Chance and Competitive Advantage

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.

Keywords: competitive dynamics, randomness, systemic technologies

Chance and Competitive Advantage

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

[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.

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.

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 k^{th} and $(k+1)^{th}$ component solutions of a given product.[3]

[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.

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 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

[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.

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 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:

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

where S_i is the attributed value of the focal firm i in a given alliance product P, $c^P_{[k][(k+1)\, mod\, n]}$ 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:

$$w_i^P = \frac{S_i^P}{S^P} \qquad (3)$$

$$w_j^P = \frac{S_i^P}{S^P} \qquad (4)$$

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:

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

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

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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* 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.

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 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.

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[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.

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).

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

[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.

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 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.

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

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:

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

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 Tables 4A and 4B 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 Tables 4a and 4b 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

[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.

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 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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FIGURE 1

Selected Component Solutions in the Smartphone Industry

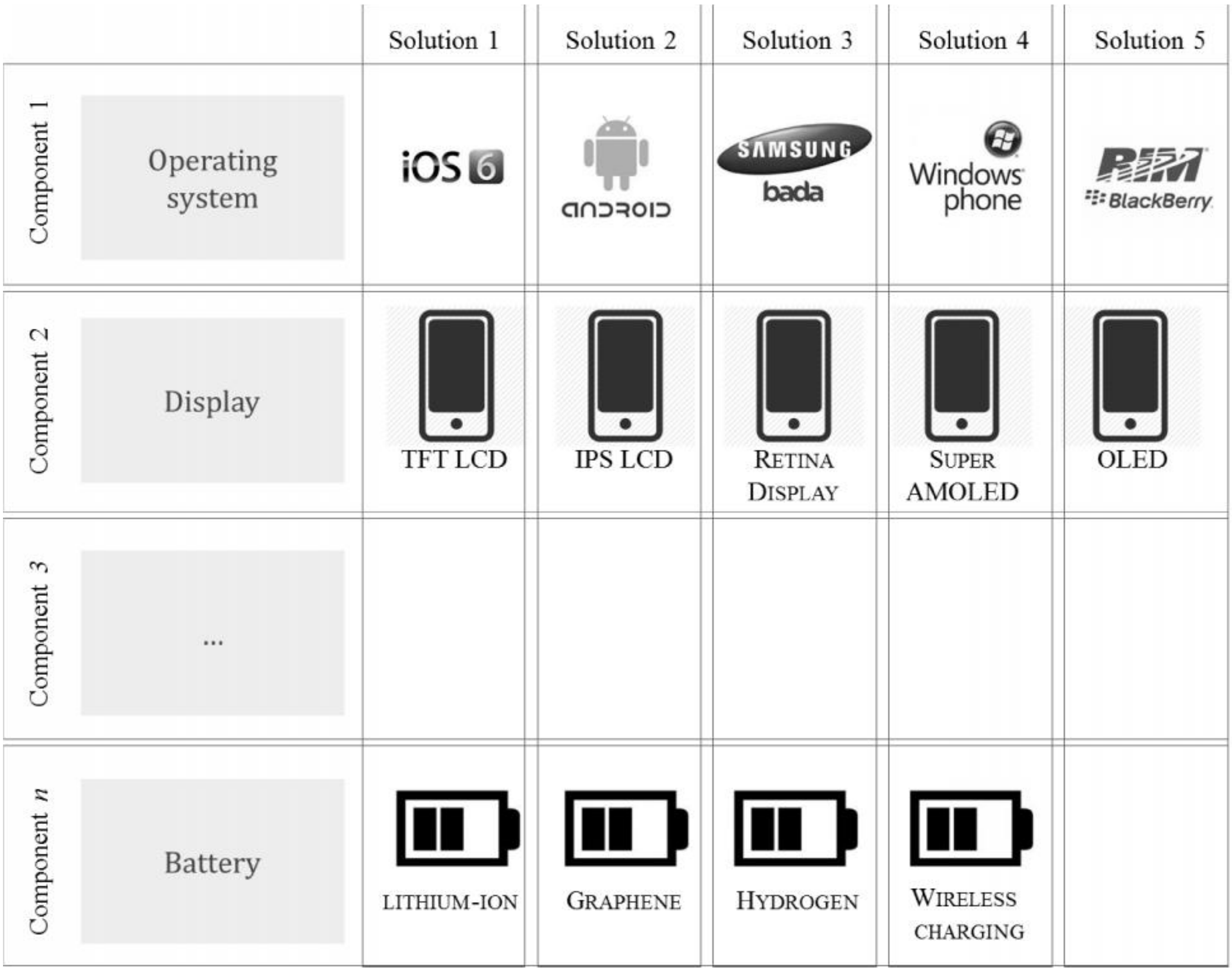


FIGURE 2

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

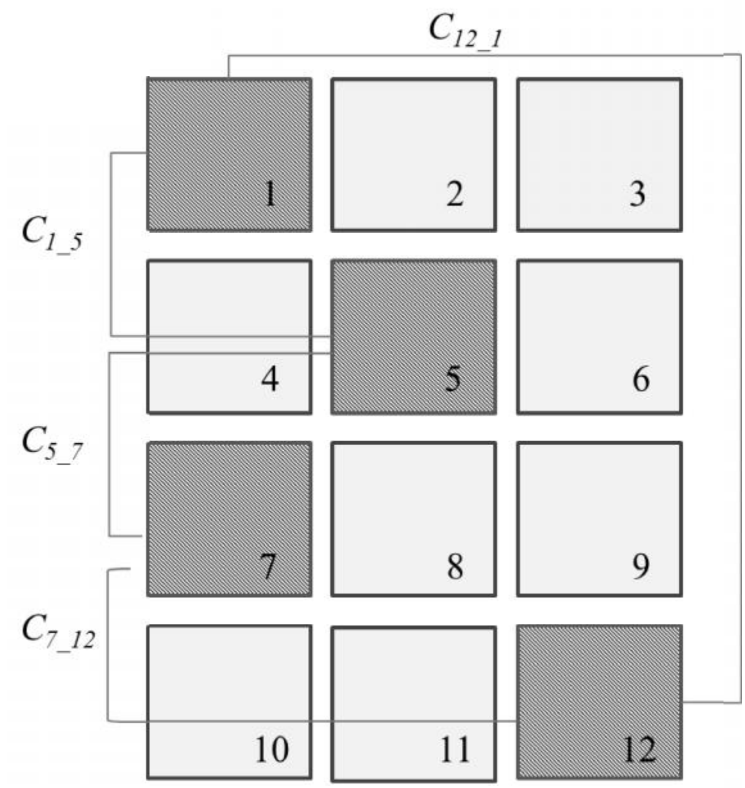
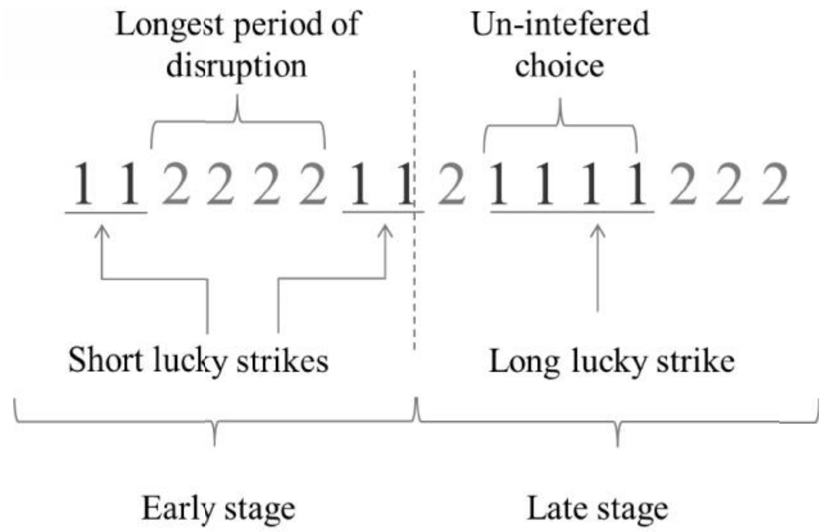


