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Dynamic competition and cooperation in systemic industries: models and experiments

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PREFACE

The title of the dissertation is “Dynamic competition and cooperation in systemic industries: models and experiments”. The dissertation consists of the three stand-alone articles which share one common thread in that they all deal with the original formalization of a real-world managerial challenge of developing a multicomponent product in systemic industries. Telecommunication, automotive, aerospace and technology intensive consumer electronics are typically classified as systemic industries. In these industries, the products are “complex systems” which are composed of several distinct functionally interrelated components. What makes these industries particularly complex from a managerial perspective – and thus more interesting to analyze - is the fact each component may have several alternative solutions that can be more or less compatible with the rest of the system. The component solutions can be thus recombined into various configurations with different functionality and final value to the consumer. The information about the technological and competitive structure of the industry is public and available for all market participants, and the residual uncertainty pertains as to which firm will manage to gain control over crucial technologies in the industry.

In the proposed model of systemic industries (hereafter referred to as *chance and choice model*), multiple agents compete with each other for control over a limited set of product components to which they sequentially get access in a randomized fashion thereby irreversibly limiting each other’s available choice sets. The novel feature of a model is that the agents are given an option to cooperate: that is, they are allowed to form bilateral alliances which guarantee both partners a positive commercial outcome. The agents are assumed to be homogenous, non-adaptive and fairly myopic in that they have identical initial endowments and follow the same decision making rules of naïve maximization. Each dissertation chapter explores different features of the model and relies on different methodologies in addressing the posed research questions.

The first chapter “Chance and choice as origins of firm performance heterogeneity – a position view on systemic industries”, co-authored with Markus Reitzig, University of Vienna, and Massimo Warglien, Ca’ Foscari University of Venice, draws upon the agent-based simulation model and is essentially concerned with understanding the role of chance in engendering firm-level performance heterogeneity among initially identical entities. The results demonstrate that making positional choices early and repeatedly benefits firm performance in technological environments where excessive competitive crowding may render the prior research efforts obsolete.

The natural question emerges, however, whether a myopic naïve maximization is realistic as a representation of a decision-making mechanism in the environments as complex as systemic ones. The second chapter "The role of alliance formation as uncertainty absorption mechanism in complex environments" addresses this question. The chapter aims at validating the behavioral assumptions of the original model in the laboratory. The results demonstrate that, when exposed to the tasks of substantial complexity, people try to proactively manage the uncertainty associated with their final outcome. In doing so, they think few steps ahead of their competitors and forestall their plans with an aim of prospective cooperation. This finding is interesting not only as a validity check of the model assumptions. It also suggests that in unpredictable environments alliances may be seen not only as a source of uncertainty, but also as a viable tool to mitigate it.

The third chapter "Checkmate or stalemate: managerial heuristics in complex industries" bridges the fields of strategy and experimental psychology. Based on the content analysis of concurrent verbal protocols reported by the subjects during the experiment, it reveals the set of the setting-specific heuristics people devise when faced with an abstract task whose conceptual structure and causal linkages mimic those of the managerial problem of sequential development of multicomponent complex goods. The implications are twofold: first, the results appear instrumental in understanding the psychological underpinnings of the strategic decision-making; second, identifying the building blocks of each heuristic will help in generating testable predictions as to in which environments it performs best.

CHANCE AND CHOICE AS ORIGINS OF FIRM PERFORMANCE HETEROGENEITY— A POSITIONAL VIEW ON SYSTEMIC INDUSTRIES

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Abstract

Chance or randomness as a mechanism to induce performance heterogeneity among originally homogeneous firms has recently been introduced to the resource-based view of the firm. In this paper, we demonstrate how chance can engender variation in performance among initially identical firms even in the absence of firm-level capability differences. Departing from the positional school of strategy, we show how and when firms in systemic industries benefit from the chance of staking positions vis-à-vis competitors in complex technology landscapes. Expectedly, the chance of making choices early and repeatedly increases a firm's profitability. Also, the value of repeated chance is higher during the early stages of an industry's evolution than during its later phases. Importantly, however, this latter effect is exacerbated by increases in competition.

INTRODUCTION

The question of what explains diversity among firms and resulting intra-industry performance heterogeneity is central to the field of strategy, and it has received considerable attention by scholars over the past few decades (Nelson and Winter, 1982; Rumelt, 1991; Rumelt *et al*., 1994; Nelson 1991; Carroll, 1997; McGahan and Porter, 1997). Until today, two schools of thought have dominated the debate as to why organizations differ in their effectiveness, all else being equal. The positioning school, on one hand, has traditionally attributed the diversity in performance among enterprises to a firm's unique market position relative to its rivals (Caves and Porter, 1977). The resource-based view (RBV) (Penrose, 1959; Wernerfelt, 1984; Barney, 1986, 1991; Peteraf, 1993), on the other hand, has argued that a firm's superior relative performance results from its possession of rare and difficult-to-imitate resources (Barney, 1986). As part of their inquiries, researchers in both veins have investigated the antecedents to the emergence of such stable performance differences across firms. Adherents of the positioning school claim that firm-level heterogeneity arises through a complex interplay between environmental conditions and managerial choices in a competitive environment (Porter, 1991), without specifying the latter in much detail, though. On the contrary, proponents of the RBV, in following the Carnegie tradition (Simon, 1947; Cyert and March, 1963), have elaborated in more detail on the emergence of inter-firm differences, emphasizing the process of resource accumulation (Dierickx and Cool, 1989) and organizational learning over time (Nelson and Winter, 1982; Cohen and Levinthal, 1990; Dosi, Nelson, and Winter, 2000; Zollo and Winter, 2002). Yet, traditionally scholars in both camps would causally link the origins of performance differences back to *ex-ante* asymmetries in market positions, resource bases, or combinations of the two (Schmidt and Keil, 2013), attesting to the established wisdom that "firm differences … are ultimately driven back to differences in initial conditions" (Nelson, 1991: 65).

Undeniably, firms are historical entities that are affected by their original endowments of resources and capabilities, the time of their birth, and their location. As such, explanations of how firm heterogeneity unfolds conditional on the existence of such original asymmetries are undoubtedly important. Yet, such investigations only complement and cannot substitute for inquiries into how original differences may occur in the first place. As regards the latter question, existing knowledge—while equally relevant to the theory of strategy—is far scarcer. In fact, the few related insights we have stem from scholars working in the RBV tradition who recently suggested that firms—even when starting with identical initial endowments—may end up displaying stable performance differences due to the cumulative effect of randomness (Nelson, 1991; Barney, 1997). More specifically, Denrell (2004), leveraging some classical results on random walks (Feller 1971), demonstrates that random resource-accumulation processes can generate sustained differences in profitability among initially identical firms with high probability (see also Henderson, Raynor, and Ahmed, 2012). Similarly, Zott (2003), by allowing for stochastic retention and selection in a model of firms' capability development, arrives at stable performance differences among originally equally endowed firms.

While representing an important first step towards understanding randomness as a determinant of original firm-level differences in performance, and notwithstanding the importance of this finding as a potential explanation for real-world phenomena, the prior models intentionally stop short of investigating the effects of luck beyond their impact on resource accumulation or learning within a focal firm. As such, Denrell's (2004) and Zott's (2003) work both provide motivation and leave ample space for researchers to elaborate on their contributions. One of the most obvious elaborations appears to be an examination of how randomness—hitherto conceived of as a determinant that indirectly engenders performance differences through inducing differences in resources—more directly affects competitive interactions and managerial choices, key tenets of the positional school of strategy.

Accordingly, in this paper we take some first steps towards integrating the ubiquitous notion of randomness into the positional school of strategy to examine how exactly chance, competition, and managerial actions jointly induce inter-firm performance differences, all else being equal. To complement earlier works in the RBV tradition, we deliberately dismiss firms' differential abilities to learn, and we account for differences arising from resource accumulation only insofar as they restrict managerial choice sets of equally capable decision-makers. Building on the idea that good fortune at some point in a focal organization's lifetime may alter other firms'—notably *competitors'*—choice sets for the future, we examine to what extent randomized exclusive access to critical resources over time can account for the emergence of profit differences among initially homogenous firms. Although the mechanisms that engender diversity among homogenously capable firms' decisions that we discuss in this paper should apply to a wide range of competitive settings, we originally introduce them by tying them to a specific industry example. To that end, we model a systemic industry as a series of (partly) modular value chains (Kretschmer and Reitzig, 2013) that allow for the production of a variety of combinatory products. Within this model, firms of equal capabilities compete to obtain control over product components required to manufacture systemic goods (Farrell, Monroe, and Saloner, 1998). More specifically, and being true to the nature of corporate R&D, we model firms' access to product components as a sequential stochastic process (or "patent race"; Reinganum, 1982) in which an organization will be able to secure unique control over a product component whenever luck would have it, and not otherwise. At the beginning of the process, no firm will control any components of the technology landscape; at the end, all components characterizing the technology landscape will be owned by either of the firms competing for the best products. Partial modularities (Baldwin and Clark, 2000) between components determine the ultimate value of the (multiple) products that can be produced and offered by the firms. These modularities are generated randomly in the beginning, and are visible to the firms' managers. We implement identical decision rules for all agents, assuming that they—when it is their turn—pick the component that maximizes the value of the best product still accessible to them, corresponding to a simple "take the best" kind of decision-making heuristic (Gigerenzer and Goldstein, 1996). Bilateral alliances between players are also possible and, once entered, cannot be dissolved until the end of a given simulation. The model is analyzed through computer simulation.

In this setting, we obtain a series of interesting findings. As far as performance asymmetries are concerned, we show that chance matters, but in differentiated ways. Expectedly, the chance of making choices in a competitive environment early and repeatedly increases a firm's profitability. Also, the value of repeated chance is higher during the early stages of an industry's evolution than during its later phases. Importantly, however, the latter effect is exacerbated by increases in the number of market participants—a finding that is owed to the specific nature of the type of the path dependency that randomness engenders in the presence of competitive crowding.

In what follows, we develop theory, provide industry context, and formalize our considerations, before presenting and discussion regression results pertaining to data simulated in accordance with our model.

ON THE ORIGINS OF FIRM-LEVEL HETEROGENEITY IN PERFORMANCE

Why and how firms differ in performance are arguably the two most fundamental questions in strategy research. Yet, whereas scholarly work over the past three decades has theoretically and empirically investigated how such differences unfold among organizations that are heterogeneous from the beginning (Nelson and Winter, 1982; Rumelt *et al*., 1994; Wernerfelt, 1984; Dierickx and Cool, 1989; Cohen and Levinthal, 1990; Henderson and Clark, 1990; Kogut and Zander, 1992; Peteraf, 1993; Teece, Pisano, and Shuen, 1997; Zollo and Winter, 2002), researchers have only recently started to address the question of what engenders such heterogeneity in the first place. Most of the related work in this domain can be traced back to two different theoretical contributions, which both invoke a combination of randomness and resource/capability development over time to mechanistically explain the origination of performance differences between firms.

One article is by Denrell (2004), and it presents a simulation model that explains how sustained competitive advantages can originate among a population of initially homogenous firms. To that effect, Denrell exposes firms' processes of (both linear and more complex) resource allocation to a classic random walk, leading to stable inter-firm frequency patterns of above-industry-average profitability at the firm level for selected organizations. Consistent with earlier works (Feller, 1971), path dependencies engendered by an initial randomization process create the sustained asymmetric deviations of the firms from the sample profitability mean.

The second article by Zott (2003) shares traits of Denrell's approach in that firms are originally homogeneous in their endowments and capabilities, and that initial randomness engenders a path dependency that will lead to sustained performance differences. Differently from Denrell (2004), however, Zott's (2003) model mimics firms' dynamic learning over time, and randomness affects firms' selection and retention of resource configurations, in turn creating variation in firms' capabilities and hence performance.

Both of the aforementioned papers mark important contributions to our understanding of how firm-level performance differences may originate in an industry. Not surprisingly, a series of scholars have followed in their tradition, refining the notions of how initially chance-driven differences in resources and capabilities lead to sustained competitive advantage.

Coen and Maritan's (2011) work resembles Zott's (2003) paper in that they analyze systematic firm-performance differences stemming from dynamic capabilities of resource allocation, with stochastics entering their model only indirectly. Their simulation results demonstrate that when initial capability endowments and search abilities are set equal across firms, firm-performance differences are levelled out. Henderson *et al*. (2012) seek to determine the threshold duration of competitive advantage exceeding which one can rule out a purely stochastic process as an explanation for empirically observable superior performance. Their results suggest that sustained firm-performance differences cannot be fully explained by time-homogeneous Markov processes and are most likely attributable to initial differences in firms' starting positions, among other things. Denrell and Liu (2012) model the behaviors of heterogeneously skilled agents in unpredictable environments, demonstrating that high-level performance does not allow the inferring of capability levels if the role of luck is significant in achieving extreme success. Finally, Denrell, Fang, and Zhao (2013) apply that same rationale to the field of strategic management.

Notwithstanding the importance of the contributions of this stream of research sparked by Denrell (2004) and Zott (2003), it would appear that important avenues to understanding the origins of firm-level differences in performance have not been examined. In fact, elaborating on the key insight by the aforementioned prior works—that is, the fact that randomness in inter-firm treatment may break initial homogeneity among organizations and lead to sustained differences between them via path dependencies—we suggest that the role of randomness has so far been single-sidedly understudied by scholars following the Carnegie tradition (March and Simon, 1958; Nelson and Winter, 1982).

Randomness, so we propose, may equally significantly and directly affect other determinants of firms' performance that are deemed central to the positional school of strategy (Porter, 1980; 1991)—notably firms' competitive environments and the managerial choices firms face as a consequence—all else being equal. The impact of randomness on such positional determinants, so we argue, will be particularly pertinent to competitive settings in which interactions between organizations are frequent and varied, and in which firms' positions on the competitive landscape can vary greatly. A case in point are systemic industries.

SYSTEMIC INDUSTRIES—MODULAR VALUE CHAINS AND STOCHASTIC R&D

Recently, researchers have shown an increased interest in understanding the interplay between firms' performance and the patterns of their R&D efforts allocation in systemic industries (Ethiraj and Puranam, 2004; Ethiraj, 2007; Kretschmer and Reitzig, 2013).

Typical examples of systemic industries include telecommunications (Leiponen, 2008), the automotive sector (Takeishi and Fujimoto, 2001), personal computers (Ethiraj, 2007), and aircraft manufacturing (Brusoni *et al*., 2001)—to name a few. Systemic industries can be broadly defined as industries in which firms compete with products that consist of different complementary modules which make up the final value proposition. A system good is thus composed of distinct, functionally interrelated components that cannot be used in isolation by consumers and that need to be integrated into a final system product in order to be commercialized (Farrell *et al.*, 1998; Somaya, 2003). While the presence of all constituent components is indispensable to ensuring the functionality of a systemic product as a whole, several alternative solutions for each component may exist in parallel. The availability of heterogeneous options for different product parts coupled with the ability to recombine them in various ways implies that multiple product configurations can potentially emerge (Schilling, 2000).

For illustrative purposes, think of a typical smartphone that can be decomposed into a set of more than 25 distinct hardware and software components including, but not limited to, memory chips, processors, operating systems, built-in cameras, connectivity devices, battery, and touchscreen displays. There are multiple possible solutions available for most of the smartphone components, however. For example, there exist several display types based on either of the two dominant technologies—LCD (liquid crystal display) and OLED (organic light emitting diode)—that all differ in image-reproduction quality, resolution, weight, power consumption, and user responsiveness (Figure 1). Similarly, the range of available solutions within operating system component spans from the platforms available to all mobile-device makers under licensing agreement (Google's Android OS, Microsoft's Windows Phone) to the proprietary solutions incompatible with third-party manufacturers' hardware (Apple's iOS, Blackberry OS, Samsung's Bada OS). Consequently, by recombining different component solutions across all layers of the technological value chain, one can potentially obtain a multitude of different smartphone specifications with similar but not equal functionality.

Insert Figure 1 about here

To the consumer, the value of a system product, however, depends not only on the quality of individual components but also on how well they fit together (Clark and Fujimoto, 1990; Baldwin and Clark, 2000),[1] or how *partially modular* (or *partially complementary*) they are. Different degrees of "synergistic specificity" between component solutions will determine both the technological functionality and the commercial value of a given product (Baldwin and Clark, 2000; Schilling, 2000; Schilling and Steensma, 2001).[2]

The extent to which the underlying structure of interdependencies between component solutions is visible to market participants depends on the stage of the focal industry's evolution. At an early stage of any industry's life, the uncertainty associated with the direction of the technology developments renders the technical interrelations between component solutions extremely volatile. As the industry matures and approaches its market stage, however, a better understanding of the general technological combinatory possibilities emerges, and much of the residual uncertainty pertains to which actor will be first or best in developing particular solutions (Ethiraj and Puranam, 2004; Brusoni, Prencipe, and Pavitt, 2001). This *pre-market stage* (Kretschmer and Reitzig, 2013), at least initially, bears many similarities to a sequential "patent race" (Reinganum, 1982)—in which industry participants concurrently competitively develop technology for crucial component solutions, but only one is lucky enough to patent the invention. As the process unfolds, however, the search patterns for the preferred component solutions may start to diverge across players due to economies of substitution (Garud and Kumaraswamy, 1995), thereby rendering the notion of a "race" less apt.

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[1] Often, but not always, network externalities of the systemic good affect customer value, too (Katz and Shapiro, 1985; Matutes and Regibeau, 1988; Schilling, 2002). For the purpose of this paper, however, we abstract from such externalities to keep our core model tractable.

[2] Note that the nature of synergies between component solutions does not necessarily need to be defined by the technical feasibility of integrating several components together. The degree of fit between component solutions may be equally driven by patent considerations of third-party technologies and suppliers' exclusivity of competitive solutions.

It is this element of luck which creates randomness that is, for the most part, exogenous to market participants and that ultimately affects the market positions competing firms can stake out in a given industry. This randomness, so we argue, can engender a path dependency of managerial choices that in turn will lead to performance differences between firms. Such path dependency differs from other hitherto studied patterns of accumulation insofar as it is centrally codetermined by the competitive interaction between different players in an industry. Thus firm-performance heterogeneity will originate even absent capability differences between firms, and even if managers have identical foresight and are equally affected by environmental uncertainty. In this paper we explore the contingencies associated with the process of R&D efforts allocation in the pre-market stage of industry evolution and their influence on firm performance in different technological and competitive environments.

A MODEL OF R&D ALLOCATION AND PATENTING IN COMPETITION

Task environment

To quantitatively assess the effects of chance and choice on firm performance eventually, we formalize the process of R&D resource allocation by firms in systemic industries within a simulation model. Here, we represent the finite set of emerging combinatorial product possibilities as an $n*m$ matrix structure in which the rows correspond to product components and the columns to component solutions.

In order to distinguish between different industries in terms of total number n of components entering the final product compared to the availability of alternatives m, we discern between "steep" ($n > m$) and "flat" ($n < m$) technological landscapes. "Square" ($n = m$) shapes serve as reference categories.

In this setup, m^n possible product configurations can be obtained by vertically combining one of the m alternative component solutions across n components. The value of each product is determined by the marginal contributions of the individual component solutions to the final configuration (Ethiraj, 2007), where these marginal contributions are quantified as pairwise complementarities between solutions of adjacent components. The underlying structure of the pairwise complementarities is generated randomly at the beginning of and remains unchanged until the end of each simulation, where a simulation comprises the population of the entire matrix by different agents (see further below). Each complementarity value is a random positive rational number drawn from a uniform distribution on an open]0;1[interval. The total value V of a product is thus calculated as a sum of pairwise complementarities between its component solutions:

$$V = \sum_{k=1}^{n} c_{[k][(k+1) mod\ n]}, \qquad (1)$$

where $c_{[k][(k+1) mod\ n]}$ is the complementarity between kth and (k+1)th component solutions of a given product.[3]

Incomplete configurations (missing a solution in at least one component) do not constitute products. Figure 2 serves as an illustration.

Insert Figure 2 about here

More specifically, Figure 2 depicts a "steep" technological landscape where products consist of four components and three different solutions exist for each component. The four shaded cells indexed 1, 5, 7, and 12 represent one of the 81 (= 3^4) possible product configurations. The value of the product is equal to $V = C_{1\_5} + C_{5\_7} + C_{7\_12} + C_{12\_1}$, where the subscripts stand for cell index numbers in the matrix between which the complementarity is calculated.

Firms' goals and behaviors

There are *p* firms endowed with equal foresight ($p \geq 2$) competing for component solutions. The patterns of pairwise complementarities as well as the number of competitors are transparent to all firms, and they can thus calculate the naïve expected value of all possible products in the matrix at any given point in time. Firms seek to naïvely maximize their utility by obtaining exclusive control over those component solutions that constitute the product with the highest value to them at any given point in time. They can obtain such control through patent protection of an individual component solution whenever chance favors them in the patent race. For a given product, firms will "race" for the control of the most valuable component solution

[3] By introducing the modulo operator in the equation, we can calculate the complementarity for $k = n$ as being the complementarity between the last and the first components solution of a given product. Thus, complementarities "wrap" the last and first component in circular fashion.

currently available (modeled as the component solution that has the highest partial complementarity within the best product currently accessible to the focal firm).

To mimic the latter, we assume that firms continuously compete for developing component solutions, and we model their patenting success true to the stochastic nature of the R&D process (Reinganum, 1982)—by subjecting it to chance. The patent race itself is sequential, and, towards the beginning of a simulation, resembles a standard race in that all firms compete for the same component solution. Once certain firms have obtained control over specific component solutions, the race becomes more differentiated, and not all firms may compete for the same component solutions any longer. This is because the success of any firm in obtaining control over a component solution changes the patenting landscape[4] and thereby potentially alters the competition for all other firms in that they need to adjust their goals. Thus, we assume that players re-evaluate their R&D allocations (treating prior investments as sunk costs) each time another firm obtains control over a given technology. The sequence of chance events (patenting successes pertaining to a component solution) ends when all component solutions are being owned by someone.

Depending on the number of competitors participating in the aforementioned race, and depending on the complexity of the system product, more often than not it may be unfeasible for a single firm to control all components required for a given product. In those instances, after successfully patenting a certain component solution, a focal firm[5] may try to market a product jointly with an alliance partner.

In the mode, alliance formation takes place automatically between two firms when it is both (i) possible and (ii) mutually beneficial for them to join forces. It is possible whenever both firms jointly hold enough component solutions to create a product, but not before (i.e., there is in-built myopia with regard to the alliance-formation process at an early stage of industry evolution). It is mutually beneficial when, for both firms, profits shares in the alliance exceed the naïve (expected) maximum value of what the firms can earn by themselves. To assess whether condition

[4] To simplify matters, we assume that any component solution may only be used only once, notably for the product with the highest value. This logic is in line with a series of real-world assumptions: (1) on the production side, a firm may be able to afford to hold the basic patents to a technology, but it may not be feasible for a firm to maintain "application-related" patent portfolios dedicated to more than one specific use of a given technology; (2) on the demand side, firms may elect not to reuse certain components across products in order to avoid cannibalization.

[5] Here we use the term "focal firm" to define a firm that wins a patent race for a given component solution.

II is being met, we must define and compare firms' shares in an alliance with the independent naïve (expected) solutions available to them.

The share of firm i in an alliance between two firms is calculated as the sum of the pairwise complementarities between the component solutions that firm *i* contributed to the jointly created product, formalized as follows:

$$S_i^P = \sum_{k=1}^{s} c_{[k][(k+1)\ mod\ n]}^P \quad , \tag{2}$$

where S_i is the attributed value of the focal firm *i* in a given alliance product *P*, $c_{[k][(k+1)\ mod\ n]}^P$ stands for the complementarity between the k[th] and (k+1)[th] component solutions of a given alliance product *P*, and *S* is the number of component solutions owned by the focal firm *i* in a given alliance product *P*.

Calculations are symmetrical for alliance partner *j*, so that the attributed shares of both partners always add up to the total value of the alliance product $S^P = S_i^P + S_j^P, i \neq j$. These relative contributions of alliance partners determine the value-division percentages:

$$w_i^P = \frac{S_i^P}{S^P} \tag{3}$$

$$w_j^P = \frac{S_i^P}{S^P} \tag{4}$$

Here, w_i^P is the percentage share of the focal firm *i* in a given alliance product *P*, w_j^P denotes the percentage share of the partner firm *j* in a given alliance product *P*, and $w_i^P + w_j^P = 1, i \neq j$. Notably, alliances are irreversible and splits are frozen at the moment of the alliance formation. Thence, alliance partners share revenues from any subsequently created products, including further component solutions they may obtain control over in the future or that they may have obtained in the past, and they share profits according to the initially fixed split.

