PERFORMANCE DIFFERENTIALS BETWEEN DIVERSIFYING ENTRANTS AND ENTREPRENEURIAL START-UPS: A COMPLEXITY APPROACH

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ABSTRACT

We investigate the relationship between firms' entry characteristics and their subsequent performance as contingent on environmental turbulence and stage of industry life cycle by simulating industry as an NKC landscape. Diversifying entrants differ from entrepreneurial start-ups in terms of the complexity of their routines. We posit that diversifying entrants outperform entrepreneurial start-ups when turbulence is high. Further, learning—possible in later industry stages—disproportionately favors entrepreneurial start-ups.
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Keywords: organizational learning, entrepreneurial start-ups, diversifying entrants, NK model, complexity, industry evolution.

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An enduring research theme is the performance consequences of heterogeneity in firms' characteristics at their time of entry into an industry (Helfat & Lieberman, 2002). Whether examined via an industry evolution focus on timing of entry (Agarwal & Gort, 1996; Lieberman & Montgomery, 1988) or via a capabilities (Helfat & Lieberman, 2002; Klepper & Simons 2000) or an organizational ecology approach (Carroll *et al.*, 1996; Carroll & Khessina, 2005), firms' attributes at the time of entry have a persistent effect on their later organizational form, and such "imprinting" explains much of the heterogeneity in the population of firms in an industry (Levinthal, 1997; Stinchcombe, 1965). However, the consensus about the long-term performance implications of initial firm characteristics is considerably weaker, particularly when taken in the context of rapidly evolving industries (Bayus & Agarwal, 2007; Klepper & Simons, 2000). Indeed, there is conflicting evidence: some evidence that firms with pre-entry experience have "dominance by birthright" and some evidence that entrepreneurial start-ups can "creatively destruct" the status quo and gain from advantages associated with the structural differences between them and the diversifying entrants.

To investigate how pre-entry experience might confer performance advantages, we employ an agent-based simulation approach that has been extensively used and tested in management research (Ethiraj & Levinthal, 2004; Fleming & Sorenson, 2001, 2004; Levinthal, 1997; Rivkin, 2000; Sorenson, 1997, 2003). Although these models have been typically used to examine within-firm dynamics, they are also relevant to questions of industry evolution.

Since performance is a consequence of the fit between organizational capabilities and environmental conditions (Helfat & Lieberman, 2002), we focus on how pre-entry experience interacts with environmental conditions measured along two important dimensions of an industry: degree of turbulence and maturity. Our simulation models suggest that diversifying entrants tend to outperform start-ups in a more turbulent environment; however, start-ups benefit disproportionately from learning when entering a mature industry.

We begin by reviewing work on the performance differences between diversifying entrants and entrepreneurial start-ups. The review enables us to identify empirical regularities that have received significant support as well as less established areas that require theoretical attention. We then develop a complexity model by mapping the NKC parameters to our specific context and developing propositions based on the simulation results. Our final section provides a discussion of the key contributions, limitations, and avenues for future research.

LITERATURE REVIEW

Pre-entry Experience and Performance

Pre-entry experience has been identified as an important source of heterogeneity among industry entrants that has consequences for postentry performance (for a review, see Helfat & Lieberman, 2002). Diversifying entrants—defined as firms that already existed before entering the focal industry—differ from entrepreneurial start-ups—firms founded in the focal industry context—on two important dimensions. First, diversifying entrants typically enter with more financial, managerial, and related technological or marketing resources and capabilities (Carroll *et al.*, 1996; Klepper & Simons, 2000; Lane, 1989). These resource advantages often provide diversifying entrants at least a short-term performance advantage, particularly if they enter from related industries, so that the degree of fit between firm resources and focal industry requirements for success is higher (Carroll *et al.*, 1996; Klepper & Simons, 2000; Mitchell, 1991). For instance, Carroll *et al.* (1996) found that diversifying entrants with relevant specialized and transferable knowledge outperformed all other automobile industry entrants. Similarly, Mitchell (1991) related the performance advantage of diversifying entrants in new diagnostic imaging markets to their access to distribution channels and complementary assets. A second dimension of difference relates to structural inertia (Hannan & Freeman, 1984). Diversifying entrants possess more inert and established processes, such as "documents, understandings and agreements intended as blueprints for future action" (Carroll *et al.*, 1996, p 120). Entrepreneurial start-ups have more fluid and organic structures that change relatively easily (Hannan & Freeman, 1984). This distinction between the two types of firms is akin to the organizational ecology distinction between generalist and specialist firms (Aldrich, 1990; Brittain & Freeman, 1980; Hannan & Freeman, 1977).[1] While superior access to resources provides an advantage to diversifying entrants, the performance consequences of structural inertia are not clear. The more inert processes and structures of diversifying entrants can enhance their legitimacy and make them appear more reliable to customers (Hannan & Freeman, 1984). However, the less inert structures of start-ups (Hannan & Freeman, 1984) and their higher rate of new-product innovations (Khessina, 2002, 2003) may enable them to span niches and quickly reorient activities. These firms are better equipped for exploration, because their fluid and organic structures and routines allow them to avoid the myopic learning (Levinthal & March, 1993) and competency traps (Levitt & March, 1988) endemic to the more established firms. The absence of ties to existing processes (Carroll *et al.*, 1996) or existing customer needs (Christensen, 1997) may enable start-ups to engage in creative destruction (Schumpeter, 1934), as was evidenced in the disk drive (Agarwal *et al.*, 2004; Christensen, 1997) and the laser industries (Klepper & Sleeper, 2005).

Thus, theoretically, the "main effect" of pre-entry experience is ambiguous, particularly when one is examining long-term consequences for performance. Not surprisingly, there is conflicting empirical evidence regarding the main effect of pre-entry experience on performance. As Table 1 summarizes, evidence exists for diversifying entrant advantage (Barnett & Freeman, 1990; Freeman, 1990; Hannan & Freeman, 1988; Rao, 1994), start-up firm advantage (Agarwal *et al.,* 2004; Carroll & Khessina, 2005; Khessina, 2002; 2003), and convergence between the two (Carroll *et al.,* 1996; Hannan *et al.*, 1998; Khessina & Carroll 2007). The contradictory evidence leads us to formulate our main question:

Question 1: Under what conditions will entrepreneurial start-ups outperform diversifying entrants, and vice versa?

[Insert Table 1 about here]

One potential route to reconciliation of these contrary findings is to look for contingency conditions that affect this relationship. In this paper, we focus on two industry-level factors that may impact the pre-entry experience–performance relationship: the extent of environmental turbulence and the accumulated stock of knowledge in an industry. We briefly review the relevant literature on each factor, with a focus on current knowledge on potential contingency effects.

Environmental Turbulence

Industry environments differ in their degrees of turbulence, or dynamism. Turbulent, or high-velocity, industries typically have ambiguous structures, blurred boundaries, fluid business models, ambiguous and shifting players, nonlinear and unpredictable change, short product cycles, and rapidly shifting competitive landscapes (Brown & Eisenhardt, 1997; Eisenhardt & Martin, 2000). In contrast, industries with low levels of turbulence represent less uncertain environments and relatively stable competitive landscapes.

Overall, scholars examining the effects of environmental turbulence emphasize the need for organizational change in more turbulent environments. Hailing back to Burns and Stalker (1961), a core theme of organization and innovation studies is that "mechanistic organizations" (those with more centralized and formal structures) perform better in stable markets that reward efficiency, while "organic organizations" (those with more decentralized and informal structures) perform better in turbulent markets (Eisenhardt & Tabrizi, 1995; Pisano, 1994). This distinction arises because the imperative to change in response to environmental shifts (Haveman, 1992) implies that fluid structures and simpler rules that enable change provide performance benefits as turbulence increases (Brown & Eisenhardt, 1997; Davis *et al.*, 2006; Rindova & Kotha, 2001).

However, recent theory and research show that excessive change can be detrimental (Sastry, 1997; Sine *et al.*, 2006; Sorenson *et al.*, 2006). For instance, Sorenson *et al.* (2006) disentangled the behavioral and positional effects of change in the organizational scope and found that although change results in positional benefits, the tendency of generalists to constantly change and expand can be temporarily detrimental. Sine *et al.* (2006) examined how organizational structure relates to the performance of small ventures in a turbulent environment. Drawing on a body of prior research, they maintained that the highly formal and routinized structures of mature firms inhibit change and yield lower performance. However, they showed that, for small ventures in very turbulent environments, formal structures actually help performance and concluded that small ventures have flexibility but need stability. Similarly, following the tradition of systems dynamics (Forrester, 1961), Sastry (1997) built a single-firm model of punctuated organizational change, focusing on the key trade-off between inertia that promotes competence versus change that destroys inertia. If an organization attempts to change in response to environmental shifts, it restarts the "inertia clock" and destroys competence. Consequently, being too responsive to change is not beneficial in turbulent environments, since it diminishes competence.

The distinction made above parallels that between generalist and specialist firms. Organizational ecologists (e.g. Aldrich, 1990; Brittain & Freeman, 1980; Hannan & Freeman, 1977) assume that organizations sacrifice some performance when they compete in a wider niche. Consequently, specialists outperform generalists in environments within the narrow band of their specialty, and generalists fare better when "environments vary across different states with some degree of uncertainty" (Aldrich, 1990: 13).

Although the literature on the effects of environmental turbulence on firm performance is relatively silent on performance differentials due to pre-entry experience, the above research raises the intriguing possibility that the degree of environmental turbulence may explain the conflicting empirical findings. Diversifying entrants arguably have more structural links and greater organizational inertia than entrepreneurial start-ups; thus, performance implications differ under varying degrees of environmental turbulence. Such a notion is consistent with the work of Khessina (2002), who found that start-ups introduce product innovations at a higher rate than diversifying entrants but nonetheless also fail at a higher rate (Carroll & Khessina, 2005). In line with this conjecture, our second question of interest is:

Question 2: How does an industry's environmental turbulence affect the performance differential between entrepreneurial start-up and diversifying entrants?

