ELSEVIER

Research Policy 30 (2001) 1019–1039

research policy

www.elsevier.com/locate/econbase

Technology as a complex adaptive system: evidence from patent data

Lee Fleming [a,*], Olav Sorenson [b,1]

[a] *Morgan T97, School of Business Administration, Harvard University, Boston, MA 02163, USA*

[b] *Anderson School of Management, University of California-Los Angeles, Suite B420, Los Angeles, CA 90095-1481, USA*

Received 22 August 2000; received in revised form 22 August 2000; accepted 23 August 2000

Abstract

This paper develops a theory of invention by drawing on complex adaptive systems theory. We see invention as a process of recombinant search over technology landscapes. This framing suggests that inventors might face a 'complexity catastrophe' when they attempt to combine highly interdependent technologies. Our empirical analysis of patent citation rates supports this expectation. Our results also suggest, however, that the process of invention differs in important ways from biological evolution. We discuss the implications of these findings for research on technological evolution, industrial change, and technology strategy. © 2001 Elsevier Science B.V. All rights reserved.

Keywords: Invention; Complexity; Interdependence; Modularity; Recombination

1. Introduction

The extensive literature on technological change primarily considers the adoption and economic impact of exogenous technologies without considering the origins of those inventions (Rosenberg, 1982; Rogers, 1983). This research typically focuses on commercial innovation rather than technological invention (Schumpeter, 1939; Ruttan, 1959), argues against considering them as distinct phenomena (Marquis, 1969; Nelson and Winter, 1982), or considers the organizational issues of technological change (Abernathy and Utterback, 1978; Tushman and Anderson, 1986; Henderson and Clark, 1990). As a result, we understand relatively well the processes of technological diffusion, commercial innovation, and the influences on or implications of technological change on organizations; however, we lack a systematic and empirically validated theory of invention.

We believe that Kauffman's (1993) recent work in evolutionary biology provides a useful framework for developing a theory of invention. Kauffman examines the role of complexity — the interaction of size and interdependence — in adaptive systems. Following an old tradition in biology, he conceptualizes evolution as a process of search over fitness landscapes (Wright, 1932). Organisms seek higher positions — that represent superior levels of biological fitness — on these landscapes. Kauffman contributes to our understanding of evolution by linking this adaptive process to the genetic structure of the organism. Specifically, interdependence between an organism's genes generates the topography of the landscapes in Kauffman's model. Because the topography of the landscape determines the likelihood of fruitful search, this connects the interdependence of the individual genes to the adaptive ability of the organism as a whole.

* Corresponding author. Tel.: +1-617-495-6613.
E-mail addresses: lfleming@hbs.edu (L. Fleming), olav.sorenson@anderson.ucla.edu (O. Sorenson).
[1] Tel.: +1-310-825-7348.

PII: S0048-7333(00)00135-9

By conceiving of technological evolution as a recombination of new and existing component technologies, we draw on Kauffman's work to develop a theory of invention as a search process over technology landscapes. Let us assume that an invention's components are analogous to an organism's genes. Under this assumption, Kauffman's findings imply a non-monotonic relationship between component interdependence and successful search. At low levels of interdependence, greater interdependence increases the probability of success by providing opportunities to combine components synergistically. Nevertheless, as the degree of interdependence rises, it becomes increasingly difficult to find these useful combinations. Kauffman's work also suggests new hypotheses regarding the relationship between the number and interdependence of components combined and the expected usefulness of those combinations. Negative binomial models of patent citation counts demonstrate empirical support for the relevance of these ideas to invention. The results also suggest ways in which the process of invention differs from biological adaptive processes.

2. A review of the contributing literatures

2.1. Evolutionary analogies in the technology literatures

This paper follows a long tradition of borrowing biological frameworks to understand technological change and the process of invention. As early as 1935, Gilfillan noted that "The nature of invention . . . is an evolution, rather than a series of creations, and much resembles a biologic process", (p. 275). A similar insight led Schumpeter to propose that the effects of inventions, ". . . illustrate the same process of industrial mutation — if I may use that biological term — that incessantly revolutionizes the economic structure *from within* incessantly destroying the old, incessantly creating a new one", (1942, p. 82). More recently, Abernathy and Utterback (1978) argued that technologies follow a 'technological life-cycle' — like living organisms, they are born, mature, obsolesce, and die. Similarly, Tushman and Anderson (1986) draw on paleontology (Eldredge and Gould, 1972) by arguing that technology moves through periods of equilibrium punctuated by intervals of rapid change. This rich history of borrowing concepts from evolutionary biology bears testament to the usefulness of these ideas to the study of technology.

2.2. Invention as a process of recombination

Many of the scholars who use evolutionary analogies also propose that technological novelty arises from the recombination and synthesis of existing technologies (Gilfillan, 1935; Schumpeter, 1939; Usher, 1954; Basalla, 1988; Henderson and Clark, 1990; Weitzman, 1996; Hargadon and Sutton, 1997).[2] Thus, one can often describe inventions as a combination of prior and/or new technologies. For example, one might think of the automobile as a combination of the bicycle, the horse carriage, and the internal combustion engine. The steam ship can be characterized as combining the boat with steam power. Similarly, one might consider the microprocessor to be a conjunction of a computer's central processing unit with integrated circuit fabrication processes. The annals of history also document a variety of unsuccessful combinations, such as the plane–automobile combination or the nuclear powered aircraft (Basalla, 1988). Following these ideas, we consider an invention to be either a new synthesis of existing and/or new technological components or a refinement of a previous combination of technologies (Henderson and Clark, 1990; Fleming, 2001). This framework allows us to think of invention as a process of recombinant search for better combinations and configurations of constituent technologies.

2.3. The landscape of recombinant search

Landscapes provide a useful way to conceptualize these recombinant search processes. Imagine a terrain with hills and valleys.[3] Each unique set of genes or

[2] Although they do not focus on recombination, many other researchers, including: Allen (1977), Nelson and Winter (1982), Von Hippel (1988), Tushman and Rosenkopf (1992), and Iansiti (1998), implicitly assume or adopt this recombinant perspective.

[3] Fitness landscapes include one dimension for each component plus an additional dimension for the fitness associated with that combination of components. Although these landscapes typically exist in many dimensions, we conceptualize search over a three-dimensional space for the intuitive value.

123	w_1	w_2	w_3	$W = \frac{\sum_{i=1}^{N} w_i}{N}$
000	.8	.6	.2	.53
001	.8	.6	.9	.77
010	.8	.7	.2	.57
011	.8	.7	.9	.80
100	.4	.6	.2	.40
101	.4	.6	.9	.63
110	.4	.7	.2	.43
111	.4	.7	.9	.67

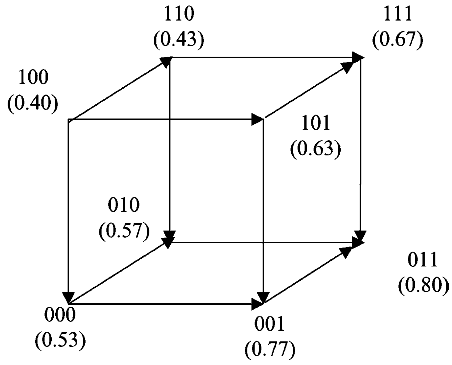

Fig. 1. Landscape without interdependence ($N = 3$, $K = 0$). This relatively correlated landscape has only one minimum and one maximum, 1 0 0 (0.40) and 0 1 1 (0.80), respectively. The component fitness contributions come from a uniform [0, 1] distribution.

components corresponds to a different landscape. On these landscapes, each location represents a particular configuration of those genes or components. The height at that location indicates the fitness (i.e. value or usefulness) of that particular configuration or architecture. In the biological sciences, higher points correspond to fitter genotypes. In the technical world, higher points correspond to better inventions. Wright (1932) first introduced these 'fitness landscapes' as a tool for understanding the distribution of genes in the population of a species. In addition to many applications in biology, organizational theorists have usefully extended this concept to the study of firms (e.g. McPherson and Ranger-Moore, 1991; Bruderer and Singh, 1996; Levinthal, 1997; Sorenson, 1997; Gavetti and Levinthal, 2000; Rivkin, 2000). We believe this concept can also inform the understanding of invention.

For our purposes, Kauffman (1993) provides an important innovation by linking the topography of the fitness landscape to the structure of the underlying components.[4] He does this by developing a simulation model that varies along two parameters, N, the number of components comprising a whole, and K, the degree of interdependence among these components. Using these models, Kauffman demonstrates that K primarily determines the topography of the landscape (Weinberger, 1991; Kauffman, 1993).

Kauffman defines an organism as a binary string of N components. Different configurations of these N components correspond to different positions on the landscape. For example, 0 0 1 represents one of eight possible configurations when $N = 3$ (as illustrated in Fig. 1, the others would be 0 0 0, 0 1 0, 0 1 1, 1 0 0, 1 0 1, 1 1 0, 1 1 1). Each of the eight vertices of the binary string correspond to different configurations and, hence, different points on the fitness landscape. The calculation of the fitness values for each configuration depends on the value of K. We examine two cases: $K = 0$ (no interdependence) and $K = 2$ (the maximum possible interdependence for $N = 3$ components).

For $K = 0$, Kauffman randomly assigns a value from the uniform unit distribution to each level (0 and 1) of the binary components. To calculate the aggregate fitness value for each configuration, he averages the fitness contributions of the components. When $K = 0$, components contribute independently to the overall fitness, so one simply averages the values for the components of that string. Fig. 1 illustrates this procedure. When $K > 0$, however, the components interact to contribute to the overall fitness. In addition to the focal component, the fitness contribution for each element depends on the values of K other elements. For example, when $K = 2$, the fitness assigned to a particular component depends not only on the value of that component (i.e. 1 or 0), but also on the value of two other components. Thus, a component can contribute any of eight ($2 \times 2 \times 2$) potential values to the fitness of the organism. Kauffman maps each of these combinations to a fitness value by randomly drawing from the uniform distribution [0, 1]. Fig. 2 depicts this process.

