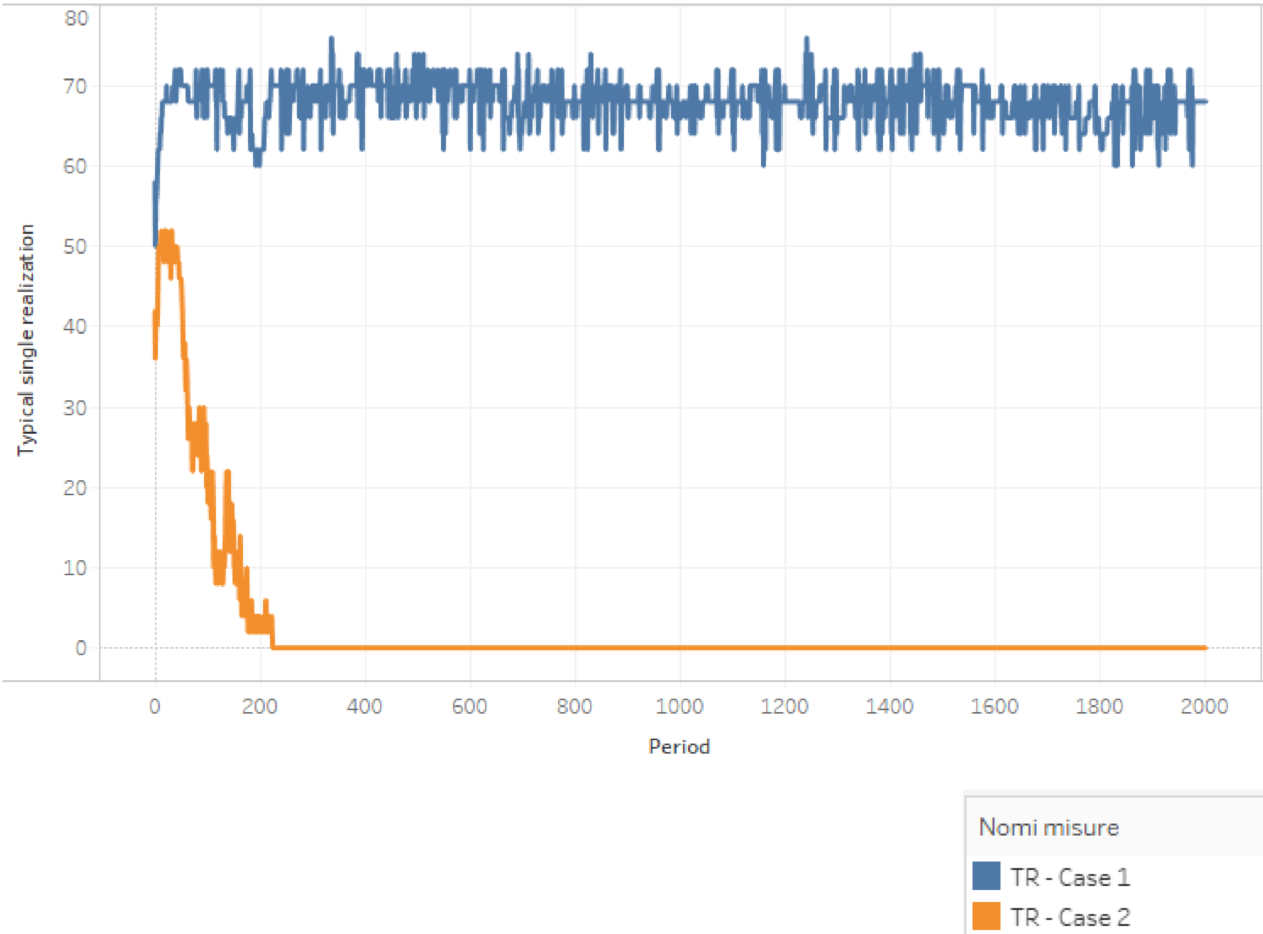
This statement is completely consistent with the original premises: firms have no chance of radically changing their strategic choice without innovation. They are just going to keep imitating each other continuously, remaining in the low-end segment forever.

However, would the results change assuming that the firms started operating within the entire product space? The code has been modified to answer to this question:



Interestingly, even in this case the line describing the high-end firms' population would be static and stable, with no particular identifiable trend. This outcome is quite surprising. In fact, one would expect the firms to reach a dynamic equilibrium, where the low-end and the high-end firms' payoffs are equal. With the selection operator still biased towards economic performance, the top firms in the most profitable segment should be targeted for imitation by the new ones, triggering a positive feedback in the system which would stop just when the payoffs of the two groups are equal. That case was already analyzed previously and the percentage of firms in the high-end should reach about 70% of the total. Here the mean over 50 simulations is about 50%.