Stage of Industry Life Cycle

Multiple research streams—in technology management, evolutionary economics, and organizational ecology—examine the evolution of industries over time (e.g. Gort & Klepper, 1982; Hannan & Freeman, 1977, 1988; Utterback & Abernathy, 1975). Reconciling these three bodies of scholarly work, Agarwal *et al.* (2002) noted that a common theme is the identification of growth and mature life cycle stages, though scholars differ on whether the underlying mechanism relates to "pre and post" dominant design (Abernathy & Utterback, 1978), legitimacy versus competitive effects of population density (Carroll & Hannan, 2000), or entrepreneurial versus routinized regimes (Audretsch, 1997; Nelson & Winter, 1982).

Importantly, although the literature is unequivocal on the survival benefits of entering in the early rather than the later stages of an industry's life cycle (Agarwal & Gort, 1996; Hannan & Freeman, 1978; Suarez & Utterback, 1995), less agreement can be seen on whether different types of entrants are differentially advantaged by timing of entry. Table 1 illustrates this lack of agreement. Klepper and Simons (2000) found evidence that diversifying entrants entering early enjoy a "dominance by birthright," yet Carroll *et al.* (1996) and Bayus and Agarwal (2007) found that these advantages erode over time and may be reversed. Similarly, while Agarwal (1997) documented diversifying entrant advantage during the growth stage across 33 industries, Mitchell (1991) found that diversifying entrants consistently outperformed entrepreneurial entrants regardless of time of entry. Among the late cohorts, Klepper (2002) found no significant performance differential among the two types of entrants; Mitchell (1991) documented support for diversifying entrant advantage; and Agarwal (1997) and Bayus and Agarwal (2007) found support for entrepreneurial start-up advantage. The conflicting evidence is also present among studies that compare early and late cohorts; some studies show support for diversifying entrants, whether entering early (e.g., Klepper & Simons, 2000) or later (e.g., Mitchell, 1991) However, researchers examining employee entrepreneurship (e.g., Agarwal *et al.*, 2004; Klepper & Sleeper, 2005) maintain that the incumbent advantage can be successfully challenged. Agarwal *et al.* (2004) found that start-up firms created by ex-employees of incumbent firms outperformed all other entrants, including diversifying and early entrants. Similarly, Klepper (2002a) showed that in the automobile industry, late start-up entrants founded by former employees of incumbent firms outperformed all other cohorts.

One reason for the conflicting findings may be the extent of later entrants' learning from an industry stock of knowledge. Indeed, a key feature that distinguishes the "stable" mature stage of the industry life cycle from the "fluid" growth stage is resolution of product standards and architecture issues; often a dominant design has evolved (Abernathy & Utterback, 1978; Anderson & Tushman, 1990; Gort & Klepper, 1982; Murmann & Frenken, 2006). Gort and Klepper (1982) described the higher development of industry-specific knowledge in the later stage as a critical difference between stages. Abernathy and Utterback's (1978) fluid and specific phases and Anderson and Tushman's (1990) eras of ferment and incremental change are similar distinctions.

Consequently, in the fluid phase or fermentation era, entrants engage in significant experimentation regarding product design and standards (Anderson & Tushman, 1990; Abernathy & Utterback, 1978). In the mature stages of an industry, by contrast, entrants have the option of learning from the established stock of knowledge and pre-meditating their entry strategies. The entrants may access learning via simple imitation (Rivkin, 2000; Schumpeter, 1934), patents (Almeida & Kogut, 1999), collaborative arrangements (Rosenkopf & Almeida, 2003), and employee mobility (Agarwal *et al.*, 2004). Thus, if learning is an important differentiating factor between early and late industry stages, the following question becomes an important one to investigate:

Question 3: How does the ability of late entrants to learn from an industry-specific stock of knowledge affect the performance differentials between entrepreneurial start-ups and diversifying entrants?

A COMPLEXITY APPROACH TO MODELING PERFORMANCE DIFFERENTIALS BASED ON ENTRANT CHARACTERISTICS

To reconcile previous findings and to shed light on understudied contingency conditions, we employ an agent-based model to simulate how organizational structures and processes may interact with environmental conditions to explain performance differentials.

The NKC Model

Kauffman's NKC model (1995) is an extension of the NK model (Kauffman, 1993: Ch. 6) widely used in research on strategy (Ethiraj & Levinthal, 2004; Levinthal, 1997; Rivkin, 2000). The NKC model was developed to model the coevolution of species and thus can be adapted to model an evolving industry with heterogeneous entrants. In particular, the framework permits us to model an industry with differentiated products and each firm occupying a certain exogenous niche. A salient aspect of the model is that it incorporates interfirm interaction: each firm's choices have an impact on the payoffs of the choices of the other firms. Such a structure allows us to focus on environmental characteristics caused by the coevolution of heterogeneous firms.

In the NKC model, there are N elements of a decision vector in each firm. Like previous researchers (Levinthal, 1997; Rivkin, 2000; Rivkin & Siggelkow, 2003), we assume that the binary bits of each firm's decision vector represent organizational attributes or routines (Nelson & Winter, 1982). We adopt Rivkin's (2000) interpretation that the binary bits represent broadly defined organizational decisions related to firm strategy, organizational form, product design, etc. We use the term "routines" to broadly represent all internal firm processes. The value of each bit– 0 or 1– represents a decision about routines (e.g., routine A vs. routine B is chosen).

The parameter K measures the degree of interdependence or *intrafirm coupling* between the N elements of the decision vector—that is, the performance contribution of each element of the vector x_i, i= 1…N, is affected by K other elements x_j, where j is not equal to i. The performance contributions of the decision elements are determined by the payoff function, which works as follows: for instance, if a coupling exists between the decision element x_1 and element x_3 in which x_1 is the focal element (x_3 affects x_1), then a change in x_3 (decision B instead of A is chosen) changes the payoff contribution of x_1 (the value is simply redrawn from the underlying distribution). When x_1 is coupled to many (K) other decisions, its payoff is redrawn whenever any of the coupled decisions changes. The overall payoff of the entire decision vector is the mean of the payoff contributions of its individual elements. A high value of K implies a "rugged landscape" arising from the underlying high interdependence of decision elements (high interdependence is also described as high coupling or complexity). Following prior work, we define the "peaks," or local optima, on the NK landscape as configurations of the elements of a decision vector that are such that it is not possible to improve the decision's overall payoff by altering any single decision element.

To describe the model formally, the NK landscape is characterized by the correspondence mapping of the vector **x** in the decision space to the outcomes (payoffs). The landscape is a mapping from the set $\mathbf{X} = \{0,1\}^N$ to R_+ An element $\mathbf{x} \in \mathbf{X}$ is a vector of binary digits of length N. The mapping assigns to each $\mathbf{x} \in \mathbf{X}$ a payoff, $\pi(\mathbf{x}) \in R_+$. The mapping π depends on the parameter K, with $\pi(\mathbf{x}, K)$ reflecting the interdependence of the individual components of **x**. The change in the payoff contribution of the ith component is influenced by the change in the ith decision x_i, and by the changes in the K other components of **x**. If K = 0, there are no interdependencies and the $\pi(.)$ function is additive. The mapping is generated by assigning a payoff $\pi_i(.)$, which is a random number from a standard normal distribution, to each decision x_i, $i = 1,\ldots,N$ and each instance in which either x_i changes or some of the K decisions that are associated with x_i change.[2] The mapping is then given by:

$$\pi(x,N,K)=\frac{1}{N}\sum_{i=1}^{N}\pi_i(x_i;x^1_{j(i)}...x^K_{j(i)}),\, i\notin j(i)\,,$$

where for any i we obtain a vector of indexes $j(i)$ mapping from N to N^K. None of the indexes of $j(i)$ can be equal to i. The notation $x^k_{j(i)}$ means that the index of x is the kth element of the vector $j(i)$. To create an overall mapping, we need to randomly generate $2^{K+1}N$ payoff values. The structure of the mapping $\pi(.)$ is often depicted as a matrix called the interaction or influence matrix. The rows and columns represent individual decision elements. The matrix has a 1 in each entry affected by a particular decision element (typically, row element affected by column element). For instance, for K = 0, the interaction matrix is an N × N identity matrix, and for K = N – 1, it is N × N matrix of ones. As in the original Kauffman (1995) models, in our models the interdependencies within each firm are assumed to be randomly distributed: the elements of the index vector $j(i)$ are generated randomly from the interval [1, N], with $i \notin j(i)$.

The parameter C specifies the extent to which individual firms' "sublandscapes" are tied together—that is, it specifies the extent of *interfirm coupling*. A high value of C implies a highly interactive environment where each firm's decision affects many decisions of other firms. If C = 0, the firms operate in completely independent landscapes. C is assumed to be outside the control of individual firms and is given by the characteristics of the environment. In the original model specification (Kauffman, 1995), the payoff of each decision within the decision vector of each firm x_i, is affected by its own value, by K other within-firm decisions, and by C decisions of each other firm in the environment. This implies that a change from $C_{\text{Kauffman}} = 2$ to $C_{\text{Kauffman}} = 3$ increases the number of couplings within a single C matrix for N = 10 from 20 to 30 links. If a focal firm is linked to three other firms, an increase of 30 links is implied. The $C_{Kauffman}$ basically controls the number of links in each row of the C matrix, assuming that all rows are filled.

Since such a specification is extremely coarse for our purposes—changes in C matter at a much finer level for the performance differentials—we modify the model by assuming that only some of the elements are linked to the other firms' decisions. The assumption seems reasonable since the decision vector **x** represents a set of broadly defined organizational attributes or decisions; that is, firms do not tend to interact along all decisions with other firms. Our C then controls the number of decision elements x_i of each firm that are linked to decisions of other firms—the number of rows of the C matrix that have at least one entry. We then introduce an $\varkappa$ parameter (and set it to 2 in all simulations but test its robustness; see Table A2) defining the number of links in each row (for C >1 there are $\varkappa$ entries per row; for C = 1, there is only one entry). These modifications allow very refined changes. For instance, with $\varkappa = 2$, an increase in C from 2 to 3 changes the number of links in a given C matrix by only 2 and changes links to all three firms by 6. The C matrix with our specification and parameter values C = 10, $\varkappa = 2$ is equivalent to C matrix with $C_{Kauffman} = 1$ in the original specification (C =10, $\varkappa = 10$ would be equivalent to $C_{Kauffman} = 10$). As with the intrafirm coupling, we assume that the links are distributed randomly across the coupled decisions. Figure A1 in the Appendix illustrates the full NKC interaction matrix for the parameter values N = 10, $K_{start\text{-}up} = 2$, $K_{divers} = 5$, C = 7, $\varkappa = 2$.