[4] This description closely follows Kauffman's (1993) explanation of the NK model on page 42.

1 2 3	w_1	w_2	w_3	$W = \frac{\sum_{i=1}^{N} w_i}{N}$
000	.5	.8	.6	.63
001	.6	.2	.1	.30
010	.2	.7	.3	.40
011	.8	.6	.5	.47
100	.4	.5	.2	.37
101	.9	.8	.9	.87
110	.7	.4	.1	.40
111	.9	.7	.3	.63

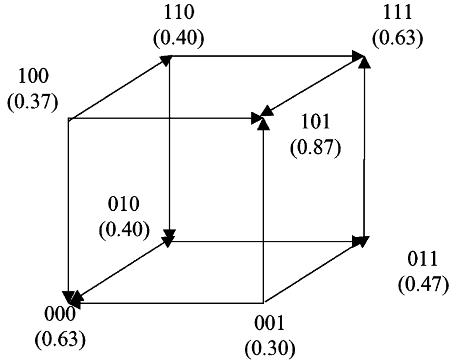

Fig. 2. Landscape with maximal interdependence ($N = 3$, $K = 2$). This relatively uncorrelated landscape has multiple local minima, 0 0 1 (0.30) and 1 0 0 (0.37), and maxima, 0 0 0 (0.63) and 1 0 1 (0.87).

Kauffman (1993) assumes that populations of organisms search locally on these landscapes. In other words, they change one component at a time and assess whether that change improves fitness. If it does, the population adopts the new combination of components. Otherwise, it retains the current combination. Graphically, this amounts to moving to neighboring positions when they offer an increase in altitude relative to the current location. Although this mode of search seems particularly relevant in the biological world, where agents (e.g. genes) often lack intelligence, researchers also note a tendency for local search across cognitive (March and Simon, 1958), organizational (Cohen and Levinthal, 1990; March, 1991; Sørensen and Stuart, 2000), and technological (Nelson and Winter, 1982; Stuart and Podolny, 1996) contexts.

The key insight from this model for our purpose is that interdependence leads to less-correlated and, hence, more-jumbled landscapes. Consider the case without interdependence in Fig. 1. As one moves between adjacent vertices, the fitness values associated with these neighboring points do not shift abruptly. Rather, the landscape changes smoothly because two of the three terms contributing to the fitness calculation remain the same. In contrast, contiguous fitness values in Fig. 2 differ drastically because all three contributing fitness scores vary even across neighboring points. When combined with a search algorithm, these landscapes allow us to predict the ease or difficulty of adaptation.

The topography of these landscapes determines the expected success of local search. For example, local search more likely yields favorable outcomes on low-*K* landscapes. These landscapes have fewer peaks (maxima). Thus, incremental improvements tend to approach the best combinations on these terrains. Moreover, low-*K* landscapes exhibit a high degree of spatial autocorrelation. In other words, the maxima tend to cluster on the landscape; knowing the location of one peak makes it easier to find other peaks. As *K* increases, however, the number of maxima increases and the average height of these maxima declines. Furthermore, as *K* rises, the degree of autocorrelation diminishes. Thus, the location of the peaks becomes increasingly dispersed and unpredictable. These effects suggest that, on average, local search and incremental adaptation strategies will generate less useful outcomes on high-*K* landscapes. Nevertheless, the increasing ruggedness of the landscape also implies that the potential for a breakthrough invention increases. Although the average peak height declines as interdependence rises, some of the 'good' positions on the high-*K* landscape dominate the best points on the low-*K* landscape.

3. Theory: invention as a process of recombinant search over an *NK* landscape

We conceptualize inventors' efforts as a search process over technology landscapes. The fruitfulness of search on these landscapes varies according to the size and the degree of interdependence of these terrains. In our framework, each distinct set of technological components offers an unique landscape that an inventor can search. For each particular set of components, fitness values indicate the usefulness of different configurations of these components. For example, given a bowl and a spoon as two components, applications tend to be more useful when the bowl faces upwards rather than downwards. Thus, the upwards configurations typically correspond to higher fitness points on the landscape than the downwards configurations.

In our conceptualization of technological search, the number of components that an inventor recombines corresponds to Kauffman's N, whereas K coincides with the interdependence among these components. Note that our conceptualization of components extends beyond mere physical hardware to include any constituent technology (Fleming, 2001). We define interdependence as the functional sensitivity of an invention to changes in these constituent components.[5] Our definition of interdependence closely mirrors Ulrich's (1995) definition of 'coupling', where, "... change made to one component requires change to another for the product to work correctly". Our definition also resembles Baldwin and Clark's (2000, p. 12), 'where (design interdependencies) exist, a seemingly small change in one design parameter can interact with other parameters to completely destroy the value of the particular artifact'. For example, a silicon semiconductor's resistance depends crucially on the amount of impurity doped into the silicon. If the dopant level changes by 1 part in 10^8, the resistance at 30°C can change by a factor of 24 100 (Millman, 1979, p. 13). In this extreme case, the modification made to one component cannot be corrected by another — the device simply fails to work. The tremendous amount of research and investment in semiconductors over the past 50 years attests to the difficulty of combining these two highly interdependent components, both in determining their optimal configuration and in manufacturing them reliably. Nevertheless, one should remember that even though interdependence makes an invention difficult to perfect, it also enables some very useful combinations.

Kauffman's (1993) simulation reveals a non-monotonic relationship between K and the fitness or peaks found by local search; essentially, an intermediate level of interdependence is best for adaptation. As K increases, the height of the highest peak on the landscape rises. This occurs because the component fitness values that contribute to the aggregate fitness value become less-correlated. Fundamentally, the randomness of the aggregate fitness values increases thereby increasing the likelihood that one of those draws yields a high value. Nevertheless, it also becomes increasingly difficult to find these good peaks (Kauffman, 1993; Rivkin, 2000). As K rises still further, the probability of conflicting constraints increases. Conflicting constraints imply that an incremental improvement along one dimension tends to coincide with a loss on another dimension, making it increasingly difficult to find monotonic and incremental paths to the peaks. This implies that the basins of attraction — the regions in which local search leads to the high peaks — become vanishingly small. Finding a high peak becomes a matter of luck. Along with the basins of attraction becoming microscopic, the peaks spread apart. Each discovery of a good peak provides less information regarding where to look for other tall peaks. Moreover, failing to find the best peaks becomes increasingly costly because the average height of peaks declines with increasing K.

To see the relation to the technological world, consider the extreme case. A complete lack of interdependence between components implies little opportunity for creativity. Inventors can change configurations easily, but they see little difference in functionality across these configurations. Ironically, engineers can and often do work to de-couple their systems, making the components less interdependent and more modular (Mead and Conway, 1980). This de-coupling makes it easier to mix and match components and reduces the uncertainty of recombinant search. Because inventors do not need to understand the internal workings of each 'black box', they can

[5] Modular design techniques make components less interdependent. We hesitate, however, to define interdependence strictly in terms of modularity because the existing literature defines modularity in a variety of ways (for examples, see McCord and Eppinger, 1993; Ulrich, 1995; Ulrich and Eppinger, 1995; Simon, 1996; Christensen et al., 1999; Baldwin and Clark, 2000). Moreover, these definitions typically arise from studying products rather than invention (Eppinger, 1999). We consider the implications of our findings for the wider modularity literature in the discussion.

simply try new combinations without designing and building everything from scratch. Nevertheless, modularity also constrains recombination to previously considered and available interfaces. Components combine easily, but they often operate less efficiently at a system level. For example, computer engineers can choose to use a modular microprocessor in their system or build the entire computer from scratch. Use of the modular microprocessor makes the process easier, more assured, and probably faster, but it also imposes various design choices upon the team, such as electrical characteristics, pinouts, and architectures. The team's chances of building a working computer increases, but their flexibility to optimize that system declines.

Technological opportunities increase, however, as interdependence increases. Inventors can take advantage of increasing sensitivities and opportunistic couplings between components. Unfortunately, the difficulty and uncertainty of the recombinant search process increases along with the opportunity (Baldwin and Clark, 2000). To understand how components interact with each other, inventors must delve into the internal workings of each 'black box'. Processing the interdependencies taxes the cognitive abilities of engineers (March and Simon, 1958). It also redirects attention, as well as cognitive and social resources, to other stages of the inventive process. Engineers spend their time trying to predict, avoid, and debug the subtle interactions between components, rather than exploring new combinations.

The optimal degree of interdependence lies somewhere between the extreme cases. Inventors must balance an increased mean outcome against decreased variability (March, 1991; Fleming, 2001). De-coupling increases the probability that the invention will function, because it truncates the downside risk, however, de-coupling also decreases the likelihood of a wildly successful breakthrough because it abbreviates the upside potential as well. The optimal degree of interdependence, therefore, lies where engineers can, "... achieve the right balance between fruitful uncertainty and overwhelming complexity", (Baldwin and Clark, 2000, p. 32).

Hypothesis 1. The usefulness of inventors' efforts increases when they combine components with an intermediate degree of interdependence.

