

AVOIDING COMPLEXITY CATASTROPHE IN COEVOLUTIONARY POCKETS: STRATEGIES FOR RUGGED LANDSCAPES

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Can firms and coevolutionary groups suffer from too much interdependent complexity? Is complexity theory an alternative explanation to competitive selection for the emergent order apparent in coevolutionary industry groups? The biologist, Stewart Kauffman, suggests a theory of complexity catastrophe offering universal principles explaining phenomena normally attributed to Darwinian natural selection theory. Kauffman's complexity theory seems to apply equally well to firms in coevolutionary pockets. Based on complexity theory, four kinds of complexity are identified. Kauffman's " $NK[C]$ model" is positioned "at the edge of chaos" between complexity driven by "Newtonian" simple rules and rule-driven deterministic chaos. Kauffman's insight, which is the basis of the findings in this paper, is that complexity is both a consequence and a cause. *Multicoevolutionary complexity* in firms is defined by moving natural selection processes inside firms and down to a "parts" level of analysis, in this instance Porter's value chain level, to focus on microstate activities by agents. The assumptions of stochastically idiosyncratic microstates and coevolution in firms are analyzed. Competitive advantage, as a dependent variable, is defined in terms of Nash equilibrium fitness levels. This allows a translation of Kauffman's theory to firms, paying particular attention to: (1) how value chain landscapes might be modeled; (2) assumptions underlying Kauffman's models making them amenable to firms; and (3) a delineation of seven of Kauffman's computational experiments. As part of the translation, possible parallels between the application of complexity catastrophe theory to coevolutionary pockets and studies by institutional theorists and social network analysts are discussed. The models derive from *spin-glass* microstate models resulting in Boolean games. Kauffman's "*Boolean statistical mechanics*" is introduced in developing the logic underlying the somewhat simplified $NK[C]$ model. The model allows the use of computational experiments to better understand how the dependent variable—value chain fitness—is affected by changes in the number of internal interdependencies K , the number of coevolutionary links with opponents C , the size of the coevolutionary pocket S , and the number of simultaneous adaptive changes, among other things. Various computational experiments are presented that suggest strategic organizing approaches most likely to foster competitive advantage. High or low Nash equilibrium fitness levels are shown to result from internal and external coevolutionary densities as a function of links among value chain competencies within a firm and between a firm and an opponent. Complexity phenomena appear to suggest a number of expected (and thus validating) and surprising strategies with respect to complex organizational interdependencies. For example, moderate complexity fares best and external coevolutionary complexity sets an upper bound to advantages likely to be gained from internal complexity. Various complexity "lessons" are discussed. Models such as the $NK[C]$ could offer insights into strategic organizing.

Key words: Coevolution; Complexity; Interdependencies, Value Chain; Competitive Advantage; Networks; Microstates; Agent-based Modeling; Rugged Landscapes.

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1. INTRODUCTION

Conventional wisdom among economists (Alchian 1950, Friedman 1953, Hirshleifer 1977, Nelson and Winter 1982), organizational evolutionists (Aldrich 1979, McKelvey 1982, Baum and Singh 1994b), and organizational ecologists (Hannan and Freeman 1977, 1989; Hannan and Carroll 1992, Baum 1996), holds that Darwinian selectionist processes drive out the less fit firms, leaving "order" to be explained as the consequence of the survival of the more fit firms. The dominance of selectionist explanations in biology, the host discipline of Darwinian theory, has been challenged by Kauffman (1993), who suggests that complexity effects may thwart selectionist effects under some circumstances. Could this also be true of organizational phenomena? Consider two possibilities:

1. **At the firm level**, Baden-Fuller and Stopford recently published a major study suggesting that some mature European firms became more innovative by making substantial reductions in complexity (1994, Chs. 6, 7). Rommel, *et al.*, (1995) report on another major European study showing that, as they title their book, *Simplicity Wins*. These calls for simplicity rather than complexity challenge other recent calls for more cross-functional integration (Dimancescu 1992, Galbraith, Lawler, and Associates 1993, Graham and LeBaron 1994, Johann 1995) and consequent increased complexity. Excepting Postrel (1998), who develops an analytical model identifying optimum ratios between functional specialization and integration based on trade-offs between specialist competence and cross-specialist understanding, little guidance or criteria are offered as to what ratio might offer selective

competitive advantage.

2. **At the supra-firm level**, Porter (1990, 1991) observes that coevolutionary pockets of intensely competing firms in geographical proximity may be an important basis of competitive advantage for nations. Understanding the dynamics of coevolutionary pockets offering nations strategic advantage stands as one of the four fundamental research issues facing strategists (Rumelt, Schendel, and Teece 1994, p. 46). Intense coevolutionary behavior seems to be an increasingly obvious part of the modern competitive landscape (Bourgeois and Eisenhardt 1988, Eisenhardt 1989, 1995; D'Aveni 1994, Galunic and Eisenhardt 1996, Thomas 1996), yet little is known about the extent to which coevolutionary complexity might moderate the success of individual firms or the competitive strength of the pocket.

To understand strategic choices and strategy implementation/organization design options available to firms in coevolutionary pockets, I translate Kauffman's (1993) model of coevolutionary complexity into a firm context by using value chain competencies as "parts" of firms, since his " NK model" calls for a reductionist analysis of firm coevolution.¹ '*Multilevel coevolutionary complexity*' is a function of the extent complexity plays a part in the nature and fitness of coevolutionary interdependencies (1) among parts within a firm; and (2) between the parts of a firm and the parts of its opponents. In this conceptualization, "parts" are

¹ Kauffman's work on this subject extends from 1969 and is largely assembled in his 1993 book.

further reduced to discrete random behavioral events, each of which is governed by a ‘*microagent*’. This approach substitutes stochastic nonlinear numerical simulation models in place of the linear deterministic event history models (Baum and Singh 1994b) and case studies (Porter 1990) heretofore used to study coevolution. Specifically, my translation of questions bearing on organizational complexity to fit Kauffman’s simulation models appears to be a useful alternative for exploring such questions as: (1) What intrafirm levels of integrative complexity affect competitive advantage? (2) What levels of integrative complexity influence how rapidly firms in coevolutionary groups reach equilibrium fitness levels, if they do so? (3) What complexity factors might affect the competitive advantage (or height) of fitness levels? and (4) What levels of integrative complexity might affect the overall adaptive success of firms comprising a coevolving system?