To assess the (expected) maximum value of an integrated product available to a given firm, the focal organization estimates its (time-variant) chance of obtaining control over the entirety of component solutions constituting the most valuable and still accessible product at time *t* as follows:

$$E(\mathrm{v}_i) = \frac{M}{p \cdot T_i} \cdot v_i \qquad (5)^{6}$$

6 Note that this calculation conservatively biases the value of an alliance relative to the expected value of an integrated product owned by one firm only. At the initial stage, firms' preferences for the most valuable component solution coincide and the probability of patenting a particular component solution indeed equals $1/p$

Here, $E(\mathrm{v}_i)$ denotes the expected value of the best available individual product for player i, v_i is the value of the best available individual product for player i, M is the total number of the remaining available component solutions, T_i is the number of missing component solutions for the available individual product with value v_i, and p is the number of firms.

Consequently, in order for condition II for alliance formation to be met, inequalities (6) and (7) must simultaneously hold true:

$$E(\mathrm{v}_i) = \frac{M}{p \cdot T_i} \cdot \max_i < S_i^P \qquad (6)$$

$$E(\mathrm{v}_j) = \frac{M}{p \cdot T_j} \cdot \max_j < S_j^P \qquad (7)$$

The time-value of chance in systemic industries

Within the setup described above, the paper's central question of how randomness affects competition, and thence managerial actions and firm performance, becomes structurally equivalent to investigating the time-value of chance. More specifically, we wonder how initially homogeneous firms benefit more or less from being lucky in a sequential patent race depending on when nature favors them, and for how long—all else being equal. While it appears trivial that firms should do ever better the more frequently they win a leg, determining this time-value of chance appears to be more difficult, and the extant literature to be scant.

One stream of research that studies the sequence of lucky events stems from the field of judgment and decision-making. Scholars in this domain have corroborated that sequences of lucky events trigger different reactions within individuals—ranging from the gambler's fallacy to the hot hand phenomenon (Tversky and Kahneman, 1974; Hahn and Warren, 2009)—focusing on a distinctly different question than the one we are concerned with, however. Another body of literature in the domain of cognitive psychology investigates the effects of delays and interruptions in planned activities (Marsh, Hicks, and Bryan, 1999; McDaniel *et al.*, 2004). It is tangential to our paper, however, in that it analyzes the consequences of possible inhibitions through a prism of memory—a characteristic that is alien to our agents here. Finally, a line of work in the

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for each firm. As the patenting process unfolds, firms' preferences for component solutions start to diverge and the number of competitors aiming at the particular component solution decreases.

management field has contrasted the value of planning with the value of spontaneous opportunity recognition and exploitation (Gruber, 2007); however, scholars in that vein again involve sets of assumptions on firms' learning and capabilities that do not apply to our setting.

Thus, pending any strong priors from the existing literature, we resort to our own critical thinking in predicting how the time-value of chance unfolds. To that end, we argue that the effect of luck on performance in systemic industries bears a stage-specific character, and that patenting crucial technology during an early stage of an industry's evolution will be more valuable than patenting tangential technology at later stages (Teece *et al.*, 1997). This effect, so we argue, is exacerbated by the path dependency that firms create through their own actions. We thus posit:

Proposition 1: *Firms benefit from the chance to make early positional choices in systemic industries, all else being equal.*

The value of a firm's chance to make decisions early is a necessary condition for obtaining an overall superior position in the industry landscape—however, an insufficient one. The largest obstacle to obtaining control over a superior product, so it would appear, is the firm's risk of being interrupted in executing its "plan" to control crucial elements of its value proposition. Such competitor interference, so we would argue, sets firms back, and more so the more often it occurs, as rivals may cross the firms' plan of action and invalidate their earlier positional choices. Consequently, firms should perform better, all else being equal, the longer the period during which they can uninterruptedly make sequential positional choices that build on one another. We therefore predict:

Proposition 2: *Firms benefit from the chance to make repeated positional choices in systemic industries without competitor interference.*

DATA AND VARIABLES

We simulated the process of firms' R&D effort allocation in systemic industries deploying the above agent-based model. To that end, we define *p* firms, *n* components, and *m* component solutions prior to generating the randomized patenting landscape. For each possible combination of parameters p, n, and m we ran a series of 100 simulations (= matrix populations), where landscapes varied in their underlying complementarity structure, leaving us with total 15,000 independent simulations.[7] To assess the effects of chance—the non-manipulable parameter in our simulation—we thence re-estimate the coefficients of (repeated) luck on the data we created. Our unit of observation is the firm, and with the number of observations for each simulation being equal to the number of firms p, we eventually obtained 67,500 observations[8] for our analysis.

Dependent variable

We use a cardinal dependent variable called *firm-level performance*. It captures the aggregate value of all products owned by a firm individually or, in the case of alliance formation, the sum of shares held by a firm in jointly owned products.[9] The variable is computed at the end of each simulation, and it takes a value of zero if a firm neither held a product of its own nor participated in an alliance. Finally, we normalize firm performance by dividing it by the number of components n, in order to facilitate performance comparisons across different technological landscapes.

Independent variables

First choice denotes the point in time when a firm succeeds in the sequential patent race for the first time and obtains control over a component solution in the technology landscape. We proxy for entry time by counting the number of component solutions that have been patented by competitors prior to the focal firm's first patenting success. The corner solution of firms never entering the technology landscape are set to $n*m$ (the total number of component solutions in a given technological landscape).

[7] The parameters for the number of components n (matrix rows) and the number of solutions m (matrix columns) take integer values in a closed [3;7] interval, the number of players p takes integer values in a closed [2;7] interval, thus resulting in a total 5*5*6 = 150 possible parameter combinations. For each parameter combination we run 100 simulations, which eventually gives us 15,000 simulations.

[8] The number of observations for a single fixed combination of parameters (n, m) is calculated as a sum of finite arithmetic progression of which the terms correspond to possible numbers of firms p in a simulation: $S_n = \frac{n*(p_{min}+p_{max})}{2} = 27$. Given that there are 25 possible combinations of (n, m) and for each parameter set (n, m, p) simulations are repeated 100 times, yielding 25*27*100 = 67,500 observations.

[9] On the path to patenting the value-maximizing combination, a firm might unintentionally create byproducts of inferior value. If at a later stage a new, better product configuration requiring already deployed component solutions becomes possible, the inferior products are dissolved and their component solutions are reassigned to the products that yield the higher value.

Un-interfered choice captures the time span during which a focal firm can execute its initially envisaged R&D agenda without having to reconsider its plans due to interim patenting successes by competitors. Un-interfered choice is measured as the maximum number of component solutions that a given firm obtains control over consecutively. In the case of alliance formation, we treat the focal firm's choices and that of its partners as one with regard to the computation of the variable.

Control variables

To exclude alternative explanations and to facilitate meaningful comparisons across simulations with different parameter sets, we include several control variables at the level of both industry and firm.

At the industry level, we first include *landscape size* (measured as the total number of component solutions $n*m$ within a given landscape simulation) as a separate explanatory variable. In doing so, we tease out the effects of firms benefiting from larger choice sets and increased chances to obtain control over sufficient numbers of components to produce independently.

Second, we control for the fact that firms may exhibit different behavior depending on the shape of the technological landscape. On one hand, increasing the number of components n constrains the feasibility of an integrated product for a firm and forces it to anticipate alliance formation under unfavorable conditions in order to secure non-zero outcomes. On the other hand, as the number of possible alternative component solutions m increases, a firm gains more flexibility in creating better integrated products, as it can leverage existing component-specific assets (Farrell *et al.*, 1998) and reap the economies of substitution by re-deploying its past investments (Garud and Kumaraswamy, 1995). As a result, vice versa, firms' performance in technological landscapes with fewer component solutions m relative to the number of components n will be systematically lower, all else being equal. To that end, and consistently with the model description above, we introduce two binary variables—"*flat*" (1 if $m > n$, 0 otherwise) and "*steep*" (1 if $n > m$, 0 otherwise), with "*square*" being the reference category. Varying m and n will also allow us to investigate whether chance equally engenders intra-industry performance heterogeneity across different types of landscapes, or not.[10]

Finally, the presence of multiple firms with similar goals and vision will naturally reduce the probability of a single firm to pioneer a crucial technological solution and exacerbate the risks of disruptions in a focal firm's envisaged patenting plan. We seek to strip off related variance in our dependent variable by controlling for *competition strength*, which is approximated by the number of competitors, p.

We also control for a variety of alliance and firm-level effects.

First, we include a binary variable called *alliance formation* that captures whether a firm entered an alliance in a given simulation (1, 0 otherwise). The variable is set to zero also for those firms that created no products in a given simulation.

Second, cumulative luck might increase corporate profit due to increased alliance opportunities, even if the conditions of staking positions early and seamlessly in the technology landscape are not fulfilled. We therefore include the *total number of chance events* variable, which is measured as the total number of component solutions held by a given firm by the end of a simulation.

Third, the presence of interruptions distorts a firm's initial intentions, but the extent to which these discontinuities in executing an envisaged agenda become irreversible also depends on the duration of the interruption: the longer the period a firm does not succeed in winning a patent race, the more likely it will have to switch to a different (and inferior) target product eventually. Consequently, we include the *longest period of disruption* variable, which counts the maximum number of times competitors succeeded in patenting between two nonconsecutive successful positional choices of the focal firm.

Finally, we include variables that capture the duration of chance at different points of the landscape population. The *number of short / medium / long lucky strikes at the early stage* counts the number of chance sequences accruing to a focal firm, which allows us to capture half (three quarters, all) of the component solutions constituting a product during the first half of a simulation.[11] The intuition behind the variable is that getting a long sequence or alternating series of short leads towards the beginning may

[10] See "Robustness checks" for further details. In that section, we discuss the convergence of running our estimations on different types of (steep, flat, and square) landscapes.

[11] The absolute number of component solutions will differ conditional on the number of components n. Results are rounded off when needed.

grant a firm access to the crucial value-maximizing components and preclude other firms from occupying them. Moreover, even being inactive on subsequent moves might not be as harmful because one gets a stronger bargaining position for an alliance. The *number of short / medium / long lucky strikes at later stages* is calculated analogically with the aforementioned set of variables, but it refers to stages in time when half the technology in the landscape is already controlled by one firm or another. The basic rationale is that a late series of "lucky" draws may potentially be beneficial as one gets a chance to accumulate enough components for an individual product, or to establish a bargaining position for an alliance. However, the choice set will be limited, and the quality of the available remaining products may be inferior. Figure 3 illustrates the computation of some of the key variables. Table 1 summarizes the description of the variables.

Insert Table 1 and Figure 3 about here

RESULTS

Table 2 contains descriptive statistics that allow checks on the internal consistency of the simulation outcomes, as well as on the usefulness of the data for the tests of Propositions 1 and 2. Minimum and maximum values of manipulable parameters correspond to expectation. Equally reassuringly, stochastically determined variables show substantial variation, and correlations between parameters exceed values of 0.5 only in systematically expected instances. Finally, preliminary indications of a relationship as predicted in Proposition 2 emerge (corr[*firm performance*, *un-interfered choice*] = 0.61, $p < 0.01$).

Insert Tables 2 and 3 and Figure 4 about here

More interestingly, Figure 4 illustrates one of the key tenets of this paper; namely that significant inter-firm performance differences materialize as a result of the way we formalized the population of the technology landscape. More specifically, Figure 4 contrasts ranked performance differences (measured as average aggregate firm payoffs across simulations, normalized by the number of components) between individual organizations.

Table 3 eventually provides results from the multivariate analysis of our data that seeks to corroborate our propositions. Models 3.1 through 3.9 provide upward-tested OLS specifications in which we explain firm performance through an increasing set of explanatory variables, including their interactions. Given that we draw on simulated data that bear no path dependency across simulations, and since we do not model agent's learning within a simulation, we treat all observations as independent pooled firm-level cross-sections.

Models 3.1 and 3.3 provide baseline parameterizations that include a subset of our control variables, and against which we compare the explanatory power of the subsequent models, particularly models 3.3 through 3.7. Model 3.4 originally introduces the *first choice* variable, confirming our first Proposition that performance suffers the later a firm is able to make its first positional choice. Notably, the effect remains robust across all subsequent specifications.

Model 3.5 provides empirical evidence for Proposition 2. The longer the un-interfered sequence of decision-making a firm enjoys, the higher the profit it attains—an effect that remains robust across specifications albeit decreasing in size depending on the inclusion of further controls (see Model 3.7). Model 3.6 provides a quasi mirror image of Model 3.5 in that it shows that a firm's performance suffers the longer that chance favors its competitors in a stretch.

Finally, models 3.8 and 3.9, originally intended to rule out further alternative explanations for our proposed relationships, reveal interesting insights in their own right. Namely, as Model 3.8 suggests, a *lucky strike*, all else being equal, benefits a firm more during the initial phases of the technology landscape population than during the later stages.[12] Pairwise comparisons of coefficients for *lucky strikes* of identical duration during the early and the late stages of the process show significant differences. This effect, so it would appear, is exacerbated by the number of competitors participating in the sequential patent race (Model 3.9). With the benefit of hindsight, we thus additionally posit:

Proposition 3a: *The effect described in Proposition 2 is more pronounced during early than during the late stages of the evolution of an industry.*

[12] Note that the variable *un-interfered choice* no longer features in models 3.8 and 3.9, as its inclusion would lead to an over-specification given the additional explanatory variables.

Proposition 3b: *The effect described in Proposition 3.a is exacerbated by the number of competitors in an industry.*

Robustness checks—selection issues, boundary conditions, and mechanistic identification

We carried out a series of robustness checks (a) to exclude that our findings would be spuriously driven by selecting a particular sample of simulated data, (b) to delimit the parameter space under which our core results would uphold, and—most importantly—(c) to ascertain that the effects of chance we report would indeed be driven by the competing firms' positional choices—in line with our theoretical claim.

To address the first issue, and given the nature of our (simulated) data, we repeatedly estimated models 3.1 through 3.9 on randomly chosen subsamples of varying size in a bootstrapping-like manner. Findings were robust with respect to both coefficient estimates and levels of individual coefficient significance.

With regard to the second point mentioned above, we ran models 3.1 through 3.9 on different subsets of flat, steep, and square technological landscapes. Expectedly, un-interfered choice is more visibly related to firm performance in industries characterized by small-component-number products (i.e., flat landscapes), all else being equal. This is because the chance sequences required to obtain a desired product are shorter, whereas the likelihood of benefiting from such a sequence stays constant. That said, results do converge across different types of industries.

Finally, in order to provide further evidence for a specific competition-related mechanism by which chance engenders firm-level performance heterogeneity, we sought to dismiss an obvious alternative explanation for our findings; namely that the product value asymmetries generated by the structure of partial complementarities in our industry landscapes alone could account for the asymmetries in firm performance we obtain. To that end, we computed the total value generated by firms within an industry—the value one would expect to observe if the firms did not compete for individual component solutions but, instead, randomly selected from the theoretically best possible products within a given landscape without competitively crowding one another out.[13] Comparing the aggregate firm-level profits that are being generated by our model with those engendered through such an alternative (naïve) random ex-post allocation procedure shows that the asymmetries we observe in models 3.1 through 3.9 are indeed characteristic of our theory of firms' positional choices in competition.

Insert Table 4 about here

To that end, Table 4a reports—for selected industries—the number of simulations (out of 100) in which the total value of the products generated in each simulation without competitor interaction is identical to or compatible with the one generated by our model-based simulations. Similarly, Table 4b reports the number of cases in which the simulated competitive process inherent in our model generates the maximum feasible number of products in a given industry when chance is limited to determining ex-post allocation of product values. From Table 4 it is apparent that the two stochastic processes produce distinctly different results; "incompatible" cases between the two explanations prevail: in most simulation runs, the probability of obtaining the same distribution of outcomes by the ex-post allocation or by simulation is close to zero. Notably, the industry structure may affect the degree of incompatibility between our modeling results and the alternative ex-post random allocation process. In particular, as competitive pressure loosens, the number of compatible cases increases. This reinforces the result of our regression analysis, showing that chance plays an ever more important role when there are more competitors.

DISCUSSION AND CONCLUSIONS

In this paper, we proposed and demonstrated within the framework of our assumptions that chance itself can induce performance heterogeneity among initially homogeneous organizations, even in the absence of capability differences between them. Such chance to make early decisions and make choices uninterruptedly, so we proposed and showed, can irreversibly affect firms' positions in an industry landscape, thereby engendering significant variation in inter-firm profits. Importantly, this type of firm-level performance difference engendered by competitive crowding significantly differs from alternative patterns of performance variation between firms that can be generated

[13] This alternative stochastic process, while equally generating asymmetries in firm performance, theoretically differs from the mechanism we propose in that the role of randomness would be limited to a generating a world of technological opportunities and distributing them among agents.

through simpler stochastic random allocation processes. Notably, our model produces results that would appear to capture empirically observable deadweight losses due to coordination failures among competing firms better than simpler random allocation processes could.

We believe our findings could appeal to a wide variety of scholars in our field as well as adjacent ones. Strategy scholars, traditionally concerned with identifying and characterizing the sources of heterogeneity in firm performance, may view our results as complementary to the findings of Denrell (2004) and Zott (2003), who earlier argued that chance introduces variation in capabilities between firms, and thence variation in performance. That said, we are also moderately hopeful that our approach and findings might also be interesting to scholars outside the core strategy domain, notably to colleagues from the field of evolutionary biology, who are equally preoccupied with the emergence of heterogeneity—albeit among organisms, not organizations (Rueffler, Hermisson, and Wagner, 2012).

Naturally, our work leaves us with at least as many questions as it provided preliminary answers. Towards the end of the paper, we pick up on those two categories of questions that appear most important to us, and that present avenues for future work.

The first category of open issues relates to the framework of assumptions we adopted in this paper. For one, we started from the premise that technology landscapes of the kind we depict are equally visible and accessible to all competitors in the market, that they do not change over time, that components are of roughly similar importance, and that markets can accommodate a variety of different products at a time. In reality, systemic industries are research-intensive industries in which different component technologies may be progressing at different rates (Ethiraj, 2007), and specialization advantages of individual organizations may exist from the beginning. Equally, firms may differentiate between core and peripheral components (Baldwin and Woodard, 2009), dismissing the simple assumption that all components have the same mean level of importance. And finally, installed base advantages may limit the viability of bringing out second and third products in a systemic industry after the initial offering has been introduced. Relaxing all these assumptions, and including them in a more comprehensive modeling approach, may appear worthwhile particularly in those instances in which scholars or practitioners seek to quantify the effect of chance on positional advantages for a given setting.

Second, and possibly more relevant from a scholarly standpoint, our current formalization—to keep the model tractable—deliberately stopped short of modeling agents' decision-making behavior in more complex ways than their pursuing of solutions with the highest naïve expected value. Deviations in either direction—by either endowing managers with more foresight or letting them resort to simpler rules of thumb (a.k.a. heuristics)—would add a sense of realism to our formalizations that should increase the explanatory power of our chosen approach. Ongoing research of ours in this paper's vein thus elaborates on agents' decision-making behavior—examining both the marginal value of deploying second-level rationality in the presence of stochastic R&D allocations and the costs of taking decision-making shortcuts in probabilistic settings.

Finally, while in this paper we deliberately modeled the emergence of performance asymmetries among firms with equal starting conditions, future extensions may, of course, additionally account for initial differences in firms' capabilities in order to provide a most nuanced view of the role of randomness in the engendering of firm-performance heterogeneity.

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FIGURES

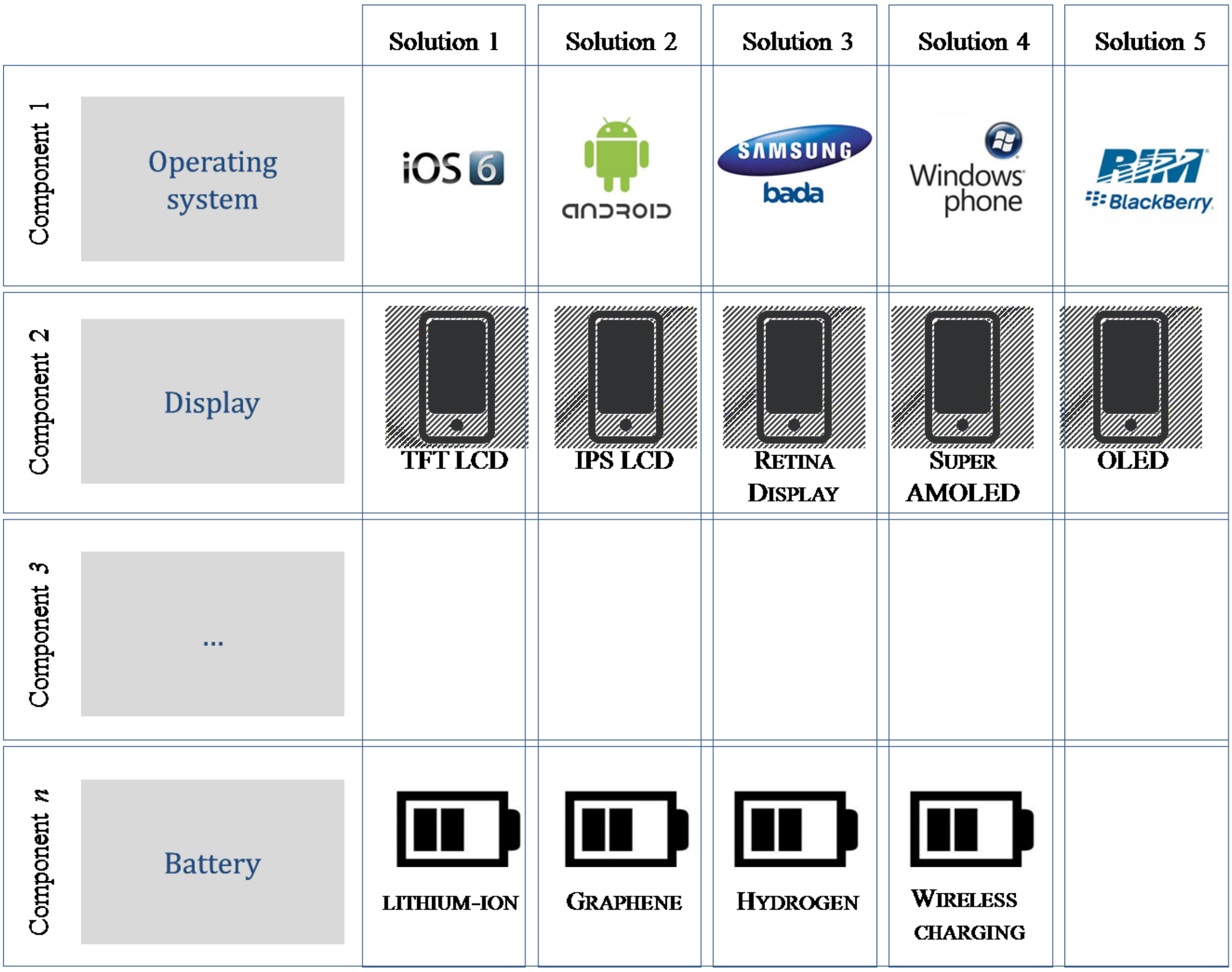

Figure 1. Selected component solutions in the smartphone industry

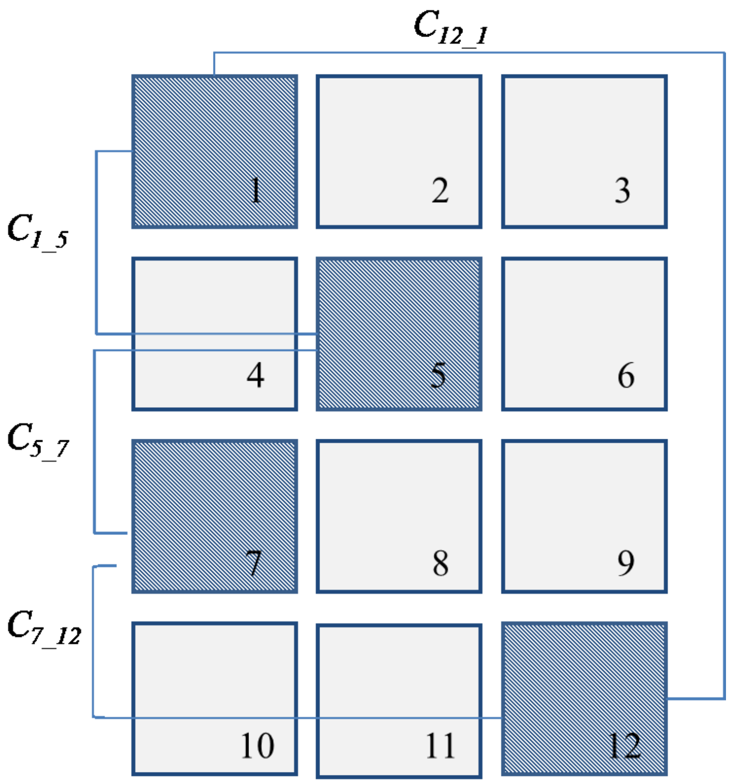

Figure 2. Calculation of the product value as a sum of pairwise complementarities between its constituent component solutions in adjacent layers.