Although *K* primarily determines the topography of the landscape, the complexity catastrophe occurs most frequently when *K* increases faster than *N* (Kauffman, 1993). We expect to see this effect in a technological context as well. When inventors work with only a few extremely interdependent components, their inventive efforts will typically fail. For example, consider the gear shifting system on a bicycle. Cyclists prefer a greater number of gears because it allows them to ride varied terrain more efficiently. Newer bicycles incorporate nine rear cogs and two front chainrings making 18 gears available. The additional rear cogs stack up to a wider spacing, however, and require a greater width of horizontal travel for the bicycle chain. Unfortunately, increasing the horizontal travel makes shifting more difficult. The extreme interdependence between the number of available gears and the shifting mechanism proves frustrating because it makes an increase in the number of gears impossible without deterioration in the shifting. Fortunately, engineers can modify a third component, the bicycle chain. By decreasing the width of the chain, they can increase the number of gears without increasing the travel width and debilitating the shifting mechanism. The additional component enables engineers to mitigate the complexity catastrophe of high interdependence within a small recombinant space.

Hypothesis 2. When combining highly interdependent components, the usefulness of inventors' efforts declines most rapidly when they combine a small number of components.

As argued in Hypothesis 1, interdependence between components also makes the outcome of invention inconsistent and unpredictable. Just as the heights of the peaks become more varied as *K* increases, inventive success becomes more varied as components become increasingly interdependent because of the difficulty in predicting their subtle interactions. Indeed, much of the benefit to de-coupling stems from making the performance of a component consistent regardless of its interaction with other technologies. Nevertheless, this reduction in risk also reduces the likelihood of inventing revolutionary new combinations because the variability of the outcome declines. Variance implies outcomes at both extremes — some much better and some much worse.

Hypothesis 3. Inventors' efforts become more varied in their usefulness as they combine components with a higher degree of interdependence.

Kauffman's (1993) work focuses on the impact of interdependence on the search process. Indeed, the *NK* model simulation results show little effect of *N* on the mean fitness of local optima (Weinberger, 1991; Kauffman, 1993). The formula for the overall fitness averages the component values, however, such that the typical fitness value converges to the mean of the underlying distribution (0.5 in the uniform [0, 1] distribution above) as *N* increases. In qualitative terms, the landscape flattens and expands. Peaks occupy a smaller proportion of the landscape's surface. If the search agents on such a landscape truly lack foresight and search only locally and incrementally, it will take them longer to find the peaks. Nevertheless, inventors search their landscapes with varying degrees of knowledge and foresight (Vincenti, 1990). Hence, they might use the expansion and leveling of the landscape to their advantage, making peaks easier to locate. Think of spotting, for example, Pike's peak from the prairies of Eastern Colorado, or Kilimanjaro from the plains of Eastern Africa.

Technological, cognitive, and social factors all suggest a positive relationship between the number of components and the fruitfulness of invention. The exhaustion of combinatoric possibilities creates a technological constraint on combining a limited set of components. Inventors can only combine a bowl and spoon in so many ways. Nonetheless, this technological constraint quickly disappears as increasing *N* explodes the combinatoric space (Weitzman, 1996). Cognitive and social exhaustion will also constrain invention if inventors become locked into established thought patterns when they work with only a few components. With variety, the juxtaposition of disparate fields of thought or physical technology can trigger new associations and breakthroughs (Adamson, 1952; Usher, 1954). Such juxtapositions increase the possibility of frame breakage (Amabile, 1988) or re-conceptualization of the problem (Kaplan and Simon, 1990). Nonetheless, the marginal benefit of variety probably decreases with the increasing number of components because inventors experience cognitive difficulty considering all the components and their potential relationships simultaneously.

Hypothesis 4. The usefulness of inventors' efforts increases, but at a decreasing rate, when they recombine a larger set of components.

The size of the recombinant search space also affects the variability of outcomes. Consider first the case with many components and little interdependence between them (high-*N* and low-*K*). Because de-coupled components do not, by definition, interact to influence inventive outcomes, inventors who combine many de-coupled components can expect to average the usefulness of their constituent components. Following the logic of the Central Limit Theorem, the variance of this mean should decrease as the number of components increases (Weinberger, 1991; Macken et al., 1991).

Hypothesis 5. At low levels of interdependence, inventors' efforts become less varied in their usefulness as they recombine a greater number of components.

Although the *NK* model does not predict an interaction effect between *K* and *N* on the variability of the landscape (Macken et al., 1991), we expect technological outcomes to become more uncertain with a larger number of interdependent components (high-*N* and -*K*) due to the cognitive limits of inventors. With intensifying interdependence, inventors find it increasingly difficult to deal with a large set of components. Cognitive and social limits become increasingly severe. Thus, inventive outcomes become more and more uncertain.

Hypothesis 6. At high levels of interdependence, inventors' efforts become more varied in their usefulness as they recombine a greater number of components.

4. Research design, data, and analysis

Our theory places several unusual demands upon our empirical work. First, we need a quantitative measure of fitness or usefulness that spans a broad range of technologies. Second, we must identify the components of each invention and develop a measure of the interdependence among those components. Finally, we must estimate the effect of the independent variables on *both* the mean and variability of usefulness to test our hypotheses.

To satisfy these demands, we analyze US patents granted in May and June 1990 ($n = 17\,264$).[6] We acquired these data from Micro-Patent. Patent data enable us to develop a quantitative measure of fitness across a broad range of technologies and to identify measures of the number of components and component interdependence. We measure fitness or usefulness as citations to these patents, N as the number of sub-classes to which each patent belongs, and K as the observed ease of recombination for each patent's sub-classes. To make maximal use of the data, we generate our explanatory variables using sub-class data from 1790 to 1989.[7] We analyze these patent citations using negative binomial models with variance decomposition (the gnbreg routine in STATA).

Patent data admittedly offer imperfect measures of invention. Companies often fail to patent process inventions and industries vary in their propensities to patent (Levin et al., 1987). Patents also do not allow us to observe all points on the fitness landscape. Because inventors probably limit their patent applications to their more successful inventions, patents presumably represent only the higher slopes and peaks on these landscapes. This implies that we must infer the topography of the underlying landscape from these truncated data. Nonetheless, simulations indicated that an increase in the mean and variance of a normal distribution generates an increased mean and variance in that distribution's right truncated observations.[8]

[6] We chose May and June at random from the months in 1990.

[7] In response to a reviewer's suggestion, we also generated interdependence using a 10 years window, from 1980 to 1989. Using this window attenuated the quadratic effect of K and increased the effects of N and the interaction, but does not alter the substantive interpretation of the results.

[8] Kauffman's (1993) model determines fitness values by averaging the component values. Because the underlying component values come from a uniform distribution, we know, by the Central Limit Theorem, that the fitness values converge to a normal distribution. Because the patent citation data represent right truncated observations of inventors' efforts, we ran simulations to determine the effects of right truncation on the distribution of observed fitness values. Contact Fleming for additional information on these simulations.

4.1. Dependent variable

We define usefulness as the number of citations that a patent receives in the 6 years and 5 months following its grant date.[9] Each patent must cite previous patents that relate closely to its own technology. Previous research has demonstrated that the number of citations a patent receives correlates highly with its technological importance, as measured by expert opinions and industry awards (Albert et al., 1991; Hall et al., 2000). Trajtenberg (1990) has also shown that the number of citations correlates strongly with the social value of patents in the computed tomography industry. Thus, citation counts offer a means of measuring inventive usefulness across a broad range of technologies.[10]

4.2. Independent variables

4.2.1. N: number of components

The number of sub-class references assigned to a patent provides our measure of the number of components of that invention. The US Patent Office uses sub-class references to indicate which technologies relate to the patent. The Patent Office develops and updates these sub-classes such that they consistently track technology back to 1790. The more than 70 000 sub-classes allow for fine-grained classification of inventions (Carr, 1995). For example, US Patent #5,136,185 covers a test circuit for computer data buses. The Patent Office classifies this invention as belonging to the test-facilitate feature, signal transmission, tristate, and current-driving technology sub-classes — all well-understood components in circuit design (McCluskey, 1986). Every patent belongs to at least one sub-class of technology and, like our example, most (92%) have multiple memberships. We also include an interaction term: interdependence K divided by the number of sub-classes N. As main effects should take the same functional form as in the interaction term, we enter the inverse of the number of sub-classes as our measure of N.

[9] We chose this period to make maximal use of our data which end in November 1996. This period should capture the bulk of citations to a patent as these citations typically peak within 3–5 years from the grant date (Jaffe and Trajtenberg, 1995).

[10] The propensity to cite varies across technologies as a function of the level of activity in that technology. We introduce controls for this activity in Section 4.3.

4.2.2. K: degree of interdependence between components

We calculate our measure of the interdependence K in two stages.[11] Eq. (1) details our measurement of the ease of recombination, or inverse of interdependence, of an individual sub-class i used in patent l. We first identify every use of the sub-class i in previous patents. The sum of the number of previous uses provides the denominator. For the numerator, we count the number of different sub-classes appearing with sub-class i on previous patents. Hence, our measure increases as a particular sub-class combines with a wider variety of other sub-classes, controlling for the total number of applications. This term captures the ease of combining a particular technology. To create our measure of interdependence for an entire patent, we invert the average of the ease of recombination scores for the sub-classes to which it belongs (Eq. (2)).[12]

$$\text{Ease of recombination of sub-class } i \equiv E_i = \frac{\text{count of sub-classes previously combined with sub-class } i}{\text{count of previous patents in sub-class } i} \tag{1}$$

$$\text{Interdependence of patent } l \equiv K_l = \frac{\text{count of sub-classes on patent } l}{\sum_{l \in i} E_i} \tag{2}$$

4.2.3. Complexity: interaction of N and K

Kauffman predicts that the complexity catastrophe occurs when interdependence is high relative to the number of components in the system. Therefore, we interact interdependence with the number of components as a ratio (i.e. K/N).