The level of interfirm coupling controlled by C also determines the level of environmental turbulence. Parameter C controls the number of firm decision variables that are tied to variables of other firms. However, the turbulence results from the changes of the tied variables of other firms. For example, if C=5, five decisions are coupled to another firm's decisions. However, if the other firm optimizes by changing only one decision and keeps the other four constant, the turbulence resulting from such a relationship will be small. As firms optimize their problems and climb peaks, the turbulence that each firm faces decreases over time, even as the level of interdependence remains constant. As firms adapt, the variability of their decisions decreases, and thus also the effect on other firms' choices. As we show below, different values of C affect firms differently depending on the complexity of their internal routines.

In keeping with prior work, we assume that firms learn primarily (or on average) through local search and exploitation. The local search is modeled by alteration of a single random bit of the decision vector. If this change implies a strictly greater payoff, the firm makes the move. Otherwise, the new vector is disregarded and the system stays at the original position. The firms search for a Nash equilibrium of the system—that is, when one firm alters a decision element, it takes the positions of the other firms as given.

Mapping the NKC Model to Our Context

As indicated earlier, our interest is in examining how entrant characteristics interact with environmental characteristics to explain differences in firm performance. We seek to model the effect that environmental characteristics related to (a) interfirm coupling leading to industry turbulence and (b) industry evolution may have on the relationship between pre-entry experience and performance. We model differences in diversifying entrants and entrepreneurial start-ups through K, differences in industry turbulence through C, and industry life cycle by permitting early and late entry into the simulation model. Firms are assumed to have a constant size, represented by a constant problem size N (i.e., all firms are assumed to make the same number of decisions), and we exclude selection.

In line with the NK models (Kauffman, 1993, 1995) and following the organizational ecology literature (Hannan and Freeman, 1977), we define performance as organizational fitness, or the probability that a given form of organizations persists in a certain environment. This definition is also consistent with survival as the key performance measure in technology management and industry evolution (Agarwal & Gort, 1996; Klepper & Simons, 2000). Our analysis focuses on the performance differentials observed during and at the end of the simulation period and on the associated dynamics, such as frequency of changes or performance variance.

Mapping K to Differences in Entrant Characteristics:

We model differences in entrant characteristics by differences in the value of the parameter K. This is in spirit similar to the assumption that differences in the degree of vertical integration correspond to differences in K (Sorenson, 1997). Following the Hannan *et al.* (2003a,b) concept of organizational intricacy and the notion of *intrafirm* coupling, we distinguish between entrepreneurial start-ups and diversifying entrants on the basis of the interdependence of their choices. Start-ups have a lower value of K—or less coupled organizational structures—than diversifying entrants. This is consistent with the characterization of start-ups as lacking strong idiosyncrasies that relate to capabilities suited for other industry contexts and intradivisional links imposed by the existence of multiple divisions. Similarly, it is consistent with the characterization of diversifying entrants as possessing predefined structures and established routines in other industry contexts with predetermined ways of resource deployment. We further assume that the level of coupling within both types of firms remains constant throughout the industry life cycle and that firms cannot easily adjust or imitate the level of coupling that would be most appropriate in a given environment.[3]

Since the assumption that diversifying entrants have more internal links than start-ups is crucial to our model, we elaborate on how and why this may be the case. Given their operations in other industries prior to entry into a focal context, diversifying entrants clearly possess pre-existing routines and capabilities. A substantial corporate strategy literature, hailing back to Penrose (1959), discusses value creation through related industry entry as a means to leverage existing firm capabilities related to technologies, knowledge, and organizational routines (Farjoun, 1998; Markides & Williamson, 1994; Miller, 2006; Teece *et al.*, 1994). However, the new industry context a firm enters often requires new capabilities and combining new skills, routines, and organizational demands with extant capabilities. This combination of new and old increases coupling, causing diversifying firms to have higher Ks when represented in an NKC model.

Holbrook *et al.* (2000) provide a rich description of the differences between start-up and diversifying entrants into the semiconductor industry. There is remarkable similarity between our assumption and their account of the differences in the early histories of two diversifying entrants—

(Sprague Electric and Motorola) and two start-ups (Shockley and Fairchild Semiconductor). In describing the actions of Sprague, a producer of electrochemical transistors that diversified into semiconductors, Holbrook *et al.* (2000) highlighted capabilities in capacitor production and experience in making small electronic components. The existence of links between the new capabilities that Sprague developed for semiconductors and its old electrochemical capabilities is evident from the following statement: "In spite of late 1950s developments using silicon instead of germanium and photolithography rather than electrochemistry to make transistors, Sprague Electric stuck with its ceramic-based hybrid circuits until well into the 1960s, trying to capitalize on its historical expertise" (Holbrook *et al.* 2000: 1022). Similarly, Motorola focused on hybrid circuits that took advantage of Motorola's capabilities and experience in the use of ceramic materials and design of rugged circuits. In sharp contrast to these diversifying entrants, which maintained links with existing capabilities and technologies, start-ups Shockley and Fairchild Semiconductor chose entirely new technologies and experimented with alternative materials and processes. Fairchild Semiconductor broke from tradition entirely to bet on silicon instead of germanium, and a photolithographic instead of electrochemical process, which led to its invention of the monolithic integrated circuit that manufactured all components on a single piece of silicon. Although the start-ups did benefit from what their founders had learned working in related industries, their organizational frameworks were created afresh. As opposed to the diversifying entrants, who maintained links to existing technologies and production processes, the start-ups were able to sever what were perceived as constraining links to capabilities built to serve other industries.

Mapping C to Industry Characteristics That Impact Turbulence

Similarly, we model differences in industry turbulence using the notion of *interfirm* coupling. We assume that the exogenous parameter C in Kauffman's (1995) NKC framework controls interfirm interdependence. Since the draws in the NKC model are random, interfirm coupling may result in either positive or negative changes in payoffs in response to other firms' moves. A high C implies high interdependence resulting either from strong competitive dynamics or from a greater need for interfirm collaboration. C parsimoniously captures both the complementary and substitute effects of the coupled moves of other firms.[4] For instance, frequent introductions of both new complementary and substitute products by other firms may translate into high turbulence and frequent need to change and adapt.

Several broad structural characteristics may cause differences in interfirm couplings and thus may serve as empirical proxies for C. The literature suggests that one characteristic in particular—*technological intensity*—may correspond to differences in C, and we expect a positive correlation. The level of technological intensity may, ceteris paribus, influence the need for close links to other firms through collaborative relationships. The effect of knowledge spillovers may be also more pronounced in technology-intensive industries. At the same time, high technological intensity may foster agglomeration, employee mobility, and pressures on factor markets, thus increasing the likelihood of competitive links. For example, studies of the semiconductor industry reveal that in highly technologically intensive industries, strong interfirm links driven by local proximity, employee mobility, and alliances (Almeida & Kogut 1999; Rosenkopf & Almeida, 2003) enable knowledge diffusion. Similarly, the history of the disk drive industry provides examples of the competitive pressures firms exert on each other (Christensen, 1997) and the many interfirm links resulting from employee mobility and entrepreneurship (Agarwal *et al.*, 2004; McKendrick *et al.*, 2000). Collaborative and competitive couplings can be also seen as endogenous to the complexity of the problems posed in an industry. Firms solving more complicated problems also have more coupled interfirm landscapes; technological intensity can be thought of as a proxy for this complexity. Supporting this conjecture, Hoetker and Agarwal (2007) showed that disk drive manufacturers' ability to build on prior innovation depended on whether the innovative firms still existed, because their private knowledge was an important complement to the public and codified knowledge.

Other industry characteristics may also affect interfirm coupling. For instance, *capital intensity* and *need for vertical integration* likely negatively correlate with C. Capital intensity broadly captures economies of scale and scope and has an opposite effect than technological intensity. While producing high volumes and/or vertically integrating may increase intrafirm coupling (Sorenson, 1997), these activities may decrease interfirm coupling. Similar to Schmalensee (1989: 978, 993) who stated that higher capital intensity (low C) results in higher profits, our model predicts that C and performance are negatively related. *Advertising intensity* and the *potential for product differentiation* may also negatively correlate with C.[5] More differentiated products imply landscapes with less coupling with other firms and less competitive interaction, and at the same time, greater differences between firms and less need for collaboration. Schmalensee (1989: 978) provides evidence that in the consumer goods industries, advertising intensity positively correlates with profits.

The above structural characteristics can thus be proxies for the nature and strength of interfirm linkages. In many cases, these proxies are in tandem. For instance, the cement industry has lower technological intensity, higher capital intensity, and higher (spatial) differentiation than semiconductors; we thus expect cement to have a higher C than semiconductors.

Modeling Early versus Late Entry

We model early versus late industry entry by substituting, midway through the simulation, new entrants of the same type for half of each firm type and then comparing the early and late cohorts. Importantly, the early and late entrants differ from each other on ability to learn from an established stock of industry-specific knowledge prior to their entry into the focal industry.

We assume that early entrants enter with random innovation. For later entrants, we model learning by building on the notion that late entry allows them to sample from the industry stock of knowledge—a pool of recombinant information generated by incumbents (firms that entered in the prior stage). The late entrants can also combine the information gathered with their own random innovation. Late entrants are able to enter at positions that maximize the payoff of the recombination of the industry stock of knowledge with their own innovation and then proceed through local search. We thus permit entrants to engage in "offline" search (e.g., Gavetti, 2005) regarding the decision vector and the interaction matrix with which they enter.[6] Specifically, while early entrants generate both the decision vector and the interaction matrix at random, late entrants have the additional choice of copying either or both from a randomly selected incumbent of the same type. Our assumption of imitating an incumbent of the same type exists to ensure no mismatch in the number of links (robustness checks reveal that the results are not sensitive to this assumption). Thus, late entrants evaluate the entry performance vector of each of the four options resulting from the combination of random or copied decision vector and interaction matrices, and they enter with the option yielding the best payoff. After entry, late entrants learn through local search, just as the early entrants do.