FIGURE 3*

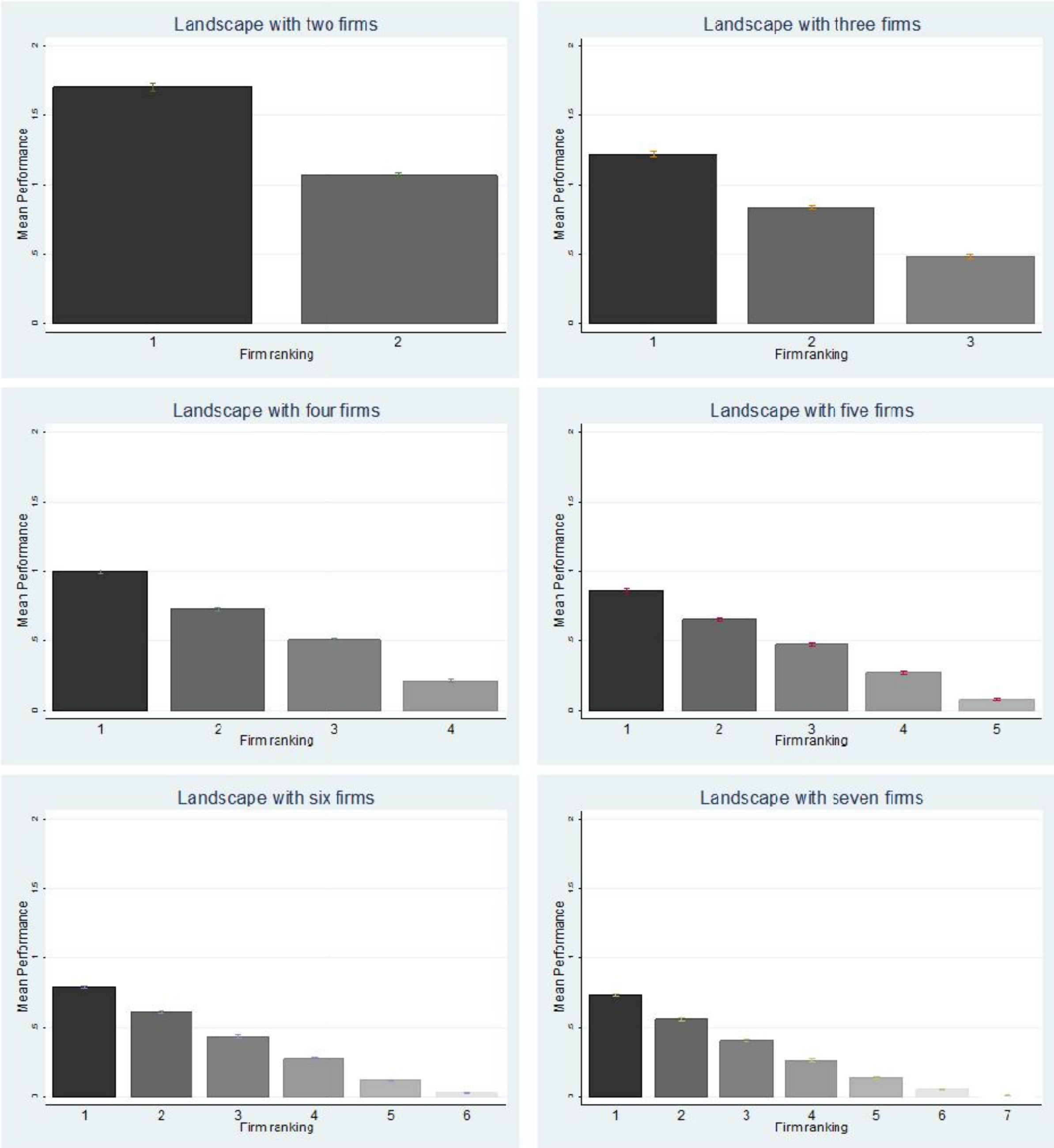
Sequence of chance events for a focal firm



*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

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	0.01***	0.01***	-0.01***	0.01***	0.01***	0.02***	-0.01***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Alliance formation	0.03***	0.08***	0.04***	0.05***	0.05***	0.07***	0.04***	0.06***	0.06***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Competition strength	-0.17***	-0.17***	-0.02***	-0.16***	-0.10***	-0.14***	-0.02***	-0.01***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Flat		0.19***	0.20***	0.18***	0.18***	0.20***	0.20***	0.15***	0.16***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Steep		-0.12***	-0.13***	-0.12***	-0.13***	-0.12***	-0.13***	-0.09***	-0.09***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Total number of chance events			0.11***				0.09***	0.07***	0.07***
			(0.00)				(0.00)	(0.00)	(0.00)
First choice				-0.01***			-0.02***	-0.02***	-0.02***
				(0.00)			(0.00)	(0.00)	(0.00)
Un-interfered choice					0.18***		0.03***		
					(0.00)		(0.00)		
Longest period of disruption						-0.03***	-0.01***	-0.01***	-0.01***
						(0.00)	(0.00)	(0.00)	(0.00)
Number of short lucky strikes at the early stage								0.11***	0.12***
								(0.00)	(0.01)
Number of short lucky strikes at the late stage								0.04***	0.13***
								(0.00)	(0.01)
Number of medium lucky strikes at the early stage								0.18***	0.25***
								(0.01)	(0.01)
Number of medium lucky strikes at the late stage								0.10***	0.18***
								(0.01)	(0.01)
Number of long lucky strikes at the early stage								0.42***	0.46***
								(0.01)	(0.02)
Number of long lucky strikes at the late stage								0.24***	0.45***
								(0.01)	(0.02)
Competition x Number of short lucky strikes at the early stage									-0.00
									(0.00)
Competition x Number of short lucky strikes at the late stage									-0.02***
									(0.00)
Competition x Number of medium lucky strikes at the early stage									-0.02***
									(0.00)
Competition x Number of medium lucky strikes at the late stage									-0.02***
									(0.00)
Competition x Number of long lucky strikes at the early stage									-0.02***
									(0.01)
Competition x Number of long lucky strikes at the late stage									-0.07***
									(0.01)
Constant	1.11***	1.08***	0.30***	1.20***	0.51***	1.01***	0.33***	0.25***	0.21***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	67,500	67,500	67,500	67,500	67,500	65,267	65,267	65,267	65,267
Adjusted R-squared	0.35	0.42	0.69	0.45	0.54	0.47	0.69	0.73	0.74

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.