4.3. Additional variables

4.3.1. Technology controls

The technology controls follow a logic similar to fixed-effect modeling. Essentially, they control for differences in the mean and variance of citation rates across technology classes. We compute each of the technology controls in two steps. First, for the technology mean control, we consider citations to patents granted between January 1985 through December 1989. We begin by calculating the average number of citations that each patent in a particular class receives from patents granted from January 1985 to June 1990 (Eq. (3a)).[13] If all patents belonged to only one class, we could use this measure to control for differences in citation likelihood across classes, but most patents belong to more than one class. Accordingly, we weight this term according to a patent's class assignments (Eq. (3b)) where p is the proportion of patent l's memberships that fall in class i. For example, if class 2 averages 2.0 cites per patent and class 16 averages 4.0 cites per patent, a patent classified in one class of 2 and three classes of 16 would have an expected citation count of $(1/4) \times 2.0 + (3/4) \times 4.0 = 3.5$. We calculate the technology variance control with a similar process. First, we calculate the average variation in citation rates for patents in each sub-class (Eq. (4a)). We then weight these estimates according to sub-class membership to create a patent specific measure (Eq. (4b)).

$$\text{Average citations in patent class } i \equiv \mu_i = \frac{\sum_{j \in i} \text{citations}_j \ (\text{before } 7/90)}{\text{count of patents } j \text{ in sub-class } i} \tag{3a}$$

$$\text{Technology mean control patent } l \equiv M_l = p_{il}\mu_i \tag{3b}$$

$$\text{Citation variance in patent class } i \equiv \sigma_i^2 = \frac{\sum_{j \in i} (\text{citations}_j \ (\text{before } 7/90) - \mu_i)^2}{\text{count of patents } j \text{ in sub-class } i} \tag{4a}$$

[11] Our measure of K only proxies for Kauffman's (1993) construct. Thus, it differs at least in scaling from his measure. For example, unlike Kauffman's K, which cannot take values in excess of N, the value of our proxy can exceed the number of components.

[12] To explore whether the 'worst' sub-class might drive the phenomenon, we also modeled interdependence as the inverse of the minimum of the ease of all the sub-classes. This specification did not substantively change our findings.

[13] We allow all patents issued between January 1985 and 30 June 1990 to enter the estimation of the technology controls. This means that the patents used to calculate the technology controls vary in the time for which they can receive citations. Alternatively, we could select a small set of patents from 1985 and base the measures on the subsequent 5 years of citations, however, this approach would ignore the patent activity just prior to our sample.

$$\text{Technology variance control patent } l \equiv V_l = p_{il}\sigma_i^2 \quad (4b)$$

4.3.2. Prior art citations

We include the number of prior art citations — references to prior patents assigned by the US Patent Office — as a control for two reasons. First, previous researchers use prior art citations as a measure of the localness of search. Local search implies that inventors seek to make incremental improvements on existing combinations, rather than searching for breakthrough recombinations. Podolny and Stuart (1995) use the number of prior art citations to measure this concept, essentially assuming that patents making more citations to prior art do so because they expand on existing knowledge more than they develop new ideas. Second, the number of citations provides an additional control for the propensity of patenting in a particular technological domain. We know that industries differ in the degree to which they patent (Levin et al., 1987). Fields that patent more heavily provide a larger pool of patents for citation. Although the technology controls should capture much of this effect, the number of prior art citations may pick up idiosyncratic differences in patenting activity that our class controls miss.

4.3.3. Single class dummy control

Eight percent of the patents in our dataset belong to only one sub-class. We believe that these inventions also come from a process of recombination, but this combination occurs at a finer grain than our measures can capture. For this reason, we include a dummy variable to control for any systematic differences generated by the coarseness of our measures.

4.3.4. Number of classes control

We include a count of the number of major classes to strengthen our test of Hypothesis 4. Patents that cover a broad range of technologies might carry a higher risk of being cited simply because future inventions from each of those fields may potentially cite it — similar to what happens when an academic article merges several literatures. Nevertheless, the high citation counts of bridging technologies and articles do not necessarily indicate that they exceed the quality of those that fit within a single socially constructed category. Fortunately, we can control for this possibility to some degree by taking advantage of the fact that the patent office hierarchically organizes the 70 000 sub-classes into one of 400 major classes of similar technologies.

4.3.5. Number of trials

We measure the number of trials on a particular landscape by counting the number of previous patents that combine exactly the same set of sub-classes. This controls for two potentially confounding issues. First, local search has its limitations. As inventors find useful combinations with a particular set of components, the potential for finding additional useful recombinations declines. In effect, inventors exhaust the combinatoric possibilities (Fleming, 2001).[14] Second, the number of trials could pick up residual information on the value of K for a particular set of components. We know that the number of peaks rises as a function of K (Kauffman, 1993). Since we expect patents to represent peaks in the landscape, the number of prior instances of a combination provides a measure of the number of peaks found to date.

4.4. Descriptive statistics

Tables 1 and 2 present descriptive statistics and bivariate correlations for our variables.

4.5. Negative binomial count models

Linear regression cannot properly estimate parameters for these models. Because the dependent variable, patent citation counts, cannot fall below zero, linear regression — which cannot account for this constraint — can yield inefficient, inconsistent, and biased coefficient estimates (Long, 1997). Count models offer a better means of analyzing these data. Researchers often use Poisson models to analyze count data, but these models constrain the variance to equal the mean. Our data, like most count data, exhibit over-dispersion (i.e. the variance exceeds the mean). To accommodate this over-dispersion, researchers can use negative binomial regression (Hausman et al., 1984). To test our hypotheses about both the usefulness and variability of invention, we use a particular variant of the negative binomial model that allows us to model

[14] Sorenson (2000) finds evidence of a similar exhaustion effect among entrepreneurs searching for new organizational forms within an existing industry.

Table 1
Descriptive statistics

Variable	Mean	S.D.	Minimum	Maximum
Citations	3.80	4.88	0.00	82.00
Mean technology control	1.19	0.41	0.33	3.03
Variance technology control	4.65	2.65	0.36	20.55
Prior art citations	7.63	6.99	0.00	110.00
Single sub-class control dummy	0.08	0.27	0.00	1.00
Number of classes control	1.78	0.95	1.00	12.00
Number of repeated trials control	2.94	15.23	0.00	716.00
1/N: 1/components	0.35	0.23	0.01	1.00
K: interdependence	0.63	0.35	0.06	5.00
K/N: complexity	0.25	0.30	0.00	4.76

Table 2
Correlation matrix

	Cites	Mean control	Variance control	Activity	Single	Classes	Trials	*1/N*	*K*
Mean control	0.308								
Variance control	0.302	0.944							
Prior cites	0.124	0.020	0.004						
Single	−0.062	0.002	0.004	−0.065					
Classes	0.077	−0.021	0.006	0.063	−0.244				
Trials	−0.033	−0.028	−0.033	−0.007	0.448	−0.143			
1/N	−0.103	0.007	−0.013	−0.106	0.829	−0.470	0.415		
K	−0.029	−0.057	−0.131	0.017	0.194	−0.275	0.364	0.329	
Complex	−0.062	−0.023	−0.067	−0.047	0.613	−0.351	0.575	0.719	0.798

heterogeneity in the variance parameter simultaneously with heterogeneity in the mean (King, 1989).

The basic Poisson model (Eq. (5)) estimates the probability of an observed value conditional on the values of a set of independent variables. To avoid negative (i.e. undefined) predicted values for the mean μ_i, Poisson models typically parameterize independent variables as an exponential function (Eq. (6)).

$$\Pr(y_i|x_i) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!} \tag{5}$$

$$E(y_i|x_i) = \mu_i = e^{x_i\beta} \tag{6}$$

The negative binomial model replaces the Poisson mean, μ_i, with the random variable $\tilde{\mu}_i$ (Eq. (7)). This replacement enables the inclusion of an error term $\delta_i = e^{\varepsilon_i}$ — and allows the predicted mean to vary according to the distribution of the error term. Most formulations specify a gamma function with parameter ν_i for the random variable δ in Eq. (7) (Hausman et al., 1984; Cameron and Trivedi, 1986; King, 1989; Long, 1997).[15] When $\tilde{\mu}_i$ replaces μ_i in Eq. (5), the probability of the observed variable becomes dependent on δ. This conditioning can be removed, however, by specifying the error distribution and integrating with its probability density function to obtain the marginal density. Eq. (8) details the marginal density as a function of the mean and dispersion parameter ν. The parameterization of the mean follows the same form as the Poisson.

$$\tilde{\mu}_i = e^{x_i\beta}e^{\varepsilon_i} = \mu_i\delta_i \tag{7}$$

$$\Pr(y_i|x_i) = \frac{\Gamma(y_i+\nu_i)}{y_i!\,\Gamma(\nu_i)}\left(\frac{\nu_i}{\nu_i+\mu_i}\right)^{\nu_i}\left(\frac{\mu_i}{\nu_i+\mu_i}\right)^{y_i} \tag{8}$$

Typically, the negative binomial model constrains the degree of over-dispersion to a constant multiple of the

[15] Although the error term can take other distributions, this parameterization is both flexible and computationally tractable.

mean. This specification, however, does not allow us to test our hypotheses regarding the variation in invention usefulness. Hence, we parameterize the dispersion term using the Negbin II formulation shown in Eq. (9) (Cameron and Trivedi, 1986). In this model, α, the inverse of ν, is also parameterized as an exponential function (similar to Eq. (6)). This specification fits best when the variance to mean ratio exceeds a linear scaling of the mean.[16] STATA estimates the joint probability distribution of Eq. (8) using maximum likelihood methods.

$$\mathrm{Var}(y_i|x) = \mu_i\left(1+\frac{\mu_i}{\nu_i}\right) = \mu_i + \alpha\mu_i^2 \qquad (9)$$

4.6. Results

Table 3 presents the results of our estimation. We began our analysis by entering controls only in model 1. We then added all first and second order terms for the number of components, their degree of interdependence, and the interaction term *K*/*N* to model 2. With the exception of the quadratic effect of the number of components on the dispersion of citations, all the independent variables in model 2 show significant deviation from zero. Model 3 drops the quadratic term in the variance because *N* appears to increase dispersion monotonically. Model 4 demonstrates that the results remain insensitive to the inclusion of control variables.