To analyze the impact of learning on postentry performance, we compared outcomes for a random late entry case with two learning algorithms, moderate and strong.[7] For moderate learning, the late entrants sample only once from the pool of interaction matrices used by the incumbents, and for strong learning, the entrants sample 10 times and select the best combination with the copied or generated decision vector.[8] To ensure a sufficient recombinant pool, the entrants sample from 10 prior runs and the baseline model is run 10 times before the learning simulation starts. Regardless of the learning algorithm employed, both types of entrants can evaluate the same mix of pre-entry options.

Model Simulations

Like prior researchers, we run the models with specific values for N, K, and C. Since the model is probabilistic and dynamic, many runs are needed to ensure the significance of results (~15,000 runs). The simulations were coded in MATLAB 7. In the Appendix, Table A1 summarizes and describes the parameters used in the model, and Tables A2 and A3 report on robustness.

We represent two types of entrants—diversifying entrants with high decision interdependence ($K_{divers}=5$) and start-ups with low decision interdependence ($K_{start\text{-}up} = 2$). The length of the decision vector is set to $N = 10$. Each firm represents a cohort of identical firms that are assumed to move through the landscape in unison as if performing local search.

To accommodate learning during the later simulations while enabling model comparisons, we run all the models with two types, but four firms; two firms of each type are identical. In the learning version of the model, we require four firms to model two types of firms and two entry periods: early and late. Although we could simulate the turbulence effects model using only two firms (one of each type), the relationship between the particular parameters chosen and the model dynamics may not be informative for the extended version of the model. As we briefly discuss below, the turbulence is a function of the number of firms present, not only of the level of interfirm coupling C. Thus, we chose to keep the number of firms constant at four as a way of controlling for "industry size" and focusing solely on the effects of C and K. The firms are assumed to occupy different segments of the industry and to interact through some of their decisions. The level of interfirm coupling is controlled by the parameter C. Firms 1 and 3 (both $K_{\text{start-up}}= 2$) and firms 2 and 4 (both $K_{\text{divers}}= 5$) have the same level of internal coupling. To eliminate possible biases associated with order in which firms search for their local peaks, we randomize this order in each step.

Baseline Simulations

Firms enter with random decision vectors and random interaction matrices and adapt through local search after they enter. We obtained results by performing 15,000 runs of the model, wherein all randomized variables, including the NKC landscape, are redrawn for each run. Figures 1-4 provide four sets of information regarding the model dynamics. Figure 1 shows the mean absolute performance for the two different firm types (the lines always show the mean performance of the two firms of the same type). Figure 2 provides the variance of absolute performance across the simulation runs. Figure 3 reports the level of turbulence that each type of firm faces, and Figure 4 provides information on the frequency of adaptation or change.[9]

As for the main effects discussed above, we observe here that several patterns hold regardless of the level of C. Figure 1 shows that *diversifying entrants always outperform start-ups initially*. Because of the diversifying entrants' higher internal coupling, their problem space is more rugged and the slopes are steeper. The initial performance improvements are thus greater for them. The performance variance diagram (Figure 2) shows that the *variance of performance is significantly higher for the start-ups* (note that the variance in mean performance reflects the significance level for the given number of runs and is close to zero). The less coupled start-ups exhibit higher risk, given more frequent changes (Figure 4). Both types of firms change and adapt optimally conditional on the myopic nature of their search (which is identical for both types of firms) and the level of intrafirm coupling (which is different for the two types). However, the less constrained *start-ups find it optimal to change and adapt more*—regardless of the value of C. The degree of change and adaptation is thus endogenous to the nature of the landscapes faced by each firm.[10] The diversifying entrants also face greater turbulence, since they compete with firms that change more (Figures 3 and 4). It is also interesting to note that the performance differentials are small relative to the absolute performance values. This outcome is related to the probabilistic nature of the framework and is a general feature of many NK models. It perhaps reveals the fact that relative differences between winners and losers in evolution are rather small compared to their absolute fitness.

[Insert Figures 1-4 about here]

Effect of Turbulence

We proceed by varying the level of C.[11] When C = 1, firms operate on almost separate landscapes, resulting in low turbulence and minimal impact of the decisions of other firms on the shape of the landscape facing each firm. In this environment of relatively stationary peaks, firms can climb peaks effectively. As seen in Figure 1, while diversifying entrants have an initial lead, start-ups eventually achieve higher performance owing to their higher adaptation and potential—the average peak on the landscape of a start-up is greater than that on the landscape of a diversifying entrant. However, it takes more steps for the start-up to discover its peak because it occupies a smoother space with flatter slopes. Over time, turbulence decreases and converges to zero (Figure 3).

When the level of interfirm coupling increases to C = 7, the firms face dynamic landscapes. The decision of any one firm affects the performance contribution of the decisions of the other firms. In such an environment, the firms sometimes "chase chimeras," since before they can discover how to climb a peak and solve the problem, the landscape changes its shape—the peaks become valleys and vice-versa—and the problem changes into a new one. On average, the firms are much further from the peaks than they are in the more stable environments depicted by C = 1. In such a situation, diversifying entrants fare better, and the start-ups can match their performance only much later. For the diversifying entrants, the higher interdependence of their decisions partially locks them in and allows them to get closer to the peaks along less constrained variables. The start-ups need to perform more steps because they need to climb flatter slopes than the diversifying entrants to reach their (albeit on average higher) peaks. The start-ups attempt to adapt excessively to any environmental change since it is myopically optimal to do so. However, the problem changes before they can exploit it, causing them, on average, to be positioned farther from the peaks. The performance achieved by all firms also converges to a lower value than in the C =1 case. Although the additional interactions favor diversifying entrants over start-ups, the interactions prevent the firms from climbing to their highest peaks. The interaction and turbulence destroy some adaptation in the industry that would otherwise be achieved through local search. The performance variance again decreases with simulation time but converges to a higher value. It is also notable that the higher level of interfirm coupling dramatically shifts the level of turbulence upward; though it decreases over time, it does not approach zero within the simulation time frame. The model's prediction is consistent with the conventional wisdom that change and environmental turbulence go hand-in-hand, since both types of firms respond to the greater turbulence by adapting more; however, the start-ups again exhibit a higher degree of change. The lower frequency of change for the diversifying entrants provides a performance benefit in more turbulent environments.

In our third case, we model stronger firm interdependence with C = 9, representing a highly coupled, turbulent environment in which individual firms' landscapes shift rapidly and their abilities to optimize are seriously compromised. The diversifying entrants continue to outperform start-ups, though both types of firms find their performance to be adversely affected by the higher turbulence. The patterns of variance, turbulence, and adaptation are consistent with the C =7 case, but much more pronounced.

Our model thus shows that *a decrease in interfirm coupling favors entrepreneurial start-ups in the long run*. Specifically, we find that diversifying entrants—who tend to undertake organizational changes less frequently than start-ups —perform persistently better when the environment is more turbulent. Accordingly, we have:

Proposition 1: The likelihood of entrepreneurial start-ups outperforming diversifying entrants in the long run decreases with the level of interfirm coupling (or degree of environmental turbulence).

We note that environmental turbulence is also a function of the interplay between the intrafirm (K) and interfirm coupling (C). Consider the case of C = 7 and an increase in the internal coupling K of the diversifying entrants from (K_{divers}= 5) to (K_{divers}= 6). This interplay causes the diversifying entrants to achieve higher performance. However, as a consequence of fewer organizational changes by the diversifying entrants (K_{divers}= 5), the environment facing the start-ups ($K_{start\text{-}up}$= 2) is also stabilized. Notably, the start-ups benefit more, with the performance differential increasing and the tipping point shifting to the left (by 12 periods; see Table A2). This highlights the fact that an increase in internal complexity as a response to environmental turbulence may help increase performance, but may also disproportionately benefit less coupled firms. As with the decrease in C above, the increase in K allows achieving a better fit in turbulent environments at the price of being overtaken by less coupled firms sooner. A similar situation emerges when we increase the internal coupling of the start-ups ($K_{start\text{-}up}$= 3). They benefit and achieve higher fit than in the case above ($K_{start\text{-}up}$= 2), but the diversifying entrants (K_{divers}= 5) benefit as well. The increase in the coupling of start-ups as a response to environmental turbulence is beneficial in the short term for start-ups, but their performance differential with diversifying firms (K_{divers}=5) decreases. Furthermore, all firms achieve higher performance than in the above cases ($K_{start\text{-}up}$= 2, K_{divers}= 5 & $K_{start\text{-}up}$= 2, K_{divers}= 6), and the tipping point shifts to an earlier period (period 17 as opposed to 20) than when $K_{start\text{-}up}$= 2, K_{divers}= 6. The internal coupling is now better distributed collectively, with both types of firms changing less, making the environment more stable and allowing the firms to get closer to their local optima.

Finally, since the number of firms can also drive turbulence, we experimented with sequential firm entry. With interfirm coupling C held constant, an increase in the number of firms activates more links and increases turbulence. A sufficient increase in the number of firms causes a reversal of performance advantage from start-ups to diversifying entrants.

Modeling Late Entry and the Effect of Learning

We model late entry by choosing C =7 and late entry period t = 35.[12] In the period 35 of the simulation, entrants (one of each type) replace two of the four incumbent firms. We report the robustness of the model in Table A3.

Figure 5 provides information on the mean fitness of each of the four types of firms represented by the interaction of timing of entry and pre-entry experience, under the three learning conditions. For the no learning (random innovation) case, firms that enter late do not capture any of the external knowledge, since both start-ups ($K_{\text{start-up}}= 2$) and diversifying entrants ($K_{\text{divers}}= 5$) generate their interaction matrices and initial decision vectors at random. Not surprisingly, the converged values are similar to the results in Figure 1. The performance of late entrants with random entry replicates the performance pattern of early entrants. However, late entrants are disadvantaged by their delay in entry and have a lower performance than the early entrants.