Computational modeling of complexity effects bearing on strategy in coevolutionary pockets (Porter 1990, 1991) involves Boolean (binary) networks and adaptive agents—complexity theory is a function of both stochastic agent behavior at vertices as well as the emergence of networked relations. Given the latter, Burt’s (1992) “*structural holes theory*” of competitive strategy, and more broadly, sociological network theory and methods (Nohria and Eccles 1992, Pattison 1993, Wasserman and Faust 1994), seem relevant. But, since complexity theory attempts to explain the composite of both agents and their networked relations, similarities between Kauffman’s approach and most sociological network density studies appear more ephemeral than real.

Kauffman’s theory does have some parallels with Burt’s structural holes theory and computer simulation studies of emergent behavior in *social movements* (Macy 1991, Marwell and Oliver 1993, Kim and Bearman 1997). The Liebeskind et al. (1996) study of how bio-tech firms use outside experts is a loose fit with the *NK[C]* model. Kauffman’s theory allows the interweaving of network sociology studies with Porter’s coevolutionary pocket and value chain “unique activities” (Porter 1985) theories, the resource- and competence-based views (Teece 1984, Wernerfelt 1984, Rumelt 1987, Barney 1991, Heene and Sanchez 1997), and multicoevolutionary views in organization science (Baum and Singh 1994b, Baum and McKelvey in press).

For background I focus on microagents, stochastic idiosyncrasy, multicoevolutionary complexity, complexity theory, and network sociology. Next, basic elements of Kauffman’s *NK[C]* simulation model are defined and translated to the context of firms. His results are then used to illustrate new ways to better understand how levels of complexity might affect the competitive advantage of coevolving firms. I conclude with a discussion of how complexity may confound findings and explanations offered solely within the context of

selectionist theory.

2. MULTI-LEVEL COEVOLUTIONARY COMPLEXITY

Organizations have been defined as *complex* for quite some time (Etzioni 1961, Perrow 1961, Haas and Drabek 1973). They have official and unofficial goals, several hierarchical levels, a number of departments, boundaries, and various technologies or activity systems (Scott 1964, Hall 1977, Aldrich 1979). This is a static description of complexity. I would like to take a dynamic approach, focusing on coevolutionary adaptive progression in a competitive context. Suppose that firms not only coevolve as whole entities, but that they also coevolve with respect to their parts. Consider also the simultaneous coevolution of one or more parts, with different levels of ‘*multicoevolutionary complexity*’ involved. To become conceptually prepared to think about firms in terms of adaptive learning models, think in terms of microagents. You might already think of your desk as both a single object and also as a composite of billions of atoms and wood cells. Now, stop thinking of a firm as a single entity or even as consisting of a CEO and employees and instead think of it as a collectivity of behavioral process microstates governed by microagents. You may then ask, How many microagents does it have? How rapidly does each one improve its functioning? Does microagent improvement enhance of the aggregate system? What kind of network is the agent embedded in? In this section I first redefine firms as collectivities of microagents. Next I argue that microagent behavior is stochastically idiosyncratic. Then I focus on multi-level coevolutionary selectionist effects among the microagents. Then I introduce ideas from complexity theory particularly relevant to Kauffman’s theory.² My final discussion identifies parts of network sociology related to Kauffman’s dynamic modeling approach.

2.1 VALUE CHAIN COMPETENCIES: AGENTS AND MICROAGENTS

This section asks you to shift your conception of firms as CEOs, employees, and hierarchy to thinking of them as resulting from hundreds and thousands of very small behavioral process events—*process level organizational phenomena*. To begin, I define value chain competencies as “parts” of firms. Though we could draw on Mackenzie’s (1986) process entities as parts, changes in the elements of Porter’s (1985) value chain seem especially important because they are so closely tied to revenue and cost streams and ultimately competitive fitness. Porter (1996, p. 62) says, “Activities...are the basic units of competitive advantage. Overall advantage or disadvantage results from all [of] a company’s activities, not only a few.”

² The background material comprising Section 2 is developed more fully in McKelvey (1997b).

Porter (1985) defines value chain activities as a key determinant of sustained competitive advantage. **Primary** activities are those “involved in the physical creation of the product and its sale and transfer to the buyer as well as aftersale assistance” (1985, p. 38), such as: Inbound Logistics, Operations, Outbound, Logistics, Marketing and Sales, and Service. **Support** activities “support the primary activities and each other by providing various firmwide functions,” including: Procurement, Technology Development, Human Resource Management, and Firm Infrastructure. Both Porter (1991) and the resource-based view (Teece 1984, Wernerfelt 1984, Rumelt 1987, Prahalad and Hamel 1990, Barney 1991, Reeves-Conner 1991, Teece, Pisano, and Shuen 1994) argue that the changing relationship between a firm’s activities and entities in its competitive environment creates whatever distinct or idiosyncratic capabilities it draws on for sustained competitive advantage. Following Heene and Sanchez (1997) and Mosakowski and McKelvey (1997), I subsume all of the resource-based view terms, such as “resources,” “core competencies,” and “dynamic capabilities,” into one term, “*competencies*.” I also include Porter’s “activities” within the competency term.