To understand the reasons for this phenomenon, the individual realizations have been analyzed one by one. Taking a closer look to the reported data, it has been noticed that the above graph represents the theoretical mean of two very different and opposite scenarios. Below these two typical individual realizations are graphically described:



These two lines constitute the most representative cases that can be observed among the entirety of the simulation runs. The blue line represents the most straightforward and corresponds to the one described above: thanks to imitation (the selection operator), the percentage of the firms in the high-end increases until the payoff between the two strategic groups is equal. The second scenario is very interesting and unexpected. However, by now it should be clear that emergence of hard-to predict behaviors is one of the main characteristics of complex systems. In the cases described by the orange line, the high-end segment disappears in few generations, probably because of bad luck in selecting the parent candidates (notice that the selection operator keeps here its stochastic component, described previously) and due to the limited dynamic capabilities. This can lead ultimately to the extinction of the most profitable strategic group. Once no strategic group is present anymore, there is no possibility for it to emerge again. As in the scenario in which every firm started in the low-end segment, firms just stick there without any chance to innovate (there is no mutation) and to reveal new profitable opportunities. The second case described here does not represent a unique exception: it actually realizes in the 24% of the cases.[43]

In conclusion, innovation (mutation) can be recognized as the key for unlocking new potential market opportunities and favorable competitive positioning. In the model the state of the world is oversimplified through both the payoff function, representing the ultimate horizon of possibility and decision-making for firms, and product quality, representing the only possible strategic choice. Reality is of course much more complex and the role of entrepreneurial innovation is even more crucial. In fact, multiple possible payoff functions coexist on multiple dimensions. Innovators have the possibility to unlock this potential on multiple levels and capture value out of innovative strategic positioning.

4.4 The payoff function[44]

In the conclusive part of their work, Lee *et al.* pointed the way of possible future lines of research on strategic group theory:

> *"Our model is a kind of idealization and thus leaves many caveats and limitations […] In reality, changes in payoff structure are possible with environmental change such as regulatory and technological changes."* (Lee, Lee & Rho 2002, p. 744)

The payoff function represents in the simplification of the model the entire horizon of possibilities within which the firms act. Modifying it allows to observe the firms'

[43] In fact, it happened 12 times out of a total of 50 simulation runs.
[44] The code related to this scenario is attached in Appendix B

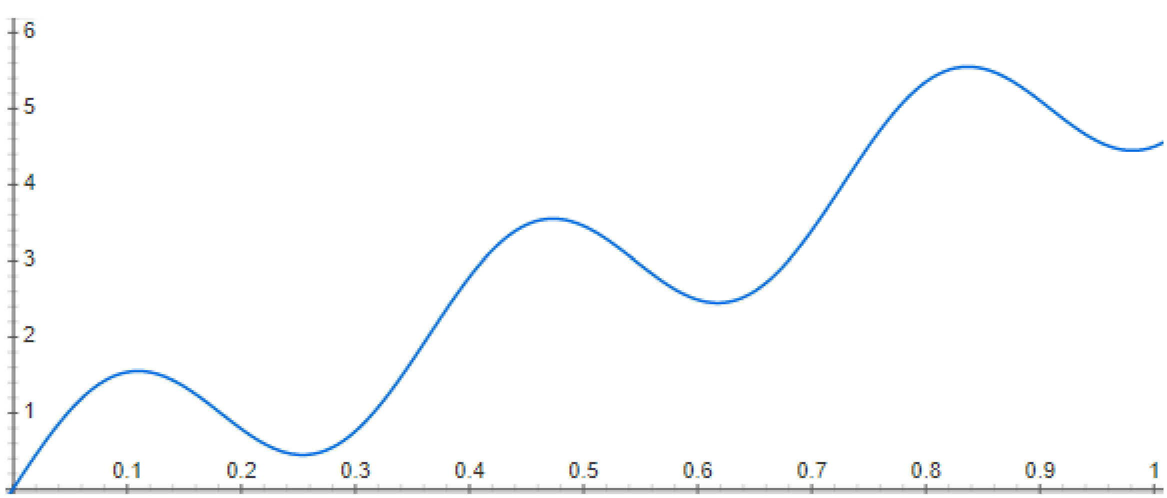
adaptation to the new context and the impact on the phenomenon of strategic interactions, when the "rules of the game" change. Finally, this modification represents a significant proof of concept, which shows clearly the extreme flexibility and adaptability of the model to different circumstances. That makes it possible to study different scenarios according to entirely different original assumptions.

For these reasons, the authors' challenge was accepted in the present research. Changing the payoff function means at the same time modifying deeply the code underlying the model. In fact, many mechanisms in play in the program are dependent on the payoff of each individual agent. Parents, for example, are more likely to be selected when they have a high economic performance, for example. Each period, then, the worst performers are substituted, and so on. When the payoff function is modified, all the related parameters are affected, as will be shown later.