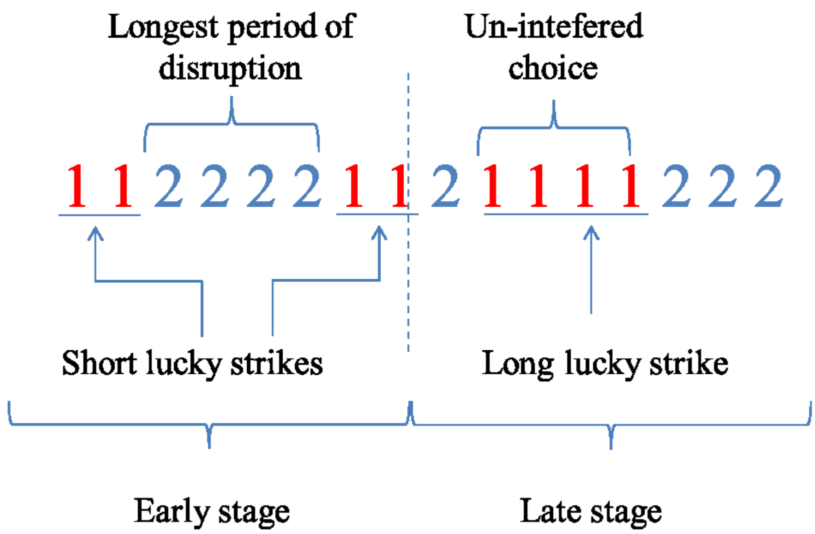

Figure 3. Sequence of chance events for a focal firm.

Legend: Chronological order of chance events accrued to firms in a given simulation can be represented ex-post as an array of length $n*m$. The elements of an array correspond to the firms' indices (1,2,..p) and their positions—to the number of component solutions captured at any given point in time. The figure illustrates a simulation for parameter combination $n = 4$, $m = 4$, and $p = 2$. Sixteen component solutions are available (*landscape size* = 16). The chance variables for firm 1 as computed as follows: Firm 1's first choice occurred when no components were captured by competitors (*first choice* = 0). Firm 1 was able to make a maximum of 4 consecutive choices (*un-interfered choice* = 4), and was losing the patent race for 4 component solutions in a row (*longest period of disruption* = 4). Overall, firm 1 was able to capture 8 component solutions (*total number of chance events* = 8). In a given simulation we set $n = 4$; thus, winning a patent race 2 (3, 4) times in a row allows a firm to capture half (three quarters, all) of the component solutions required for the complete product. Depending on whether firms' activity relates to the period before or after the first 8 component solutions are captured, we distinguish between the early and later stages on the technology landscape population. In the first half of the simulation, firm 1 had 2 series of short lucky strikes (*number of short lucky strikes at the early stage* = 2) and 1 long series towards the end of the simulation (*number of long lucky strikes at later stage* = 1).

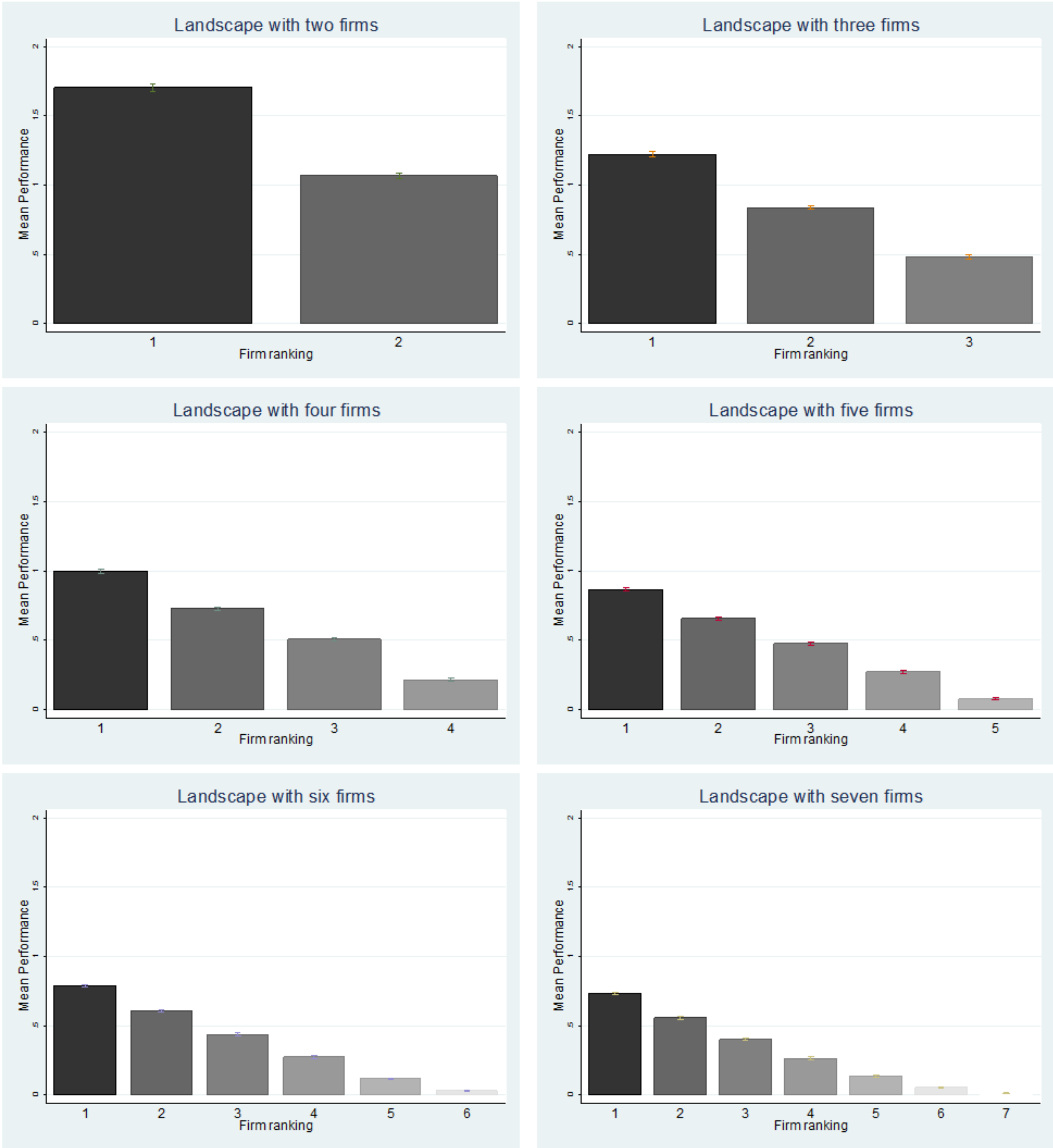

Figure 4. Differences in ranked aggregate firm payoffs across simulations for setups with different numbers of competitors. Differences between bars are statistically significant.

TABLES

Table 1. Description of variables.

Variable	Definition	Expected sign
Firm-level performance	Cardinal variable. Normalized value accumulated by a firm in a given simulation	
Flat	Binary variable; set to 1 for industry landscapes in which the number of available solutions to each product component exceeds the total number of components, 0 otherwise	+
Steep	Binary variable; set to 1 for industry landscapes in which the number of available solutions to each product component falls behind the number of components, 0 otherwise	-
Competition strength	Count variable denoting the number of firms in a given simulation	-
Landscape size	Count variable capturing the total number of available component solutions in a given simulation	+
Alliance formation	Binary variable denoting the fact of alliance formation by players (baseline: no alliance formation occurs)	-
First choice	Count variable denoting the total number of component solutions captured by competitors prior to a firm's first success	-
Total number of chance events	Count variable denoting the total number of component solutions a firm managed to capture by the end of a simulation	+
Longest period of disruption	Count variable denoting the maximum number of component solutions that were consecutively captured by a firm's competitors	-
Un-interfered choice	Count variable denoting the maximum number of component solutions that were captured consecutively by a firm without being interrupted by competitors	+
Number of short lucky strikes at the early (late)stage	Count variable denoting the number of sequences of a length that consecutively would allow a firm to get ownership of half of a product in the early (later) stage of the landscape population	+
Number of medium lucky strikes at the early (late)stage	Count variable denoting the number of sequences of a length that consecutively would allow a firm to get ownership of three quarters of a product in the early (later) stage of the landscape population	+
Number of long lucky strikes at the early (late)stage	Count variable denoting the number of sequences of a length that consecutively would allow a firm to get ownership of all of a product in the early (later) stage of the landscape population	+

Table 2. Descriptive statistics and correlations.

		Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Firm-level performance	0.54	0.50	0	4.70	1.00															
2	Landscape size	25	10.20	9	49	0.24	1.00														
3	Alliance formation	0.40		0	1	-0.07	0.06	1.00													
4	Competition strength	5.15	1.58	2	7	-0.53	-0.00	0.20	1.00												
5	Flat	0.40		0	1	0.24	-0.04	-0.15	-0.00	1.00											
6	Steep	0.40		0	1	-0.24	-0.04	0.15	-0.00	-0.67	1.00										
7	Total number of chance events	5.76	4.04	0	35	0.75	0.57	-0.04	-0.55	-0.04	-0.00†	1.00									
8	First choice	5.88	8.34	0	49	-0.34	-0.10	-0.09	0.25	-0.01†	-0.02	-0.35	1.00								
9	Un-interfered choice	1.94	1.19	0	15	0.61	0.23	-0.02	-0.51	-0.02	0.02	0.73	-0.33	1.00							
10	Longest period of disruption	7.79	4.50	1	43	-0.28	0.46	0.09	0.36	-0.00†	-0.02	-0.18	-0.09	-0.21	1.00						
11	Number of short lucky strikes at the early stage	0.14	0.39	0	4	0.36	-0.06	-0.15	-0.25	0.18	-0.16	0.23	-0.14	0.26	-0.14	1.00					
12	Number of short lucky strikes at later stage	0.17	0.42	0	4	0.29	-0.06	-0.02	-0.23	0.17	-0.15	0.23	-0.09	0.27	-0.20	0.13	1.00				
13	Number of medium lucky strikes at the early stage	0.07	0.27	0	3	0.30	-0.12	-0.14	-0.20	0.17	-0.15	0.12	-0.10	0.21	-0.14	0.43	0.09	1.00			
14	Number of medium lucky strikes at the late stage	0.08	0.28	0	3	0.25	-0.13	-0.05	-0.18	0.18	-0.15	0.12	-0.07	0.22	-0.19	0.11	0.39	0.15	1.00		
15	Number of long lucky strikes at the early stage	0.03	0.18	0	2	0.35	-0.07	-0.10	-0.24	0.12	-0.10	0.20	-0.08	0.41	-0.14	0.02	0.09	0.03	0.12	1.00	
16	Number of long lucky strikes at the late stage	0.03	0.17	0	2	0.28	-0.07	-0.04	-0.20	0.11	-0.09	0.18	-0.06	0.37	-0.14	0.10	0.00†	0.11	0.02	0.14	1.00

The reported Pearson correlation coefficients are significant at 1%. Correlation coefficients marked with † are not statistically significant.

Table 3. Modeling firm performance (OLS regression estimates)

Model	3.1	3.2	3.3	3.4	3.5	3.6	3.7	3.8	3.9
Landscape size	0.012***	0.012***	-0.012***	0.011***	0.007***	0.018***	-0.006***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Alliance formation	0.027***	0.076***	0.041***	0.048***	0.047***	0.065***	0.041***	0.062***	0.064***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Competition strength	-0.171***	-0.174***	-0.022***	-0.158***	-0.104***	-0.140***	-0.020***	-0.013***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Flat		0.191***	0.197***	0.180***	0.182***	0.204***	0.203***	0.153***	0.157***
		(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Steep		-0.116***	-0.125***	-0.124***	-0.132***	-0.115***	-0.127***	-0.088***	-0.091***
		(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Total number of chance events			0.107***				0.085***	0.069***	0.069***
			(0.001)				(0.001)	(0.001)	(0.001)
First choice				-0.011***			-0.015***	-0.018***	-0.018***
				(0.000)			(0.000)	(0.000)	(0.000)
Un-interfered choice					0.178***		0.034***		
					(0.002)		(0.002)		
Longest period of disruption						-0.033***	-0.009***	-0.013***	-0.014***
						(0.000)	(0.000)	(0.000)	(0.000)
Number of short lucky strikes at the early stage								0.107***	0.118***
								(0.004)	(0.010)
Number of short lucky strikes at the late stage								0.040***	0.130***
								(0.003)	(0.009)
Number of medium lucky strikes at the early stage								0.176***	0.251***
								(0.005)	(0.014)
Number of medium lucky strikes at the late stage								0.100***	0.178***
								(0.005)	(0.014)
Number of long lucky strikes at the early stage								0.419***	0.462***
								(0.009)	(0.021)
Number of long lucky strikes at the late stage								0.236***	0.446***
								(0.009)	(0.020)
Competition x Number of short lucky strikes at the early stage									-0.003
									(0.002)
Competition x Number of short lucky strikes at the late stage									-0.021***
									(0.002)
Competition x Number of medium lucky strikes at the early stage									-0.021***
									(0.003)
Competition x Number of medium lucky strikes at the late stage									-0.020***
									(0.003)
Competition x Number of long lucky strikes at the early stage									-0.020***
									(0.005)
Competition x Number of long lucky strikes at the late stage									-0.066***
									(0.005)
Constant	1.110***	1.076***	0.295***	1.096***	0.510***	1.010***	0.330***	0.245***	0.207***

	(0.009)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)
Observations	67,500	67,500	67,500	67,500	67,500	65,267	65,267	65,267	65,267
Adjusted R-squared	0.345	0.418	0.691	0.449	0.539	0.465	0.691	0.733	0.737

Standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%

Table 4a. Comparing aggregate firm-level profits within different types of industries for different types of chance mechanisms

Landscape dimensions (n*m)	**2 firms**	**3 firms**	**4 firms**
4 * 3	21	9	1
4 * 4	8	2	2
4 * 5	11	3	1
4 * 6	8	1	0

Cases (out of 100) in which the total value of the products generated in each run of the simulation (using ex-post random allocation) is identical to the one generated by the simulated competitive process.

Table 4b. Comparing the total number of products generated within different types industries for different types of chance mechanisms

Landscape dimensions (n*m)	**2 firms**	**3 firms**	**4 firms**
4 * 3	32	17	5
4 * 4	11	4	3
4 * 5	14	4	2
4 * 6	17	1	1

Cases (out of 100) in which the simulated competitive process generates the maximum feasible number of products.

THE ROLE OF ALLIANCE FORMATION AS UNCERTAINTY ABSORPTION MECHANISM IN COMPLEX ENVIRONMENTS

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Abstract

The "chance and choice" model of resource allocation represents an agent-based formalization of managerial decision-making process in complex technological environments. The model has been originally developed to examine how chance, competition and managerial choices jointly co-determine performance differences among initially identical agents which are programmed to "naively" maximize their respective short-term individual profits without taking the intentions of their opponents into consideration. In this paper, I am primarily interested in uncovering the actual decision-making mechanisms and validating the behavioral assumptions of the original model through a laboratory experiment. The results suggest that in perceivably uncertain environments people strategically manage uncertainty by hedging the risks upfront via anticipated alliance formation. In doing so, human subjects consider the future intentions of their opponents beforehand and maneuver potential partners into positions in which alliance becomes a mutually beneficial choice.

INTRODUCTION

The “chance and choice” model of resource allocation represents an agent-based formalization of managerial decision-making process in complex technological environments (Arkhipova et al., 2014). In the proposed model, multiple agents compete with each other for control over a limited set of product components to which they sequentially get access in a randomized fashion thereby irreversibly limiting each other’s available choice sets. Agents’ choice behavior is assumed to be homogenous and fairly myopic in that they are programmed to “naively” maximize their respective short-term individual profits without taking the intentions of their opponents into consideration (Levinthal and March, 1993).

The model has been originally developed to examine how chance, competition and managerial choices jointly co-determine performance differences among initially identical agents and was analyzed through a series of computer simulations. Whereas setting decision rules equal across all agents was essential for isolating the effect of chance factors on individual-level performance, this approach casts some doubts on whether the adopted formalizations adequately portray the decision making strategies people would actually use should they be confronted with a similar resource allocation task. In this paper, I aim at addressing the aforementioned shortcoming by testing the decision rules of the simulation model through a laboratory experiment.

Testing in the lab the behavioral assumptions underlying the formal models of decision-making is becoming increasingly widespread in management science (Knudsen et al., 2012; Billinger et al., 2013; Christensen, 2014). During the experiment, human subjects are placed in an artificial decision-making environment whose problem structure, available information set, objective function and feedback mechanisms closely mirror those of the model (Sterman, 1987). Yet, whereas modelled agents’ actions are defined by a set of theory-derived algorithms, experimental subjects make choices the way they prefer (Sterman, 1987; Scandura and Williams, 2000; Harrison et al., 2007).

The game-like structure of the “chance and choice” model naturally lends itself to exploration through a laboratory experiment. In the simulation model, agents are allocated the possibility to make choices in a stochastic fashion. On his turn, an agent is assumed to pick a component with the highest marginal contribution to the most valuable product configuration still available individually, or – should the individual opportunities be already exhausted – to access missing components by concluding an alliance with one of the competitors on mutually beneficial terms. In the experiment, human subjects have no control over the timing of their choice either, but they are not necessarily following the simple “naïve maximization” rules as to which components to choose and how to interact with one another. Moreover, overwhelming evidence shows that people may systematically depart from the principles of probability and statistics, rely on imprecise computations and make choices conflicting with the expected value maximization (Tverksy, 1975; Simon, 1979; Rabin, 1998; Gigerenzer, 2000). In this paper, I am primarily interested in uncovering the actual decision-making mechanisms and validating the behavioral assumptions of the original model.

The paper reports the key findings from the experiment compared to the simulation with the same parameterization. Whereas the performance differences on both individual and group levels are virtually non-existent, most of the deviations pertain as to how people self-organize into emergent coalition structures. The results suggest that in perceivably uncertain environments people strategically manage uncertainty by hedging the risks upfront via anticipated alliance formation. In doing so, human subjects consider the future intentions of their opponents beforehand and maneuver potential partners into positions in which alliance becomes a mutually beneficial choice.

In what follows, I commence by introducing the model and describing the experimental procedure. Next, I formulate a series of propositions regarding the differences between simulated and experimental results I expect to observe and compare experimental results against the simulated benchmark. I conclude by discussing the implication of the results for the management science and outlining potential avenues for future research.

MODEL DESCRIPTION

In what follows, I shortly summarize the structure and behavioral assumptions employed in the original simulation model.

Problem structure

I shall consider a setup where the finite number of agents (representing firms) is competing for control over the limited number of components that make up an abstract product (see Arkhipova et al. (2014) for the detailed description). Each component has several alternative solutions which can be recombined into a variety of different product configurations perceived as substitutes by consumers. The value of each product configuration is calculated as an arithmetic sum of the pairwise complementarities between its constituent component solutions whose values are drawn from a uniform continuous distribution on a closed (0.2; 1.0) interval.[14] The number of components m, the number of the corresponding alternatives n and the matrix of pairwise complementarities are set exogenously and jointly co-determine the technological landscape on which the agents operate. The technological landscape can be therefore visualized as a two-dimensional matrix M of size $m \times n$. For each element a_{ij} of the matrix M there exist a set of corresponding complementarity values c_{ijk}, where i and j stand for the position of the element in the matrix M, and k corresponds to the column index of a component solution in the adjacent row $i+1$ that enters a product configuration in question. The total number of potentially feasible product configurations equals to $n^{m.}$

Behavioral assumptions

The model is analyzed through a series of independent computer simulation rounds (or games). At the beginning of a new simulation round, all component solutions of the technological landscape are available and the structure of pairwise complementarities is newly regenerated.

Agents are programmed as myopic expected utility maximizers following identical decision-making rules. The uncertain nature of success in the complex technological environments is operationalized in the model as a sequential randomized assignment of turns to the agents, thus capturing the core idea that the availability of each agent's choice set at any given point in time is contingent on her competitors' precedent choices. Upon her turn, a focal agent scans through the entirety of available individual products and identifies the one with the highest expected value. In doing so, she (1) factors in the probability of her turn being drawn sufficient number of times to obtain the remaining components till the end of a round; and (2) ignores those component solutions that either have been taken by the competitors or that the focal agent herself has used in the existing and more valuable products already. After the best available product is identified, the focal player chooses the constituent component solution with the highest complementarity value.

[14] In order to keep the simulation product values consistent with the ones generated in the experiment, the lower interval boundary was changed with respect to the original model (in Arkhipova et al. (2014) the values of pairwise complementarities were drawn from an open interval (0; 1)).

Alternatively, agents are allowed to form disjoint bilateral coalitions with each other. In the model, agents are assumed to ally only if the aggregate alliance revenues are large enough to compensate for dropping the potential opportunity to appropriate full earnings from an individual product. That is, an alliance event occurs if three conditions are simultaneously satisfied:

(1) when the value of an individual product (expected or actual) is less than the immediate sum of shares of all possible alliance-based products;
(2) if the same is true for the other party;
(3) both agents have jointly enough components to create a product immediately.

The intra-alliance value division scheme is calculated at the moment of alliance formation according to the relative contribution of partners to the best product created together. The revenues from any subsequently created products are split in the fixed proportion.

A simulation round terminates when no more components remain available, and each agent's resulting payoff is calculated as an aggregate value of all products owned individually or as a sum of shares held in alliance-based products.

To sum up, the model represents a dynamic competition problem in which agents with *ex-ante* opposed interests are given an opportunity to coordinate efforts to their mutual benefit. What makes the model particularly interesting is a special kind of path dependency between agent's own choices. More specifically, the agent's own past actions affect her final payoff not in a strictly cumulative way: the value of each component solution is calculated conditional on the type of the solution acquired in the adjacent component layer on a subsequent move. Hence, given that an agent's available choice set depends on her opponents' actions that enter the stage in unpredictable sequence, her initially planned strategies may be inadvertently undercut and therefore need to be constantly adjusted. Even if all the model ingredients are known and probability distributions are of common knowledge, due to the presence of many "moving parts" it appears highly unlikely that any actor would embark upon a venture of solving the problem analytically by backward induction. Simulation allows capturing the complexity of the system and generating predictions regarding the emerging payoff and interaction patterns.

MODEL REPLICATION IN THE LAB

Experimental design

The experiment was performed with the fixed set of exogenous parameters which made the model replication in the lab feasible and yet comparable to the original simulation. The matrix dimensions were fixed to four rows and three columns, and the total number of players was limited to four.[15] The four participants were interacting with each other through an experimental computerized interface which displayed (1) matrix-shaped action space; (2) color-based complementarity structure between matrix cells; (3) alliance formation options with other players; (4) game statistics and reporting section showing individual cumulative payoff and alliance value percentage split. The Processing programming language (www.processing.org) was used to code the experimental software[16]. The snapshot of the experimental interface is shown on Figure 1.

[Insert Figure 1 about here]

Matrix-shaped action space

The action space of each participant is represented by a matrix with four rows and three columns, thus allowing for 3^4=81 theoretically possible product configurations[17]. The turns to act are allocated to the four players sequentially at random. On her turn, a player can make a choice of a component solution by clicking on a corresponding matrix cell; the choices of the players are visible to all participants and are updated instantaneously. The appropriated cells are marked with the player‘s identification number positioned in the center of a cell. Once a cell is occupied, it can no longer be accessed by other players unless they form an alliance with the player who

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[15] The combination of the model parameters – the matrix dimensions (m=4; n=3) and the number of players (p=4) – permits to keep a reasonable balance between manageability and complexity of the problem structure, while at the same time generating sufficient competitive crowding to make the effects of mutual dependence of agents' choices pronounced enough.