[Insert Figure 5 about here]

In the moderate learning algorithm, the performance patterns depicted in Figure 5 deviate from the baseline case depicted in Figure 1. The performance of the late start-up entrant converges to a significantly higher value than that of the late diversifying entrant. Choosing from multiple entry options permits the late start-up to enter in a significantly improved initial position than in the random entry case. On the other hand, the late diversifying firm is not able to fully capitalize on the available stock of knowledge and ends up as the poorest performer. We note that this occurs despite the fact that both types of entrants evaluated the same mix of pre-entry options. *The implication is that the additional internal coupling of the late diversifying entrant resulted in a situation in which it was not optimal for this entrant to fully internalize and incorporate the information available through the learning options.* To establish the argument further, we examine the performance of the late entrants utilizing the strong learning algorithm. Remarkably, the gap between the late diversifying and late start-up entrant is much wider than the gap under moderate learning. Facing a less coupled internal environment, the late start-up is able to capitalize on the improved learning mechanism and gain a stronger lead.

Our results also show that the late start-up becomes the best performer in the strong learning case. The late diversifying entrant is either the worst, or better than the early diversifying entrant. The ordering between the early and late entrants is thus sensitive to the learning algorithm employed. Additional simulations have shown that if we make the late entrants even more powerful, the late diversifying entrants also outperform both types of early entrants. However, the *increase in* *learning differentially favors the late start-up* and, with sufficiently strong learning, it is likely to become the best performer. Increase in learning strength thus has the opposite effect of increase in interfirm coupling. Therefore, we can put forward our next propositions:

Proposition 2: If learning from a prior stock of external knowledge is possible, entrepreneurial start-ups will outperform diversifying entrants.

Proposition3: The likelihood of entrepreneurial start-ups outperforming diversifying entrants (among late entrants) increases with the strength of the learning mechanisms the entrants can employ.

Proposition 4: The performance ordering between the early and late entrants will depend on the strength of the learning mechanisms employed by the late entrants. With sufficiently strong learning, the late entrepreneurial start-ups are likely to become the best-performing cohort.

Robustness Analysis

To investigate the sensitivity of our results to the parameter space, we ran simulations for multiple parameter value combinations of K, C, and $\varkappa$. We report a representative subset of these simulations in the appendix (see Tables A2 and A3). The observed patterns are consistent with our model predictions with one boundary condition. For very low values of K (e.g., $K_{\text{divers}}= 2$, $K_{\text{start-up}}= 1$), diversifying firms outperform start-ups even when C is very low (e.g., $C = 0$). This exception relates to the underlying property of the NK landscape implying that for low values of C, the relationship between K and the payoff values takes an inverted U-shape. As depicted in Figure A2, the payoffs peak at around $K = 3$ for local search and $N = 10$, $C = 0$. For our analysis, the implication is that for $K < 3$, diversifying entrants have a universal advantage over start-ups, since the payoff values are increasing in K up to this point.

Our learning algorithm specification relies on completely probabilistic structure of the NKC model without explicitly modeling similarity between the sublandscapes of the individual firms (e.g., Gavetti, 2005). The learning algorithm can be thus seen as a way of considering multiple options before entering, with random innovation and the imitated decision vector having equal likelihoods of success. Modeling similarity may generate additional insights but would not change our propositions, which are related to very fundamental properties of the NKC model. As additional checks, we considered several alternative mixes of learning algorithms; for example, we varied learning strength, dimension which is being strengthened in the strong version of learning as well as assumed that late entrants could learn from exiting incumbents, from incumbents of both types, or only from the opposite type; all yielded identical performance dynamics.

Our model explicitly excluded the effect of population variance and selection on performance. Per March (1991), while only mean performance matters when comparing a random diversifying entrant to a random start-up, when comparing the *best* firms in each population with each other, variance grows in importance as the number of firms increases. To illuminate this problem more formally, we grouped the results of independent simulation runs into populations and then selected best performers within each group. As in March (1991), greater variance of the start-ups has a positive impact on the ranking of extreme performers of this group vis-à-vis the diversifying entrant population, and such benefit increases with population size. However, we found that, consistently with Proposition 1, an increase in C always causes a reduction in the performance of start-ups relative to that of diversifying entrants. Since the variance of start-ups exceeds the variance of diversifying entrants, measuring performance using best performers shifts the tipping point in favor of the start-ups, but it is unlikely to change the qualitative predictions of our model. As March (1991) pointed out, one needs to incorporate variance explicitly when the model mechanics affect the variance. In our model, exogenous coupling drives variance.

The notion of selection is closely related. Many underperforming firms are selected out before they can match and overtake the better performers. If selection operates strongly on the lower tail of the distribution, the higher variance is both a blessing and a curse for the start-ups. It shifts the tipping point to the left, but only for the surviving start-ups. Since their lower tail is thicker than that of the diversifying entrants, start-ups have higher hazard rates, consistent with empirical literature (e.g., Carroll & Khessina, 2007). Importantly, we found that across population sizes, the performance of the best start-ups temporarily fell short of the performance of the best diversifying entrants. This suggests that the mean is informative about the differences between the two types of firms. Although incorporation of both variance and selection likely affects the tipping points, the qualitative effects of C and the different types of learning are likely to remain unchanged.[13]

DISCUSSION AND CONCLUSION

Strategy, organizational studies, and entrepreneurship scholars have all emphasized the importance of studying how firm characteristics at the time of an industry entry may have enduring effects on performance, and pre-entry experience has been identified as a critical determinant of firm success. However, the empirical evidence on performance differentials between entrepreneurial start-ups and diversifying entrants is mixed, partly because of trade-offs in the theoretical mechanisms that underlie such differentials. The overarching question in this paper is whether contingent conditions can switch the performance advantage from diversifying entrants to start-ups. Using an NKC model, we highlighted industry turbulence and life cycle stages as contingencies that may explain the performance differentials.

Our model predictions conform to the empirical patterns established in the literature and, importantly, provide a potential rationale for the contrary findings identified in the literature review section (Table 1). Our model replicates the unequivocal empirical finding that diversifying entrants have a short-run performance advantage (Agarwal, 2001; Carroll *et al.*, 1996; Klepper & Simons, 2000; Klepper, 2002a, b; Mitchell, 1991). Further, in keeping with studies of organizational change (Haveman, 1992, Sastry, 1997, Sine *et al.*, 2006) and organizational ecology (e.g. Aldrich, 1990; Brittain & Freeman, 1980; Hannan & Freeman, 1977), the model predicts that organizational change in response to environmental shifts is not always beneficial. In line with Khessina (2002) and Khessina and Carroll (2007), our model predicts that start-ups change more frequently and face greater performance variance.

Importantly, the model also provides an answer for how environmental turbulence impacts the performance differential between start-ups and diversifying entrants. The main effect of turbulence is detrimental to firm performance for both types of entrants, yet increases in turbulence advantage diversifying entrants over start-ups. Even though both types of entrants adapt more frequently in more turbulent environments, the effect is stronger for diversifying entrants, consistent with studies emphasizing that moderate levels of structures are best in dynamic markets (Brown & Eisenhardt, 1997). Diversifying entrants, by definition, have exhibited the ability to adapt to new market opportunities by entering a new industry, and our model highlights that in more turbulent environments, their coupling provides them with additional stability benefits that the less coupled entrepreneurial start-ups lack. Thus, for instance, when diversifying entrants had access to the accumulated process innovation in related industries, the coupling provided long-term benefits, which may have played an important role in some industries like television and penicillin (Klepper & Simons, 2000). Similarly, Mitchell's (1991) finding of diversifying entrant advantage due to strong complementary assets may be linked to the beneficial effects of coupling in turbulent industries.

Our model also provides a potential resolution to the conflicting findings on performance differentials due to pre-entry experience based on timing of entry. The key question that we answer is whether the ability to learn from established industry-specific knowledge advantages start-ups over diversifying entrants. Our model predicts that this is indeed the case: diversifying entrants retain their long-term advantage in industry environments in which knowledge spillovers are constrained and learning is limited. This may explain why diversifying entrants in the television receiver industry (Klepper & Simons, 2000) and in new markets of medical diagnostic imaging (Mitchell, 1991) enjoyed a "dominance by birthright." In other industry contexts, start-ups may benefit from some learning potential, resulting in the observed convergence of performance between the two types of firms in the automobile and tire industries (Carroll *et al.* 1996; Klepper 2002a). Importantly, our model predicts that later-stage start-ups can outperform early-stage diversifying entrants in instances of high learning potential. This prediction is consistent with the empirical evidence from industries where employee mobility and entrepreneurship have been identified as critical for learning (e.g., Agarwal *et al.*, 2004; Klepper & Sleeper, 2005).[14] We note that an important condition for such a reversal is that the mature stages of the industry have low to moderate levels of turbulence. High turbulence implies that the landscape changes rapidly, thus reducing the value and usefulness of learning. If an environment is persistently turbulent as a result of denser interfirm linkages, the usefulness of the learning algorithm rapidly deteriorates.[15]

Limitations and Future Research

Our study has several limitations. We assumed that interfirm coupling (C) and the interdependence of internal firm decisions (K) are exogenous and constant throughout the simulation. It is possible that, with the establishment of a dominant design and a shift from product to process innovation (Anderson & Tushman, 1990; Gort & Klepper, 1982), some decisions across firms are decoupled, or that technological intensity decreases as an industry matures. Firms may also become more internally coupled as a response to an initially turbulent environment and as a way to manage their growth. Aside from unforeseen interactions, such dynamics should magnify the proposed effects; both the decrease in C and the increase in K of incumbents will lead to a stronger effect of learning, with more positive benefits accruing to less coupled firms. Further, our assumption that a firm's size and the niche width it faces are constant puts more emphasis on the positive aspects of interfirm interactions.[16] Similarly, the assumption of fixed industry size (i.e. holding demand constant) translates into lower performance of all firms in a turbulent environment.[17]

In addition to the avenues for future research that the limitations of our study open, several fruitful possibilities stem from our results. For instance, future in-depth examination of the relative importance of learning for late entrants and of the contingencies that impact this relationship is needed. Further, the implication of our model that the performance differential between the late start-ups and late diversifying entrants should be larger in industries where learning is easy—in industries with weak protection of intellectual property rights and frequent employee mobility—merits empirical investigation. The study may also stimulate more studies on the long-term performance effects of pre-entry firm characteristics through its emphasis on contingencies.