The results support the applicability of Kauffman's model to the process of invention. Due to the difficulty of simultaneously interpreting the various *NK* terms, we graph their estimated effects from model 3. Figs. 3 and 4 depict the effect of the various size and interdependence terms on the mean from two different angles (both graphs depict the same surface).[17] The figures clearly show a non-monotonic effect with respect to *K*. As predicted in Hypothesis 1, an intermediate amount of interdependence optimizes invention usefulness. At the mean value of *N*, 4.2, the optimal value of *K* equals 1.37. Most importantly, the best and worst points on this figure differ by almost 600%. To understand the magnitude of this effect, note that the median citation count is 2 and the 94th percentile lies at 12. In other words, the number and interdependence of the elements recombined can make the difference between an invention being average versus being in the top 6% of successful patents.

One might worry that we force *K* to take a quadratic relationship to the expected number of citations by including only linear and quadratic terms in the model. *K* might actually increase citation rates at a decreasing rate since the bulk of our data lie before the estimated inflection point. To investigate this possibility, we created a detailed spline of the estimated multiplier effects across the range of *K*.[18] The points in Fig. 5 appear to conform to a quadratic relationship, though the inflection point appears to occur at a slightly lower level of *K* than when modeled as a quadratic function.

Returning to Figs. 3 and 4, we find little evidence of the intensification of the complexity catastrophe for low-*N* in technological evolution. Hypothesis 2 predicted that inventors would face a technological complexity catastrophe when they combine a few highly interdependent components. At high levels of interdependence (lower left in Fig. 3), increasing *N* does lead to increasing usefulness. Nonetheless, the weak slope of the bottom edge in Fig. 3 illustrates the practical weakness of this effect.[19] Still, these results support consideration of technology as a complex adaptive system, as motivating such an interaction effect from the

[16] In contrast, the Negbin I holds the degree of over-dispersion to be constant with increases in the mean. Following Cameron and Trivedi (1986), we verified use of the quadratic formulation by linear regression of (citations − predicted citations)^2/predicted citations on predicted citations from a simple Poisson model. This regression estimated the coefficients of the constant and regressor as 2.64 (0.510) and 0.617 (0.123), indicating an over-dispersed Poisson whose variance exceeds a linear scaling of the mean. The 95% confidence interval of the regressor [0.377, 0.857] lies above 0; if it included 0, then we could not reject the Negbin I in favor of the Negbin II. Negbin II models also demonstrated higher log likelihoods.

[17] Figs. 3, 4 and 6 present multiplier effects. A multiplier of 1 essentially indicates no effect. Thus, a multiplier of 0.6 indicates that the independent variable depresses citation rates by 40% at that particular level of the variable. In multiplicative models, multiplier rates provide the easiest means of evaluating the effects of a variable because they do not require one to make assumptions regarding the levels of the other variables.

[18] We sorted the data by *K* and split the variable into 20 equal sized categories (i.e. fifth percentiles). We assigned each category a dummy variable, except the bottom category which we used as a baseline (hence, the intersection at the origin).

[19] The 10 years truncated measure of *K* demonstrated stronger and significant support for the complexity catastrophe.

Table 3
Negative binomial models of citation counts[a]

Variable/models	Model 1	Model 2	Model 3	Model 4
Effects on the mean				
Mean technology control	0.8940*** (0.0196)	0.9019*** (0.0196)	0.9014*** (0.0196)	
Activity control	0.0185*** (0.0012)	0.0170*** (0.0012)	0.0170*** (0.0012)	
Single sub-class dummy control	−0.2406*** (0.0367)	−0.1135 (0.2330)	−0.1134 (0.2324)	
Number of classes control	0.0906*** (0.0084)	0.0432*** (0.0099)	0.0432*** (0.0099)	
Repeated trials control	−0.0002 (0.0005)	−0.0009 (0.0006)	−0.0008 (0.0006)	
$1/N$		−1.5823*** (0.3305)	−1.5812*** (0.3296)	−1.6788*** (0.1439)
$1/N^2$		0.8778+ (0.5093)	0.8777+ (0.5082)	0.7005*** (0.1406)
K		0.2893*** (0.0648)	0.2901*** (0.0649)	0.1854** (0.0684)
K^2		−0.1225*** (0.0298)	−0.1225*** (0.0298)	−0.1571*** (0.0324)
Complexity		0.2571* (0.1074)	0.2553* (0.1073)	0.4253*** (0.1108)
Constant	−0.0978** (0.0319)	0.1933** (0.0660)	0.1932** (0.0658)	1.6490*** (0.0354)
Effects on dispersion parameter				
Variance technology control	−0.0175** (0.0054)	−0.0203*** (0.0054)	−0.0202*** (0.0054)	
Activity control	−0.0008 (0.0019)	−0.0001 (0.0020)	−0.0001 (0.0020)	
Single sub-class dummy control	0.2472** (0.0722)	−0.5465 (0.4401)	−0.2124+ (0.1155)	
Number of classes control	−0.0559** (0.0163)	−0.0300 (0.0192)	−0.0274 (0.0189)	
Repeated trials control	−0.0058** (0.0018)	−0.0036+ (0.0020)	−0.0036+ (0.0020)	
$1/N$		0.4942 (0.6306)	0.9707*** (0.1753)	0.9655*** (0.1280)
$1/N^2$		0.7613 (0.9677)		
K		−0.6098*** (0.1227)	−0.6292*** (0.1201)	−0.4733*** (0.1024)
K^2		0.2544*** (0.0490)	0.2558*** (0.0489)	0.2805*** (0.0445)
Complexity		−0.3984+ (0.2109)	−0.3734+ (0.2084)	−0.6866*** (0.1632)
Constant	0.0093 (0.0476)	0.0616 (0.1214)	0.0019 (0.0949)	−0.0119 (0.0551)
Log likelihood	−41135.58	−41024.85	−41025.16	−42204.68

[a] S.E. in parentheses (and $n = 17\,264$ for all models).
+ $P < 0.10$.
* $P < 0.05$.
** $P < 0.01$.
*** $P < 0.001$.

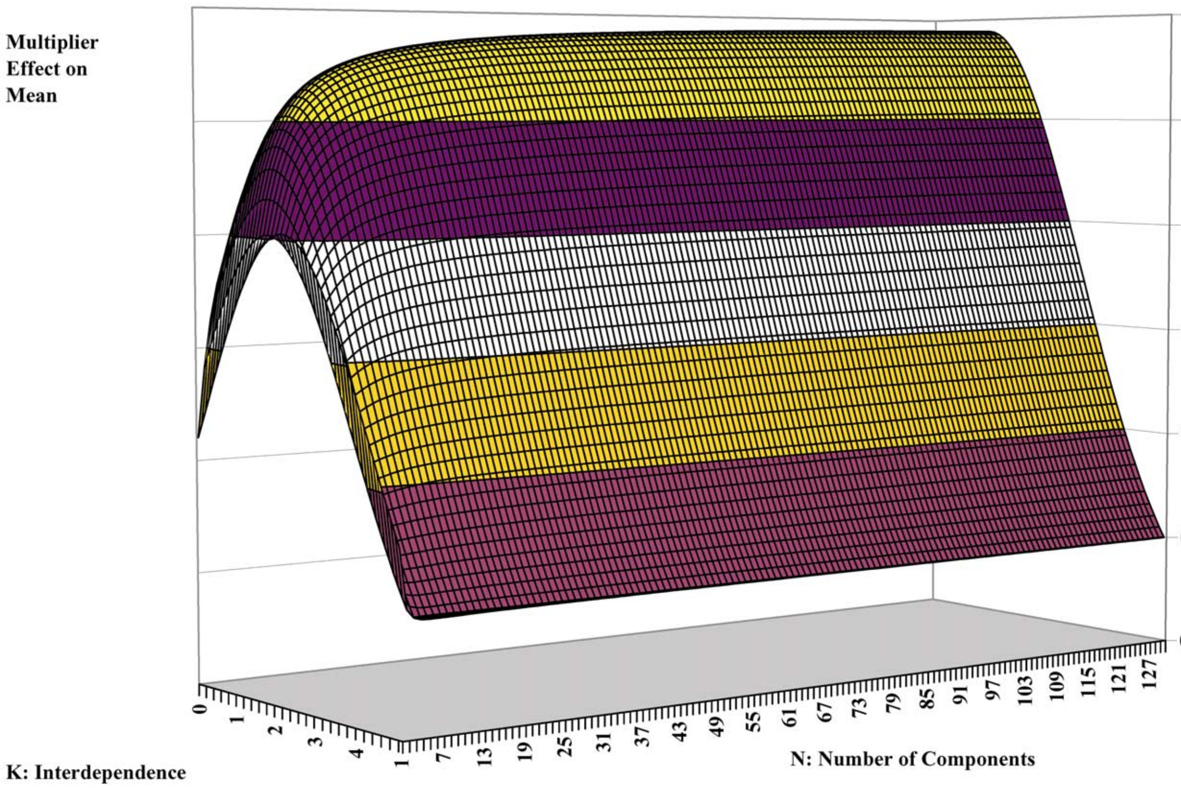

Fig. 3. Expected mean multiplier effect as a function of N and K (estimated from model 3): $\mu_i = \exp(x_i\beta) = \exp\left(-0.11\text{single} - \frac{1.58}{N} + \frac{0.88}{N^2} + 0.29K - 0.12K^2 + \frac{0.26K}{N}\right)$.

classical literature on technological evolution would prove difficult.