[16] The source code is accessible in Processing language (.pde extension) via the following link: https://www.dropbox.com/s/puiiw5go3wnalfu/Experimental%20Source%20Code%20FINAL%20Arkhipova.zip?dl=0. The excerpts of the source code are also available in the .pdf format: https://www.dropbox.com/s/qa2sbefqc7pe5pn/Experimental%20Interface_Source%20Code_Arkhipova.pdf?dl=0.

[17] The assumption that each component solution can be used once in its value-maximizing configuration allows for the simultaneous co-existence of maximally three distinct products (out of the 81 potentially possible products).

already got hold of the cell in one of the precedent moves. No time pressure is imposed on experimental subjects.

Color-based complementarities

The idea of the pairwise complementarities is translated in the experiment as the degree of similarity between the different colors of the matrix cells – the intuition being that the two component solutions of similar colors work better together, and vice versa. The eight pre-selected colors (red, orange, yellow, light-green, dark green, cyan, dark blue, purple) are symmetrically arranged around a circle (i.e. color wheel), and the smaller the distance between two colors, the higher is the complementarity between them.[18] For simplicity, the complementarity values are assumed to be symmetric, take eight discrete values in the range from 0.2 to 1 with 0.2 increments, and correspond to a fixed set of colors. The combinations of the same colors have the maximum complementarity of 1. The subjects navigate the interactive color wheel which is subdivided into eight equidistant color segments and has a blank inner circle. By positioning a mouse over a segment of a particular color, a subject is automatically displayed the values of complementarities with any of the other colors. Thus colors facilitate the perception of complementarities but the subjects still need to use numeric information to calculate the final product values.

Alliance formation

The alliance formation dialog box is activated automatically when a player has jointly enough components to form a product with another player; earlier alliances are not possible. The program automatically suggests the players which are available for the alliance formation. A player may send an invitation to ally by clicking on the corresponding button; the game remains frozen until the invitee responds to the request by either accepting or rejecting the alliance offer. A coalition is named by concatenating its constituent members in the order which places an initial component owner (or subsequent decision-maker) first: thus, “12” and “21” will refer to the same alliance of players 1 and 2, but “12” will be displayed on the cells which were occupied by player 1, and vice versa. Similarly to the simulation, the coalitions are binding, the value is split between players according to one’s marginal contribution to the first best alliance-

[18] It is noteworthy to mention that while in color theories the term “complementary” is used to describe the opponent colors on the diametrically opposed ends of the colorwheel (Judd, 1917), in this paper the neighboring colors of the color wheel are referred to as complementary.

based product and a player cannot quit a coalition until the experimental round is finished.

Subjects

Experiment participants were recruited from the subject pool of the Laboratory of Experimental Economics at Ca' Foscari University of Venice, Italy. Subjects were financially rewarded for their participation.[19] The financial reward consisted of a fixed part (8 euros) and a variable part, the variable part was proportional to each subject's cumulative individual performance over the consecutive 20 rounds (periods) of the experiment. The individual performance was measured in experimental currency units that were converted to euros at the end of the experiment. I report the results from 20 experimental sessions with groups of four participants (total of 80 subjects) that I ran at the Laboratory of the Experimental Economics at the Ca' Foscari University of Venice, Italy in November 2013. Prior to conducting the large-scale experimental series, I have tested the experimental instructions and computer software, calibrated the rewards in the four pilot experimental sessions in March 2013. The average participant payoff was 21 euros (SD=2.8).

Procedure

The four subjects were randomly seated in four experimental booths equipped with noise-insulating headsets and microphones. The booths were isolated from each other with separators, so that participants could not observe each other's screen choices or be disturbed by other participants thinking aloud.[20] Prior to the experiment, they were shown 10-minutes video instructions which contained screenshots and off-screen voice commentary with explanations of the game objectives and how to navigate the experimental interface.[21] The video instructions were duplicated in a traditional paper

[19] Since the ability to distinguish colors was essential for the successful conducting of the experiment, the participants with color vision deficiencies were not admitted.

[20] The thinking aloud method was used during the experiment: the subjects were asked to verbalize their thoughts as they play, and their verbal protocols were recorded. The verbal protocols analysis is out of scope of the present essay and is reported in chapter 3 of the dissertation.

[21] The video instructions in English language are accessible via the following link: https://www.dropbox.com/s/riicv43akhwh9c2/Instructions%20with%20audio%20ENG%20HD.mp4?dl=0. The decision to use video instructions was inspired by the pilot sessions for which I had used the conventional printed paper instructions as a default option. The feedback that I have got from the participants was that instructions were too long to focus on reading, and that the actual experiment required lots of interaction with dynamic elements of the interface which do not lend themselves to the static representation on paper (i.e. dynamic colorwheel, alliance creation). Video "tutorial" presents a viable alternative as off-screen voice commentary substitutes for experimenter's reading out loud, some concepts benefit from pictorial representation

form and were available for the subjects for consultation throughout the experiment. The subjects were given an opportunity to ask clarification questions before the experiment. The communication between the subjects during the experiment was not permitted (excluding anonymous alliance message exchange stipulated by the experimental instructions).

EXPERIMENT AND SIMULATION BENCHMARK COMPARISON

Operational compatibility

The simulations generate a set of predictions about the agents' performance and endogenously emerging alliance structures provided that all agents are equally endowed with the identical naïve maximization decision-making rules. The behavior of the experimental subjects is then directly compared against the benchmark behavior observed under the assumptions of the simulation model[22].

In order to enable meaningful comparisons, the decision-making context of the experiment is aligned with the one of the original model. In both instances, the dimensions of the action space are set identical; the players' turns are drawn from the discrete uniform probability distribution; the combinatorial principles of product composition and the additive nature of product value calculation are preserved. The simulation was run 400 times to replicate the experimental design of 20 sessions of 20 rounds each.

One of the aspects in which the structure of the experiment departs from the simulation relates to the type of numeric values we use to define complementarities. In order to reduce computational costs for the subjects we convert continuous complementarity values into the set of discrete values[23]. One should keep in mind that

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compared to verbal description, and finally, by the time the actual experiment starts, subjects already familiarize themselves with the experimental interface. To avoid priming the subjects to choose the colors selected in the demonstration version, I have used two different color schemes for the instructions and the actual experiment.

[22] Ideally, to enable direct comparison between the experiment and the simulation, one should extract the stochastically generated parameters (notably, complementarities and turn allocation sequences) for each experimental round and rerun simulations under the set of experimental parameters. Although I am planning to address with issue later on for the publication version, here I rely on the assumption that any discrepancies in data caused by random number generation are levelled out over the multiple repetitions provided the values are drawn from the same distributions.

[23] I have run a series of checks on whether conversion to discrete values systematically alters the values of the generated products. The values of the most salient possible products (automatically generated) are lower on average in the simulation than in the experiment (3.39 vs. 3.57; $t = -11.21$, $p<0.01$) due to the higher variability in the composite complementarity values. Similarly, the values of the best actually created products are lower in the simulation compared to the experiment (3.15 vs. 3.32; $t = -6.24$, $p<0.01$).

whereas the discrete approximation comes at the potential expense of accuracy of the simulation vs. experiment performance comparisons, the emerging behavioral patterns I am primarily interested in will remain unaffected.

Similarly to their modelled counterparts, human subjects are incentivized to maximize their payoffs and are provided the same sets of available information. Given that the timing of component appropriation is out of control of the players, the only actions human subjects can take full control of relate to positioning on the technological landscape and to cooperating with other participants. As regards the latter, whereas in the simulation an alliance is automatically concluded if mutual benefit condition is satisfied, the experimental design leaves ample space for the discretionary behavior of the decision-makers as to whether they decide to enter an alliance or decline to cooperate.

The summary of the discrepancies and potential assessment of any biases they can engender is reported in Table A1 in the Appendix.

Five dimensions for comparison

In what follows, I formulate a set of propositions about how the actual human decision making strategies may potentially deviate from the simulation benchmark along the performance- and the four alliance-related dimensions.

Performance

The *performance* dimension is related to the quantifiable output both on individual and group[24] levels. In the simulation, agents rationalize in terms of expected value maximization and are endowed with computational ability which at any given point in time allows them to calculate the value of the best available product configuration and to evaluate the probability of completing it. Numerous studies in behavioral economics and experimental psychology, however, have demonstrated that the actual human judgment is biased when it comes to the probability assessments (Tversky and Kahneman, 1974); and that in performing complex tasks people are unlikely to carry out the full-fledged computations due to their information processing limitations (Simon, 1957; Newell and Simon, 1972). The problem structure of the present model would appear to be sufficiently complex to evoke simplified decision-

[24] Group performance is measured as a sum of individual payoffs of all participants in a given round.

making behavior in human subjects. Yet, it still provides a risk-based formalization of an uncertain environment, in which statistical reasoning and thorough calculations are supposed to yield more accurate decisions than simple heuristics would do (Artinger et al., 2014; Mousavi and Gigerenzer, 2014). Hence, I expect that people's tendency to resort to cognitive simplifications – as potentially reflected in erroneous perceptions of chance and approximate mathematical calculations in the experiment- may result in inferior performance compared to the simulation agents. I therefore posit:

Proposition 1: Experimental subjects will exhibit lower performance on both individual and group levels than their simulation counterparts.

Alliance formation timing

The second dimension describes the temporal aspect of alliance formation. The model allows any two participants to consider alliances only when they jointly have at least *n* components to create a product instantaneously. In simulation and experiment, the earliest point in the game when an alliance-based product can technically come into existence is when at least *n* component solutions are occupied. At this point in time, however, the expected value of any alternative individual product for each player may still exceed the immediate alliance share, and hence a risk-neutral agent in the simulation may opt to pursue an individual solution. Conversely, in the experiment, the mere fact that the individual outcome is probabilistic in nature may induce subjects to exhibit more risk-averse behavior (Kahneman and Tversky, 1979). Thus people may elicit preferences for the immediately guaranteed alliance outcomes and will be willing to pay a substantial risk premium to reduce the uncertainty inherent to the risky future individual options. I therefore propose the following:

Proposition 2: Alliance formation will occur earlier in the experiment than in the simulation.

Alliance experience

The alliance experience dimension investigates how alliance formation behavior in the experiment evolves over time. In the simulation, agents do not have memory about their past choices. Conversely, in the experiment – and in line with the extant evidence obtained in repeated games in various laboratory settings - human subjects will inevitably look backwards and adapt their future behavior accordingly. In so doing, people will therefore reinforce actions that either yielded positive results in the past (Roth and Erev, 1995; Erev and Roth, 1998; Camerer, 2003), or that they regret of not having undertaken in due time (Ert and Erev, 2007; Marchiori and Warglien, 2008). Whereas finding a learning model which would best account for the behavior observed in the laboratory is beyond the scope of the present paper, it appears natural to assume that people will initiate alliances more frequently as they get positive reinforcement from alliance success or learn that "going solo" choices may eventually result in zero payoffs, as stated in the following proposition:

Proposition 3a: In the experiment, the number of alliance proposals will increase with experience.

Moreover, once having experienced the regret related to the foregone alliance opportunities, subjects are likely to display the tendency to accept the proposals more frequently (and symmetrically, reject less). I therefore conjecture:

Proposition 3b: In the experiment, the number of accepted (rejected) alliances will increase (decrease) with experience.

Alliance output

The alliance output dimension provides further insights into human reasoning by examining the values of alliance-based products. The behavior of agents in the simulation is assumed to be myopic – that is, agents remain negligent about the opponents' prospective behavior, and others' choices affect agents' decision-making inasmuch as they reduce the available choice set. In the experiment, subjects are expected to reason about opponents' precedent moves, predict others' prospective strategies and take actions in response to these beliefs (Camerer et al., 2004). Whereas my endeavors to extract the actual beliefs from the experimental subjects are reported in the next chapter, one might argue that the eventual co-development of the *salient* product could serve as an indication of the subjects' forestalling behavior. The salient product is hereafter defined as the best product in terms of its value out of the total n^m technically feasible product configurations. Whereas the value of the salient product *per se* depends solely on the underlying structure of complementarities generated in each round, the actual creation of the salient product – be it individually or through an alliance – implies that the best product created as a result of agents' (players') actions was also the best one theoretically possible in a given round.

In the simulation, the salient product will be automatically identified by an agent who gets to make the first choice as a product with the highest expected value, and hence its constituent component(s) will be occupied in the first instance.

In the experiment – due to the color-based complementarity representation - the salient product would be conspicuous to the eyes of the subjects as it will be made up of the similar colors, and once a player starts to occupy its constituent components, her strategy becomes visually noticeable to her opponents. As a reaction, an opponent who gets to make the next move is likely to identify the salient product as an opportunity for coordination, and will deliberately "block" its remaining components thereby forcing the player into a prospective alliance (Bacharach, 2006). In the simulation, on the contrary, even if an opponent's choice inadvertently precludes a player from completing the salient product, she will simply switch to the next best product. As a result, in the experiment one might expect to observe salient products to materialize through alliances more frequently than in the simulation. Thus,

Proposition 4: In the experiment, the salient products will be created via alliances more frequently than in the simulation.

Alliance composition

The alliance composition dimension explores the observed intra-alliance membership structures at the level of the dyad and examines the underlying motives for alliance formation in terms of the partners' individual characteristics. The specific rationale behind entering a coalition in the experiment, so I argue, is contingent on how many of the component solutions a player controls prior to the eventual alliance formation. In this regard, two cases are possible. First, a player may enter an alliance out of *resource interdependence considerations* as she lacks components required to complete a desired product. I label these player types as "incomplete product owners". Alternatively, a player might regard alliance solely as a *value-improving tool*: at the moment of alliance formation a player already owns a complete product and is willing to increase her payoff by creating a more refined product configuration through an alliance. I refer to these player types as "complete product owners".

As it has been repeatedly mentioned above, simulation agents are risk-neutral and are programmed to follow the expected value maximization rules and, however the agents' considerations might be classified *ex-post*, in the simulation alliances will only materialize should the three conditions be satisfied simultaneously. Thus, the two incomplete product owners will form a coalition only if the individual options are already exhausted for both of them; and a complete product owner will ally only if her share in prospective alliance exceeds the value of the existing individual product.

One may expect that in the experiment human subjects are likely to deviate from the line of behavior predicted in the simulation due to the reference level effects (Rabin, 1998). Namely, I conjecture that complete product owners will be subjected to the *status quo bias* and thus will be reluctant to lose a share of their own product even if it might be offset by the resulting overall increase in value of a co-developed product (Samuelson and Zeckhauser, 1988; Kahneman et al., 1991). This effect is likely to be exacerbated by the uncertainty associated with the unlikely ability of subjects to calculate the trade-offs with high precision (Simon, 1957). To that end, I expect to observe fewer alliances involving complete product owners in the experiment (and, symmetrically, more alliances between two incomplete product owners), which leads to the following proposition:

Proposition 5: Alliances involving complete product owners will be less frequent in the experiment than in the simulation.

In line with the resource-based view, the intuition behind coalition formation in the model primarily emphasizes the agents' necessity to get hold of the otherwise inaccessible component technologies (Penrose, 1959; Barney 1986; Hamel, Doz and Prahalad, 1989; Kogut and Zander, 1992). In the experimental context, a player's decision with whom to ally might be additionally affected by *trust* engendered by the prior history of successful cooperation with a certain partner (Granovetter, 1973; Gulati, 1995; Gambetta, 2000). That is, in the course of several recurrent interactions, two players may establish interpersonal ties which in turn will increase their proclivity to ally with each other on the subsequent rounds. Consequently, in each experimental group, coalitions between certain pairs of players will be observed more frequently as opposed to the simulated benchmark scenario in which alliances are formed between two oblivious and purely economically motivated agents. The following proposition concludes this section:

Proposition 6: In the experiment, certain pairs of partners will form alliances more frequently than in the simulation.

An overview of the conceptual framework in illustrated on Figure 2.

[Insert Figure 2 about here]

RESULTS

Table 1 provides a comparative summary of the experimental and simulation results[25]. The results demonstrate that simulation agents and experimental subjects perform similarly in terms of average group- ($t= 1.0948$; $p = 0.2739$) and individual-level ($t= 0.8191$; $p = 0.4128$) payoffs. That is, notwithstanding the fact that experimental subjects are likely to „satisfice" when it comes to complex calculations, the experimental performance indicators are quantitatively similar to the predictions of the simulation model. Similarly, I do not find any significant simulation *vs.* experiment differences in terms of the total number of products created ($\chi^2(1)=0.65$; $p=0.42$), the total number of alliances formed ($\chi^2(1)=1.44$; $p=0.23$) or the number of instances when zero outcomes were obtained ($\chi^2(1)=0.39$; $p=0.53$).

[Insert Table 1 about here]

Before I proceed to testing the alliance-related propositions, it is useful to start with descriptive analysis of the types of coalition structures that have emerged. Coalition structures distributions (see Table 2) demonstrate that the proportion of rounds in which no alliances were formed (i.e. all products were created individually by one or more players) is roughly the same in the simulation (18 %) and in the experiment (18,25 %). . Major differences are observed with regards to alliance-building behavior. There are significantly fewer cases when alliance-based and individual products co-exist in the experiment (26%), generating "hybrid" industry structures compared to the simulation (56%). On the contrary, the coalition structures, either when only one coalition manages to reap all the possible benefits or when all players are allied prevail in the experiment (37% and 18% respectively) compared to simulation (19% and 6% respectively). The chi-squared statistics ($\chi^2 = 139.71$, $p=0.000$) indicates that there are significant differences in alliance formation strategies adopted by human subjects and simulation agents. In what follows I intend to investigate where these differences are rooted.

[Insert Table 2 about here]

As regards the timing of alliance formation, the results generally support the claim that human subjects ally earlier ($\chi^2 = 219.77$, $p=0.000$). The frequency distributions are plotted in Figure 3, where the horizontal axis shows how much time has elapsed since the beginning of a round (measured as the number of component solutions occupied) and the height of the bars corresponds to the proportion of alliances that were formed at a given point in time. As seen on Figure 3, the distribution for the experiment is shifted to the left compared to the simulation with allying on the 8th move being a modal choice of the subjects. In the simulations, in no case alliance was formed in the first half of the game and the modal behavior is to ally on the 10th move (although it accounts only for 28% of the alliances formed)[26]. The results suggest that even if expected value maximization rules would dictate to form alliances "as a last resort" when one is at risk of earning nothing, people seem to prefer to cooperate upfront, thus supporting the risk-aversion argumentation of the proposition 1.

[Insert Figure 3 about here]

The effects of learning are tested only on the experimental data for the obvious reason that no learning processes are present in the simulation. Figure 4 illustrates the average number of alliance proposals per round (across 20 experimental groups). Contrary to the prediction, I do not find any compelling evidence that subjects use alliance formation more as they become more experienced: the dynamics of the total number of alliance proposals remains stable over time ($t=-1.14$; $p=0.26$) implying that the subjective attractiveness of proposing an alliance is not affected by experience (Figure 4). However, some noticeable learning patterns are revealed with regards to the total number of accepted alliance proposals. As it can be inferred from Figure 4, there is a stable upward trend for the number of alliances accepted ($z=4.69$; $p<0.01$). Since the total number of proposals does not change significantly, such upward trend corresponds to the downward trend for rejections ($z=-9.45$; $p<0.01$), thus supporting proposition 3b

[Insert Figure 4 about here]

In order to test the proposition pertaining to the alliance output, I compare the proportions (and counts, respectively) of the alliance-based salient products obtained in the simulation to the ones of the experiment. To enable meaningful comparisons of the count data, 400 independent simulation rounds were randomly grouped into 20 equal-

[26] I have also looked at whether behavior changes over time and whether people learn to ally earlier as they gain more experience but it does not seem to be the case as I observe no visible dynamics on round-by-round basis (not reported here).

sized subsets (hereafter referred to as "simulated sessions"); within each simulated session the observations were randomly assigned a rank from 1 to 20 (hereafter referred to as "simulated rounds") to imitate the experimental design of 20 group sessions of 20 rounds each. Table 3 reports the remarkable differences: in the experiment, in 47% of the cases (188 out of the total 400 experimental rounds) the salient products were created via alliances as opposed to only 4.75% (19 out of the total 400 simulated rounds) in the simulation ($\chi^2 = 286.64$, p=0.000)[27].

[Insert Table 3 about here]

The results support the prior conjecture that subjects can prefigure the intentions of his or her opponent in case the latter pursues the most obvious product configuration. So far my analysis was restricted to the cases when the two players mutually recognize each other's strategies and eventually cooperate. One might suspect, however, that a subject's "blocking" strategy may as well result in the decreased number of individually created salient products. The results in Table 3 provide the additional supporting evidence: the individually created salient products account only for 9.75% of the cases (39 out of 400 experimental rounds) in the experiment as opposed to 21.5% (86 out of 400 simulated rounds) in the simulation ($\chi^2 = 62.76$, p=0.000). Thus the results suggest that in the experiment, unless a player is a first-mover and has sufficient number of consecutive moves to conclude a salient product, he or she is likely to be deliberately prevented by the opponents from doing so.[28] Albeit no conclusive inferences can be drawn from the temporal dynamics of the strategizing behavior due to small number of observations, the results serve as preliminary indication that the strategizing behavior is acquired over time by human subjects (Figures 5A and 5B).

[Insert Figure 5A and Figure 5B about here]

[27] The temporal dynamics of salient alliance-based products was analyzed by comparison of the successive rounds. The descriptive analysis (not reported here) suggests that, in the experiment, in each round, at least half of salient products are created through alliance (median=10; IQR= 2), while in the simulation it happens only in 1 out of 20 simulated rounds (median=1; IQR=1). The results show that the instances of alliance-based salient products in the experiment increase over time (z=3.39; p<0.01). The positive trend in the simulation, albeit statistically significant (z=3.37,p<0.01), is driven solely by the outlier value in simulated round 20 (see Figure 5A).

[28] The temporal dynamics of salient individual products was analyzed by comparison of the successive rounds. In each experimental round, in 50% of the cases, in at least 3 rounds (out of 20) salient products were created individually (median=3; IQR=2), while in the simulation in happened more frequently (median=5, IQR=2). The results demonstrate the stable downward trend for the experiment (z=-2.79; p<0.01) and the simulation (z=-1,72; p<0.1), which, however, should be interpreted with caution due to the small number of observations.

With regard to the impact of resource considerations on the alliance membership, the results in the simulation and in the experiment appear to be strikingly similar (χ^2=2.04; p=0.36). As seen in Table 4, the majority of alliances occurs between two incomplete product owners both in the simulation (90%) and in the experiment (88%)), pointing to the importance of the strategic resource interdependencies as a prerequisite for the successful cooperation in a given setting. The proportions of alliances involving complete product owners in the experiment (12%) is roughly the same as in the simulation (9%), thus disconfirming my initial proposition that human subjects would systematically depart from the economic rationale when value trade-offs are involved.

[Insert Table 4 about here]

Finally, I examine the role of the recurrent dyadic relationships on the alliance formation. Naturally, any interpersonal ties leading to trust may only emerge within a fixed group of subjects. Figure 6 combines the results for 20 experimental groups and is intended for the graphical analysis only: the height of each colored bar corresponds to the number of times (out of total 20 experimental rounds) in which a given pair of subjects has allied. The preliminary visual data inspection does not suggest that any pair of subjects has allied more frequently than the other[29].

To that end, I subdivide the possible alliance structures into 10 mutually exclusive categories (6 single alliances, 3 combinations of two alliances and no alliance) and test the observed distributions for 20 experimental sessions (Table 5A) and 20 simulated sessions (Table 5B) against the simulated equi-probability benchmark using chi-squared test. The fact that the observed distributional differences for the simulated sessions with knowingly artificial agents are significant ($p<0.01$) indicate that given the low numerosity of observations, the results should be interpreted with caution as

[29] The final goal is to compare the theoretical uniform distribution of the possible alliances emerging with the equal probability (which would be obtained by running a large number of simulations with agents not endowed with memory) with the actually observed distributions in the experiment. The difficulties arise when it comes to statistically testing if the observed distributional differences are significant. The problem naturally lends itself to the chi-squared goodness-of-fit test between the equi-probability and the observed distributions, but given that the alliance events are not mutually exclusive and not collectively exhaustive (two alliances can co-exist within the same round), running chi-squared test will not give plausible results.

randomness cannot be excluded as an explanation for the observed patterns[30]. The irrelevance of the repeated interactions for alliance formation possibly stems from the fact that the period of interaction is not prolonged enough for trust to emerge or, alternatively, may serve as an indication that tangible inputs of partners take precedence in a given setting.