The new chosen payoff function is the following:

$$y = \text{sine}\ (5.5\pi\ x) + 5.5\ x$$

This function describes three strategic groups, instead of three, since it presents now three different peaks. The below graph shows it more clearly:



This specific payoff function was chosen because it makes it possible to observe an entirely new and more complex dynamic of interactions. The three identifiable strategic groups are:

- Low-end strategic group ($0 \leq x < 0.25$)
- Middle-end strategic group ($0.25 \leq x < 0.62$)
- High-end strategic group ($0.62 \leq x \leq 1$)

x can refer to whatever dimension related to strategic choice. For simplicity and consistency with the previous simulations, it has been assumed that this variable represents again the product quality. If a good proxy for a real industry with just two strategic groups was the pharmaceutical, a good one in this case may be represented by the smartphone industry. In fact, three different types of manufacturers operating there could be recognized. Some offer a very cheap product, with less functionality and durability; some others position themselves in the middle, selling average phones, and eventually very high-end producers emerge, manufacturing products with the best technical qualities and captivating design.

With the new proposed payoff function, the most important difference in the code pertains the parameter p, which originally represented the probability for a firm to enter or maintain its competitive positioning in the high-end segment. However, now both a middle- and a high-end segment are identifiable. Should the probability to join one of them be the same? The proposed answer here is here negative. In fact, the mobility barriers between different strategic groups may highly vary. It could be, for example, much easier to enter the middle-end strategic group from the low-end one, than going from the middle-one to the top one. At the same time, the preemptive effect of strategic interactions, operated by incumbents, could be higher for the most profitable competitive positioning. To render this aspect in Netlogo, p has been set up as the results of different parameters, which come into play depending on the cases.

In the current model, two different types of thresholds regarding mobility barriers, strategic interactions and dynamic capabilities were created: one for the middle-end segment, establishing the probability for a low-end firm to enter it, and one for the high-end segment, determining instead the probability for a middle-end firm to join the most profitable group. To operationalize that, the parameter representing the age had to be split in two as well. In fact, the age was a determining factor in distinguishing whether a determined firm was a new entrant or an incumbent in a specific strategic group. Given that the strategic groups are three now, a firm could potentially be an incumbent in the middle-end segment and a potential new-entrant in the high-end. That is why, under the current circumstances, an age for the middle- and one for the high-end segment had to be created, determining respectively the number of consecutive periods in which a firm manages to keep its competitive positioning in a determined group. Hence, the p in the present model is represented by the following equations:

$$
\begin{array}{ll}
p = MB\text{-}m & \text{if } age\text{-}m = 0 \text{ and } n < S \\
p = SI\text{-}m & \text{if } age\text{-}m = 0 \text{ and } n \geq S \\
p = DC\text{-}m & \text{if } age\text{-}m > 0 \\
p = MB\text{-}h & \text{if } age\text{-}h = 0 \text{ and } n < S \\
p = SI\text{-}h & \text{if } age\text{-}h = 0 \text{ and } n \geq S \\
p = DC\text{-}h & \text{if } age\text{-}h > 0
\end{array}
$$

The -m suffix means that the parameter belongs to the middle-end segment, while -h to the high-end. Notice that S, the threshold for igniting strategic interactions, was assumed to be the same for both the cases (= 5 firms). In fact, there is no convincing reasons for the preemptive effect of strategic interactions to be triggered by a different number of firms depending on the different strategic group. The final payoff of each firm is given by the following equations, which replicate the original ones, appropriately fine-tuned:

$$
\begin{aligned}
&y = \mathit{sine}\,(5.5\pi\, x) + 5.5\, x && \text{if } 0 \le x < 0.25 \\
&y = \mathit{sine}\,(5.5\pi\, x) + 5.5\, x && \text{if } 0.25 \le x \le 0.62 \text{ and } r \le p \\
&y = 0 && \text{if } 0.25 \le x \le 0.62 \text{ and } r > p \\
&y = \mathit{sine}\,(5.5\pi\, x) + 5.5\, x && \text{if } 0.62 \le x \le 1 \text{ and } r \le p \\
&y = 0 && \text{if } 0.62 \le x \le 1 \text{ and } r > p
\end{aligned}
$$