Contributions

Multiple research streams have examined the question of whether pre-entry experience results in persistent differences in performance. The findings have been mixed. Strategy scholars have found support for diversifying entrant advantages (Klepper & Simons 2000; Mitchell 1991); entrepreneurship scholars have shown performance benefits for start-ups (Cooper *et al.,* 1986; Levitt

& March 1988; Levinthal & March 1993; March 1991); and organizational ecologists have found convergence in long-run advantage (Carroll *et al.*, 1996; Hannan *et al.*, 1998). We contribute to these literature streams by specifying the contingencies in the performance differentials due to pre-entry experience. Our modeling approach allows us to abstract from resource endowment differences and focus on the trade-offs that result from differences in the underlying structures of the two types of firms (Hannan & Freeman, 1984). Further, our study explicitly brings the notion of learning from an external stock of knowledge into the discussion on entry. Late start-ups can overcome the disadvantage due to lack of their own pre-history (Helfat & Lieberman, 2002) by tapping industry-specific stock of knowledge. Thus, our study highlights the potential compensation for internal lack of knowledge by external sources.

The paper also contributes to the literature on NK modeling. To our knowledge, this is the first simulation study that utilizes the co-evolutionary NKC model to show industry evolution with strategic firm interaction. Our work is similar in spirit to Sorenson's empirical work (1997, 2003) on the relationship between vertical integration and performance contingent on environmental turbulence. Sorenson tested Kauffman's (1995) original predictions by assuming that vertically integrated firms are more complex. Though the context is different, our paper contributes by refining the theory used in the empirical studies.

Finally, our model contributes to the organizational ecology literature (Britain & Freeman, 1980; Hannan & Freeman, 1977) by building a model of the dynamics between generalists and specialists using different primitives (coupling in our model versus niche width in the organizational ecology literature) and modeling factors like inertia and change as endogenous to the level of coupling. If one assumes that links in the NK model are analogous to intricacy in models of cascading organizational change (Hannan *et al.*, 2003a, b), we contribute to this stream of organizational ecology by emphasizing the benefits of intricacy.

In conclusion, the purpose of our study is to refine the theory of industry evolution through application of a complexity simulation model. We provide a framework that helps to explain the mixed empirical evidence on the performance differentials between diversifying and start-up industry entrants. Our approach emphasizes the roles of environmental turbulence and learning potential in later stages of the industry life cycle as potential contingency factors. Our model highlights that the relative success of entrants depends on their ability to capture prior knowledge, the strength of intrafirm linkages, and the strength of firms' interactions. Although industry turbulence favors diversifying entrants, start-ups can capture greater benefits from accumulated industry-specific knowledge. Thus, the relative performance of firms based on pre-entry experience is conditional on the environmental conditions that favor particular underlying mechanisms over others.

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[1] The generalism/specialism dichotomy does not map precisely to diversifying/start-up entrants since both entrants may compete in a same-width niche in the focal industry. The comparison is applicable, though, to the extent that diversifying entrants can be thought of as occupying a wider range of activities than the focal industry alone.

[2] Kauffman (1993, 1995) uses a uniform [0,1] distribution for the draws. Our use of a standard normal distribution—for computational reasons and to better represent economic payoffs where unusually high and low payoffs are very unlikely—has no qualitative effect on the results (it does not change ordering) and is asymptotically (for large K) equivalent to the uniform distribution due to the central limit theorem.

[3] Our assumption is that on average imprinting lasts and that most firms retain their initial characteristics until their failure.

[4] This is analogous to the discussion of K in Rivkin (2000), who describes the difference between Milgrom and Roberts's (1990) definition of "complementarity" and the notion of interactions in the NK models.

[5] Advertising intensity can be seen as a proxy for product differentiation.

[6] Our results should not change substantially if we instead assumed that late entrants entered at random positions and then vicariously learned along the way. However, our assumption makes the analysis more transparent and facilitates discerning the effects of learning.

[7] In case of random late entry, the entry decision vector as well as the interaction matrix is randomly generated.

[8] The dimension along which the late entrants are more powerful is arbitrary (see the robustness section).

[9] The turbulence is calculated as the mean number of decision payoff components π_i that are redrawn as a result of the moves of other firms (up to N components may be redrawn in each step). When calculating the payoff values that change, we hold the position of the focal firm fixed and calculate it after all other firms make their moves— i.e., this turbulence measure captures the effect of changes in the coupled decisions. The frequency of adaptation is calculated as the mean number of decision changes at a given step over all runs. Within each run the adaptation is coded 1 when the agent changes the decision at time $t + 1$ compared to t (the measure starts at time period 2). Both turbulence and adaptation measures are averaged over all 15,000 simulation runs.

[10] We are grateful to the special issue editor for helping us frame the model.

[11] The parameter $\varkappa$ is set to 2 for all runs. In Table A2 we show results of robustness testing.

[12] We assume that mature industries are not in the most turbulent regime. As Figure 4 shows, the level of turbulence decreases over time even for a constant C. The model at the time of late entry represents an industry where initial peak turbulence has diminished and accumulated pertinent knowledge that the new entrants can exploit is present.

[13] Whether the points would shift to the left or right depends on the number of factors such as the strength of selection pressures, population sizes, and the speed of selection relative to adaptation.

[14] Additional effects not currently modeled that may affect performance differentials between the early versus late entrants by favoring early entry are the increasing returns associated with the technological adoption.

[15] For instance, when we model the case of C = 9 and a moderate-strength learning algorithm, the ability of late entrants to learn does not help. The effect of turbulence overpowers the effect of learning, and the competencies are quickly destroyed. Although the late entrants enter at positions better than in the random entry case, their advantage is not built upon. Only the relative stability arising from internal coupling matters, and the diversifying entrants dominate.

[16] We note, however, that although our prediction that diversifying entrants always outperform start-ups in the short run can be explained by size (or resource endowment) differences, such differences do not explain why start-ups outperform diversifying entrants in less turbulent environments—it is theoretically unclear why endowment effects are conditional on environmental conditions without resorting to coupling.

[17] If demand sufficiently increases with turbulence, turbulence and performance may correlate positively.

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APPENDIX

TABLE A1: NKC MODEL PARAMETER AND ASSUMPTIONS SUMMARY

Parameter	Description	Value used in text	Underlying assumptions	Robustness Tested	Possible empirical proxies
N	Problem size (number of decision elements)	10	Fixed firm size, fixed resources	10	Patent based measures (Fleming and Sorenson, 2001), firm size (crude proxy)
K	Number of linkages within a firm landscape (for each row of the interaction matrix), Randomly distributed within interaction matrix	$K_{start-up}=2$ $K_{divers.}=5$	Diversifying entrants are relatively more coupled internally. The differences in coupling are persistent and easy adjustment or imitation is not possible.	0-9 (all combinations for differences of 0 to 4 between the K of start-up and divers.)	Patent based measures (Fleming and Sorenson, 2001), product design matrix (Rivkin and Siggelkow, 2007), vertical integration (Sorenson, 1997)
C, $\varkappa$	Number of linkages across firm landscapes (C is the number of rows in the C matrix with linkages and $\varkappa$ is the number of interactions in each row of the C matrix). Randomly distributed within the relevant partition of the C matrix. All firms linked to each other	C=1,7, 9 $\varkappa=2$	Fixed structural characteristics of an industry determine the inter-firm coupling.	C: 0-10 $\varkappa$: 2,3	Technological intensity, Capital intensity and potential for product differentiation (Schmalensee, 1989)
S	Number of firms	4	Fixed industry size	4	Industry size
Number of periods	To observe performance differentials. Number of firms “walking” at the end ranges from 0% to 60% depending mainly on K and C.	50, 100	Performance not measured in the “infinite” time limit. Firms face real time constraints when operating in dynamic environments.	15-150	
Simulation runs	To obtain 1% significance for the mean.	15,000	Mean is informative of the qualitative performance differentials	15,000~20,000	
Nature of search	Local search post-entry. Random entry vs. pre-entry learning with different strength. Constant optimization speed (number of adaptation attempts) and no selection.	Random entry, moderate and strong learning	Firms have the opportunity to sample information from the environment in mature industries.	Different sources of information, different entry periods, different mixes for the learning algorithm	Intellectual property regime, prevalence of employee mobility, etc.