DISCUSSION AND CONCLUSIONS

The purpose of this study was to test empirically the plausibility of the behavioral assumptions of the "chance and choice" model. To that end, I have reconstructed the decision-making environment in the laboratory and compared the behavior of human subjects against a simulated benchmark. The experimental results point to several interesting findings.

First, alliances in the experiment are formed earlier than in the simulation. This result can be naturally explained in terms of risk-aversion: people anticipate alliances as a precautionary measure against the uncertainty. Alternatively, the subjects may subjectively underestimate their chances to succeed individually and therefore seek to maximize the aggregate output from the joint coordinated effort (as opposed to maximizing the expected value of a single product).

Second, the results suggest that people learn to cooperate more. Although the exact learning mechanisms cannot be inferred from the data at this stage, several explanations arise. On the one hand, whereas learning does not seem to affect the behavior when it comes to proactively initiating an alliance, people tend to adapt their strategies when they act as passive recipients of alliance invitations. One might therefore tentatively conjecture that people feel less regret in case they have not offered an alliance themselves as opposed to the case when they have erroneously rejected the alliance opportunity once it was openly proposed to them (Zeelenberg et al., 2002), and hence will avoid repeating the latter mistake on the subsequent rounds. On the other hand, the positive trend of alliances accepted might be observed due to the fact that

[30] I have also looked at the temporal aspect of the coalition formation; albeit decreasing the numerosity of observations even further, the idea behind this exercise was that, if any trust is emerging, it should develop over time, which would result in more cooperative arrangements between the same two players towards the end of the experiment. To the end, I have split the 20 rounds for each group in two stages – the first 10 rounds and the last 10 rounds – and examined the alliance frequency distributions differences between them. Based on visual data inspection (not reported here), I find no evidence of stable coalition formation behavior. On the contrary, the data might suggest that the distribution of different alliance arrangements becomes more uniform at the later stage, indicating that the human subjects become more flexible with the partner's choice and do not develop any stable preferences.

people learn interactively as they *ex-post* rationalize about the past choices of their opponents (Levinthal and March, 1993; Marchiori and Warglien, 2008). Lastly, one of the candidate explanations could be that subjects learn to make qualitatively better proposals.

Third, the experimentally observed behavior appears to be at odds with the in-built assumption of myopia. Notably, the results substantiate a claim that people tend to exhibit higher levels of strategic thinking. The essence of the strategy is thus to become indispensable in the eyes of the opponents by forestalling their most desirable choices. This strategy plays out best when – in the absence of possibility to negotiate – players can venture correct guesses about their opponents' intentions, and *vice versa*.

Interestingly, I find no evidence that subjects' computational limitations result in performance losses or invoke decision-making biases contradicting the value-maximizing logic. The possible explanations might be that people make reasonable approximations or, over the course of several repetitions, develop cognitive shortcuts that compensate for the lack of computational strength (Gigerenzer and Todd, 1999).

Finally, the findings seem to refute the role of interpersonal trust as an essential precondition for cooperation in a given setting. Much of the literature emphasizes the importance of prior relational linkages between partners for coalition formation to the extent they help to resolve the uncertainty associated with opportunistic behavior (Williamson, 1991; Parkhe, 1993) and partners' capabilities (Gulati, 1995; Doz, 1996). In the context of the "chance and choice" model, however, these considerations are found to be of less relevance as alliance agreements are set to be binding and the size of one's contributions primarily depends on luck rather than on one's personal abilities.

Cumulatively, these findings draw a different picture of a decision-maker which openly challenges the model's assumptions of myopia, risk-neutrality and "memorylessness" about past events. Whereas in the simulation agents conclude alliances only in the worst case scenario, people use alliances as uncertainty absorption mechanisms to reduce their exposure to failure. In situations when the long history of foregone opportunities can set a decision-maker back irreversibly, people tend to hedge the safe bets in advance and jointly exploit more risky opportunities later on. Thus, calibrating agent's decision-making rules accordingly will bring more realism to the original context and enhance the validity of the conclusions.

The implications of the results may be extended beyond the experimental context and tangentially contribute to managerial literature on alliance formation.

Broadly speaking, the interfirm collaboration has been traditionally explicated in the literature by transaction costs arguments (Coase, 1937; Williamson, 1991; Dyer, 2002), learning considerations (Hamel et al., 1989; Hamel, 1991; Khanna et al., 1998), external pressures for conformity and legitimacy (Hannan and Freeman, 1984; Baum and Oliver, 1991), and social network effects (Gulati, 1995; Dyer and Singh, 1998; Gulati, 1998). To my knowledge, whereas the aforementioned streams of literature have repeatedly acknowledged the importance of managing alliance risks (Das and Teng, 1999; Shah and Swaminathan, 2008), alliances *per se* as viable instruments to manage risks and uncertainty have not received due attention in scholarly research so far (Gomes-Casseres, 2000). One might argue, however, that in the actual business environments with their inherent complexity and unpredictable dynamics – as presumably captured in the proposed model to some extent– managers will form alliances upfront to gain a foothold in the industry and mitigate the risks of technological lock-out. The present findings indicate that this might be a call for separate and more in-depth investigation.

One of the possible criticisms I foresee relates to the generalizability of the observed individual decision-making strategies to the real-world scenarios. To that end, an additional field study will be required to reveal whether managers' cognitive representations of the like problems bear any similarities to the proposed abstract matrix structure. Moreover, the analysis of concurrent verbalizations produced by subjects during the experiment will shed more light on individual information processing in perceivably complex environments.

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FIGURES

Figure 1. Snapshot of the experimental interface

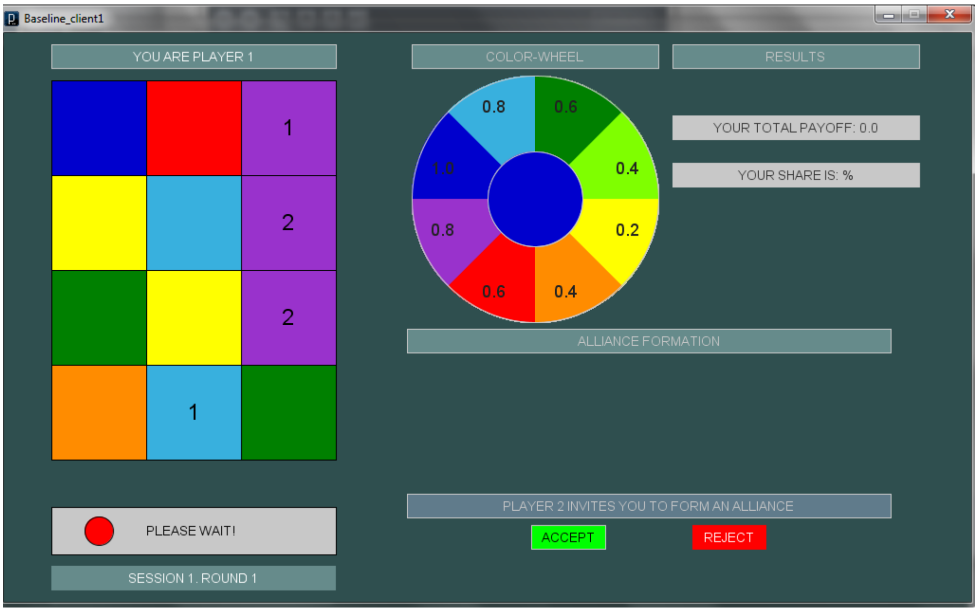


Figure 2. Analysis framework

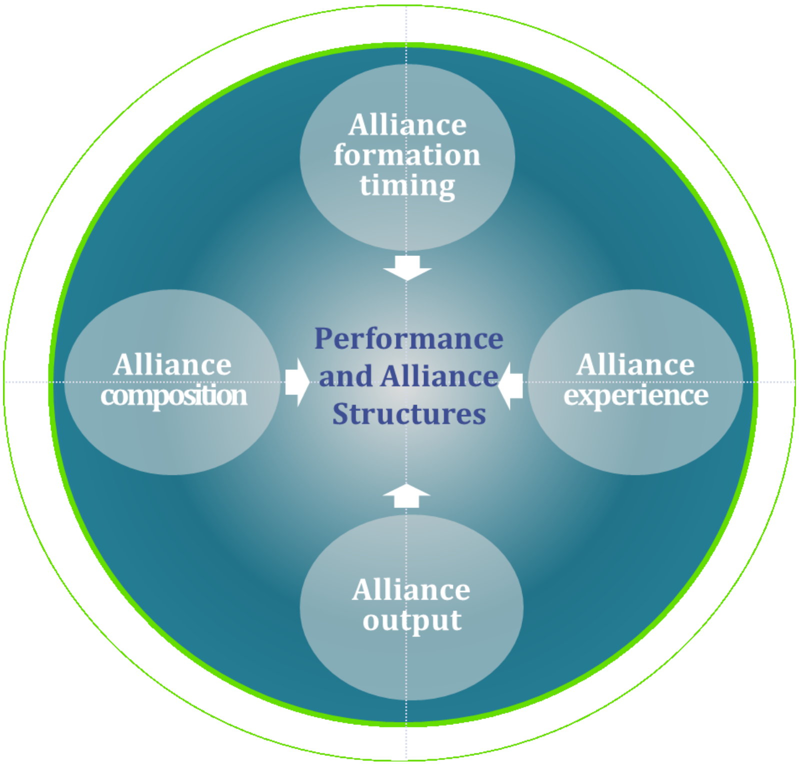


Figure 3. Alliance formation timing

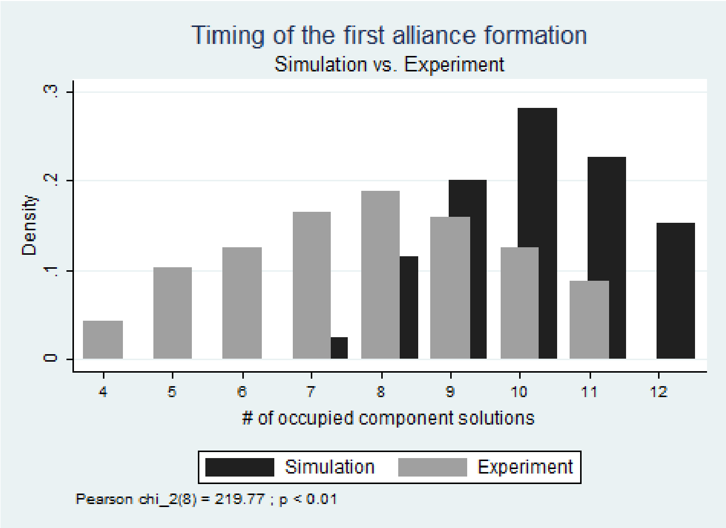


Figure 4. Alliance experience: dynamics of alliance learning

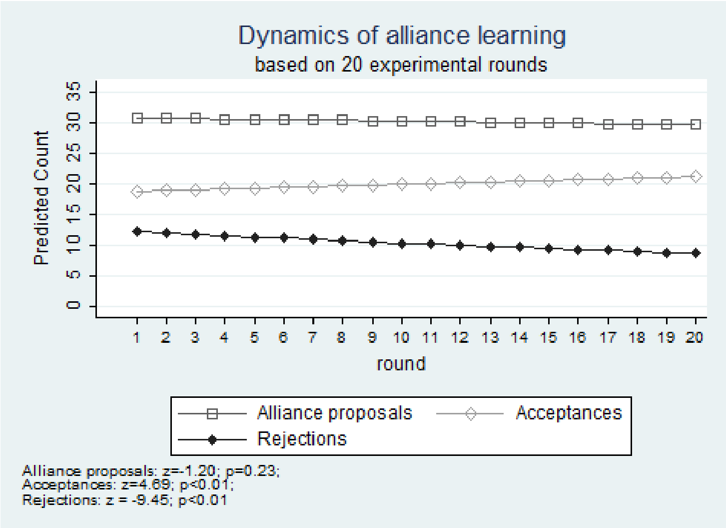


Figure 5A. Alliance output: dynamics of alliance-based salient products

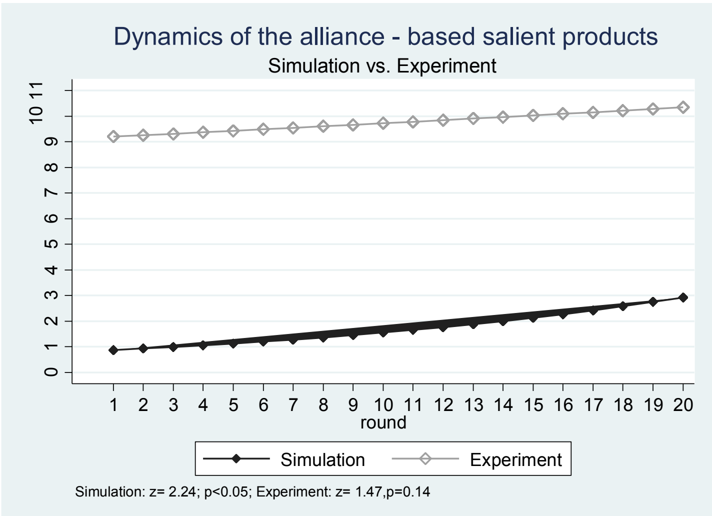


Figure 5B. Alliance output: dynamics of independent salient products

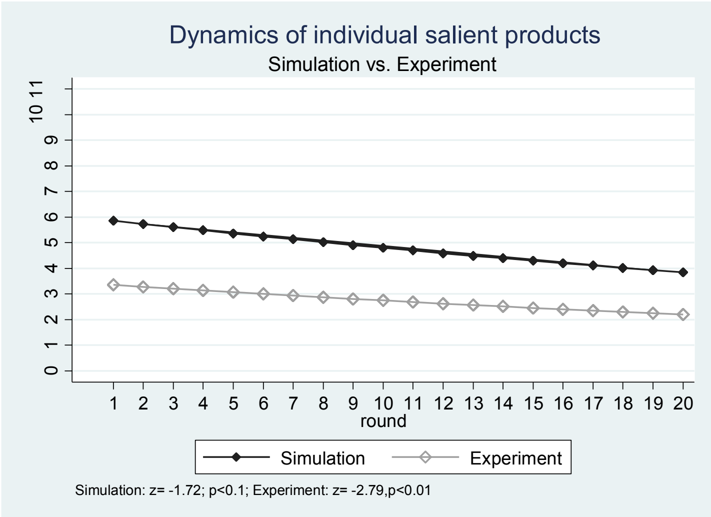
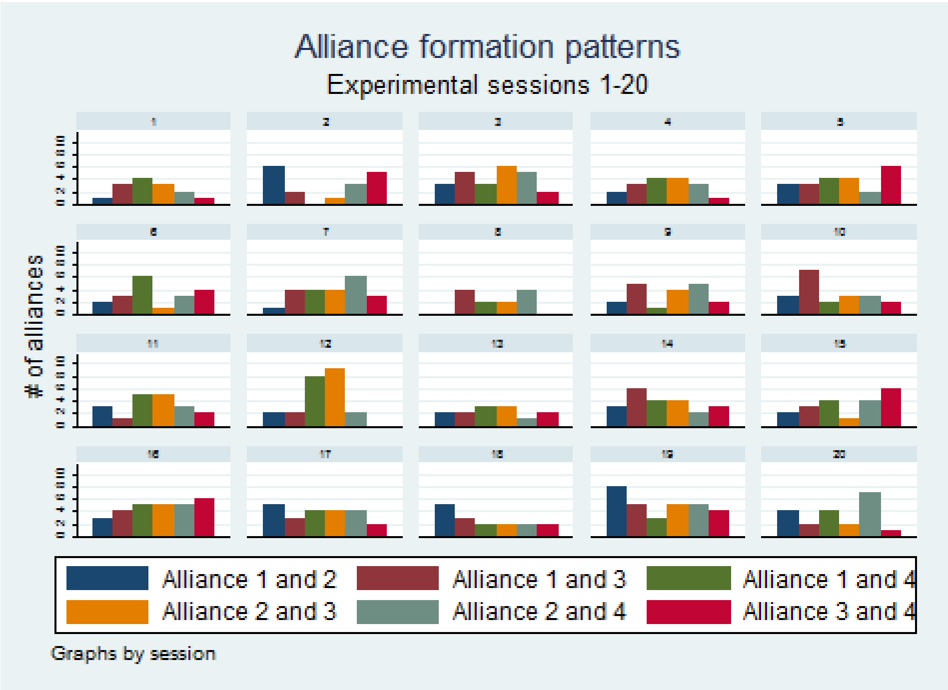


Figure 6. Alliance composition: stable alliance formation patterns



TABLES

Table 1. Comparison of high-level simulation and experimental results

	Simulation	Experiment	Significance tests
Mean player-level performance	1,34	1,31	t= 0.82; p = 0.41
Mean group performance	5,37	5,24	t= 1.09; p = 0.27
Total number of products	732 (61%)	678 (57%)	$\chi^2(1)=0.65$; p=0.42
Total number of alliances	352 (44%)	399 (50%)	$\chi^2(1)=1.44$; p=0.23
Total number of zero player-level outcomes	539 (34%)	599 (37%)	$\chi^2(1)=0.39$; p=0.53

Table 2. Frequency distributions of the emergent coalition structures: simulation vs. experiment comparison

	Simulation		**Experiment**	
	Frequency	Percent	Frequency	Percent
No alliance	72	18,00%	73	18,25%
One alliance	79	19,75%	150	37,50%
Alliance + Individual	225	56,25%	105	26,25%
Two alliances	24	6,00%	72	18,00%

Pearson χ^2 (3) = 89.66, $p < 0.01$

Table 3. The number of alliance-based and individually created salient products: simulation vs. experiment comparison

	Simulation		**Experiment**	
	Frequency	Percent	Frequency	Percent
Alliance-based salient products*	19 (out of 400)	4.75%	188 (out of 400)	47%
Individually created salient products**	86 (out of 400)	21.5%	39 (out of 400)	9.75%

* Pearson χ^2 (1) = 286.64, $p < 0.01$;
**Pearson χ^2 (1)= 62.76, $p < 0.01$

Table 4. Frequency distributions of alliance composition types: simulation vs. experiment comparison

	Simulation		Experiment	
	Frequency	Percent	Frequency	Percent
Incomplete + incomplete	318	90%	352	88%
Incomplete + complete	2	1%	0	-
Complete + complete	32	9%	47	12%

Pearson χ^2 (2) = 2.04, p = 0.36

Table 5A. Percentages of the emerging alliance structures based on experimental data

Alliance structure	12	13	14	23	24	34	12 & 34	13 & 24	14 & 23	No alliance	Pearson χ^2 (9)	p-value
Experimental group 1	5	10	15	10	5	5	0	5	5	40	52,36	0,000
Experimental group 2	20	10	0	5	15	15	10	0	0	25	63,68	0,000
Experimental group 3	15	10	5	20	10	10	0	15	10	5	136,33	0,000
Experimental group 4	10	10	15	15	10	5	0	5	5	25	19,30	0,023
Experimental group 5	10	10	15	15	5	25	5	5	5	5	46,19	0,000
Experimental group 6	10	15	30	5	15	20	0	0	0	5	53,67	0,000
Experimental group 7	5	15	10	10	25	15	0	5	10	5	75,09	0,000
Experimental group 8	0	10	0	0	10	0	0	10	10	60	216,78	0,000
Experimental group 9	10	20	0	15	20	10	0	5	5	15	36,94	0,000
Experimental group 10	15	30	0	5	10	10	0	5	10	15	80,27	0,000
Experimental group 11	10	0	20	20	10	5	5	5	5	20	37,57	0,000
Experimental group 12	10	0	10	15	0	0	0	10	30	25	465,63	0,000
Experimental group 13	10	10	15	15	5	10	0	0	0	35	27,63	0,001
Experimental group 14	10	25	10	10	5	10	5	5	10	10	61,97	0,000
Experimental group 15	5	10	15	0	15	25	5	5	5	15	54,06	0,000
Experimental group 16	0	10	10	10	15	15	15	10	15	0	238,44	0,000
Experimental group 17	20	5	10	10	10	5	5	10	10	15	81,69	0,000
Experimental group 18	25	5	10	10	0	10	0	10	0	30	70,49	0,000
Experimental group 19	25	5	0	10	5	5	15	20	15	0	383,25	0,000
Experimental group 20	15	5	15	5	30	0	5	5	5	15	68,91	0,000
Benchmark	**14**	**13**	**13**	**14**	**11**	**11**	**2**	**2**	**2**	**18**		

Table 5B. Percentages of the emerging alliance structures based on simulated data

Alliance structure	12	13	14	23	24	34	12 & 34	13 & 24	14 & 23	No alliance	Pearson χ^2 (9)	p-value
Simulated group 1	10	20	15	10	5	0	10	5	0	25	61,8576	0,000
Simulated group 2	5	5	20	25	10	20	0	0	0	15	37,0754	0,000
Simulated group 3	10	20	10	5	15	5	0	0	0	35	38,1729	0,000
Simulated group 4	25	15	0	5	10	10	5	5	5	20	41,6403	0,000
Simulated group 5	5	15	15	10	0	20	0	0	0	35	47,9631	0,000
Simulated group 6	10	20	5	20	0	10	5	0	0	30	39,9975	0,000
Simulated group 7	35	0	20	15	10	5	0	0	0	15	58,2043	0,000
Simulated group 8	20	5	10	10	5	15	0	5	10	20	52,7792	0,000
Simulated group 9	20	5	20	5	20	5	0	5	5	15	39,1858	0,000
Simulated group 10	10	5	20	0	5	20	0	0	5	35	59,0271	0,000
Simulated group 11	10	20	15	20	15	20	0	0	0	0	40,6094	0,000
Simulated group 12	20	10	5	10	15	10	0	5	5	20	22,0973	0,009
Simulated group 13	25	10	5	15	10	10	5	0	10	10	56,567	0,000
Simulated group 14	5	10	5	20	25	15	5	0	0	15	42,2453	0,000
Simulated group 15	10	15	0	25	15	20	0	5	0	10	43,9671	0,000
Simulated group 16	10	20	30	20	0	5	0	0	0	15	50,487	0,000
Simulated group 17	10	15	15	10	20	10	0	5	0	15	19,3556	0,022
Simulated group 18	5	20	20	25	15	15	0	0	0	0	48,8761	0,000
Simulated group 19	35	5	10	5	10	10	5	0	5	15	54,5829	0,000
Simulated group 20	15	15	10	25	15	0	0	5	0	15	31,1688	0,000
Benchmark	**14**	**13**	**13**	**14**	**11**	**11**	**2**	**2**	**2**	**18**		

Note: Alliance structures categories are kept mutually exclusive and are labelled by concatenating its members, i.e. 12 denotes the rounds when only players 1 and 2 allied, while 12 & 34 refers to the rounds when two alliances – between players 1 and 2 and between players 3 and 4 – were formed. Benchmark distribution is generated based on 400 simulation rounds.