To aid explication, consider a notebook computer firm as consisting of 24 chain competencies (an illustrative set is given in Table 1). In my analysis, chain competencies are the “parts” in firms. Competencies, as parts, may or may not be isomorphic with organizational units shown on organization charts. Several levels of competencies may exist, such as, division, departmental, functional, or process level competencies. For example, competence parts could represent the elements of notebook computers typically used as the basis of market competition, as illustrated in *PC World*, *PC Magazine*, or *Computer Shopper*. Each competence might be housed in a particular department within the firm, headed by a department manager as a decision making agent, or it might be spread among several departments with a sort of “virtual” agent (perhaps in the form of an interdepartmental team) in charge of its incremental improvement. In addition, think of each department’s competencies as reflected in some number of an ongoing stream of value chain related behavioral process events which are instigated by the employees within the department. These events might be in response to directives from the manager, ideas and events created by other employees in the department in carrying out the daily business of the department, or they might be in response to competition from an equivalent department by a competitor. Or they could just be events created by an employee for his or her own particular needs at the time and may or may not be responsive to firm goals. Not all behavioral events exhibit a particular competence, only some of them. These are termed ‘*competence events*’.

>>> Table 1 about here <<<

Suppose we consider that each competence event is governed by the utility function that an employ brings to bear to cause that particular event. Now, instead of the many daily events caused by a particular employee as a single agent, just think of each competence event as a microstate governed by its own microagent. This “virtual” microagent applies the part of the employee’s total utility function that is specifically relevant to a particular event. Thus, instead of thinking of multiple behavioral events making up the composite behavior of an employee, think instead of the employee as decomposed into a set of virtual microagents, each of which causes an event or microstate.³ Finally, consider the possibility that, based on conversations and observations, each competence event (microstate) might be incrementally improved (by its microagent) as the employee goes about the daily business of contributing to the competence of the value chain.

2.2 THE STOCHASTIC IDIOSYNCRASY ASSUMPTION

Sciences form a hierarchy (Schwab 1960, Barrow 1991): physics, chemistry, biology, psychology, economics.⁴ Separating each level of science is a ‘*molecular lower bound*’ acting as a cut-off point below which a given science stops explanatory attempts. The “matter” comprising the lower bound consists of atomic particles, molecules, genes, neurons, or actors (respectively, for each science) which make up an ‘*interactive microstate system*’. While they may be particles or molecules to natural scientists, think of them generally as interactive microstates.

Traditionally sciences assume microstates are *uniform*—they all have the same predictable energy state or genetic code, or in the case of economists, all actors are rational (Friedman 1953). The uniformity assumption is an ‘*instrumental convenience*’ (McKelvey 1997b), accepted to simplify mathematical analysis rather than because it is true. It acts as a platform upon which the theories of

³ Since brains are really fragmented into discrete neuron networks, they already behave as fragmented microagents (Leviton and Kaczmarek 1991, Morgan 1997, Ch. 4)—we just tend to think of them “wholes” so as to be consistent with our more composite concept of self.

⁴ A referee wondered why I did not include sociology. One reason is that sociology and economics are more parallel than one above or below the other. If I had added it in between psychology and economics, I suspect some sociologists would complain, seeing their discipline as more macro than economics. The other less charitable reason is that since sociology as a total discipline ranks pretty low on the standard scientific criteria of formally modeled theory and experimental testing, many observers are not convinced sociology belongs in the same ranking as those listed. Note that I did not include organization science either. Actually the ranking is in terms of the “size” of the microstates comprising the lower bound—people, social systems/economies being larger than particles, molecules, and cells—that is, it is reductionist. Since this essay focuses on molecular reduction rather than atomic reduction, physics is at the bottom because it has the smallest microphenomena in its lower bound, not because it is most prestigious.

each science are built. For example, for the 200 years since Adam Smith, economists have assumed that rational actors uniformly attempt constrained maximization (Hogarth and Reder 1987). During the 20th century the uniformity assumption slowly gave way to a *stochastic idiosyncrasy* assumption in natural science, in which particle or microstate behavior is assumed to consist of idiosyncratic microstates which have some probability of occurrence (Prigogine 1962, Depew and Weber 1995). Only recently has the uniformity assumption been challenged in economics, yet it is still ignored by most economists (Hogarth and Reder 1987). All sciences have been slow to switch from the uniformity to the stochastic assumption. Boltzmann was so depressed at the lack of acceptance of the statistical mechanics of particles (based on Brownian motion discovered in 1828) over three decades after he proposed it in 1870 that he committed suicide in 1906. Physicists adopted it circa 1928, given quantum mechanics.⁵

Biologists in general now accept the stochastic assumption (Nei 1987, Depew and Weber 1995). The choices of microagents in Kauffman's *NK* model are always stochastic: "...[T]he ways in which different alleles at the *N* loci might be coupled to one another epistatically⁶ to produce an overall fitness for each genotype might be extraordinarily complex. In general, we truly have almost no idea what those mutual influences on overall fitness might be.... This complexity suggests that it might be useful to confess our total ignorance and admit that, for different genes and those which epistatically affect them, essentially arbitrary interactions are possible. Then we might attempt to capture the statistical feature of such webs of epistatic interactions by assuming that the interactions are so complex that we can model the statistical features of their consequences with a random fitness function" (Kauffman 1993, p. 41).

Applications of complexity theory to firms also assume stochastic idiosyncrasy and nonlinearity (Stacey 1991, 1995, 1996; Thiétart and Forgues 1995). The force causing emergent structure is viewed in terms of tension between organic vs. mechanistic systems (Burns and Stalker 1961). Tension gradients may be of virtually any kind and cause emergent structures of both organic and mechanistic or formal and informal kinds—they are not limited to the organic, informal emergent systems of traditional natural system theory (Scott 1998). Thus, any kind of organizational structure, emerging from negentropic causes, appears as an emergent structure.

⁵ Actually it was the American, Gibbs, whose book in 1902 brought Boltzmann's work back to life. In English, it first influenced the British physicists and only a decade or two later did it seep into the network of German physicists.

⁶ Epistatic interdependencies have an effect only if they force a lower fitness than what is "drawn" by an agent—hence they always act to limit the fitness yield an agent otherwise might obtain from the draw.