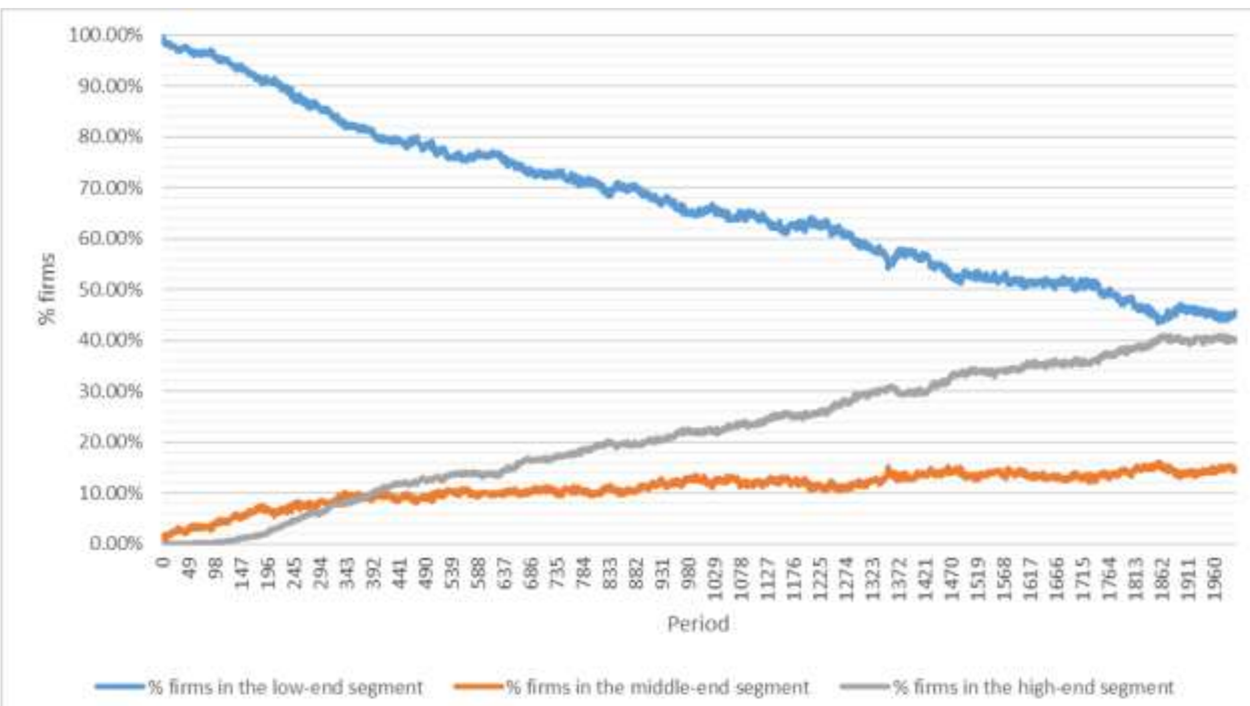
Notice that r remains unaltered, representing just a random number drawn each period to determine the payoff realization according to the above formulas. The assumption that firms start operating in the low-end segment has been kept as well. Of course, given that the low-end segment represents turtles with a x value smaller than 0.25, all the agents will start with values representing just that initial product range. In the current model, mutation was operationalized as in the previous paragraph: every firm has a 5% likelihood of mutating. The only slight change refers to the normal probability distribution describing the magnitude of the mutation, whose mean (μ) is in the current model 0, with a standard deviation (σ) of 0.10. The selection operator is unaltered too (the "tournament size" is equal to 5), as well as the boundary of rivalry.

Computational results

The first 50 simulations have been run under the circumstances typical of the standard scenario, introducing the difference between the two types of parameters (-m and -h):

MB-m	= 0.10
SI-m	= 0.10
DC-m	= 0.96
MB-h	= 0.10
SI-h	= 0.10
DC-h	= 0.96
σ	= 0.50

Notice that with the above set-up, there is virtually no difference in the probability to access either of the two strategic groups. The difference lies only in the dissimilar payoffs generated by each group. In fact, the purpose of these first simulations was to understand how the firms react to a different payoff structure, regardless of differences in the success probability in joining either of the two. The related results are the following:



The behavior of the agents is quite interesting. The firms, thanks to mutation and selection operators, start entering the middle-segment. That triggers a positive feedback by the system: the number of firms in that group starts increasing (it can be observed up to around the 250th period). This group starts nonetheless to be rapidly substituted by the high-end one, which starts emerging with a similar dynamic. At this point, the percentage of middle-end firms (the orange line) is rather stable until the end, while the high-end group starts increasing constantly at the low-end group expenses. Nonetheless, this last group is still the most numerous after 2000 periods, as shown also in the below table, representing the average percentage over the entire generation sample:

% Firms In The Low-End Segment	67.29%
% Firms In The Middle-End Segment	10.96%
% Firms In The High-End Segment	21.75%

This behavior is consistent with our premises. In fact, with the likelihood of entering the middle- and high-end segment being equal, the firms continue their imaginary journey to reach the best competitive positioning in a relatively steady way. The middle-end group under these circumstances represents almost just a buffer between the two extremities. If the number of periods were higher, the market would eventually reach a dynamic equilibrium where the payoffs of each group is equal. In the next paragraph, the parameters related to p will be modified according to different assumptions.