APPENDIX

Table A1. Operational compatibility between simulation and experiment

	Simulation	Experiment	Misalignment description
Decision-making algorithm	Naïve profit maximization	Subjective strategies	**NA**
Total payoff calculation	Sum of products composed from the set of non-overlapping components		**Fully aligned**
Product value calculation	Sum of the four pairwise complementarities (including pairwise complementarity between top and bottom row)		**Fully aligned**
Alliance formation conditions	Alliance takes place if (a) both players have enough cells jointly to create a product immediately (b) if it is mutually beneficial for both partners	Alliance can take place if both players have enough cells jointly to create a product immediately.	**Partially aligned, as accepting or rejecting an alliance offer remains at the discretion of each participant**
Alliance rejection option	Given behavioral rules, rejection never occurs: Alliance takes place automatically iff it is mutually beneficial for both partners	Alliance offer can be rejected	**Partially aligned, a player does not lose his/her chance to occupy an alternative cell if alliance offer was rejected**
Alliance value split rule 1	A player's share in alliance product is proportionate to the number and quality of cells (sum of complementarities of the contributed cells) contributed the alliance		**Fully aligned**
Alliance value split rule 2	Alliance share is fixed at the moment of alliance formation and remains fixed till the end of the round		**Fully aligned, in case there are two best products of equal value are created, takes the average of the two**
Complementarity values	Complementarities are continuous and take any value between 0.2 and 1.0, endpoints included	Complementarities are discrete and take any value between 0.2 and 1.0 (interval 0.2, endpoints included)	**Partially aligned, simulation product values may have a downward bias**

Instructions

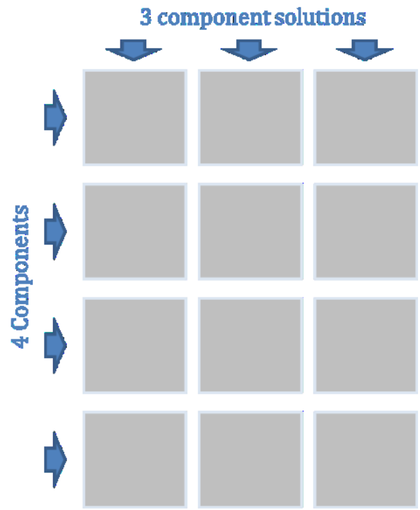
Welcome to the Symmetry Breaking experiment! Before starting the experiment, please listen to these short instructions, at the end of which you will learn:

- What is your task
- What are the rules of the game
- How your financial reward is calculated
- What is thinking aloud method and how does it work

What is your task?

- Your overall goal is to create the best product(s) out of the available components.
- The number of components is limited and you are competing for them with 3 other players.

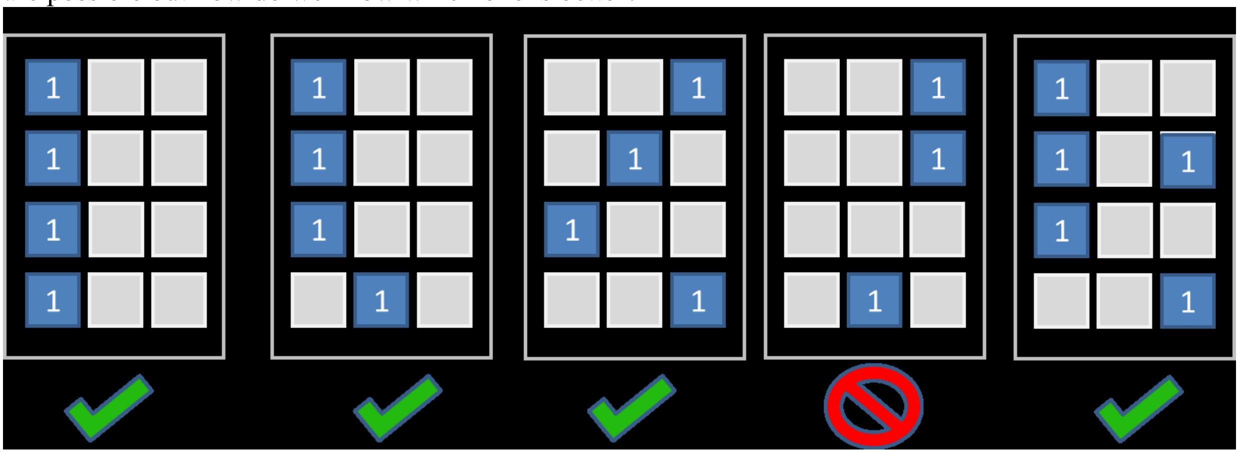
Your action space is represented by a matrix, the rows of which can be thought of as components of a product while the columns represent different possible solutions. In this game, the product will consist of 4 components and each component will have 3 alternative solutions.



A product is considered to be completed **if you own all 4 components**, but **solutions** for each component **may be different**. In other words, you should occupy at least one cell in each row, but the columns may vary.

- For example, on the first picture all components are in place and all are using the first solution. The number in the center of a cell is the ID of a player who owns it, this is an example for player 1.
- The solutions do not need to be in the same column, however, in this case on the second picture we use the second solution for the last component.
- The solutions do not need to be located in the adjacent columns either. The main thing is to occupy at least one cell in each row.
- To sum up, you can combine your component solutions in multiple ways, but if at least one component is missing, your product is not completed and is worth nothing. This case is shown on this fourth picture in front of you.

So far we have looked at the cases when only one product was created. When you occupy more than one cell in a row, several product options emerge. On this picture there are two products that are possible but how do we know which one is better?



Now after we have figured out what is the product in our experiment, we can start thinking about how one calculates its value.

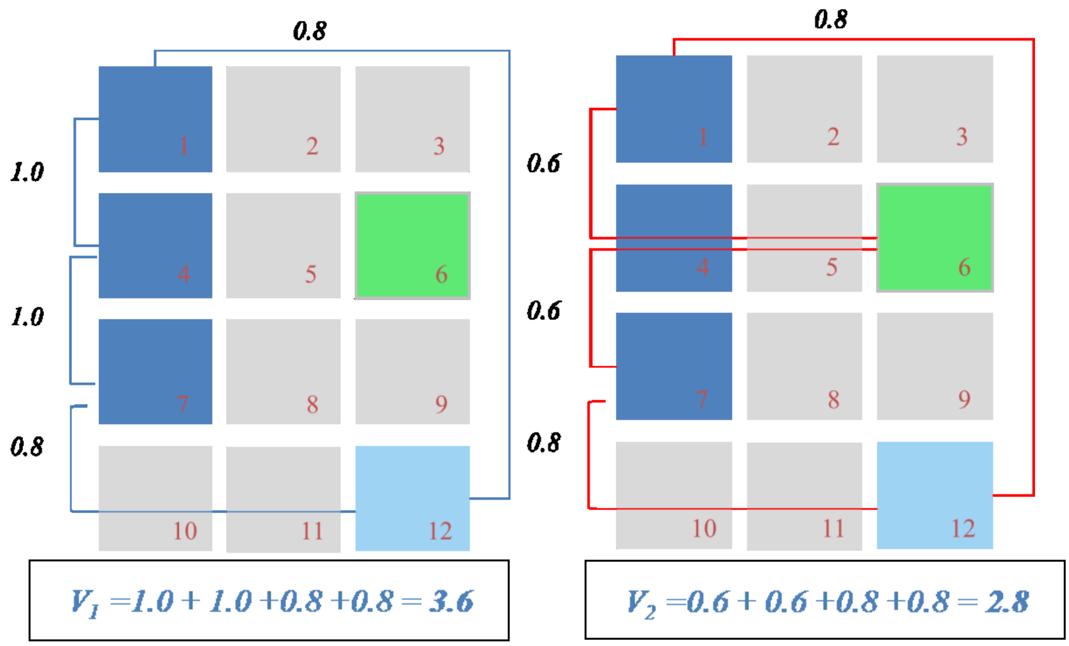
The value will depend on how well components in adjacent rows fit with each other. The degree of fit depends on the similarity of colors of components: the basic logic is that **the components of similar colors work better**, conversely, the components of distant colors work worse with each other. A colorwheel contains information about the level of fit.

When you place a mouse over an segment of the colorwheel, the color of the inner circle changes and levels of fit with all other colors are automatically shown to you. Where 0,2 is the minimum level of fit with the opposite color and the 1,0 being the maximum level of fit with the same color.

Let's have a look at our matrix; it became slightly more complex because cells have different colors now. And let's use the colorwheel in order to calculate the value of the products owned by player 1.

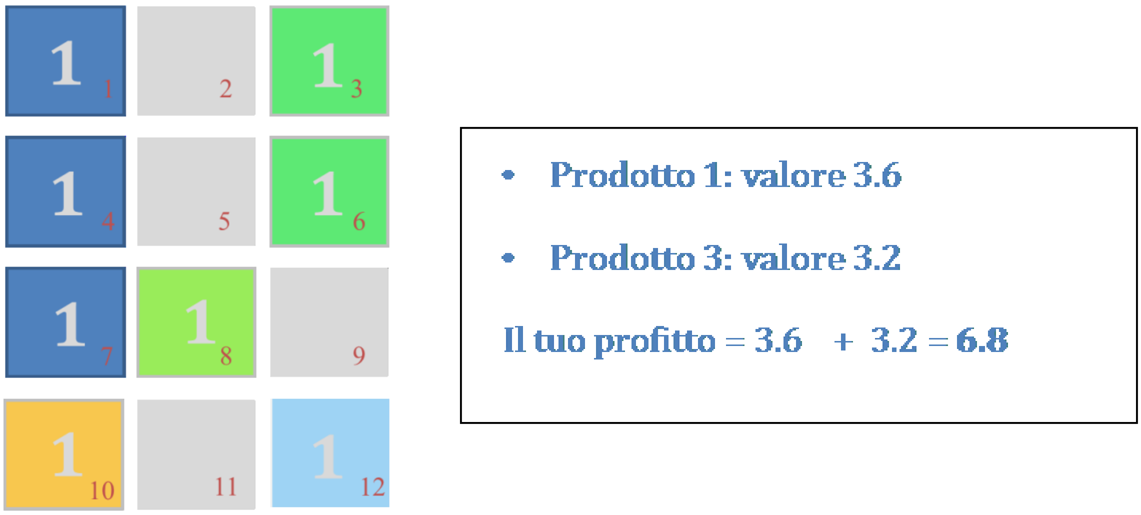
In our specific case, the first product consists of three dark blue and one light blue cell. For each component, we need to calculate the level of fit with a component located in the adjacent row below. That is, blue with blue equals 1, again two blue cells equals 1, blu and light blue will give 0.8 and– don't forget about the complementarity between the last and the top rows – the fit between blue and light blue is equal to 0.8 as well. We obtain the total value of the product by summarizing all four values and in this case it is equal to 3.6.

In a similar vein, we calculate the value of the second possible product containing this green cell and it is equal to 2.8.



Your payoff will be equal to the value of your best possible product. In this case, out of the two possible products you will be rewarded for the one with the largest value which is equal to 3.6.

It may happen that a player has enough cells to create two products out of the distinct components. In this case, a player will earn the sum of his both products.



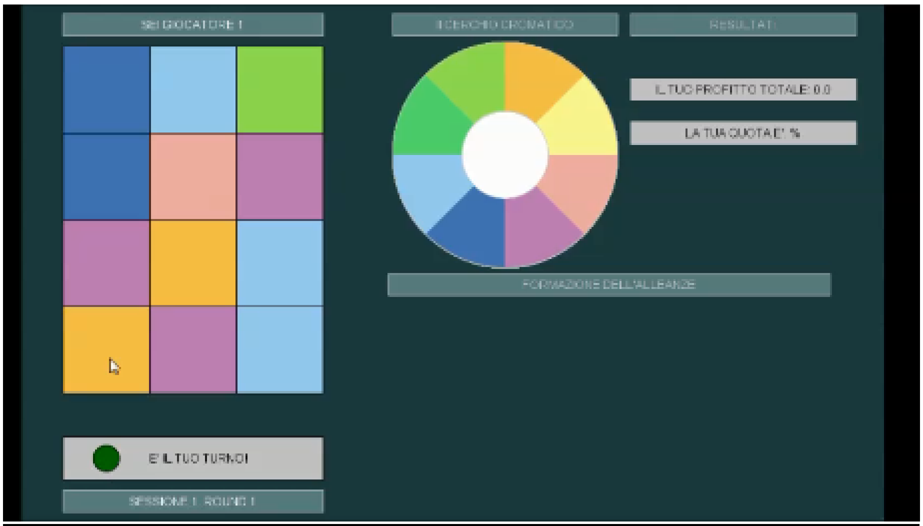
You don’t need to calculate the value of products by yourself; it will be automatically calculated for you.

<u>What you need to remember:</u>

- A product is considered to be completed if a player owns all 4 components
- Solutions for each component may be different
- The value of the product depends on how well its components fit with each other
- Your payoff is the value of the best product possible
- If you have created several products consisting of distinct cells, your payoff is the sum of these products

What are the rules of the game?

You can now see the real experimental interface in front of you and now we'll learn how to navigate it.

1. 

- When the game round starts, all components are available
- There are four players, but this is a demonstration for 2 players only. Your playerID is shown the top left corner on the screen
- The turns are assigned randomly between players
- You can pick a component only when it is your turn to play. It is your turn to act when you see a green traffic light and the text "IT'S YOUR TURN" in a text box located at the bottom left corner of the screen.
- You pick a component by clicking on it
- When a player picks a component, his player ID appears in the center of a cell and it becomes unavailable to the other players. Similarly, when you see that a cell has a number other than your player ID, it is no longer accessible to you.
- Please do not click on the cells that are already occupied by other players or already belong to you
- The round finishes when all cells are occupied, and your payoff is calculated automatically for you.
- You click on the big red button in order to continue, and the new round begins.
- The game has 20 rounds, you can trace the round number in a text box located at the bottom left corner of the screen.
- Session finishes after 20 rounds, and payoffs of all players are summarized and shown to you in a table form.

So far we looked only at the cases when the players were creating products individually. However, at the point in the game when two players have jointly enough components to create a product together, there appears an option to form an alliance.

- You can send an invitation to form an alliance by clicking on a button with an ID of the player you wish to ally with. You will receive a notification whether your invitation was accepted or rejected.
- Similarly, when a player offers you to form an alliance, there appear two buttons by clicking on which you can either accept or reject the offer.
- When you form an alliance with another player, you get access to all cells owned by your alliance partner. Jointly owned cells are marked with double-digit number where the first digit stands for the ID of the player who initially owned them before alliance formation or occupied them after alliance formation on his/her turn. The second digit stands for the partner's ID.
- Once you form an alliance, it cannot be dissolved till the end of the round and you share the values of all products that you have jointly created according to the percentage that is fixed till

the end of the round. This percentage is calculated automatically based on quality and quantity of components you have contributed to the alliance in the first best product that you have created together with your alliance and it is shown to you in this box on the right-hand side.

What you need to remember:

- Turns are allocated randomly between all players
- You can pick a cell on your turn only
- If you have enough cells jointly to create a product, you can offer an alliance when it is your turn
- When you form an alliance, all product values will be shared in a fixed proportion till the end of the round

How your financial reward is calculated

- As you know, your total payoff consists of the fixed and variable parts
- The fixed part is fixed at 8 euro, this is your sure gain
- Your total payoff will define the amount of your variable part.
- Your total payoff is measured in experimental units, not EURO equivalent.

In order to obtain your variable reward in euros, you should divide your total payoff by 2

What is thinking aloud method and how does it work

- This experiment will be audio-recorded
- Please as you play the game, try to say everything that goes through your mind
- Imagine you are trying to explain to a friend that is sitting next to you why you are taking a certain action
- Please say out loud the number of the round each time the new round begins

CHECKMATE OR STALEMATE: MANAGERIAL HEURISTICS IN COMPLEX INDUSTRIES

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Abstract

This exploratory study aims at discovering the new types of heuristics people employ in the complex environments by simulating the real-world business challenge of developing a multicomponent product in systemic industries in the experimental lab. Based on the analysis of the verbal protocols, I obtain a series of interesting findings that contribute to the field of behavioral strategy and to the "fast-and-frugal" heuristics in management research agenda. First, the results suggest that in the dynamic environments where the decision-makers can reciprocally affect each other's choices, people are likely to seek collaboration with their opponents. Second, the picture that emerges from the verbal data analysis indicates that subjects use a set of simple heuristics conditional on the state of the environment they face.

„Of course, analysis can sometimes give more accurate results than intuition but usually it's just a lot of work. I normally do what my intuition tells me to do. Most of the time spent thinking is just to double-check."- Magnus Carlsen, World Chess Champion, 2013

INTRODUCTION

There has been a resurgent academic interest in studying how decision-makers reason when they make important strategic decisions (Moldoveanu, 2009; Gary and Wood, 2011; Gary et al., 2012). Much of the recent scholarly work related to managerial decision-making rests on the ideas of the Carnegie school, advocating the view of a boundedly rational manager - a decision-maker who adopts simple rules of thumb, or heuristics, when operating in complex and uncertain environments (March and Simon, 1958; Simon, 1957; Cyert and March, 1963; Simon, 1979).

In the field of experimental psychology, the notion of heuristics has been traditionally associated with the deviations of human judgments from the laws of probability and statistics (Tversky and Kahneman, 1974). More recently, the "fast-and-frugal" heuristics program has put forward an alternative view on heuristics as simple and yet effective decision rules which are used adaptively in their respective environments (Gigerenzer and Selten, 2002; Todd and Gigerenzer, 2012). Whereas jointly these two streams of literature have documented a substantial variety of heuristics people use in general decision-making contexts, the research aimed at uncovering a distinct set of management-related heuristics – with some notable exceptions – remains at its infancy stage until now.

The existing strategy-related research on heuristics is predominantly qualitative in nature and is concerned with validating the relevance of the well-known cognitive biases to managerial settings (Bardolet et al., 2011, Bazerman and Moore, 2012; Kahneman and Lovallo, 2003), and documenting the emergence of "simple rules" as a result of organizational learning and domain-related knowledge accumulation (Eisenhardt and Sull, 2001; Bingham and Eisenhardt, 2011; Astebro and Elhedhli, 2006; Katsikopoulos, 2011, Dane and Pratt, 2007; Wuebben and Wangenheim, 2008). Notwithstanding the importance of the aforementioned studies, the question remains as to which extent the case-based evidence of organizational heuristics is generalizable beyond the subset of organizations participating in each study.

In this paper, I venture an alternative approach to discovering the new types of heuristics people employ in the complex environments: I simulate the business environment in the laboratory. In doing so, I draw on the assumptions of the information processing theory suggesting that general decision-making mechanisms devised in the simplified abstract tasks will share substantial commonalities with those that would have been employed in similarly structured real-world scenarios (Newell and Simon, 1972; Simon, 1979). In the experiment, the human subjects are exposed to the computerized interactive task whose features – albeit admittedly incompletely – mimic the real-world business challenge of developing a multicomponent product in systemic industries. I then analyze the verbal protocols reported by the experimental subjects to elicit the actual thought processes underlying the human decision-making in a given context.

I obtain a series of interesting findings that contribute to the field of behavioral strategy and to the "fast-and-frugal" heuristics in management research agenda. First, the results suggest that in the dynamic environments where the decision-makers can reciprocally affect each other's choices, people are likely to seek collaboration with their opponents. The psychological underpinnings of this behavior are rooted in iterative reasoning and pattern recognition. Second, the picture that emerges from the verbal data analysis indicates that subjects use a set of simple heuristics conditional on the state of the environment they face. These decision rules are then presented as a sequence of logical steps; and the features of the environment that triggers them are highlighted.

The paper is structured as follows: I start with outlining the major features pertinent to the managerial decision-making challenge in question and how they map onto the abstract problem representation used in the experiment. Next, I describe the verbal protocol analysis methodology and the analysis framework I have developed. I conclude by the discussion of the results and their contribution to the strategy research.

HUMAN PROBLEM SOLVING

As a starting point, I briefly summarize the relevant work that has addressed the topic of managerial problems complexity and cognition mechanisms managers have devised to cope with it.

Internal and external representations

Managerial problems are notoriously known for their complexity which manifests itself in the presence of multiple conflicting solution paths, imprecise mean-end connections, ambiguous or/and time-delayed outcomes and overall uncertainty associated with the consequences of one's past actions (March and Simon, 1958; Campbell, 1988; Fernandes and Simon, 1999).

When faced with complex and computationally intractable problems, managers will use rules of thumb that are consistent with the simplified mental models of the business environments they operate in (Gary and Wood, 2011; Baer et al., 2012; Johnson-Laird, 1983). Mental models (or internal representations) are defined as mental organizations of the problem-related concepts and their causal relationships. The information about the environment is stored in individual memory in a form of knowledge-related schemas, or categories. Depending on the association that a particular problematic situation triggers in mind, a special schema is activated in memory (Bartlett, 1932; Simon and Chase, 1973; Smith 1995; Schwenk, 1984). The activation of a particular category then guides the subsequent information retrieval and the corresponding action (Dutton and Jackson, 1987; Cowan, 1990).

In the business context, having an accurate mental model implies having a comprehensive understanding of the structural elements of an industry and their respective interdependencies (Gary and Wood, 2011). As the knowledge required for constructing an accurate internal representation is for the most part specific to one's accumulated experience (Dane and Pratt, 2007), so would be the decision-making rules it will invoke.

In order to be able to make meaningful generalizations in presence of the idiosyncratic internal representations and the respective heuristics evoked thereupon, I draw on the adjacent stream of literature in cognitive science suggesting that the mental models and the subsequent choice of a decision strategy are also contingent on the way the problem is presented to a problem-solver (Larkin and Simon, 1987; Jonas and Schkade, 1995; Zhang, 1997). More specifically, it was argued that external representations of information – be it verbal, pictorial or numerical - can guide and determine the pattern of the behavior directly, i.e. without mediation from memory or other cognitive processes that involve internal representations (Zhang, 1997). Thus, exposing decision-makers to an abstract representation reflecting the key features of a managerially relevant problem, so I argue, will instantiate decision-making processes that are not "contaminated" by unnecessary analogies related to a personal domain-related experience of the decision-makers. The business challenge in question is the development of complementary component technologies in systemic industries.

Task structure

An important subset of managerial problems in the domain of strategy relates to design and development of multicomponent systems (Garud and Kumaraswamy, 1995; Brusoni et al., 2001; Baldwin and Woodard, 2007). The selection and prioritization of R&D goals becomes crucial in technology-intensive industries where the actions of aggressively innovating competitors may render one's prior component-specific R&D efforts obsolete (so-called systemic industries). Systemic industries are thus defined as multitechnology industries in which firms compete with complex end-products consisting of multiple partially modular components (Kretschmer and Reitzig, 2012). What makes these industries particularly interesting – and much more challenging for the managers to operate in – is the fact that for the most of the components there exist several alternative solutions with different degrees of functional and commercial compatibility with one another. The information about the interdependencies between different component solutions is public and available to all industry participants (Ethiraj, 2007; Baldwin and Woodard, 2007), but the residual uncertainty pertains as to which firm will be able to develop and control which component technology. To summarize, the managerial task of multicomponent product development in these industries appears to be sufficiently complex to invoke heuristics decision-making and yet unambiguous enough to be brought into a lab.

To that end, I regard the chance and choice model of systemic industries (Arkhipova et al., 2014; Arkhipova, 2014) to be a viable candidate for exploring heuristics decision-making. The core features of the model are expected to invoke mental models of an environment whose structural elements and causal links capture the dynamism and the complexity of a real-world task[31].

[31] The detailed analysis of to which extent the model abstraction is representative of the real-world systemic industries is beyond the scope of this study, but several obvious limitations appear noteworthy. First, in the reality I expect the number of components (rows) to be much larger and the number of technological solutions (columns) to vary for each component. Second, the complementarity structure is more complex in that the functional interdependencies will involve all components of the system, not just the adjacent ones. The reduced setup, however, already imposes significant cognitive demands on decision-makers when it comes to calculating the total number of possible product configurations and their respective values in mind. These simplifications were warranted in the laboratory as subjects were not supposed to be overwhelmed by the environmental complexity to the extent they would start randomizing. Finally, the alliance formation and intra-alliance payoff division processes are not as straightforward as they are modelled.

LABORATORY EXPERIMENT

In this section, I present a general overview of the laboratory experiment with a special emphasis on the aspects of the experiment which matter for the verbal reporting procedure. A complete description of the experiment is reported in Arkhipova (2014).

Experimental design

The experiment is a computer-based interactive game played for 20 rounds in a fixed group of four anonymous participants which mimics the managerial problem of developing product components in systemic industries. The problem space is visualized as a vertically oriented matrix of size 4x3. The participants are asked to create abstract products by sequentially appropriating and vertically combining their component solutions across matrix rows. The choice of a component solution is left at the discretion of each player and can only be effectuated when it is one's turn to make a move. The turns are assigned to players in a randomized fashion. The complete products are then sold on a fictitious market, and the value of each product configuration depends on the level of fit between the constituent product components. The degree of fit is visible to all participants and depends on the similarity of cell *colors*. The players can either compete individually or cooperate by forming bilateral alliances which guarantee a non-zero outcome and cannot be dissolved until the end of an ongoing round. A game round begins when all component solutions are available, and is terminated when the whole matrix is filled. The subjects were asked to think aloud for the entire time they were playing the game.