Stacey rests much of his argument on the tension between formal and informal systems and between stability and innovation—bifurcated attractors leading to chaotic behavior. Thiétart and Forgues identify tension gradients across a broad range of organizational structure and process—shown in Table 2.

>>> **Table 2 about here** <<<<

Mackenzie (1986) points to thousands of organizational processes associated with employees having idiosyncratic "sensemaking" of their phenomenal world (Weick 1995). Firms have idiosyncratic official and unofficial goals (Perrow 1961), unique employees, unique hierarchical relations among employees, unique emergent cultures (Frost, *et al.* 1985), and unique value chains (Porter 1985). Postpositivists (Lincoln 1985) and postmodernists (Chia 1996) view much of intrafirm behavior as idiosyncratic. Mosakowski (1997) argues that stochastic idiosyncrasy underlies the resource-based view of strategy. Barney (1994) observes that firms are not just governed by one "game" by the CEO but rather myriad games played throughout firms. Thus, it seems reasonable to conclude that the complexity theorists' assumption also applies to firms, and that most, day-to-day human interaction events in firms are stochastically idiosyncratic. Substitute *part* for *allele* and *firm* for *genotype* and the earlier quote from Kauffman fits organization science.

2.3 MULTICOEVOLUTIONARY COMPLEXITY

Biologists apply Darwinian selectionist theory both to whole organisms and their *parts*, as does Kauffman (Depew and Weber 1995). Roughly, the parts making up biological organisms are, from bottom to top: amino acids, proteins, cells, multicellular fibers and tissues, and units such as organs, bones, and skin (Simmonds 1992). In some examples Kauffman uses traits, which are attributes of parts, rather than actual parts. Kauffman's usage of his model is robust in the sense that it does not require application to specific kinds of parts. All that is required is that there is a *whole* (which could be a species, cell, or chromosome) and *parts*, like organs, biomolecules, or genes that may mutate. Each part may be treated as a microagent.

Following biological practice in studying the effects of competitive selection,⁷ I apply selectionist theory to microagents, specifically to value chain competencies, as a means of studying the competitive selection of whole firms. A variety of alternative "part-whole" analyses of organizational adaptation appear in Baum and McKelvey (in press). I assume that changes in chain competencies are most likely to influence selective advantage for the firm as a whole. We could therefore identify, as the microstates for my application of Kauffman's model, the most critical chain competencies necessary for a firm's

⁷ For a review of micro- and macroevolutionary analysis in biology, see Eldredge (1995) and Depew and Weber (1995).

survival, as viewed from a top management or strategic perspective—or we could take a more emergent natural system perspective and pick parts naturally emerging as evolutionarily significant (those most likely to change which offer selective advantage for the firm as a whole). Obviously, the competencies viewed from the top would comprise more encompassing groupings of activities than, say, critical competencies from the perspective of a person operating the paint shop in an automobile assembly plant. If we were studying the coevolution of paint shops in auto firms, the latter might be more important to model.

Table 1 lists 14 primary, and 10 support value chain competencies upon which notebook computer makers might make adaptive advances so as to stay competitive. Where “hardware” items, such as disk size or docking station are mentioned, my focus is on the underlying competence. And competence in adopting a particular hardware item may depend on in-house competence or competence at finding, working with, helping upgrade, and contracting out to vendors. It is possible that, because of a solid understanding of transaction cost economics (Williamson 1975, Groenewegen 1996), a firm might hold selected competencies in-house and maintain access to others via contractual means. Two or more of these competencies may be interdependent in the sense that a competitive advance on one cannot occur without a change in another. For example, leading edge adaptive progression on disk size, chip speed, heat dissipation, and weight may interact. Other competencies, such as docking station design, or upgradability may remain independent. Alternatively, interdependencies may be high for leading edge lightness, compactness, and technical capability, but may be low for clumsier, slower, cheaper notebooks.

Coevolution is defined as mutual causal changes between a firm and competitors, or other elements of its niche, that may have adaptive significance (Roughgarden 1976). Key elements of coevolution are: (1) Niches and firms coevolve mutually causally as a population changes resource consumption capabilities; and (2) Niches contain competitors who have also coevolved along with the target firm and are able to compete more or less effectively for the same resources.⁸ Coevolution means that changes by firms are made in the context of changes by competitors and changes in nonfirm elements such as technology, markets, government policy, and so forth.

Institutional theory corroborates biology. The “mimetic isomorphism” of DiMaggio and Powell (1983) recognizes the reciprocal influence process as firms coevolve under conditions of uncertainty. DiMaggio (1992) explicitly reemphasizes the connection between structural network description, actor choices, the

embeddedness of networks in institutional contexts, and the initial structuration of institutions (DiMaggio 1988). Starting with classic statements by Selznick (1949), on cooptation, and how organizations and individuals influence institutions (Stinchcombe 1968), Scott (1995) reviews the literature on both the determinants of institutions and the effects of institutions on organizations in a demonstrably coevolutionary analysis. Further, Scott’s analysis demonstrates the multilevel effects of reciprocal influence (see Table 3.3, p. 57), a clear example of multilevel coevolution. As a composite, the chapters in Nohria and Eccles (1992) also portray the fit of sociological network analysis with a multilevel coevolutionary approach.

Several studies of coevolution appear in the Baum and Singh (1994b) volume on evolutionary dynamics. Porter (1990, 1991) notes the competitive advantage that nations attain when they have pockets of firms competing in intense coevolutionary relationships—Silicon Valley in California, Route 128 around Boston, the Industrial Triangle in North Carolina, for example. Firms in strong coevolutionary relationships push each other to “continuously improve, innovate and upgrade their competitive advantages over time” (1991, p. 111). The Porter “diamond” (firm strategy, factor conditions, demand conditions, related and supporting industries) is a dynamic system with each part mutually causing improvements in the other parts. Coevolutionary niche and firm dynamics also may be the basis of competition groups (Bogner, Mahoney, and Thomas 1993, Cho and McKelvey 1996), suggesting that these groups behave similarly to coevolutionary pockets.