The interactions between three strategic groups under asymmetrical conditions

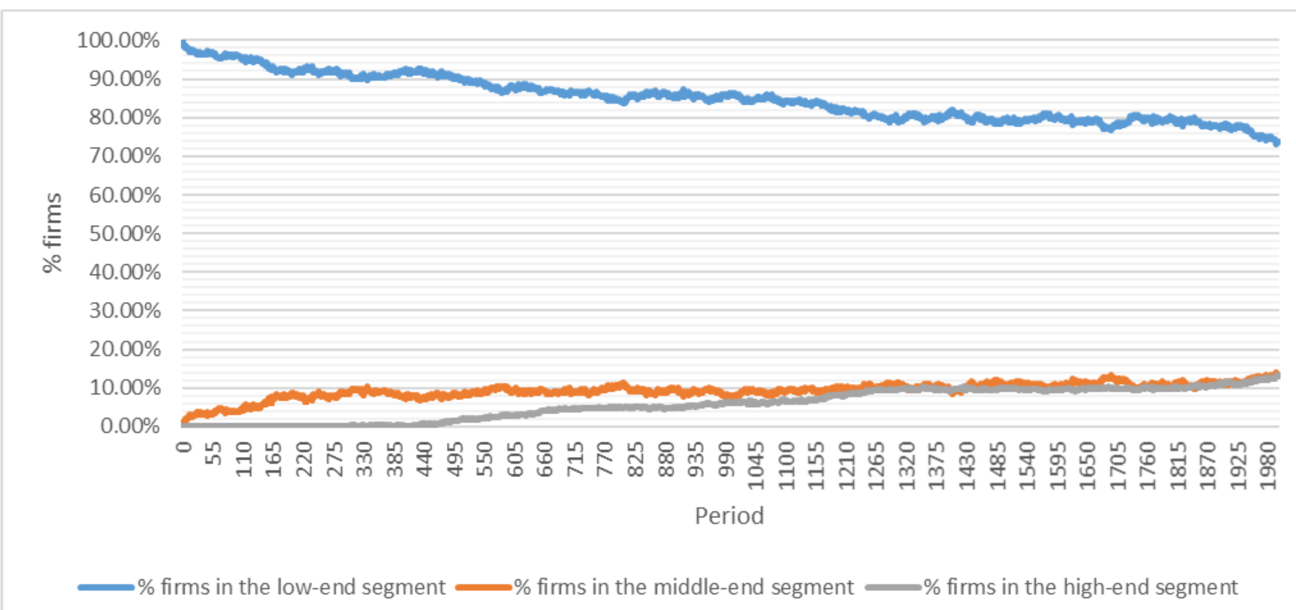
In the previous scenario, the probability for a firm to enter the middle- and high-end segment was the same. In fact, the two different values for mobility barriers, strategic interactions and dynamic capabilities had been set at the same values. However, there are many reasons to believe that the actual obstacles to enter one group or the other may vary dramatically. In fact, firms in the high-end segment may have higher mobility barriers, because of more structural difficulties in developing high-end products with respect to both the low and middle-end ones. At the same time, the higher profitability of incumbents in that segment may result in an increase of collusive activities, in order to protect their most favorable and hard-earned competitive positioning. This scenario seems to be arguably closer to reality.

Therefore, it has been assumed under the new circumstances that the two different strategic groups have a different MB, SI and DC values. The parameters that have been chosen are the following:

MB-m	= 0.10
SI-m	= 0.10
DC-m	= 0.96
MB-h	= 0.05
SI-h	= 0.04
DC-h	= 0.88
σ	= 0.50

The firms trying to enter the middle-end from the low-end segment have a 10% success probability due to structural barriers. There are no preemptive effects from incumbents here (SI = MB = 10). The dynamic capabilities of incumbents are 0.96. These values replicate exactly the original standard scenario. The situation changes for firms trying to enter the high-end segment. It has been assumed here that the success probability is equal to just 5%, due to higher mobility barriers. They could be attributed to an increased difficulty in developing a high-end product with a superior technology. When the threshold for strategic interactions (S = 5) is reached, the success probability further decreases by 1 percentage point, for a total of 4%. It has been assumed that incumbents try to actively obstacle new entrants in order to protect their favorable competitive positioning. Notice that, in theory, a firm could jump from a low-end segment directly to the high-end thanks to mutation. However, the likelihood for it to happen is close to 0. In fact, mutation probability distribution has a mean of 0 and a standard deviation of 0.10. For a firm in the low-end (i.e. with a product quality less than 0.25) to reach the high-end (which requires a product quality higher than 0.62), the magnitude of the mutation should comprise (at least) slightly less than 4 standard deviations. The probability for it to happen is close to 0 (ca. 0.03%). That could represent a limit to the truthfulness of the model, since in reality it would be possible to depict a scenario, albeit rare, in which a firm selling a low-end product switched to premium one. However, for modeling purposes, it was not possible to operationalize mutation differently. In fact, if the magnitude of mutation in terms of standard deviation were higher, the end results would have been dramatically compromised.