Subjects

The subjects were 80 undergraduate students recruited from the subject pool of the Laboratory for Experimental Economics at Ca' Foscari University of Venice, Italy. In accordance with the common protocol analysis practice, requiring the subjects to verbalize their thoughts in their native language (Ericsson and Simon, 1984), most of the participants were native Italian speakers (95%). The remaining 5% of the subjects – which were invited to substitute no-show participants on ad-hoc basis - were not native Italian speakers, and were requested to produce verbalizations in non-native language (English) to facilitate the subsequent protocol transcription by the experimenter. The subjects were incentivized financially. The reward was calculated proportionally to their overall performance (mean = 21 euros; SD=2.8), but was unrelated to the quality of the verbal reports they have produced.

Procedure

Each group of four subjects was allocated a 1.5 hour long time slot; running experimental sessions with several groups at the same time was not permitted. Upon arrival, a subject was asked to be seated in any of the four pre-selected individual booths that were intentionally located at a considerable distance from one another. Each booth was semi-isolated from the rest of the room with a removable separating panel that muffled the participants' voices and prevented the subjects from looking at each other's screens. All booths were equipped with the noise-insulating headsets and microphones. Audacity ® (http://audacity.sourceforge.net/) free open-source software was utilized to record and transcribe the verbal protocols.

In the final part of the 10-minute video instructions (duplicated in paper form) the participants were explicitly asked to verbalize everything what goes through their minds while performing the experiment. In doing so, they were instructed to imagine that they are explaining their actions to a person who is sitting next to them.[32] No explicit examples were provided to prevent potential bias in reporting towards a given example. The subjects were expected to produce continuous verbalizations, but some pauses in verbal reporting were allowed if they occurred during the periods of involuntary inactivity (e.g. when another subject was taking time to think). Otherwise, the experimenter prompted the subjects to resume reporting by showing a neutral "Please, keep talking" reminder.

Verbal protocols as method

Verbal protocol (VP) as a method for observing human mental behavior dates back to 1920 (Watson, 1920), and has been used extensively in the domain of information processing psychology to explore problem solving processes in chess games (De Groot, 1965; Newell and Simon, 1972), abstract puzzle-like tasks (Kotovksy et al., 1985; Ericsson, 2006), crypt-arithmetic and logic tasks (Newell and Simon, 1972). In management and economic science, a number of studies has effectively used

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[32] The request to report the actions in explanatory mode was added to the experimental instructions after analyzing the verbal protocols from the pilot sessions. The trial protocols revealed that when asked to think aloud, some subjects produced simple descriptions of their actions ("now I am taking the red cell"), and thus no meaningful inferences could be made on which information was actually attended to.

verbal protocol data to explore the task-related decision-making processes (Isenberg, 1986; Highhouse, 1994; Fernandes and Simon, 1999, Tor and Bazerman, 2003), while others were mostly concerned with the applicability of the VP methodology (Schweiger, 1985).

The validity of verbal protocol data has been challenged on the grounds of being uncorrelated with the cognitive processes (i.e. epiphenomenal), obtrusive to the task performance and prone to social and retrospective biases (Nisbett and Wilson, 1977; Bainbridge and Sanderson, 1995). While the two latter objections are admissible and have to be considered when drawing inferences based on verbal data, the epiphenomenality argument was refuted by Ericsson and Simon (1984) who argued that once a thought was articulated verbally, one might infer that it was actually used in generating the problem solution. In other words, "information that is reported is information that is heeded".

The *concurrent* verbal protocol (or thinking aloud) that I use in this study is a type of verbalizing procedure that requires subjects to report their thoughts directly *during* the experiment[33]. The concurrent reports are known to be well-suited for estimating the frequencies of certain decision rules, but there are two important caveats associated with it. First, subjects might think of something without actually saying it. Fortunately, underreporting is likely to bias the results conservatively in that the usage of a particular heuristics will be even more frequent than could be inferred from the verbal reports. Second, subjects might say something without actually doing it. Thus, in the analysis one should make a clear distinction between subjects' intentions and actions as such. The extent to which the reported actions actually correspond to the factual ones can be validated by manually mapping the sequence of choices to the verbal reports.

ANALYSIS FRAMEWORK

In order to identify and quantitatively evaluate the regularities in subjects' heuristics reasoning, one should develop a category scheme prior to encoding the data. The contents of the verbal data are then mapped onto one or several pre-defined categories.

[33] The second type of the verbalization procedure is the *retrospective* report which is provided *after* the experiment and is prompted by the specific questions of the experimenter. The discussion of retrospective verbalizations remains out of scope of this paper.

The category scheme for this study was developed and iteratively refined based on a separate subset of trial 16 verbal protocols generated in four pilot sessions.

Categories

The categories are organized hierarchically in three levels (Figure 1) and are intended to correspond to different decision rules which, in turn, are inferred based on the type of information a subject has attended to. The categories are not meant to be mutually exclusive as the subjects are likely to alternate between different decision-making strategies as the game round progresses. On the most general level, I differentiate between *naïve maximization* decision rules and *forward reasoning* (Figure 1, level 1).

Naïve maximization is a default category for the non-strategic behavior. Thus, any explicit references to the information that will be naturally heeded after a subject has read and understood the experimental instructions will fall into this category. For instance, the verbal descriptions of how one is calculating product values *("the product with red cells is the best one here")*, consulting the color wheel *("yellow and orange have compatibility of 0.8")* and estimating one's own chances *("there are still many free cells left")* will be classified as naïve maximization. This category will also include any verbal evidence that a subject is solely driven by the notions of color-based complementarities in her decision-making process *("I take orange because it has high complementarity with my red cell")* and reasons about the opponents' actions only to the extent they reduce her choice set *("the red cell is taken so I have to take a yellow one instead")*. Missing or incomplete reports were also encoded as default to keep the dataset balanced.

Forward reasoning category, on the contrary, is used for the statements containing the evidence that a subject thinks strategically either by *predicting* the moves of her opponents or by *planning* one's own strategy several steps ahead (Figure 1, level 2). Hence, a statement is categorized as prediction if it discusses the prospective moves of other players without explicitly reasoning about one's own response to them *("players 1 and 2 are about to form an alliance", "player 2 is going for the green cells")*. Conversely, a statement containing the formulation of one's own laid-out plan of actions without taking into account what they others would do is classified as planning *("on my next turn, I will take a blue cell, then a green cell, and then I will try to form an alliance with player 3")*.

Albeit subjects produce the statements that unambiguously belong to either of the level 2 subcategories, they are most likely to adopt strategies in which predictions and planning are combined (Figure 1, level 3). Based on the pilot study, I have identified three most prominent decision making strategies which I term as quasi-rationality, anticipated blocking and non-interference. The statements are classified as *quasi-rational* if they serve as an indication that a subject engages in some form of complex iterative reasoning *("if player 2 gets to play next and occupies the blue cell, then I can take a purple cell and he will propose me an alliance")*. *Anticipated blocking* occurs when a subject prefigures a strategy of her opponent and makes a deliberate move that constrains the opponent to ally with her *(„player 1 played blue so I also go for blue in the next row hoping to create an alliance with him")*. Finally, when using the *non-interference* strategy, a subject also tries to predict the future choices of her opponent but prefers to stay out of her opponent's way by targeting an alternative product *("here the optimal product consists of the blue cells. But they are being occupied by player 2… so I will concentrate on the orange product instead")*.

Uncodable or irrelevant statements related to the expressions of emotions and ex-post reasoning are retained as general comments in *miscellaneous* category and then discarded.

Analysis technique

To analyze the verbal protocols, I followed the classic transcription-segmentation-encoding procedure described in Ericsson and Simon (1984). As a starting point, I have manually transcribed the subjects' concurrent verbalizations in a raw form. In doing so, I have subdivided the protocols into segments on a level of a single statement which could come in a form of complete thoughts, sentences, phrases or even single words. If subjects produced abrupt verbalizations, then pauses of a certain duration, intonation changes and activity switches (e.g. from problem-solving to information search) were used to delineate the boundaries of a specific segment (Chi et al., 1997). Then, each segment was encoded in terms of one (or several) of the seven pre-determined categories. As can be inferred from the concrete example in Table A1 (see Appendix), I have presented the protocol segments (rows) and the list of categories (columns) in a tabulated form in Microsoft Excel and assigned binary codes to the statements that contained explicit references to the heuristics categories I am after (1 if true, 0 otherwise).

Next, the encoded segments were aggregated on a level of a round for each player. The considerations behind collapsing the data in the bottom-up fashion are several. First, in the proposed dynamic setting, the protocols segments within a single round are not independent in that they may describe the elements of a more global strategy of a player and therefore cannot be analyzed in isolation. Second, subjects may think of different heuristics interchangeably within the same round. Third, subjects may devote equal amount of attention to either category-related information but one would require richer verbal descriptions than the other. Hence, the frequency of explicit category-relevant statements within a single round may not adequately reflect the frequency of occurrence of each heuristics. Forth, some subjects may produce more statements than others *ceteris paribus* due to the inherent individual differences in the rates of verbalization (Ericsson and Simon, 1984). Thus, analyzing the data on round-level brings all verbal protocols "to the common denominator" by treating multiple category-related segments on yes/no basis.

RESULTS

Descriptive statistics

Table 1 provides the descriptive summary of the data. Verbal protocols were transcribed for 80 subjects (20 experimental sessions of 20 rounds with groups of four participants each)[34]. The experimental sessions lasted on average 64 minutes (SD=16), resulting in approximately 77 hours (4,652 minutes) of the recorded speech and 8,897 transcribed segments. Subjects' protocols varied from 419 words to 3,935 words in length, with the average being 1,444 words (SD=676). The graphical representation of the verbal activity for the three cases (minimum, average and maximum) is reported in Figures 2a, 2b and 2c, respectively. The individual rates of verbalization ranged from 5 words/minute to 61 words/minute thus reflecting the inherent idiosyncratic differences in subjects' ability to verbalize their thoughts. The mean rate of verbalization of 23 words/minute is somewhat low compared to the normal continuous speech producing 150-200 words/minute but is comparable to 25-30 words/minute observed in complex anagram-solving tasks (Ericsson and Simon, 1984). The lower rates of verbalization in the present study can be explained by the dynamic and interactive nature of the task: the

[34] Out of total 80 verbal protocols, seven were incomplete or missing due to technical reasons or inability of certain subjects to vocalize their thoughts. The descriptive statistics analysis therefore excludes the missing VP data.

need to refocus the attention on the frequently changing visual stimuli may decelerate the verbalization process.

[Insert Table 1 about here]

Content analysis

Table 2 reports the frequencies of occurrence of each heuristics (and their respective percentages) across all experimental rounds[35]. The results demonstrate that subjects make allusions to the elements of naïve maximization strategy in 92.44% of the cases (1,479 instances). The intensive usage of the default heuristics is of little conceptual interest for this study as it simply indicates that subjects were paying substantial attention to the information in the experimental instructions and, without being explicitly told to do so, were identifying the best available product configuration and were seeking to get control of the components with the highest partial complementarity first. The chain of reasoning thus progresses as follows:

"...I chose the green cell because there are many green and yellow cells in this matrix…
... I choose another green because it is of the same color I have just selected... hope that yellow will remain available for my next turn…"

Whereas the kind of behavior described above is typical for those who get to make the opening move(s), entering the game at a later stage restricts the number of possible moves and thus requires subjects to get more creative. Notably, the verbal protocols provide some anecdotal evidence that late entrants may prioritize the positional importance of a component over its potential marginal value contribution (I label it as *fill-the-gap* heuristic[36]), as demonstrated in the following statements:

"...I would take the light green cell because there are many of them but now I see that in the first row there is only one empty cell left, so I need to take it…"
"...I do not want to be left without a product so I will take the last cell in the second row…"

Furthermore, subjects are found to compare the component solutions across the same row horizontally to estimate the quality of the viable back-up alternatives in case the preferred option becomes unavailable (I label it as *take-the-irreplaceable* heuristics):

[35] A unit of observation is the instance of particular heuristics-specific information being heeded by a subject in a given round (1 if was heeded, 0 otherwise). The verbal reports of the subjects belonging to the same group are treated as independent observations. There are total 1600 observations (20 sessions x 20 rounds x 4 players), and the reported frequencies correspond to the total number of rounds in which subjects collectively made explicit references to a particular heuristics.

[36] The logic of the decision rule naturally lends itself to the "take-the-last" label which I do not use intentionally to avoid confusion with the take-the-last heuristics discussed in Gigerenzer and Goldstein (1999).

"…There are three purple cells… I choose the one in the fourth row because in the other rows there are other good possibilities… like red or blue… they are still very compatible with the purple…"
"…The nice route is purple with dark blue, purple can be exchanged with red, but not in the first row, so I take the first row…"

The two aforementioned heuristics are not claimed to be generalizable provided the scarcity of the evidence, but they do exemplify how decision-makers may deviate from the naïve maximization rules in a non-strategic way by performing immediate situation-specific tactical maneuvers.

[Insert Table 2 about here]

As regards strategic thinking, the results suggest that subjects apply various forms of *forward reasoning* in at least 59.94% of the cases (959 instances); in 52.56% of the cases (841 instances) naïve maximization and forward reasoning were combined by a single player within the same round. On the one hand, subjects may formulate their long-term goals and enumerate the series of intermediate steps required to get to the desired state (i.e. planning):

"… I have taken the light blue cell in the third row and I hope to do the same in the second row if it is still available… After that I will click on the light green cell because it would guarantee higher profits…"
"… I need to get the yellow and then the light green… so I would take the yellow first, then I will take light green and ask for alliance to get the dark green…"

On the other hand, subjects may speculate about the possible reactions and intentions of their opponents (i.e. predicting):

"… I see that player 3 has taken the blue cell and player 1 has taken the yellow… player 1 already has a product and will not be interested in alliance…"
"… Player 1 chooses red, I think that player 4 might choose yellow and players 2 and 4 will form an alliance…"

While the explicit references to either planning or prediction are not uncommon (9.93 % (159 instances) and 15.69 % (251 instances), respectively), the most recurring strategy – anticipated blocking (27.94%; 447 instances) - blends the elements of both. The essence of the strategy is to look at the game from an opponent's prospective, prefigure her next best move based on her past choices and prevent her from actually making it. The ultimate goal of the strategy is thus to disrupt the opponent's plan and to constrain her to form an alliance, as can be inferred from the following quotations:

"… Player 3 took the blue in the last row, so I will take the blue in the first row hoping to create a product together with him…"
"… Player 4 has taken a yellow, I also going to take the yellow… so we can form an alliance if we both follow the same strategy…"

"… Player 4 managed to take the blue… I will take the blue over there, this way I am sure I will be asked for an alliance…"

Two things appear noteworthy here. First, when trying to predict others' strategies, players typically assume their opponents to exhibit less sophisticated levels of thinking (Camerer et al., 2004) and to follow simple naïve maximization rules. Second, due to their information processing limits players are more likely to engage in iterative reasoning in the situations when making accurate predictions about opponents' strategies is relatively easy, i.e. when the opponent is visibly following a single monochromatic combination.

Other "hybrid" strategies are much less pervasive. The elements of the non-interference strategy are conceived of in 6.94% of the cases (111 instances). Similarly to the anticipated blocking, one makes a move conditional on what the future moves of the opponents might be. In doing so, however, one has no intention to thwart others' plans and force oneself into an alliance eventually. Instead, the inherent logic behind the non-interference strategy is to create a (possibly inferior quality) product individually while the attention of the competitors is diverted to the development of the more "premium" components:

"… There are many purple cells here but they are being taken by player 2… so I take the yellow to follow the product with yellow, orange, light green… not to enter in competition with player 2…"

" … Player 2 has chosen the red, so if it is my turn, I will choose blue to contrast him…"

"… I choose blue color because it is opposite of those selected by players 1 and 2…"

The non-interference strategy is inherently risky as its outcome depends entirely on chance. That is, irrespective of the product value, one would still require at least four moves to complete a product individually. The excessive dependence on the external forces might serve as a candidate explanation of why, despite of its appealing non-conflicting nature, the non-interference strategy is infrequently conceived of by subjects.

Quasi-rationality heuristics (5.44%; 87 instances) presupposes that subjects premeditate some kind of contingency plan of action in advance. The building blocks of the quasi-rational strategy thus involve evaluating one's own and opponents' strategic positions several moves ahead, defining an array of possible moves and their likely consequences:

"… I would choose the green one… if player 3 chooses the green one to the right; I could then choose… the yellow is the closest one… I take the green one as I can choose the orange later…"

"… Player 3 has chosen light blue, so he has the same choices as that other player, so they will choose the purple in the last row next… for me light green would be the good choice to have a

product, only if they do not take the light blue in the last row… in this case I would choose the dark green…“
“… In any case I will take the forth component and will offer an alliance for player 3… if player 3 then takes a cell in the second row, we can create two products together…”

The cognitive processes underlying quasi-rational strategy are likely to be much more complex than reported because as a subject starts to attend to many aspects simultaneously, the attention moves too fast; and the speed of information retrieval would exceed the speed of verbalization

Models of heuristics

It has been recently recognized that heuristics research should not limit itself to the enumeration of the vague decision rules but rather should be focused on the computational models of heuristics that can be tested by computer simulations (Gigerenzer, 2008). In Table 3, I make the first preliminary attempt to formalize the four[37] decision mechanisms – fill-the-gap, take-the-irreplaceable, anticipated blocking and non-interference – as an ordered set of logically connected building blocks[38]. It is noteworthy that while fill-the-gap or take-the irreplaceable heuristics constitute single actions, anticipated blocking and non-interference heuristics describe strategies that require multiple moves. The observable actions are illustrated as stylized “before and after” experimental display snapshots, thus representing a type of positional allocations and task structures that are likely to trigger particular decision-making heuristics[39] (Table 3).

DISCUSSION AND CONCLUSIONS

Human decision-making in the complex environments is likely to take an intermediate form between the two theoretical extremes. At one extreme, there is a textbook case of rationality in a game-theoretical sense: a purely rational agent plans several moves ahead and optimally responds to any move his opponent(s) might make.

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[37] Quasi-rationality is excluded due to the inherent complexity of the underlying cognitive mechanisms it entails.

[38] The formalization of the exact logical steps subjects make when performing a certain type of heuristics will require more elaborate analysis of temporal sequences in which the information was heeded (as opposed to content analysis), and remains out of scope of the current paper.

[39] The author has manually synchronized the transcribed verbal protocols and actual observable actions for the 16 verbal protocols of the four pilot sessions; the results demonstrate substantial concordance between the actions taken and their corresponding verbalizations.

At the other extreme[40], there is an overly simplistic naïve maximization case: an agent defines the target and pursues it by sequentially appropriating its components in the order of their priority. In doing so, naïve maximizer views the changing environment as a series of stationary snapshots and makes the best possible move at each point in time. Whereas the former type of reasoning is virtually impossible due to the computational limits imposed by the bounded rationality, the latter type has proven to give an incomplete representation of actual human behavior in a given context (Arkhipova, 2014). In this article, I made an attempt to identify the persistent regularities in types of information people attend to and to trace the psychological underpinnings of the recurrent behavioral patterns in a stylized complex environment.

Perhaps one of the most important albeit somewhat intuitive findings is that people do resort to heuristics in uncertain and dynamic environments. In doing so, they actively exploit the complex structure of the decision-making context and attend to multiple informative elements of the experimental display simultaneously. More specifically, subjects evaluate such environmental factors as the actual number of controlled cells, their value (e.g. color combinations), positions and grouping (e.g. vertical blocks of cells, multiple scattered cells, or single cells). Furthermore, they "look beyond the proximate" (Gavetti, 2012) and reason about how they can reciprocally alter each other's choice possibilities.

The most coherent behavioral pattern emerging from the verbal protocol analysis – anticipated blocking heuristic - indicates that subjects engage in iterative thinking of a simple kind. That is, the players narrow down their attention span to the most evident opponents' strategies and make the positional choices *ex-ante* that would subsequently render them indispensable in the eyes of the potential allies.

The behavioral strategies based on long-term contingent planning (such as quasi-rationality heuristic) or entailing unwarranted risks and delayed ambiguous outcomes (such as non-interference heuristic) are relatively uncommon in the complex dynamic settings as the one in question. This might be partially explained by the fact that subjects do realize that the positional advantages may be temporary and chance-dependent, and therefore seek to devise strategies that proactively manage uncertainty and secure profits upfront.

[40] Theoretically, pure randomization would be considered as the diametrically opposed case of pure rationality, but in this context a minimal form of profit-maximizing and goal-seeking behavior is assumed.

The extensive usage of the naïve maximization rule in conjunction with other heuristics may serve as an indication that the devised heuristics are *stage-specific*. That is, it is possible that a player makes a series of opening moves consistent with the naïve maximization logic, but then, if the game round does not unfold as initially expected, reverses her decision and starts thinking ahead. Conversely, when a player is lagging behind, she is more likely to forestall her competitors or make positional choices based on fill-the-gap heuristics.

There is therefore no ideal "one size fits all" strategy in this dynamic setup and the mastery of the game depends on one's ability to rapidly recognize the situations in which one decision rule is more appropriate than the other. That is, based on the previous exposure to the similar problematic situations, one's associative memory will be activated in response to the perceptual or cognitive stimuli of the external environment thereby instantiating the possible response in mind. It is therefore not forward reasoning or naïve maximization *per se*, but the ability to recognize when it is appropriate to apply them is what makes these heuristics succeed (Todd and Gigerenzer, 2012).

It would be erroneous to extrapolate the heuristics uncovered in the fictitious setting directly to the real-world environment and I have no intention of doing so. In order to understand whether managerial decision rules share any similarities with the heuristics that manifested themselves in the experimental setting, a large-scale field study is needed. Instead, the goal of this exploratory study was to indicate the direction in which the search for similarities should evolve. Namely, it would be interesting to see whether and, if so, in which environments managers tend to monitor the technological advancements of their competitors and purposefully strengthen their core component business in the pursuit of successful collaboration (anticipated blocking), spread their research efforts across multiple technological layers in order to reduce their dependence on other market participants (non-interference), focus on the development of the groundbreaking technologies (take-the-irreplaceable) or concentrate on the currently undervalued quality solutions to keep both individual and alliance-based options open in the future (fill-the-gap).

When faced with complexity and uncertainty, one needs to combine strategic foresight and short-term operational excellence: like a chess player who aims at gaining a long-term positioning advantage over her opponent through a series of tactical moves, so does a manager when taking intermediate action steps to gain competitive advantage vis-à-vis competitors. The chess metaphor is not accidental: the inherent controversy has always been whether it is analytical forward search or pattern recognition is what makes a grandmaster (Gobet and Simon, 1996; Chabris and Hearst, 2003). Whether this controversy can be resolved in the field of strategic management constitutes a promising avenue for the future research.