Economists point to the coevolution of bottom line measures such as cost, price, quality or reputation in describing firm/opponent comovements toward competitive equilibrium via game theory (Rasmusen 1994, Kreps 1990, Camerer 1994, Saloner 1994). *Multicoevolutionary complexity* exists when simultaneous coevolutionary changes occur among two or more value chain competencies at more than one level. Some organization scientists have taken a multilevel view of coevolution, that is, niche/community, population, and firm levels (Brittain and Freeman 1980, Astley 1985, Barnett 1994, Baum and Singh 1994a, Brittain 1994, Rosenkopf and Tushman 1994, 1998; Van de Ven and Grazman in press). I wish to take the coevolutionary competition idea *one level lower* inside firms by focusing on intrafirm-to-intrafirm coevolutionary effects at the value chain level—technical decisions and processes—as do Van de Ven and Garud (1994) and Baum (in press); Ingram and Roberts (in press); Rosenkopf and Nerkar (in press).

Suppose, for example, that the contest between two notebook computer firms drops down from overall product price competition to competition over more specific parts of the chain, say, competencies underlying weight or chip speed. Once coevolution starts between

⁸ An elaborated discussion of coevolution is given in McKelvey (1997b).

two firms on one competence, it could spread to other competencies such as: memory technology, power systems, processor/motherboard/bus systems, ease and speed of upgrading, docking station configuration, reliability upon purchase, waiting time for service calls, and so forth. Firms may compete in terms of many value chain competencies. Competitive improvements may occur on some of these items at a very rapid pace (Eisenhardt 1989, 1995). While the primary chain elements are most obvious, clearly there might also be severe coevolutionary competition on support competencies as well.

2.4 COMPLEXITY THEORY

To offer an alternative explanation of natural biological or organizational order other than selectionist theory, complexity theory has to show an alternative basis for structure to emerge from stochastic microstates. Cramer (1993) identifies three levels of complexity: “*Subcritical complexity*” exists when the amount of information necessary to describe the system is less complex than the system itself. Thus a rule, such as $F = ma = md^2s / dt^2$ is much simpler in information terms than trying to describe the myriad states, velocities, and acceleration rates pursuant to understanding the force of a falling object. “Systems exhibiting subcritical complexity are strictly deterministic and allow for exact prediction” (1993, p. 213). Cohen and Stewart (1994) term this “simple-rule” based explanation since Newtonian kinds of complexity are amenable to maximum algorithmic compressibility (Barrow 1991)—meaning that it takes few information bits to explain this kind of complexity. At the opposite extreme is Cramer’s “*fundamental complexity*” where the minimum number of bits necessary to describe the behavior of a system is no less than the complex number of bits comprising the system in the first place. Cramer lumps chaotic and stochastic systems into this category, although deterministic chaos is recognized as fundamentally different from stochastic complexity (Morrison 1991, Gell-Mann 1994), since the former is “simple-rule” driven, while the latter consists of probabilistically distributed random events.⁹

In between Cramer puts “*critical complexity*.” The critical aspect of this category is the possibility of emergent simple-rule deterministic structures (fitting subcritical complexity criteria), even though the underlying phenomena remain in the fundamental complexity category. It is here that natural forces ease an investigator’s task by offering intervening objects as “simplicity targets” the behavior of which lends itself to simple-rule explanation. As Cramer sees it:

⁹ Complexity theorists such as Gell-Mann (1994) make a further distinction between systems composed of purely random bits having equal probability of occurrence and systems in which the rate of appearance of bits or microstates is governed by different probability distributions.

1. Newton’s laws about simple physical equilibrium processes fit under subcritical complexity.
2. Heisenberg’s uncertainty principle, Bénard convection cells, statistical mechanics, statistical laws, dissipative structures, biological macromolecules, organisms, and species fit under critical complexity.
3. Chaotic, stochastic, turbulent systems, biotropes, and many kinds of human behavior fit under fundamental complexity. (Cramer 1993, pp. 215–217)

Complexity theorists define systems in the critical complexity category as being in a state “*far from equilibrium*” or “*at the edge of chaos*.” The critical question becomes, what keeps emergent structures in states of equilibrium far above entropy—states counter to the 2nd law of thermodynamics?¹⁰ Prigogine (Prigogine 1962, Prigogine 1980, Prigogine and Stengers 1984, Nicolis and Prigogine 1989) observes that energy importing, self-organizing, open systems create structures that in the first instance increase negentropy,¹¹ but nevertheless ever after become sites of energy or order dissipation, thereby accounting to the 2nd law. Consequently he labels them “*dissipative structures*” because they are the sites where the imported energy is dissipated. If energy ceases to be imported the dissipative structures themselves eventually cease to exist. Dissipative structures may exhibit *persistence* and *nonlinearity*. Drawing on Eigen’s work (Eigen and Schuster 1979), Depew and Weber observe that “the most effective way of building structure and dissipating entropy is by means of autocatalysis” (1995, p. 462) wherein a chemical, product, or process event is produced that furthers the autocatalytic process (though remaining unchanged itself), thereby leading to a positive feedback “*autocatalytic cycle*.” Given their sensitivity to initial conditions, autocatalytic dissipative structures “are capable of generating dynamics that...produce order, chaos, or complex organization at the edge of chaos” (1995, p. 462). Complexity caused self-organizing structures are now seen as a ubiquitous natural phenomenon, and may be equally ubiquitous in organizations (Stacey 1995, 1996; Thiétart and Forgues 1995).

Depew and Weber note that the behavior of dissipative structures is nonlinear, creating marked explosions or crashes of structure, a situation far from Darwin’s gradualism. They go on to say that when “...a system is constrained far from equilibrium, macroscopic order arises not as a violation of the second law of thermodynamics but as a consequence of it” (1995, p. 464). This order may appear as Cramer’s subcritical

¹⁰ The 2nd law holds that all ordered or high energy structures move inexorably toward a disordered or low energy (entropic) state.