As predicted in Hypothesis 4, increasing the number of components leads to increased citation counts. Nevertheless, this increase does not occur at an increasing rate with respect to N. Rather, an increase in the number of components dramatically improves citation rates at low values, but this effect diminishes at higher values of N. This sharp immediate rise suggests that small recombinant search spaces severely constrain researchers. Inventors need at least some critical number of components to generate useful inventions. Yet, beyond this threshold, adding components to the mix does little to improve invention. We suspect that cognitive limitations prevent inventors from taking full advantage of increasingly large search spaces.

Fig. 6 illustrates the effect of the same variables on the dispersion of citations. As predicted in Hypothesis 3, K contributes to an increase in dispersion, but mostly at higher values. Over much of its range, K negligibly impacts variance. The interaction between size and complexity provides additional support for the applicability of the NK model. At low levels of K, increasing numbers of components stabilize invention. In contrast, an increase in components *decreases* the certainty of outcomes with highly interdependent components. Inventors appear capable of coping with increasing numbers of components as long as those components do not interact. Although the results demonstrate statistical support for the variability Hypotheses 3, 5 and 6, only the effect of increasing interdependence appears to entail important practical implications. Though significant, Fig. 6 shows that the main effect of interdependence dramatically overshadows the consequences of the number of components.

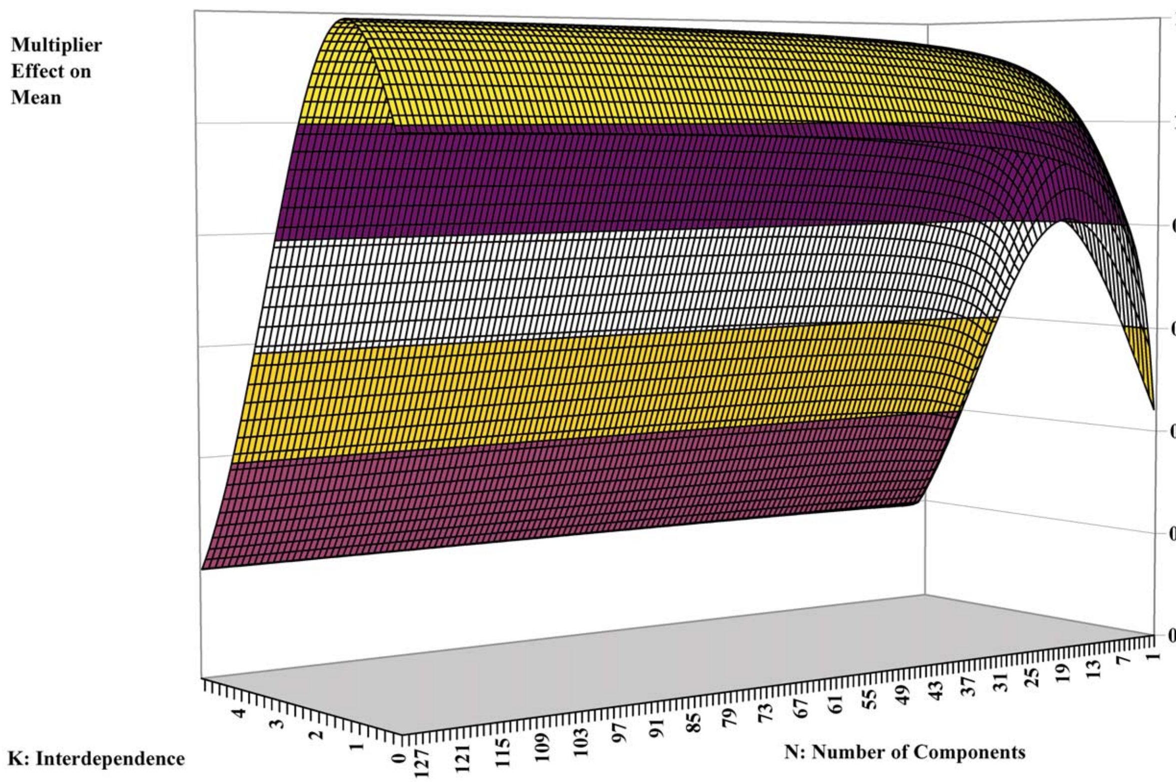

Fig. 4. Expected mean multiplier effect as a function of N and K (estimated from model 3): $\mu_i = \exp(x_i\beta) = \exp\left(-0.11\text{single} - \frac{1.58}{N} + \frac{0.88}{N^2} + 0.29K - 0.12K^2 + \frac{0.26K}{N}\right)$.

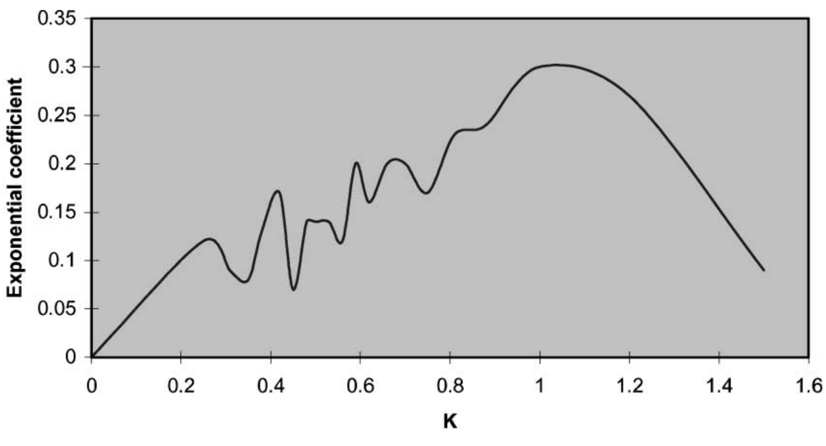

Fig. 5. Piece-wise estimate of relation between expected mean and K.

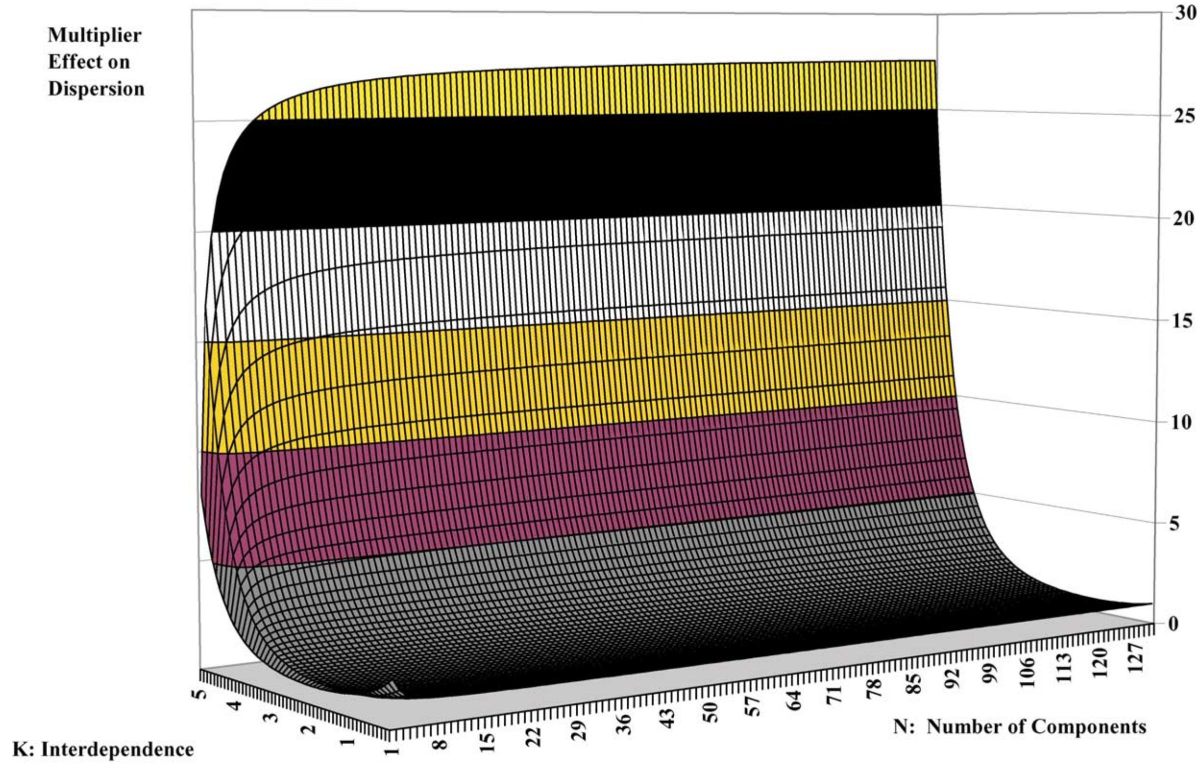

Fig. 6. Estimated dispersion parameter multiplier effect as a function of N and K (estimated from model 3): $\alpha = \exp(z_i\gamma) = \exp\left(-0.21\text{single} + \frac{0.97}{N} - 0.63K + 0.26K^2 - \frac{0.37K}{N}\right)$.

Although our results broadly confirm Kauffman's (1993) *NK* model of evolution in a technological context, they return disappointing results with respect to the relative importance of factors traditionally thought to influence inventive processes. In particular, despite arguments for the ubiquity and efficacy of local search (March and Simon, 1958; Nelson and Winter, 1982; March, 1991; Stuart and Podolny, 1996), such strategies seem far less important to the outcome of invention than the topography of the search space. Amongst the local search and number of trials variables, only the effect of the number of prior art citations on the mean differed significantly from zero. Most dramatically, although earlier research points to this as an important determinant of patent usefulness (Podolny and Stuart, 1995), the effect of prior art citations on the mean is an order of magnitude weaker than the *NK* terms.