The results of the 50 simulations under the above circumstances are the following:



The below table represents the average percentage of firms in the respective strategic groups over all the periods:

% Firms In The High-End Segment	5.78%
% Firms In The Low-End Segment	84.94%
% Firms In The Middle-End Segment	9.28%

The data show very different outcomes with respect to the previous scenario. In both the cases, the middle-end segment is the first to emerge. It is almost impossible for a high-end strategic group to emerge before a middle-end one is present, as explained above. Nonetheless, after the appearance of the middle-end segment, the dynamic of interaction differs. In the first case, analyzed before, it was easier for the agents to discover a better payoff in the high-end segment, since the success probability was the same as in the middle-end. Things change when the success probabilities for the two groups differ, as in the second case. In fact, the emergence of firms with a product quality higher than 0.62 is much slower and more difficult. The average percentage of firms in the middle-end is comparable to the one obtained previously, as expected since the parameters' values are the same. However, in this case the percentage of high-end firms is significantly lower on a total of 2000 runs. That shows the increased difficulty in reaching the most profitable competitive positioning.

The results are overall consistent with the literature on strategic groups. The results related to the percentage of strategic group emergence, considering the total of middle- and high-end, is similar to the one obtained originally by Lee *et al*. The modification of the payoff function with the introduction of a third strategic group represents an important result of the present research. In fact, it makes it possible to observe the dynamic of strategic interactions under different and more complex conditions. The firm's ability to adapt to external changes was so far measured by the dynamic capabilities. However, it must be noticed that this parameter did not determine a real change in the context of interactions. In fact, the payoff function and, in general, the “rules of the game” were exactly the same for each generation. The true systemic response to change can be just analyzed actually modifying the external environment. The modification of the payoff function, representing the ultimate guide of actions for the firms, points out the direction of future research.

Conclusions

The main purpose of this thesis was to show, at a very high-level, how complexity could be employed in the field of management where until recently it was neglected in favor of a reductionist paradigm. Reductionism is the belief that the whole consists in the simple sum of its parts. According to this view, analyzing these single parts separately is the key to understand the whole as well. This perspective characterized the western approach to science at least until the 19th century and its roots can even be traced back to the very beginning of western philosophy.[45] The reductionist dream was dramatically disappointed in the last century by a countless number of failures or inadequacies in the explanation of "wicked" problems, such as climate change, pandemics, global financial crises, to poverty and uneven development. In recent decades, many scientists started to feel the need for an alternative approach to face these challenges, leading eventually to the birth of the concept of complexity. Finally, it was recognized that the whole can be more than the sum of its parts. Analyzing each single part separately does not help in understanding and explaining complex systems where the interactions between simple agents can cause unpredictable outcomes, slight changes in the outside environment can trigger unexpected response at a macro-level, and where the system as whole exhibits self-organizing and adapting behaviors. All these characteristics apply to a wide range of cases and fields of study such as ant colonies, immune systems, genetic structures, and, as it will be clear by now, to strategic group emergence.

The present research was focused on this specific subject in order to provide the work with a higher degree of consistency and conceptual depth. However, this case might well represent a virtuous example of the application of complexity tools to

[45] Thales, considered the first western philosopher, had concluded that the ἀρχή (the "principle") had to be the water using a reductionist approach *ante litteram.* In fact, since everything, if broke up into its original parts, contains some water, then water must be the beginning of everything.

management-related topics still much characterized by reductionism (especially in the form of the neoclassical approach). In the academic literature, the phenomenon of strategic group emergence brought different and often conflicting results. The misunderstanding was mostly related to the fact that strategic groups were considered as static features of an industry; as a single part of this particular whole. The empirical research partially contradicted this statement: in some industries group structure seemed to emerge and in in others they did not. J. Lee, K. Lee and S. Rho addressed the non-falsifiability fallacy of the strategic groups theory by employing a complexity perspective. Inspired by Alchian's and Tintner's evolutionary framework, they conceived the firms within an industry as agents endowed with bounded rationality that act under uncertain conditions. In this view, strategic groups represent the result of the firm's complex behavior under certain conditions, specifically dependent on structural barriers, preemptive actions by incumbents, dynamic capabilities, and boundary of rivalry. These different parameters combined made it possible to understand which aspects influence the likelihood for a group structure to emerge and therefore respond satisfyingly to the non-falsifiability fallacy.

The first theoretical contribution of this thesis consists in the successful replication of Lee *et al*'s model, which provided an important external proof of its validity. In addition to that, the program, implemented in Netlogo, has the possibility to be modified easily according to new assumptions. This versatility can be fruitfully employed in order to explore totally different scenarios, be it the result of entirely different theoretical premises or just fine-tuning alterations to take into account industry-specific conditions. In the last chapter of this work, this possibility was taken advantage of in order to redefine the most important operators (selection and mutation) to exclude organicist biases and to further explore the role of randomness, uncertainty and innovation. The most relevant modification pertained the payoff function, which led to the emergence of more than just two strategic groups. The development of different versions of the program shows the inherent possibilities provided by such a tool and represents the second important theoretical contribution to the research about strategic groups. It is believed here that the future directions of research on the matter should focus indeed on the payoff function, which represents the ultimate horizon of possibilities for the agents in the model. In addition, it is believed that complexity tools can be fruitfully employed in many different management related subjects, notably organizational theory and innovation to change and knowledge management, just to mention the most promising.