¹¹ Negentropy, coined by Schrödinger (1944), indicates a reversed energy flow (requiring energy inputs) toward increased order. It may occur from adding energy or simply by dividing (finite) structures. Entropy results simply from the merging of structures. Mergers and acquisitions often follow this principle, despite the best intentions of Wall Street gurus or managers—with the result that entropy usually dominates synergy!

systems. But in chaos theory, a dissipative structure acts as a “*point attractor*” as it grows, attracts more energy, and then dissipates more energy. Thus, as the energy gradient increases (between the “far from equilibrium” state and a more entropic equilibrium state), and the stress of maintaining the negentropic state increases, there is a likelihood that the system will oscillate between two different equilibria—one with structure and one with much less structure—thereby creating chaotic behavior.¹² If the adaptive stress increases beyond some additional limit, the chaotic behavior will change to stochastic behavior—no possibility of structure. By this line of reasoning, Prigogine, Ulanowicz (1989), and Depew and Weber use adaptive tension to explain how the various states of complexity come to exist. Exceeding a first critical value in adaptive tension creates emergent structure “at the edge of chaos” that is organized around point attractors. Exceeding a second critical value sends the system into chaotic behavior. Exceeding a third critical value sends the system back into unstructured stochastic microstates—but with much higher (frenetic) energy than when below the first critical value.¹³ With this focus on emergent structure between stochastic microstates and chaos, complexity theory identifies a source of emergent order alternative to selectionist theory.

2.5 NETWORK SOCIOLOGY: STATICS AND DYNAMICS

Since it is a small step from “complexity” to “network density;” Kauffman’s model works from a Boolean networks of agents; and sociological network theory is making inroads into the management and strategy fields (Burt 1992, Nohria and Eccles 1992), is Kauffman’s complexity research a straightforward extension of network sociology or fundamentally different? Sociological network theorists study role, cohesion, status, power, control, affiliation, workflow, and communication networks and network forms of organization (Burt 1982, 1992; Lincoln 1982, Krackhardt and Porter 1985, Krackhardt 1990, 1992, 1997; McPherson, Popielarz and Drobnic 1992, Podolny and Page 1998), focusing on people as agents at the vertices. Via the study of strategic alliances (Yoshino and Rangan 1995), a conflation of the classic “Bain-Mason-Caves-Porter” strategy view with the sociological network approach appears at hand. Burt (1992) goes so far as to add “*social capital*” to the basic theory of the firm equation of capital, labor, and human capital. Social capital is a function of network relations, he says, not individual attributes.

Network analysts’ methods mostly rely on the use of

algebraic formulas to make static analyses of network equivalences (Pattison 1993, Wasserman and Faust 1994) when the networks involved show density coefficients between the extremes of 0 and 1—comparing several “*empty*” or “*complete*” density networks being trivial. In contrast, dynamic network models study the interacting effects of agent, task, and network variances, given endogenous and exogenous forces bearing on the system, particularly as the system searches for more optimum energy, knowledge, or fitness states. Frequently these are dynamical systems showing stochastic, nonlinear, recursive, and self-referencing agent behaviors (Morrison 1991, Masuch and Warglien 1992, Carley and Prietula 1994). Though static comparative network studies have been the mainstay of organization science heretofore (Nohria and Eccles 1992), there is an increasing use of dynamic models of the same genre as Kauffman’s *NK* model. In addition these models are applied at various organizational levels of analysis, including process microstates, together with the use of skills and processes as vertices/entities/agents rather than people, as elaborated by Carley and Newell (1994).

Cohen, March, and Olsen (1972), Masuch and LaPotin (1989), and Warglien (1996) use agent-based artificial intelligence networks to model “garbage can” problem-solving behavior. Cohen (1996) creates a model from the garbage can family using a network in which “solutions” are the microagents grappling with various organizational problems. Durfee (1988) focuses on networks of skills and agent-based models in his treatment of distributed computing/intelligence. March (1991) and Carley and Svoboda (1996) use agent-based models to study organizational adaptation. Glance and Huberman (1994) model the appearance of subclusters in a network as agents search for improved cooperation. Levitt et al. (1994) define agents as information processors deciding on which activities to perform and where to communicate the outcome in a design team network. Padgett (1997) models rates of skill production as a function of network activity. Krackhardt (1997) simulates the diffusion of innovations, though he uses a deterministic model. Carley’s simulations of agent performance at various organizational levels (Carley 1991, 1992; Ye and Carley 1995, Lin and Carley 1995, Carley and Lin 1995, Carley 1997, Carley and Lee 1997, Carley and Lin in press), are the most comprehensive studies of agent performance under varying organizational and environmental conditions—they are multilevel and numerous.

A significant exception to the static algebraic comparative tradition in sociology appears in the recent work on dynamic network attributes associated with emergent collective behavior, stimulated by Granovetter’s (1978) article on threshold models. In this exciting new development formal models are used in conjunction with agent-based simulation models to

¹² Space precludes discussion of *point*, *periodic*, or *strange* attractors here, but some related discussion exists in Levy (1994) and for further elaboration see Gleick (1987).

¹³ For an example of this “critical value complexity theory of adaptive tension” applied to firms, see McKelvey (in press-a).

unravel the effects of various network conditions and agent functions on the likelihood of emergent collective behavior (Oliver, Marwell, and Teixeira 1985, Marwell, Oliver, and Prahl 1988, Marwell and Oliver 1993, Macy 1990, 1991; Kim and Bearman 1997).

3. COMPLEXITY VS. SELECTION: KAUFFMAN'S THEORY

For the 20th century at least, biologists have uniformly assumed that “order” was due to the effects of selection, as developed under the general label of Darwinian selectionist theory (Depew and Weber 1995). Kauffman challenges the unquestioned universal applicability of selectionist theory by suggesting that under some circumstances complexity may intervene to offer alternative bases of biological order. In this section I first outline Kauffman's theory. Then I apply the fitness landscape concept to value chains in firms and argue that Kauffman's assumptions apply equally well to firms. Finally I pose questions of interest bearing on strategy and organizing.