These results should be viewed cautiously for a variety of reasons. The typical reservations regarding the use of patent data apply, most notably that patenting practices and effectiveness vary across industries (Levin et al., 1987). Although the models controlled for differences in technology and patent characteristics, they did not introduce explicit controls for industries. In addition to differences in citations across communities, the accuracy of the independent variables also varies across communities. Sub-classes and the inverse of their ease of recombination provide only a proxy for inventors' components and interdependence. Although the sub-classes of some technologies may correspond very closely to engineering components, other sub-classes may not. For example, while sub-classes for digital hardware may match inventor's components quite closely (Fleming, 2001), others in fields such as genetics and finance may not. Given the difficulty of measuring interdependence, however, particularly across a large sample, the work provides promising initial results for the applicability of complexity theory to invention. The positive results justify more detailed measurement of interdependence in future research.

4.7. Discussion

Although the results provide broad statistical support for the application of Kauffman's model, two of these effects — the number of components and the interaction between components — only imply marginal practical import. In this sense, the 'complexity catastrophe' operates almost entirely as a function of the degree of interdependence among the system components. Since this diverges from the predictions of the *NK* model, these findings suggest a need to consider seriously how evolution in social systems differs from biological evolution.

At first glance, technological evolution differs from evolution in biological systems in at least one important respect: the agent of recombination (Basalla, 1988). In natural evolution, recombination occurs primarily through haphazard sex. In contrast, inventors can purposely combine elements in technological evolution. Because inventors have a much higher degree of intelligence than the automata that navigate Kauffman's landscapes, they can move beyond simple search patterns, such as hill-climbing or random combination. Understanding the impact of more realistic search heuristics strikes us as an important subject for future research. For example, inventors might develop systems for hierarchically decomposing the search space (Simon, 1996). If these techniques allow them to deal more effectively with changes in the number of components than changes in the degree of interdependence among those components, one would expect the reduction in the importance of the number of components that we find.

Similarly, the ability of humans to move beyond blind search algorithms might systematically alter the nature of technological evolution over time. Intelligent actors can develop conceptual models, not just of the topography of the landscape, but also of the forces that create that terrain. Over time, inventors might become increasingly 'foresighted' and able to predict the outcomes of previously untried combinations (Vincenti, 1990). The development of broader scientific and technological knowledge might also improve the search process. Although the inherent difficulty of combining interdependent technologies does not change, inventors become more proficient in searching these landscapes. Thus, the *effective* difficulty of using interdependent technologies declines with time and experience.

To the extent that this knowledge transforms the search process, the social construction of technological communities will influence search and, thus, shape the evolution of technology. Although inventors might gain an understanding of the underlying forces creating interactions among some limited set of technological components, they cannot know the interdependencies of all technologies. Cognitive limits constrain such technological expertise to narrow fields. For this reason, people concentrate on particular subjects in the course of their schooling and work. Since social processes largely define these subjects and the boundaries between them, these divisions might fail to provide researchers with the most relevant set of knowledge to explore new lines of invention. Moreover, these socially constructed categories could inhibit useful search that would cross social boundaries because inventors typically focus their efforts within the boundaries of their field of expertise (Fleming, 2001). For example, computing and amino acids appear to have little in common. Nevertheless, scientists recently used amino acids to compute a solution to the traveling salesperson problem (Adleman, 1998). When socially disparate fields manifest useful interactions, the technological community must often restructure the social definitions of fields, or even create a new field, to support exploration of these new recombinant regions. The emergence and continued straddling of software engineering between departments of mathematics and electrical engineering provides an example of this process.

Regardless of the social constraints across different technological communities, our results have strategic implications for inventors. Inventors need not search locally to avoid risk and produce useful new technologies. Indeed, as shown by the weak effect of our control variables, if they only refine existing combinations they will rarely enjoy breakthrough success. To maximize the likelihood of useful invention, researchers should work with a large number of components that interact to an intermediate degree. We suspect, however, that inventors might work with pathological pressures for modularity.

Engineers generally drive the interdependence out of their designs to reduce the uncertainty of their inventive outcomes.[20] Such risk aversion might simply be human nature (Simon, 1945), but educational institutions and organizational pressures (March, 1991) reinforce this tendency. Indeed, scholars in both the engineering and social sciences support these efforts. For example, Mead and Conway (1980) receive credit for simplifying integrated circuit design through modularity (admittedly at the expense of performance and silicon real estate). McCord and Eppinger (1993) developed a technique to map component interdependencies into a design and task structure matrix. They argue that engineers should strive to contain interdependencies behind standard modular interfaces. Baldwin and Clark (2000) propose that the modularization of IBM's mainframes in the 1960s generated the firm's windfall profits of the time. Given available modules, they propose that engineers can more easily create value with six simple operators: splitting, substituting, augmenting, excluding, inverting, and porting. These institutional, organizational, and scholarly influences lead inventors to prefer modular components over less modular alternatives.

In addition to providing modular methods, many scholars also argue that engineers actually underutilize the benefits of modularity. Although we agree that modularization decreases inventive uncertainty, our results show that intermediate levels of interdependence produce the most useful inventions. Engineers may unwittingly limit the long run development of many technologies by systematically de-coupling their components. These design practices move recombinant search from intermediate to very low-K landscapes and our results suggest that such movement ultimately generates less useful inventions. Christensen et al. (1998) also find evidence that modularity does not uniformly benefit design in their study of thin film heads in the disk drive industry. The impact of modularization on recording density exhibits a non-monotonic curve with respect to time; at first negative, then positive, and finally insignificant. The onset of complete modularity severely limits opportunity. As Christensen et al. (1999) propose, "... modularity narrows degrees of freedom in design".

Our results suggest a contingent resolution. When technologies exhibit extreme interdependence, engineers should actively promote efforts to make the technology more modular. For example, computer hardware probably entailed too much interdependence when IBM began their modularization efforts (Baldwin and Clark, 2000). And continuing efforts to make software more modular, for example, object oriented code, probably represent a rational and proper response to the development of an extremely interdependent technology.[21] Past a certain point, however, lab directors might need to encourage inventors to play with more interdependent technologies.

Our contingent explanation of the benefits of modularity remains consistent with work in the evolution of technological life-cycles and industrial change. Utterback (1996) proposes that radical innovations often synthesize well-known components. Radical innovations use these components in unintended ways, however, such that inventors do not know or poorly understand the interdependencies between the components. A high degree of uncertainty surrounds these new combinations–most fail, but some reveal unforeseeable usefulness. Engineers then modularize and refine the successful inventions, using the operators described by Baldwin and Clark (2000). This effort moves the technological field from its early high-K landscape to the intermediate-K landscape. This highly productive period in the technological trajectory might correspond to the region around $K = 1$ in Fig. 5. From that point, further modularization becomes increasingly less productive. This period might correspond to the region from $K = 0.8$ to 0 in

[20] This perspective suggests a subtle definitional difference between interdependence and modularity. When working with fundamental materials such as basic elements or natural materials, the intrinsic interdependence of those physical components constrains engineers. As they build more complex, hierarchical systems, engineers gain control over the interdependence of their components through design. Thus, interdependence is the intrinsic or potential interaction between components, while modularity is the consciously designed de-coupling of components.

[21] Setting aside the debate of whether software is technology or knowledge of how to use technology, it clearly meets our definition of extreme interdependence. One bit out of place amongst millions can mean the difference between an incredibly useful or a crashed and useless tool.

Fig. 5. Unless inventors introduce new materials or reintroduce interdependence among the components, the technological trajectory exhausts itself.

Unlike biological organisms, technology life-cycles do not necessarily progress in a uni-directional fashion. If we think of invention as a continuous and interdependent search process, we explicitly avoid the idea that novel technologies appear by chance and then progress monotonically through maturity and death. Instead, inventors' recombinant search efforts drive technological life-cycles. These efforts alternate continuously between new syntheses and modularization. Inventors begin the process by trying completely new combinations of components. They then discard the obvious failures and re-organize the most promising combinations and interfaces between components. This modularization of the initial synthesis decreases the effective interdependence between components. Without new syntheses, however, the modularization process eventually exhausts creative potential. Thinking of invention as a process of recombinant search over an interdependent landscape provides a more complete and causal explanation of the technological sources of the life-cycle, from birth by synthesis, growth and productivity through initial modularization, eventual exhaustion from complete modularization, and rebirth through new interdependent syntheses.

5. Conclusion

This paper develops and tests a theory of invention as a process of recombinant search over technology landscapes. The work contributes a theory of invention that complements our more extensive understanding of technological diffusion, innovation, and organizational implications. In contrast to the bulk of previous work that has relied primarily on simulation-based studies (Simon, 1996), our study also presents empirical support for complex adaptive systems theory. Although we find that local search affects the outcome of invention, the interdependence and size of the search space impacts the likelihood of successful search more than any other characteristic of the invention process. Indeed, the effect of interdependence K and the number of components N can make the difference between a median invention and one in the top 6%.