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FIGURES

Figure 1. Coding scheme for verbal protocol analysis

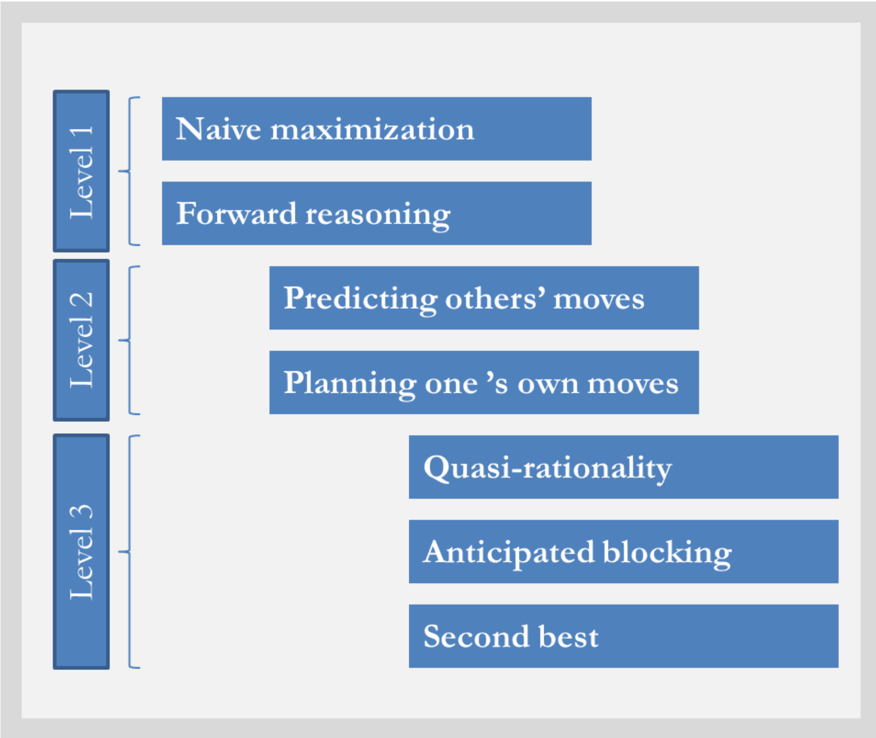


Figure 2A. Activity graph – maximum activity (3935 words)

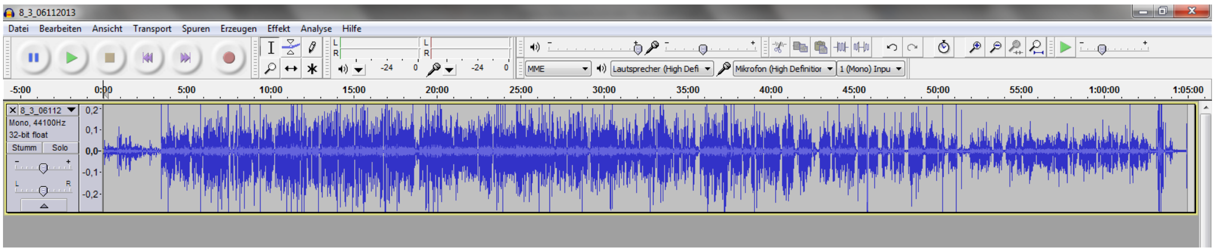


Figure 2B. Activity graph – average activity (1400 words)

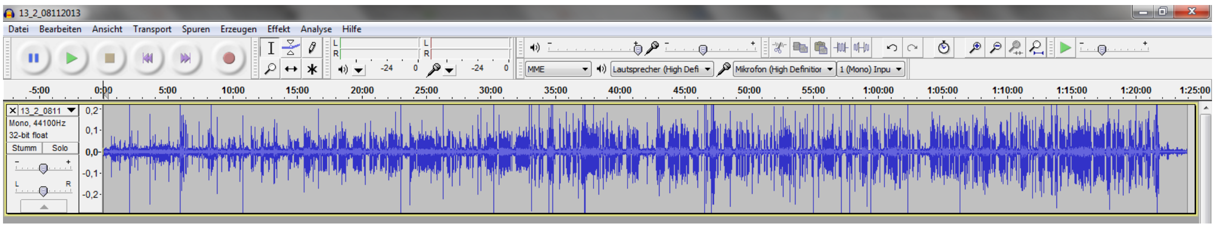
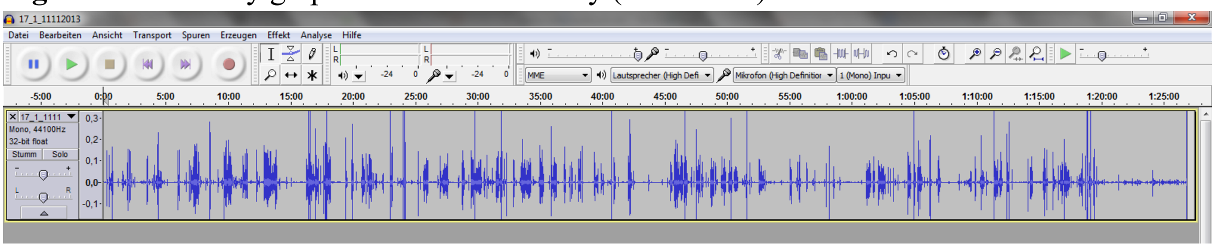


Figure 2C. Activity graph – minimum activity (419 words)



TABLES

Table 1. Descriptive statistics of verbal protocols

	Mean	Min	Max
Average protocol length, words	1444 (SD = 676)	419	3935
Session duration, minutes	64 (SD = 16)	27	85
Average rate of verbalization (words per minute)	23 (SD = 10)	5	61

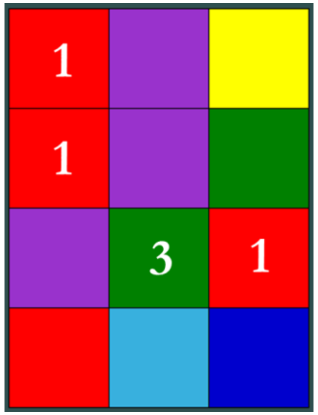
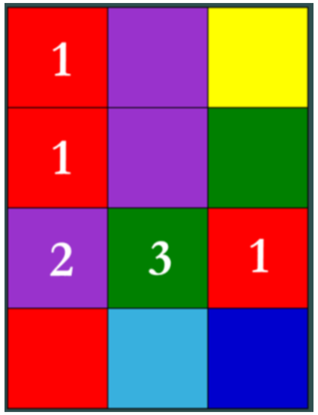
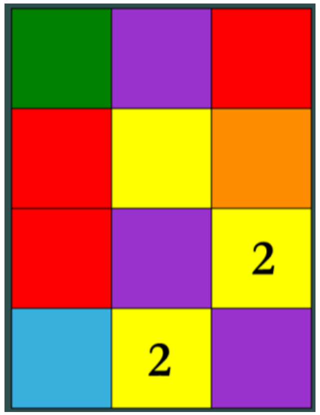
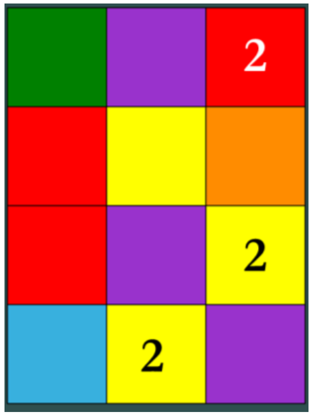
Note: Analysis excludes the missing or incomplete verbal protocols data

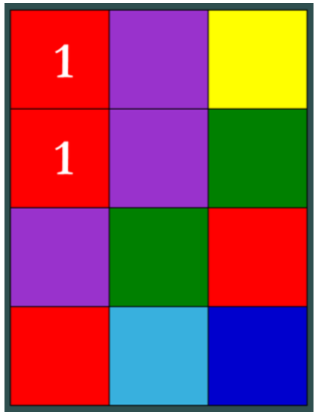
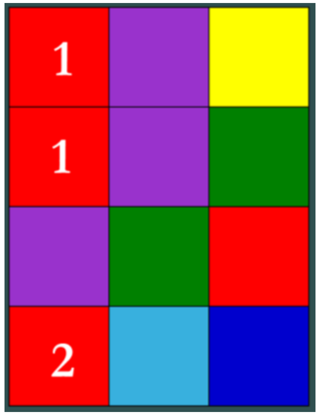
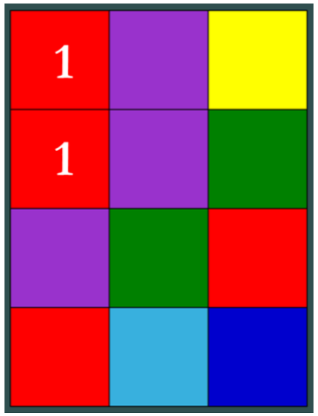
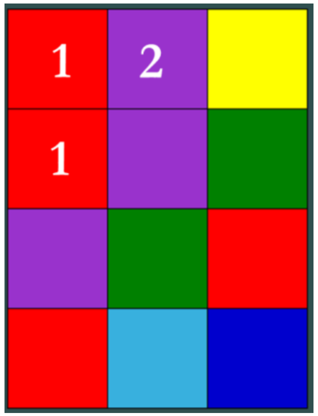
Table 2. Verbal protocol analysis results

Heuristics category	% of total observations (N=1600)	Number of instances (rounds) mentioned
Naïve maximization (non-strategic)	**92.44%**	**1,479**
Forward reasoning (strategic)	**59.94%**	**959**
Predicting	54.25%	868
Planning	48.50 %	776
Quasi-rationality	*5.44%*	*87*
Anticipated blocking	*27.94%*	*447*
Non-interference	*6.94%*	*111*

Note: Level 3 heuristics (quasi-rationality, anticipated blocking and non-interference) are coded as an intersection of predicting and planning (level 2) and jointly account for 645 observations (87+447+111). References made exclusively to either predicting or planning categories within a single round were observed in 183 (868-645) and in 91 (776-645) cases, respectively. In 68 cases players produced separate statements for both prediction and planning categories within the same round. In 25 cases, the anticipated blocking and second-best heuristics co-existed within the same round; there were three instances in which all level 3 categories were attended to within the same round. Thus, the total number of forward reasoning (level 1) application cases 959 is calculated as a union of the six disjoint categories: prediction (183), planning (91), prediction & planning (68), quasi-rationality (87), anticipated blocking (447), non-interference (111), minus the intersection of two (25) and three (3) co-existent level-3 categories.

Table 3. Heuristics as formal algorithms: building blocks

Heuristic	Logic algorithm	Situation (condition)	Response (action)	Illustrative quotes
Fill-the-gap	1. Check if individual product is still feasible 2. Check if there are rows with only one cell left free 3. If (2) is true, check if not already present in that same row 4. If (3) if false, take the last empty cell			Player 2: *"…I would take the purple cell because there are many of them but now I see that in the third row there is only one empty cell left, so I need to take it…"* Note: player 2 targets a purple combination and notices that he may miss the opportunity to create a product if the purple cell in the third row is gone. Take the purple cell in the 3rd row.
Take-the-irreplaceable	1. Identify the target cells of a product 2. Compare complementarities horizontally across missing rows (i.e. how similar are the colors within the same row) 3. Compare missing rows with regards to how dissimilar the complementarities are 4. Pick the target cell in a row with most dissimilar complementarities			Player 2: *"I choose the red one in the first row because in the second row there are other good possibilities… like red or orange… they are still very compatible with the yellow…"* Note: player 2 follows the red-yellow-yellow-yellow product, and becomes aware that the target yellow cell in the 2nd row has better substitutes than the red in the top right corner. Takes the red cell in the 1st row.

Heuristic	Logic algorithm	Situation (condition)	Response (action)	Illustrative quotes
Anticipated blocking	1. Check if any of the competitors follow a monochromatic product 2. If (1) is true, take the cell of the same color as competitor is following			Player 2: *"… Player 1 has taken a red, I also going to take the red… so we can form an alliance if we both follow the same strategy…"* Note: Player 2 prefigures that player 1 is following the red product and takes the red cell as well (in this context he will be indifferent between 3^{rd} and 4^{th} row)
Non-inferences	1. Check if any of the competitors follow a monochromatic product 2. If (1) is true, check if there are other viable product options that do not overlap with the competitor 3. If (2) is true, follow that different product and take one of its constituent cells			*Player 2: "… I choose purple color because it is opposite of those selected by player 1…"* Note: Player 2 prefigures that player 1 is following the red product and that there is a purple product that player 1 is not going to follow. Decides to follow a purple product and picks the purple cell in the top row.

Note: The examples are adjusted for illustrative purposes.

APPENDIX

Table A1. Example of a verbal protocol: segmentation and coding

Round	Verbal protocol	Naive max	Forward reasoning	Predicting	Planning	Quasi-rationality	Anticipated blocking	Non-interference	Misc
1	I choose red because it is the one that seems to be more compatible with the others	1	0	0	0	0	0	0	0
1	I did not create any product because I only had one turn	0	0	0	0	0	0	0	1
2	Yellow seems to be the best color, I think I will choose it	1	0	0	0	0	0	0	0
2	it is my turn, I choose yellow because seems better than others, I have occupied the last row because in the first one there are yellow and orange with more compatibility	1	0	0	0	0	0	0	0
2	first row has already been occupied, so now I can't occupy a product on my own	1	0	0	0	0	0	0	0
2	so I try to look for an alliance, let's find out who could be interested	0	1	1	0	0	0	0	0
2	3 has its product, with 1 we can't create anything, I'm going to ask to 2	0	1	1	0	0	0	0	0
3	I think I'll choose a piece, better be pale green from second row	1	0	0	0	0	0	0	0
3	3 had three turns, it chose all yellow pieces	1	0	0	0	0	0	0	0
3	3 is taking everything, last row has been occupied by 1.. And the first one as well	0	0	0	0	0	0	0	1
4	1 and 3 have already done…	1	0	0	0	0	0	0	0
4	it's not my turn yet	1	0	0	0	0	0	0	0
4	now it's my turn, I think I'll pick the bluish which could match quite well with green	1	0	0	0	0	0	0	0
4	it's still my turn, I'll pick another bluish	1	0	0	0	0	0	0	0
4	it's still my turn, I'll pick violet for the first box	1	0	0	0	0	0	0	0
4	if I do on my own my profit would be 3.2, while if I choose to ally with 3 I'd have some profit... I've chosen to not create any alliance.. I made a mistake	1	0	0	0	0	0	0	0
5	I think I'll pick blue which could match well with violet	1	0	0	0	0	0	0	0
5	among all colors, I choose blue on the row where all other colors have less compatibility with blue	0	1	0	1	0	0	0	0
5	so I choose the second row	1	0	0	0	0	0	0	0
5	1 chose a blue piece	1	0	0	0	0	0	0	0
5	I think I'll choose the blue piece which is compatible with mine, in the last row	1	0	0	0	0	0	0	0
5	it's still my turn, I'll choose a bluish piece.. Or maybe violet... I choose bluish	1	0	0	0	0	0	0	0
5	I can form an alliance with 2 and 3	1	0	0	0	0	0	0	0
5	3 has yellows	1	0	0	0	0	0	0	0
5	2 has violet which has more compatibility	1	0	0	0	0	0	0	0
5	I think I won't form an alliance, but I'll choose a red piece	1	0	0	0	0	0	0	0
6	different colors.. My turn, 2 chose violet	1	0	0	0	0	0	0	0
6	watching the CC, if I choose yellow.. Violet has more similar colors, but it has already been chosen by 2.. So I choose yellow in the first row to get a yellow product, orange... Pale green.. And not get into competition with 2	0	1	1	0	0	0	1	0
6	I choose yellow which is has the best compatibility with the yellow I chose before	1	0	0	0	0	0	0	0
6	3 took orange which I wanted	0	1	1	0	0	0	0	0
6	so I could choose bluish or make an alliance with 3	0	1	0	1	0	0	0	0
6	I choose to take pale green from bottom line	0	1	0	1	0	0	0	0

Round	Verbal protocol	Naive max	Forward reasoning	Predicting	Planning	Quasi-rationality	Anticipated blocking	Non-interference	Misc
6	If I'll have another chance, I will make an alliance with 3 which has another orange, so I can have more success	0	1	0	1	0	0	0	0
6	it's my turn... I propose an alliance with 3	0	1	0	1	0	0	0	0
6	it has been accepted, so I've got A with 3	0	0	0	0	0	0	0	1
7	colors ... are blue, which has already been chosen so I would like to distinguish me from him	0	1	0	1	0	0	1	0
7	I could go for pale green, pale green.. After yellow... I choose orange	0	1	0	1	0	0	1	0
7	23 created an alliance	1	0	0	0	0	0	0	0
7	my turn, I choose to take another orange for compatibility with mine	1	0	0	0	0	0	0	0
7	everybody chose the second row, so I don't have necessary pieces	1	0	0	0	0	0	0	0
7	I take a dark green piece, so they take less	0	0	0	0	0	0	0	1
8	dominant colors are red and blue	1	0	0	0	0	0	0	0
8	1 chose red, so I go for blue and from the same line, so I have less competition	0	1	0	1	0	0	1	0
8	all my 3 pieces are blue	1	0	0	0	0	0	0	0
8	I should try to get another violet piece so to create a blue product	0	1	0	1	0	0	0	0
8	they took a violet piece from me, I could make an alliance with 1	0	1	0	1	0	0	0	0
8	1 proposed me an alliance… ehhhhh… I accept it because I've no rounds, I can't win	0	1	0	1	0	0	0	0
8		1	0	0	0	0	0	0	0
9	there's no dominant color	1	0	0	0	0	0	0	0
9	I'll choose violet in the row where also pale green is	1	0	0	0	0	0	0	0
9	2 proposed me an alliance, I've got violet, 2 has blue, so I accept	1	0	0	0	0	0	0	0
9	If I hadn't accepted an alliance, maybe I couldn't make the product	0	0	0	0	0	0	0	1
10	the predominant and the dark green which has already been chosen by 1… I can choose green in order to ally with 1 or go for another color	1	0	0	0	0	0	0	0
10	dark green… I choose it and I force them to a possible alliance	0	1	1	0	0	1	0	0
10	2 chose yellow	1	0	0	0	0	0	0	0
10	1 chose pale green	1	0	0	0	0	0	0	0
10	I can make an alliance with one, if I do that I'm sure I can create the product… so I choose to ask for an alliance with 1, I'm waiting for an answer from him	1	0	0	0	0	0	0	0
10	I took the check boxes where there were less free spots	0	0	0	0	0	0	0	0
10	we succeed in creating two products	0	0	0	0	0	0	0	1
11	dominant color is dark green, bluish and blue	1	0	0	0	0	0	0	0
11	I decide to take bluish because has more compatibility	1	0	0	0	0	0	0	0
11	I take another bluish, I take last bluish check box available	1	0	0	0	0	0	0	0
11	now I can create an alliance with someone else, he could not have rounds to create the second product	1	0	0	0	0	0	0	0
12	dominant color is violet, I'm going to start, I choose violet	1	0	0	0	0	0	0	0
12	my turn again, I'll choose violet	1	0	0	0	0	0	0	0
12	3 took another violet piece from me, so I can't take another violet piece	1	0	0	0	0	0	0	0
12	I create an alliance with 3	1	0	0	0	0	0	0	0
12	Maybe I'll choose the best violet compatibility piece… I choose to create an alliance with 3	1	0	0	0	0	0	0	0
12	3 accepted	1	0	0	0	0	0	0	0

Round	Verbal protocol	Naive max	Forward reasoning	Predicting	Planning	Quasi-rationality	Anticipated blocking	Non-interference	Misc
12	if I've got no other rounds, I'm sure I did good	1	0	0	0	0	0	0	0
12	maximum compatibility with violet, they go blue or red	1	0	0	0	0	0	0	0
13	dominant color is yellow, it has been chosen by 3	1	0	0	0	0	0	0	0
13	I could go for another color if it's going to be my turn	1	0	0	0	0	0	0	0
13	I could choose pale green to force an alliance with yellow… or dark green	0	1	1	0	0	1	0	0
13	1 and 3 created A	1	0	0	0	0	0	0	0
13	2 took another dark green compatible with mine	1	0	0	0	0	0	0	0
14	blue is the dominant color	0	0	0	0	0	0	0	0
14	blue has been chosen from 2… I can take blue or ored, I take blue	0	1	1	0	0	1	0	0
14	2 has taken all the other blue squares and formed an alliance with 1	1	0	0	0	0	0	0	0
14	1 and 2 took all the second row and it doesn't count which choice I'll take… I had just two rounds	1	0	0	0	0	0	0	0
15	dominant colors are light green and dark green… I choose light green for the best yellow compatibility	1	0	0	0	0	0	0	0
15	it's my turn, maximum compatibility is dark green, so I choose dark green	0	0	0	0	0	0	0	0
15	1 and 2 created A	0	0	0	0	0	0	0	0
15	my turn, I choose the violet one where I have just a single free check box	0	0	0	0	0	0	0	0
15	I've bluish and orange… I choose bluish for the compatibility, I managed to create a product	1	0	0	0	0	0	0	0
15	I can take an orange piece or form an alliance with 3… I will have just a single product. I choose to not form an alliance… I'd have just a single product anyway	1	0	0	0	0	0	0	0
16	dominant colors are blue and bluish	1	0	0	0	0	0	0	0
16	I can choose… I choose in a line where somebody else already took… I choose bluish to leave free the check boxes from last row	0	1	0	1	0	0	1	0
16	1 and 3 created A	1	0	0	0	0	0	0	0
16	my turn, I choose to take the violet one or the one… with the best compatibility with blue and dark green	1	0	0	0	0	0	0	0
16	1 and 2 could choose it, so I'll choose violet in order to not let them choose it	0	1	1	0	0	0	0	0
16	I choose violet	1	0	0	0	0	0	0	0
16	I can form an alliance with 2…. I'm forced to create an alliance with 2	1	0	0	0	0	0	0	0
17	I'll choose dark green from the single column	1	0	0	0	0	0	0	0
17	2 took another green piece from me, now it has the best compatibility with pale green and bluish	1	0	0	0	0	0	0	0
17	I decide to take orange from first row to guarantee to me the possibility to have a product	0	0	0	0	0	0	0	0
17	I choose to form no alliance, I take pale green	1	0	0	0	0	0	0	0
17	if I don't accept the alliance, I have a profit of… let's accept the alliance	1	0	0	0	0	0	0	0
17	we managed to take two products	0	0	0	0	0	0	0	1
18	yellow is dominant… I choose yellow	1	0	0	0	0	0	0	0
18	2 is choosing dark green, that's good, he leaves me the yellows	0	1	1	0	0	0	0	0
18	I can create an alliance with 1 or decide to do not… if I create an alliance with 1, I'll have the product… otherwise I could never see the product created… if I were 1, I'd refuse my proposal… and so… if 1 were rational, he woudn't accept my alliance... let's hope he will accept... my request has been denied	0	1	1	0	0	0	0	0
18	I have necessarily. Otherwise I can't do anything	1	0	0	0	0	0	0	0
18	I won't ask to 2, I'll ask to 1, my request has been denied again	1	0	0	0	0	0	0	0

Round	Verbal protocol	Naive max	Forward reasoning	Predicting	Planning	Quasi-rationality	Anticipated blocking	Non-interference	Misc
18	let's ask 2… and accepted	1	0	0	0	0	0	0	0
19	there are no dominant check boxes	1	0	0	0	0	0	0	0
19	I choose violet…	1	0	0	0	0	0	0	0
19	I choose another violet	1	0	0	0	0	0	0	0
19	I can create an alliance with 3… if I create with 3, I'm sure… if I don't form it, I can hope for a good product… this time I'll try to go on my own	1	0	0	0	0	0	0	0
19	1 and 2 made an alliance	1	0	0	0	0	0	0	0
19	another round would be enough for me to take a piace from last row and create a product	1	0	0	0	0	0	0	0
19	I can't create a product on my own, It should be convenient for him as well	0	1	1	0	0	0	0	0
20	bluish is dominant, with three check boxes	1	0	0	0	0	0	0	0
20	last row has been occupied, I've to make an alliance	1	0	0	0	0	0	0	0
20	1 cannot create any product… I choose to aim for an alliance with 2	1	0	0	0	0	0	0	0
20	I choose orange from last row hopefully allying with 2	0	1	1	0	0	1	0	0
20	2 and 3 made an alliance; I cannot do anything with one… so… I take the first row, so they cannot create two products	1	0	0	0	0	0	0	0

Estratto per riassunto della tesi di dottorato

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CICLO: **XXVI**

TITOLO DELLA TESI:
Dynamic competition and cooperation in systemic industries: models and experiments

ABSTRACT:
The dissertation introduces a dynamic model of competition in systemic industries. In the proposed model, firms compete for a limited set of partially modular components to which they sequentially get access in a randomized fashion. The model additionally incorporates an element of cooperation in that firms are given the opportunity to form bilateral alliances when it is mutually beneficial for them to do so. In chapter 1 through a series of computer simulations we examine how the role of chance accounts for the emergence of performance heterogeneity between initially identical firms. In chapter 2, we take a complementary experimental approach and validate the behavioral assumptions of the original model in the laboratory. In chapter 3, we seek to identify the context-specific heuristics people use in decision making environments characterized by complexity and uncertainty.

La tesi introduce un modello dinamico di competizione nelle industrie sistemiche. Nel modello proposto, competono per un numero limitato di componenti modulari parzialmente a cui sequenzialmente ottengono accesso in modo randomizzato. Il modello incorpora inoltre un elemento di cooperazione con il quale alle imprese viene data l'opportunità di formare alleanze bilaterali qualora fosse mutualmente conveniente. Nel capitolo 1, attraverso una serie di simulazioni al computer, esaminiamo come influisca il ruolo dell'opportunità nell'emersione dell'eterogeneità tra le imprese inizialmente identiche. Nel capitolo 2, adottiamo un approccio sperimentale e convalidiamo le ipotesi comportamentali del modello originario in laboratorio. Nel capitolo 3, cerchiamo di identificare le euristiche specificamente contestuali che gli esseri umani utilizzano negli ambienti dei processi decisionali caratterizzati da complessità e incertezza.

Firma dello studente