3.1 FITNESS LANDSCAPES

Kauffman (1993, pp. 33–34) begins with “*fitness landscapes*,” drawing on Wright (1931 1932). These landscapes have features causing variations in their “*ruggedness*.” Primarily, ruggedness is a function of the number of parts comprising the evolving organism, N , and the amount of interconnectedness among the parts, K (1993, pp. 40–54):

1. When $K = 0$ the landscape appears as gently rolling ridges coming off a towering volcano—Kilimanjaro and surrounding plains. This landscape has one very high global optimum. Kauffman argues that the “correlation structure” of this landscape is high; the fitness value for one neighbor is highly similar to that of other neighbors, and that any move toward increased fitness will inexorably lead toward the global optimum.

2. When $K = N - 1$, the landscape is very jagged—perhaps like the modest peaks, valleys, and ridges of the Alpine Dolomite landscape where there are many peaks and ridges and their sides are precipitous. This landscape is uncorrelated in that one kind of move in no way predicts what happens with some other move.

3. As K increases from 0 to $N - 1$, the number of optima peaks increases, the level of precipitousness increases, the correlation among fitness moves decreases, and the height of the peaks decreases.

As N and K increase, the number of fitness optima available to a player vastly increases, the level of fitness at any given optima diminishes so peaks are less valuable if attained, the predictability of finding a better than average fitness peak diminishes rapidly, and players more likely will be trapped on suboptimal fitness peaks. Kauffman holds that any selectionist progression toward properties that are rare in a coevolving system of entities may be overwhelmed by large numbers of mutations toward the statistically typical central tendencies of other properties comprising the population that are more numerous. Three forces may suppress selection (1993, p. 25):

1. “Selection is simply too weak in the face of mutations to hold a population at small volumes of the ensemble which exhibit rare properties; hence typical properties are encountered instead.”

2. “Even if selection is very strong, the population typically becomes trapped on suboptimal peaks which do not differ substantially from the average properties of the ensemble.”

3. Each of the foregoing limitations on selection “become more powerful as the *complexity* of the entities under selection increases” (his italics).

In the face of weakened selection, the “spontaneous order” resulting from the more numerous “typical” characteristics of ensembles will “shine through.” “In short, this theme...states that much of the order in organisms may be spontaneous. Rather than reflecting selection's successes, such order...may reflect selection's failure” (1993, pp. 29–30).

Kauffman states the two fundamental elements of his theory using the landscape metaphor:

1. One premise holds that in landscapes containing some fitness peaks having clearly superior adaptive advantage, if selection forces are weak and thus fail to hold members of a population high up on the peaks, the apparent order in the population is due to the typical properties of the majority of the population still spread around the valley. That is, “adapting systems exhibit order not *because* of selection but *despite* it” (1993, p. 35; his italics).

2. The other premise holds, given (1) that as peaks proliferate they become less differentiated from the general landscape; and (2) that in precipitous rugged landscapes adaptive progression is trapped on the many suboptimal “local” peaks; that even in the face of strong selection forces, the fittest members of the population exhibit characteristics little different from the entire population.

He labels these “*complexity catastrophes*” because either one or the other is inevitable if the “complexity of the entities under selection increases.” Thus, complexity imposes an upper bound on adaptive progression via selection “when the number of parts exceeds a critical value” (1993, p. 36). In this way complexity catastrophe thwarts the selection process. Complexity theorists talk about structures “at the edge of chaos.” Kauffman adds another edge—the “edge of catastrophe.” In his view evolution takes place in a narrow band of complexity between the edges of catastrophe and chaos. Over the catastrophe edge and selection stops—over the chaos edge and order stops.

Kauffman ends Part I of his book on a coevolutionary note, where C denotes the number of coevolving links between parts of competitors. For example, an advance in the bus speed and heat-sink of one firm's notebook is matched or “one-upped” by an advance in the bus and heat-sink in a competing firm's notebook. The complexity measured by K is now complicated by the complexity measured by C . Kauffman observes that evolution is always coevolution with respect either to abiotic constraints and resources or other competing organisms. “The true and stunning success of biology reflects the fact that organisms do not merely evolve, they *coevolve* both with other organisms and with a changing abiotic environment” (1993, p. 237; his italics).

3.2 TRANSLATION OF KEY ASSUMPTIONS

Kauffman uses two kinds of models, interactive particle systems or *spin-glass* models from statistical physics (Fischer and Hertz 1993) and *cellular automata*

originating in electronic computer design (Weisbuch 1991)—neither of biological origin. Thus, my model translation is not actually from biology to firms but rather from interactive particle systems (physics) or automata (computer science) to firms. What I find most striking is that the modeling assumptions Kauffman makes about the applicability of the electrodynamic microstate lattice models to the biological world really are more readily applicable to the competitive world of firms. Table 3 presents material defining the model’s parameters and translating Kauffman’s NK landscape into the context of value chain competencies composed of microstates governed by microagents—a “chainscape” in which microagents governing the value chain *parts* of firms take adaptive walks. Table 4 offers additional notes on what happens as the model iterates through its time-periods. Taken together the definitions and notes in these tables detail the logic underlying my translation of Kauffman’s $NK[C]$ model from organisms to a *parts* level multicoevolutionary analysis of, for example, notebook computer firms. I keep some biological material in the table to support my contention that the assumptions for firms are actually more straightforward than for organisms.