A final thought is still needed to conclude the present work. Throughout the chapters, the focus has often been about models, codes, algorithms, agents, variables, etc. This was believed to be necessary, considering that one of the most important objectives of this research was first to test and then to create a tool for investigating the phenomenon of strategic group emergence. However, it must be kept in mind that every model is *fundamentally* wrong, inasmuch as its condition for functioning relies on heavy simplifications of the reality, excluding different and vital aspects. It must be reminded that a model is just a tool to *deepen* the understanding of a determined phenomenon. The ultimate objective of the research is not the model itself, but rather what it is hidden behind it. Its purpose is to shed light on the most obscure angles of the reality, the ones that are not possible to fully grasp initially. Wittgenstein's proposition 6.54 of the *Tractatus Logico-Philosophicus* really comes in handy in this case:

"My propositions serve as elucidations in the following way: anyone who understands me eventually recognize them as nonsensical, when he has used them – as steps – to climb beyond them. (He must, so to speak, throw away the ladder after he has climbed up it). He must transcend these propositions, and then he will see the word aright."

Appendix A – Netlogo Program (Lee, Lee & Rho's Replication)

Lee, Lee & Rho (2002), v0.5 - 14 feb 2020 - Andrea Gallucci

```
globals [
  S                        ; threshold for strategic interactions
  Alpha                    ; parameter related to sigma-rivalry
  tournament-size          ; stochastic component for the selection operator
]
```

; the "globals" are the general variables that are going to be heavily used in the program and that do not pertain the agent per se

```
turtles-own [
  x                        ; product-quality (the strategic choice of the firm)
  age                      ; parameter used to determine whether the firm is an incumbent or
                           ; a new-entrant
  r                        ; random uniform number to assign payoff,
                           ; to be drawn again every generation
  p                        ; probability to get the high payoff if the high-end segment
  pay                      ; single firm's last payoff
```

```
  wr                              ; working register
]


; turtles-own describe the characteristic owned by the agents and determine their rule of behavior


to setup
  clear-all
  reset-ticks
  set S 10
  set alpha 0.5
  set tournament-size 5
  crt firms [
    set x random-float 0.5; firms start operating in the low-end segment (x < 0.5)
    set r random-float 1
    set age 0
  ]
end
```

; to setup represents a command that sets the initial conditions of each parameters for generation 1

```
to go
 if ticks > 2000 [stop]
 ask turtles [
  set r random-float 1
  update-p
  ifelse x < 0.5
  [set pay payoff x]                ; following Lee et al's assumptions, the payoff
                                    ; in the low-end segment is always safe

  [ifelse r <= p                    ; instead, the payoff in the high-end is risky can lead
                                    ; to a payoff equal to 0
   [set pay payoff x]
   [set pay 0]
  ]
                                    ; the following lines of code are the
                                    ; operationalization of the sharing function
```

```
  let neigh turtles with [abs (x - [x] of myself) < sigma-rivalry]

  let mx x

  ask neigh [set wr 1 - (abs (x - mx) / sigma-rivalry) ^ alpha]

  let m sum [wr] of neigh

  set pay pay / m

  ifelse x >= 0.5 [set age age + 1] [set age 0]

                                        ; the age of the firms in the high-end segment

                                        ; is increased by one each generation. In this

                                        ; way, the difference between incumbents and

                                        ; new-entrants can be kept

  set ycor age

 ]

selection

tick

end


;; to go determines all the rules of behavior for the agents


to update-p
```

```
  let n count turtles with [x >= 0.5]            ; number of firms in the high end
  if age = 0 and n < S [set p mb]
  if age = 0 and n >= S [set p mb - psi]         ; psi represents the preemptive effect
                                                 ; of strategic interactions
  if age > 0 [set p dc]
  let si mb - psi
end
```

; to update-p represent a procedure create to determine which one of the three success probability should be applied to the single firms (MB, SI or DC)

```
to selection
let survived max-n-of 45 turtles [pay]
let dead min-n-of 5 turtles [pay]                ; each generation, 5 firms have
                                                 ; the possibility to reshuffle their
                                                 ; strategic choice
  ask dead [die]
  repeat 5 [
    let t1 max-one-of (n-of tournament-size turtles) [pay]
```

```
  let t2 max-one-of (n-of tournament-size turtles) [pay]
  let lambda random-float 1
  crt 1 [
    set x lambda * ([x] of t1) + (1 - lambda) * [x] of t2
    set age 0
    set x x + random-normal 0 0.2
    if x > 1 [set x 1]
    if x < 0 [set x 0]
  ]
 ]                                        ; 5 new firms with new strategies
                                          ; replace the old ones.
                                          ; the population is kept unaltered (50)
end
; this procedure replicates and operationalize selection

to-report payoff [number]
 let y number * 180 / pi
 report sin (3 * pi * y) + 3 * number
end
```

```
to-report average [a b]
  report (a + b) / 2
end
```