TABLE A2: MODEL ROBUSTNESS: EFFECT OF TURBULENCE

C = 0	**HK-LK=2**								**HK-LK=3**								**HK-LK=4**					
K	1	3	3	5	5	7	7	9	0	3	2	5	4	7	6	9	0	4	2	6	4	8
Period 1 (perf.)	0.08	0.10	0.10	0.12	0.12	0.14	0.14	0.15	0.06	0.10	0.09	0.12	0.11	0.14	0.13	0.15	0.06	0.11	0.09	0.13	0.11	0.15
Period 5	0.29	0.35	0.35	0.37	0.37	0.37	0.37	0.35	0.23	0.35	0.32	0.37	0.36	0.36	0.37	0.35	0.23	0.36	0.33	0.37	0.36	0.36
Period 50	0.65	0.70	0.70	0.66	0.66	0.60	0.60	0.53	0.56	0.70	0.69	0.66	0.68	0.60	0.63	0.53	0.56	0.68	0.69	0.63	0.68	0.57
Tipping point	>50	>50	11	11	6	6	3	3	>50	>50	16	16	6	6	4	4	>50	>50	12	12	6	6
Still Walking 1	1%	1%	1%	0%	1%	0%	0%	0%	0%	1%	1%	1%	1%	0%	0%	0%	0%	1%	1%	0%	1%	0%
Still Walking 3	2%	2%	2%	2%	2%	1%	1%	1%	1%	2%	3%	2%	2%	1%	1%	1%	1%	2%	2%	1%	2%	1%
C = 7	**HK-LK=2**								**HK-LK=3**								**HK-LK=4**					
K	1	3	3	5	5	7	7	9	0	3	2	5	4	7	6	9	0	4	2	6	4	8
Period 1 (perf.)	0.06	0.09	0.09	0.11	0.11	0.13	0.13	0.15	0.04	0.09	0.08	0.11	0.10	0.13	0.12	0.15	0.04	0.10	0.07	0.12	0.10	0.14
Period 5	0.20	0.25	0.26	0.28	0.28	0.29	0.30	0.29	0.15	0.25	0.24	0.28	0.28	0.29	0.29	0.29	0.15	0.26	0.24	0.28	0.28	0.29
Period 50	0.37	0.41	0.45	0.44	0.48	0.45	0.49	0.45	0.29	0.39	0.41	0.41	0.48	0.44	0.50	0.44	0.30	0.40	0.44	0.42	0.49	0.43
Tipping point	>50	>50	17	17	7	7	4	4	>50	>50	32	32	9	9	5	5	>50	>50	20	20	8	8
Still Walking 1	24%	24%	20%	18%	14%	13%	9%	8%	24%	25%	23%	20%	16%	14%	11%	9%	24%	23%	21%	18%	15%	13%
Still Walking 3	55%	53%	45%	42%	33%	30%	23%	21%	56%	56%	51%	46%	37%	33%	26%	23%	55%	52%	48%	41%	36%	30%
C = 10	**HK-LK=2**								**HK-LK=3**								**HK-LK=4**					
K	1	3	3	5	5	7	7	9	0	3	2	5	4	7	6	9	0	4	2	6	4	8
Period 1 (perf.)	0.05	0.08	0.08	0.11	0.10	0.12	0.13	0.14	0.03	0.08	0.07	0.11	0.10	0.13	0.11	0.14	0.03	0.10	0.07	0.12	0.09	0.13
Period 5	0.16	0.20	0.21	0.23	0.24	0.25	0.26	0.26	0.12	0.20	0.19	0.23	0.23	0.25	0.25	0.26	0.12	0.22	0.19	0.24	0.23	0.25
Period 50	0.20	0.24	0.26	0.28	0.31	0.31	0.35	0.33	0.15	0.24	0.24	0.27	0.30	0.30	0.34	0.32	0.16	0.25	0.25	0.28	0.31	0.30
Tipping point	>50	>50	>50	>50	14	14	5	5	>50	>50	>50	>50	>50	>50	7	7	>50	>50	>50	>50	15	15
Still Walking 1	37%	35%	33%	31%	28%	26%	21%	20%	38%	36%	35%	31%	30%	27%	23%	21%	38%	33%	34%	30%	29%	25%
Still Walking 3	73%	70%	67%	64%	58%	54%	47%	44%	75%	71%	70%	64%	62%	57%	50%	46%	74%	68%	70%	63%	61%	54%
K = 2, 5	**ϰ = 2**												**ϰ =3**									
C	0		2		4		6		8		10		2		4		6		8		10	
K	2	5	2	5	2	5	2	5	2	5	2	5	2	5	2	5	2	5	2	5	2	5
Period 1 (perf.)	0.09	0.12	0.09	0.12	0.08	0.12	0.08	0.11	0.08	0.11	0.07	0.11	0.09	0.12	0.08	0.12	0.07	0.11	0.07	0.10	0.06	0.10
Period 5	0.32	0.37	0.31	0.34	0.28	0.32	0.25	0.29	0.22	0.26	0.19	0.23	0.31	0.35	0.27	0.31	0.23	0.27	0.19	0.23	0.14	0.18
Period 50	0.69	0.66	0.67	0.64	0.60	0.59	0.49	0.48	0.36	0.37	0.24	0.27	0.67	0.65	0.57	0.55	0.42	0.42	0.28	0.29	0.16	0.20
Tipping period	16	16	16	16	17	17	24	24	>50	>50	>50	>50	16	16	20	20	23	23	>50	>50	>50	>50
Still Walking 1	1%	1%	3%	3%	9%	8%	16%	14%	26%	24%	35%	31%	3%	3%	12%	10%	22%	20%	33%	30%	41%	38%
Still Walking 3	3%	2%	9%	8%	23%	20%	40%	35%	57%	52%	70%	65%	9%	7%	29%	25%	50%	46%	66%	62%	77%	73%

Note: the measures Still Walking 1(3) were calculated as the proportion of runs where the agent moved in the last 1(3) periods.

TABLE A3: LATE ENTRY MODEL ROBUSTNESS

Vary K, Fixed C=0 (entry=35)	**HK-LK=1**									**HK-LK=3**								
K$_{\text{start-up}}$, K$_{\text{divers.}}$	0,1			4,5			8,9			0,3			3,6			6,9		
Type of learning (rand, weak, strong)	R	W	S.	R	W	S	R	W	S	R	W	S	R	W	S	R	W	S
Late$_{\text{start-up}}$-Late$_{\text{divers}}$ (period 35)	-0.02	-0.18	-0.34	-0.01	0.00	0.01	-0.01	0.11	0.22	-0.05	-0.20	-0.35	-0.03	0.01	0.02	-0.02	0.12	0.25
Late$_{\text{start-up}}$-Late$_{\text{divers}}$ (period 40)	-0.06	-0.18	-0.31	0.00	0.01	0.02	0.01	0.07	0.15	-0.12	-0.19	-0.30	-0.02	0.03	0.05	0.02	0.10	0.19
Late$_{\text{start-up}}$-Late$_{\text{divers}}$ (period 100)	-0.09	-0.17	-0.27	0.02	0.03	0.03	0.03	0.05	0.09	-0.14	-0.19	-0.24	0.07	0.09	0.10	0.10	0.12	0.16
Late$_{\text{start-up}}$ > Late$_{\text{divers}}$ (period)	>100	>100	>100	43	36	36	39	36	36	>100	>100	>100	44	36	36	39	36	36
Late$_{\text{start-up}}$ > Early$_{\text{start-up}}$ (period)	99	88	>100	>100	60	45	98	55	40	>100	>100	>100	>100	57	44	98	62	43
Late$_{\text{start-up}}$ > Early$_{\text{divers}}$ (period)	>100	>100	>100	70	53	42	58	46	37	>100	>100	>100	60	47	39	50	42	36
Still Walking 3 (mean)	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Vary K, Fixed C=7 (entry=35)	**HK-LK=1**									**HK-LK=3**								
K$_{\text{start-up}}$, K$_{\text{divers.}}$	0,1			4,5			8,9			0,3			3,6			6,9		
Type of learning (rand, weak, strong)	R	W	S	R	W	S	R	W	S	R	W	S	R	W	S	R	W	S
Late$_{\text{start-up}}$-Late$_{\text{divers}}$ (period 35)	-0.02	-0.09	-0.16	-0.01	0.00	0.00	-0.01	0.03	0.06	-0.05	-0.12	-0.17	-0.03	-0.02	0.00	-0.03	0.03	0.08
Late$_{\text{start-up}}$-Late$_{\text{divers}}$ (period 40)	-0.05	-0.09	-0.12	-0.01	0.00	0.00	0.01	0.02	0.03	-0.10	-0.12	-0.14	-0.02	0.00	0.02	0.01	0.03	0.06
Late$_{\text{start-up}}$-Late$_{\text{divers}}$ (period 100)	-0.05	-0.07	-0.11	0.01	0.01	0.01	0.02	0.03	0.03	-0.09	-0.11	-0.11	0.03	0.04	0.04	0.06	0.07	0.07
Late$_{\text{start-up}}$ > Late$_{\text{divers}}$ (period)	>100	>100	>100	46	41	38	38	36	36	>100	>100	>100	48	42	38	40	36	36
Late$_{\text{start-up}}$ > Early$_{\text{start-up}}$ (period)	66	70	70	>100	81	36	>100	93	36	70	70	66	>100	72	36	>100	>100	36
Late$_{\text{start-up}}$ > Early$_{\text{divers}}$ (period)	>100	>100	>100	75	54	36	54	44	36	>100	>100	>100	59	44	36	44	39	36
Still Walking 3 (mean)	59%	59%	58%	37%	37%	37%	16%	15%	15%	55%	55%	55%	39%	38%	38%	21%	20%	20%
Vary K, Fixed C=10 (ent.=35)	**HK-LK=1**									**HK-LK=3**								
K$_{\text{start-up}}$, K$_{\text{divers.}}$	0,1			4,5			8,9			0,3			3,6			6,9		
Type of learning (rand, weak, strong)	R	W	S	R	W	S	R	W	S	R	W	S	R	W	S	R	W	S
Late$_{\text{start-up}}$-Late$_{\text{divers}}$ (period 35)	-0.01	-0.05	-0.07	-0.01	-0.02	-0.01	-0.01	0.00	0.02	-0.05	-0.08	-0.10	-0.03	-0.03	-0.02	-0.02	-0.01	0.01
Late$_{\text{start-up}}$-Late$_{\text{divers}}$ (period 40)	-0.03	-0.05	-0.05	-0.01	-0.02	0.00	0.00	0.00	0.00	-0.08	-0.09	-0.09	-0.02	-0.02	-0.01	0.00	0.01	0.01
Late$_{\text{start-up}}$-Late$_{\text{divers}}$ (period 100)	-0.04	-0.04	-0.04	0.00	0.00	-0.01	0.02	0.01	0.01	-0.09	-0.09	-0.09	-0.01	-0.01	-0.01	0.02	0.02	0.02
Late$_{\text{start-up}}$ > Late$_{\text{divers}}$ (period)	>100	>100	>100	54	45	40	41	36	36	>100	>100	>100	>100	>100	>100	42	39	36
Late$_{\text{start-up}}$ > Early$_{\text{start-up}}$ (period)	38	36	36	42	36	36	44	36	36	48	36	36	41	36	36	37	36	36
Late$_{\text{start-up}}$ > Early$_{\text{divers}}$ (period)	>100	>100	>100	54	36	36	39	36	36	>100	>100	>100	>100	36	36	43	36	36
Still Walking 3 (mean)	75%	75%	75%	63%	63%	63%	40%	40%	40%	73%	72%	73%	63%	63%	64%	47%	47%	47%
Vary Entry Period and C, K$_{\text{start-up}}$=2, K$_{\text{divers.}}$=5																		
K$_{\text{start-up}}$, K$_{\text{divers.}}$	0,1			4,5			8,9			0,3			3,6			6,9		
Type of learning (rand, weak, strong)	R	W	S	R	W	S	R	W	S	R	W	S	R	W	S	R	W	S
C	0						7						10					
Entry period	15			55			15			55			15			55		
Late$_{\text{start-up}}$-Late$_{\text{divers}}$ (period 35)	-0.04	0.00	0.02	-0.03	0.00	0.02	-0.03	-0.02	-0.01	-0.04	-0.02	-0.01	-0.04	-0.03	-0.02	-0.03	-0.03	-0.03
Late$_{\text{start-up}}$-Late$_{\text{divers}}$ (period 40)	-0.04	0.03	0.05	-0.03	0.02	0.05	-0.03	-0.01	0.00	-0.04	-0.01	0.01	-0.04	-0.04	-0.03	-0.04	-0.04	-0.04
Late$_{\text{start-up}}$-Late$_{\text{divers}}$ (period 100)	0.03	0.06	0.09	0.04	0.06	0.09	0.01	0.02	0.03	0.00	0.01	0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03
Late$_{\text{start-up}}$ > Late$_{\text{divers}}$ (period)	32	16	16	69	56	56	42	26	21	78	69	59	>100	>100	>100	>100	>100	>100
Late$_{\text{start-up}}$ > Early$_{\text{start-up}}$ (period)	>100	26	16	>100	75	63	94	19	16	>100	82	56	19	16	16	63	56	56
Late$_{\text{start-up}}$ > Early$_{\text{divers}}$ (period)	47	24	16	89	70	61	73	32	16	>100	77	60	>100	>100	16	>100	>100	56
Still Walking 3 (mean)	0%	0%	0%	1%	1%	1%	43%	43%	43%	46%	46%	45%	71%	67%	70%	67%	70%	66%