This study opens doors for a broad range of future research. Our strong empirical results should motivate the development of more specific *NK* simulation models. Given that intelligent actors do not blindly recombine components, future simulations need to explore the consequences of intelligent agents that can imitate and learn from experience (see Gavetti and Levinthal (2000) and Rivkin (2000) for steps in this direction). Moreover, future simulations should also consider the implications of truncated observation schemes, given the potential for testing these outcomes with patent citation data and negative binomial variance decomposition models. Such simulations would ideally give rise to the over-dispersed Poisson distributions so commonly observed in the patent citation data. These simulation efforts and additional empirical work might lead to new theoretical insights as well. For example, how does scientific knowledge influence search over an interdependent landscape? Finally, how does the structure of interdependence affect invention? Previous work on modularity, architecture, and hierarchy suggests advantages to pockets of interdependent components linked by more modular interfaces (Ulrich and Eppinger, 1995; Baldwin and Clark, 2000). Thus, the mean level of interdependence might capture only a portion of the relevant design characteristics that influence invention. These and other opportunities suggest that conceptualizing technology as a complex adaptive system can yield useful new insights into our understanding of inventive processes.

Acknowledgements

Both investigators contributed equally to this research; authorship follows alphabetical order. We would like to thank our anonymous reviewers, Phillip Bromiley, Steven Eppinger, Carliss Baldwin, Marco Iansiti, Laurie Calhoun, and the participants of the TOM Innovation and doctoral seminars at the Harvard Business School for their useful feedback. In particular, we wish to thank Jan Rivkin. We would also like to thank the Department of Research, Harvard Business School for their support, Firooz Partovi and William Simpson and the Faculty Research Center, Harvard Business School for their computing resources, and Corey Billington and Ellen King of Hewlett-Packard for donation of their patent database.

References

Abernathy, W., Utterback, J., 1978. Patterns of industrial innovation. Technology Review June, 40–47.

Adamson, R., 1952. Functional fixedness as related to problem solving: a repetition of three experiments. Journal of Experimental Psychology 44, 288–291.

Adleman, L., 1998. Computing with DNA. Scientific American August, 54–61.

Albert, M., Avery, D., Narin, F., McAllister, P., 1991. Direct validation of citation counts as indicators of industrially important patents. Research Policy 20, 251–259.

Allen, T., 1977. Managing the Flow of Technology. MIT Press, Cambridge, MA.

Amabile, T., 1988. A model of creativity and innovation in organizations. Research in Organizational Behavior 10, 123–167.

Baldwin, C., Clark, K., 2000. Design Rules: The Power of Modularity. MIT Press, Cambridge, MA.

Basalla, G., 1988. The Evolution of Technology. Cambridge University Press, Cambridge.

Bruderer, E., Singh, J., 1996. Organization evolution, learning, and selection: a genetic-algorithm-based model. Academy of Management Journal 39, 1322–1349.

Cameron, A., Trivedi, P., 1986. Econometric models based on count data: comparisons and applications of some estimators and tests. Journal of Applied Econometrics 1, 29–53.

Carr, F., 1995. Patents Handbook: A Guide for Inventors and Researchers to Searching Patent Documents and Preparing and Making an Application. McFarland, Jefferson, NC.

Christensen, C., Suarez, F., Utterback, J., 1998. Strategies for survival in fast-changing industries. Management Science 44, S207–S220.

Christensen, C., Verlinden, M., Westerman, G., 1999. Product Modularity, Vertical Disintegration, and the Diffusion of Competence. Working Paper, Harvard Business School, Boston, MA.

Cohen, W., Levinthal, D., 1990. Absorptive capacity: a new perspective on learning and innovation. Administrative Science Quarterly 35, 128–152.

Eldredge, N., Gould, S., 1972. Punctuated equilibria: an alternative to phyletic gradualism. In: Schopf, T. (Ed.), Models in Paleobiology. Freeman, San Francisco, CA.

Eppinger, S., 1999. Personal Communication in Sloan School of Management Seminar. 1 November.

Fleming, L., 2001. Recombinant uncertainty in technological search. Management Science 47, 117–132.

Gavetti, G., Levinthal, D., 2000. Looking forward and backward: cognitive and experiential search. Administration Science Quarterly 45, 113–137.

Gilfillan, S., 1935. Inventing the Ship. Follett Publishing Co., Chicago.

Hall, B., Jaffe, A., Trajtenberg, M., 2000. Market Value and Patent Citations: A First Look. NBER, Working Paper 7741.

Hargadon, A., Sutton, R., 1997. Technology brokering and innovation in a product development firm. Administrative Science Quarterly 42, 716–749.

Hausman, J., Hall, B., Griliches, Z., 1984. Econometric models for count data with an application to the patents–R&D relationship. Econometrica 52, 909–938.

Henderson, R., Clark, K., 1990. Architectural innovation: the reconfiguration of existing product technologies and failure of established firms. Administration Science Quarterly 35, 9–30.

Iansiti, M., 1998. Technology Integration: Making Critical Choices in a Dynamic World. Harvard Business School Press, Boston, MA.

Jaffe, A., Trajtenberg, M., 1995. Flows of Knowledge from Universities and Federal Labs: Modeling the Flow of Patent Citations Over Time and Across Institutional and Geographic Boundaries. National Academy of Sciences Colloquium on Science, Technology, and the Economy, 20 October.

Kaplan, C., Simon, H., 1990. In search of insight. Cognitive Psychology 22, 374–419.

King, G., 1989. Event count models for international relations: generalizations and applications. International Studies Quarterly 33, 123–147.

Kauffman, S., 1993. The Origins of Order. Oxford University Press, New York.

Levin, R., Klevorick, A., Nelson, R., Winter, S., 1987. Appropriating the returns from industrial research and development: comments and discussion. Brookings Papers On Economic Activity 3, 783–831.

Levinthal, D., 1997. Adaptation on rugged landscapes. Management Science 43, 934–950.

Long, J., 1997. Modeling Frequency and Count Data. Oxford University Press, Oxford.

Macken, C., Hagen, P., Perelson, A., 1991. Evolutionary walks on rugged landscapes. SIAM Journal of Applied Mathematics 51, 799–827.

March, J., 1991. Exploration and exploitation in organizational learning. Organization Science 2, 71–87.

March, J., Simon, H., 1958. Organizations. Blackwell, Cambridge, MA.

Marquis, D., 1969. The anatomy of successful innovations. Innovation 1, 35–48.

McCluskey, E., 1986. Logic Design Principles with Emphasis on Testable Semi-Custom Circuits. Prentice-Hall, Englewood Cliffs, NJ.

McCord, K., Eppinger, S., 1993. Managing the integration problem in concurrent engineering. Working paper 3594, MIT Sloan School of Management, Cambridge, MA.

McPherson, J., Ranger-Moore, J., 1991. Evolution on a dancing landscape: organizations and networks in dynamic Blau space. Social Forces 70, 19–42.

Mead, C., Conway, L., 1980. Introduction to VSLI Systems. Addison-Wesley, Reading, MA.

Millman, J., 1979. Microelectronics. McGraw-Hill, New York.

Nelson, R., Winter, S., 1982. An Evolutionary Theory of Economic Change. Belknap Press, Cambridge, MA.

Podolny, J., Stuart, T., 1995. A role-based ecology of technological change. American Journal of Sociology 100, 1224–1260.

Rivkin, J.W., 2000. Imitation of complex strategies. Management Science 46, 824–844.

Rogers, E., 1983. The Diffusion of Innovations. Free Press, New York.

Rosenberg, N., 1982. Inside the Black Box: Technology and Economic Change. Cambridge University Press, New York.
Ruttan, V., 1959. Usher and Schumpeter on invention, innovation, and technological change. Quarterly Journal of Economics 73, 596–606.
Schumpeter, J., 1939. Business Cycles. McGraw-Hill, New York.
Simon, H., 1945. Administrative Behavior: A Study of Decision-making Processes in Administrative Organizations. Free Press, New York.
Simon, H., 1996. The Sciences of the Artificial. MIT Press, Cambridge, MA.
Sørensen, J., Stuart, T., 2000. Aging and organizational innovation. Administrative Science Quarterly 45, 81–112.
Sorenson, O., 1997. The complexity catastrophe in the computer industry: interdependence and adaptability in organizational evolution. Unpublished Ph.D. dissertation, Sociology Department, Stanford University.
Sorenson, O., 2000. The effect of population level learning on market entry: the American automobile industry. Social Science Research 29, 307–326.
Stuart, T., Podolny, J., 1996. Local search and the evolution of technological capabilities. Strategic Management Journal 17 (Summer special issue), 21–38.
Trajtenberg, M., 1990. A penny for your quotes: patent citations and the value of innovations. Rand Journal of Economics 21, 172–187.
Tushman, M., Anderson, P., 1986. Technological discontinuities and organizational environments. Administrative Science Quarterly 31, 439–465.
Tushman, M., Rosenkopf, L., 1992. Organizational determinants of technological change: toward a sociology of technological evolution. Research in Organizational Behavior 14, 311–347.
Ulrich, K., 1995. The role of product architecture in the manufacturing firm. Research Policy 24, 419–440.
Ulrich, K., Eppinger, S., 1995. Product Design and Development. McGraw-Hill, New York.
Usher, A., 1954. A History of Mechanical Invention. Dover, Cambridge, MA.
Utterback, J., 1996. Mastering the Dynamics of Innovation. Harvard Business School Press, Boston, MA.
Vincenti, W., 1990. What Engineers Know, and How They Know It? Johns Hopkins University Press, Baltimore, MA.
Von Hippel, E., 1988. The Sources of Innovation. Oxford University Press, New York.
Weinberger, E., 1991. Local properties of Kauffman's *NK* model: a tunably rugged energy landscape. Physical Review A 44, 6399–6413.
Weitzman, M., 1996. Hybridizing growth theory. In: Proceedings of the American Economics Association. May, pp. 207–212.
Wright, S., 1932. The roles of mutations, inbreeding, crossbreeding and selection in evolution. In: Proceedings of the 11th International Congress of Genetics, Vol. 1. pp. 356–366.