Appendix B – Netlogo Program (Payoff function)

Modified payoff function. v0.6 - 14 feb 2020 - Andrea Gallucci

```
globals [
  S                    ; threshold for strategic interactions
  Alpha                ; parameter related to sigma-rivalry
  tournament-size      ; stochastic component for the selection operator
]

turtles-own [
  x                    ; product-quality (the strategic choice of the firm)
  age-m                ; parameter used to determine whether the firm is an
                       ; incumbent or
                       ; a new-entrant in the middle-end segment
  age-h                ; parameter used to determine whether the firm is an
                       ; incumbent or
                       ; a new-entrant in the high-end segment
  r                    ; random uniform number to assign payoff,
                       ; to be drawn again every generation
  mutation             ; random number to determine whether the agent
                       ; mutates or not
  p                    ; probability to get the payoff in the high-
```

```
                                          ; and middle-end segment
  pay                                     ; single firm's last payof
  wr                                      ; working register
]
```

to setup

```
  clear-all
  reset-ticks
  set S 5
  set alpha 0.50
  crt firms [
    set x random-float 0.25
    set r random-float 1                  ; firms start operating in the low-end segment (x < 0.5)
    set age-m 0
    set age-h 0
  ]
  set tournament-size 5
end
```

to go

```
  if ticks > 2000 [stop]
  ask turtles[
    set r random-float 1
```

```
set mutation random-float 1
update-p
ifelse x < 0.25
[set pay payoff x]                    ; following Lee et al's assumptions, the payoff
                                      ; in the low-end segment is always safe
[ifelse r < p                         ; instead, the payoff in the high-end is risky can
                                      ; lead to a payoff equal to 0
  [set pay payoff x]
  [set pay 0]
]
                                      ; the following lines of code are the
                                      ; operationalization of the sharing function
let neigh turtles with [abs (x - [x] of myself) < sigma-rivalry]
let mx x
ask neigh [set wr 1 - (abs (x - mx) / sigma-rivalry) ^ alpha]
let m sum [wr] of neigh
set pay pay / m
ifelse x >= 0.25 and x < 0.62 [set age-m age-m + 1] [set age-m 0]
ifelse x >= 0.62 and x <= 1 [set age-h age-h + 1] [set age-h 0]
                         ; age of the firms in the high- and middle-end segment
                         ; is increased by one each generation. In this
                         ; way, the difference between incumbents and
                         ; new-entrants can be kept
```

```
   set ycor age-m
   set ycor age-h
  ]
  selection
  variation
  tick
end

to-report sh [d]
  ifelse d < sigma-rivalry [report (1 - d / sigma-rivalry) ^ alpha]
  [report 0]
end

to update-p
  let m count turtles with [x >= 0.25 and x < 0.62] ; number of firms in the middle-end
  let h count turtles with [x > 0.62 and x <= 1]       ; number of firms in the high-end
  if age-m = 0 and m <= S and x >= 0.25 and x < 0.62 [set p mb-m]
  if age-m = 0 and m > S  and x >= 0.25 and x < 0.62 [set p mb-m - psi-m]
  if age-m > 0 and x >= 0.25 and x < 0.62 and x <= 1[set p dc-m]
  if age-h = 0 and h <= S and x >= 0.62 and x <= 1 [set p mb-h]
  if age-h = 0 and h > S and x >= 0.62 and x <= 1 [set p mb-h - psi-h]
  if age-h > 0 and x >= 0.62 and x <= 1 [set p dc-h]
end
```

to selection

```
let survived max-n-of 45 turtles [pay]
let dead min-n-of 5 turtles [pay]             ; each generation, 5 firms have
                                              ; the possibility to reshuffle their
                                              ; strategic choice
ask dead [die]
repeat 5 [
 let t1 max-one-of (n-of tournament-size turtles) [pay]
 let t2 max-one-of (n-of tournament-size turtles) [pay]
 let lambda random-float 1

 crt 1 [
  set x lambda * ([x] of t1) + (1 - lambda) * [x] of t2
  set age-m 0
  set age-h 0
  if x > 1 [set x 1]
  if x < 0 [set x 0]
 ]

]                                            ; 5 new firms with new strategies
                                              ; replace the old ones.
                                              ; the population is kept unaltered (50)
```

```
end

to variation
  ask turtles [
    ifelse mutation <= 0.05 [set x x + random-normal 0 0.10] [set x x]
    if x > 1 [set x 1]
    if x < 0 [set x 0]
  ]
end

to-report payoff [number]
  let y number * 180 / pi
  report sin (5.5 * pi * y) + 5.5 * number
end

to-report average [a b]
  report (a + b) / 2
end
```

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