FIGURE A1: INTERACTION MATRICES

NKC Interaction matrix =

$$\begin{bmatrix} NK_{Matrix,Startup\#1} & C_{Matrix} & C_{Matrix} & C_{Matrix} \\ C_{Matrix} & NK_{Matrix,Divers.\#1} & C_{Matrix} & C_{Matrix} \\ C_{Matrix} & C_{Matrix} & NK_{Matrix,Startup\#2} & C_{Matrix} \\ C_{Matrix} & C_{Matrix} & C_{Matrix} & NK_{Matrix,Divers.\#2} \end{bmatrix}$$

Note: The ones in C matrices are randomly distributed within each row of the partition of the size C=7. The off-diagonal elements of the NK matrices are also randomly distributed within each row. The entries in all matrices are drawn independently for each C and NK matrix and each simulation run. The firms search by changing elements within their own matrices.

Example of a $C_{\text{Matrix, N=10, C=7,}\,\kappa=2} =$

$$\left(\begin{array}{ccccccc:ccc} 1 & & & & 1 & & & & & \\ & 1 & & 1 & & & & & & \\ & & & & 1 & & 1 & & & \\ 1 & & & 1 & & & & & & \\ & 1 & 1 & & & & & & & \\ & & & & 1 & & 1 & & & \\ & & 1 & & & & 1 & & & \\ \hdashline & & & & & & & & & \\ & & & & & & & & & \\ & & & & & & & & & \end{array}\right)$$

Example of an $NK_{\text{Matrix, Divers. \#1, N=10, K=5}} =$

$$\begin{pmatrix} 1 & & 1 & & & 1 & 1 & & 1 & 1 \\ & 1 & 1 & & 1 & & 1 & & 1 & 1 \\ & 1 & 1 & & 1 & 1 & & 1 & 1 & \\ 1 & 1 & & 1 & 1 & & 1 & 1 & & \\ & 1 & 1 & & 1 & & 1 & 1 & 1 & \\ 1 & 1 & 1 & & & 1 & 1 & 1 & & \\ & 1 & & 1 & & 1 & 1 & & 1 & 1 \\ 1 & & & 1 & 1 & & 1 & 1 & & 1 \\ & 1 & 1 & 1 & & 1 & & & 1 & 1 \\ 1 & & 1 & & 1 & 1 & & 1 & & 1 \end{pmatrix}$$

FIGURE A2

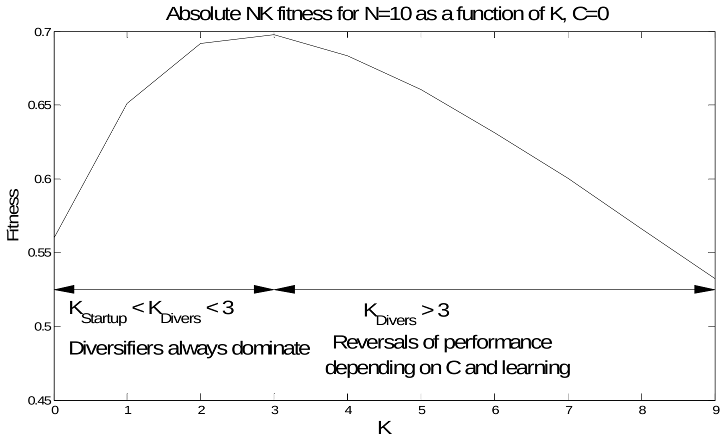

TABLE 1: LITERATURE ON PERFORMANCE DIFFERENTIALS BETWEEN DIVERSIFYING ENTRANTS AND START-UPS

Type of relationship	Performance Measure & Comparison	Best performing entrant type:	
		Diversifying entrants	Start-ups
Main effects	Survival, fitness	Barnett & Freeman (1990), Freeman (1990), Hannan & Freeman (1988) Hannan et al (1998), Klepper & Simons (2000), Rao (1994)	Agarwal, Echambadi, Franco & Sarkar (2004) – for spinouts
		Convergence: Carroll et al (1996), Hannan et al (1998), Khessina & Carrol (2002), Mitchell (1994)	
	Innovativeness (frequent changes – also leads to higher variance and risk)		Carrol & Khessina (2005), Khessina (2002, 2003)
Contingency: Turbulence			
High turbulence (high C)	Survival, fitness	Aldrich (1990), Brittain & Freeman (1980), Hannan & Freeman (1977), Sastry (1997), Sine et al. (2006)*	
Low turbulence (low C)	Survival, fitness		Aldrich (1990), Brittain & Freeman (1980), Hannan & Freeman (1977), Sastry (1997), Sine et al. (2006)*
Contingency: Industry cycle			
Growth stage	Survival, Short-run post entry	Agarwal (1997), Agarwal (2001), Carroll, Bigellow, Seidel & Tsai (1996), Mitchell (1991), Klepper & Simons (2000), Klepper (2002a, b)	
	Survival, Long-run post entry	Klepper & Simons (2000) - in the TV industry	
		Convergence: Carroll, Bigelow, Seidel & Tsai (1996), Klepper (2002a) - in the car and tire industries	
Mature stage	Survival, market share, Late entrants only	Mitchell (1991)	Agarwal (1997), Bayus & Agarwal (2007)
	Survival, market share, Late entrants vs. early entrants	**Early diversifying entrants**: Klepper & Simons (2000) – in the TV industry, Mitchell (1991),	**Late start-ups:** Bryman (1999), Klepper (2002a), Klepper & Sleeper (2005)

Note: To map the findings of the organizational ecology literature onto our categories of diversifying and start-up entrants we assume that diversifying entrants are generalists and start-up firm are specialists. To map the findings of Sine et al (2006) we assume that diversifying entrants have more formal and routinized organizational structure than start-ups. To map the findings of Sastry's simulation model we assume that the firm with more frequent changes corresponds to a start-up.

FIGURE 1

PERFORMANCE MEAN

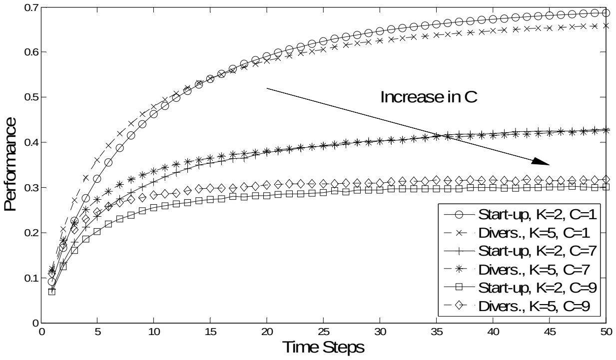

FIGURE 2

PERFORMANCE VARIANCE

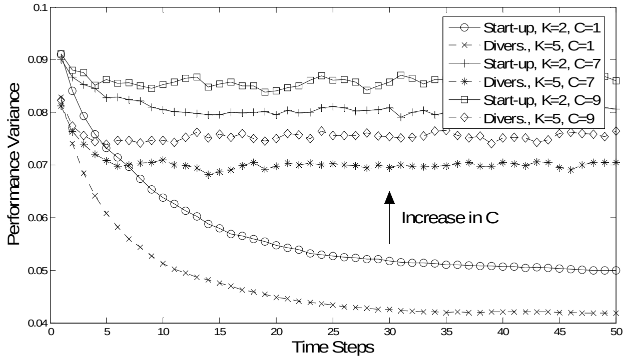

FIGURE 3

LEVEL OF ENVIRONMENTAL TURBULENCE

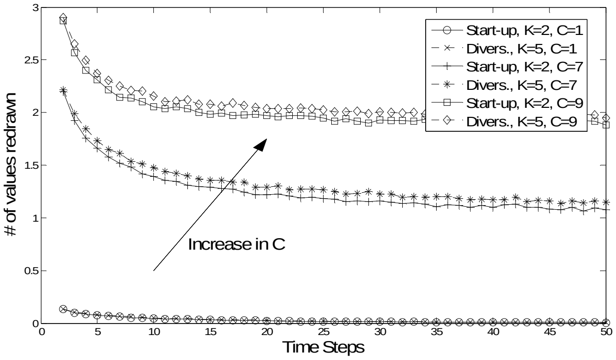

FIGURE 4

PROBABILITY OF ORGANIZATIONAL ADAPTATION

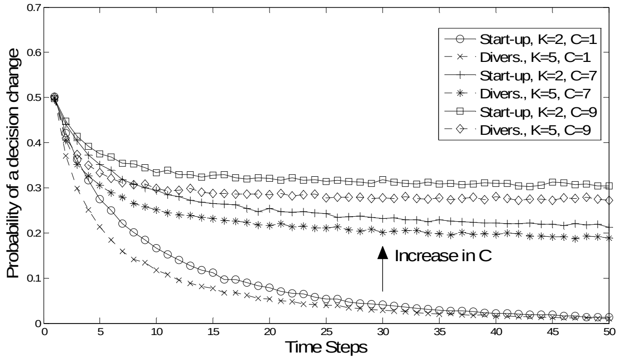

FIGURE 5

LATE ENTRY, MEAN PERFORMANCE

Entry period 35, Performance observed in period 100, C=7