>>> Tables 3 & 4 about here <<<

3.3 KAUFFMAN VS. THE SOCIOLOGISTS’ DENSITY COEFFICIENT

Network theorists will recognize Kauffman’s K as a measure of network connectivity—“the degree to which members of the network are linked to one another...” (Lincoln 1982, pp. 6–7). In the NK model edges are unidirectional, with the arrow of influence flow pointing toward the vertex/agent in question, with up to $K = N-1$ possible interdependencies, that is, epistatic links. In the $NK[C]$ model there are two networks, one internal to the subject firm and one between agents in the subject firm and agents inside a competitor. Since firms are assumed to have similar numbers of agents, the densities are $\Delta_K = 2K/N(N-1)$ and $\Delta_C = 2C/N(N-1)$. These expressions are identical to network analysts’ density coefficient, Δ (Wasserman and Faust (1994, p. 101). It is no wonder that observers might claim an obvious overlap. But in fact the overlap is deceiving and the differences are fundamental. Several are worth noting.

First, causal paths are more fluid and complicated for sociologists than in agent-based models. A review of Nohria and Eccles (1992) indicates that Δ stands out as a primary network attribute for many network analysts. The sections of the book treat density as an independent or dependent variable. They range from locating networks solely within firms to between and among firms. The role of environments as deterministic-downward-causative is more prominent in the study of interorganizational alliances than it is in the formation of internal networks. Still, people dominate as the causal agents—they precipitate different network forms as a

result of their perceptions of environmental or internal organizational conditions, very much in the spirit of Child’s (1972) strategic choice framework. Depending on agent choices, internal or external contexts, or individual agent friendship, trust, power, etc., preferences, appear as dominant causal forces.

Second, a parallel to Kauffman’s combination of separate Δ_K and Δ_C effects is missing in network sociology. For example, sociologists study hierarchies vs. network forms (Powell 1990, Podolny and Page 1998), how interorganizational network Δ s affect level of innovation (Powell and Brantley 1992, Powell, Koput, and Smith-Doerr 1996), and the effects on firms of external Δ s: market ties on a firm’s size and power (Baker 1990); Δ s of external networks on internal firm capabilities (Freeman 1991, Hagedoorn 1995); embeddedness in external networks on the likelihood of acquisition (Palmer et al. 1995) or failure (Uzzi 1996); Keiretsu networks on corporate performance (Lincoln, Gerlach, and Ahmadjian 1996), or technological networks on organizational growth (Podolny, Stewart, and Hannan 1996). These kinds of studies relate firms to external networks of other firms in a subject firm’s “organizational field” (Scott, 1995).

Kauffman’s combination of Δ_K and Δ_C significantly differs from the above. Δ_C measures the number of links agents in the value chain of one firm have with agents in the value chain of a competitor—it is a measure of the Δ s between agents across the boundaries of two networks (or more if the number of firms $S > 2$). To illustrate, suppose that professors in a department all pursue internal network relations to discuss salaries, each trying to decide whether he or she is underpaid. Δ_K indicates the density of this network. Now suppose, also, that some professors start checking with friends in a similar department of another university— $S = 2$ or multiple departments— $S > 2$. Δ_C indicates the density of the network between one department’s agents and agents in the other department(s). (If a professor can only stay the same or ask for an increase, the network is Boolean and we have a situation essentially the same as what the $NK[C]$ model studies, except that salary is substituted for fitness.) Two studies could appear loosely related to “ Δ_C ” type studies. Galaskiewicz and Zaheer (forthcoming) investigate interfirm networks of individuals, such as CEOs and Board members, but they really are surrogates for firms as entities. Liebeskind et al. (1996) study links between internal networks and external scientists who are at *many* other institutions. But S is nearly 60% of N for both firms studied (less than two agents per external firm) and 86% of the “institutions” are not competing firms. Furthermore, no explicit measures of Δ_K , Δ_C , or complexity catastrophe are used. But they do focus on the numerator effect of Δ_C .

Third, agent “improvement” in terms of a nonrelational attribute such as fitness also seems absent. As already

mentioned, in addition to including both Δ_K and Δ_C , Kauffman's model is dynamic (learning and adaptive), stochastic, recursive, and nonlinear, whereas sociological network models are static, descriptive, algebraic, and linear deterministic. A check of the notation glossary (Wasserman and Faust 1994, pp. 819–825) confirms that the main use of probability in network sociology is for goodness-of-fit tests between model and real world and measurement error.¹⁴

Fourth, sociological models are “*connectionist*”—they vary by richness of edges to a vertex rather than by changing agent behaviors. Thus, centrality or power are measured in terms of the number of links connected to a particular vertex/agent and the number of connections at each vertex varies. In agent-based models emphasis is on using links to cause “bit-flipping” (cellular automata), and via bit-flipping, changed energy quotients (spin glass) or changed fitness levels of agents (NK), based on the bit, energy, or fitness change of the agent at the other end of the link, as the model iterates through all possible combinations of agent links. The network remains constant while agents keep changing energy or fitness levels until the model reaches equilibrium or gives indication of indefinite oscillation. Though in the NK model the number of connections K always remains the same for each agent, there is nothing to say it could not vary.¹⁵ Note, however, that cellular automata (Toffoli and Margolus 1987, Weisbuch 1991) and neural nets (Wasserman, 1989, 1993; Freeman and Skapura 1993) allow both agent changes and variations in links to cells.

Fifth, complexity as Kauffman measures it is uninteresting to network analysts. For the latter, as a network becomes complete ($\Delta = 1$), analysis becomes trivial, even though for Kauffman complexity is highest. The reason is that static comparisons are most interesting (difficult) when $\Delta = 0.5$, but with Kauffman's dynamic analyses of agents' adaptive searches, interesting results occur across the entire scale. Though “complexity” is not a term for which sociological network analysts have

a coefficient (see Patterson 1993 and Wasserman and Faust 1994 for confirmation), a measure of complexity that might be interesting occurs as Δ recedes from 0 or 1. Complexity could then be a function of the number of structurally equivalent indirect paths and catastrophe could be a function of a growing number of competing paths that might “fuzz-up” information (the opposite of information theorists' redundancy), or the rate at which the indirect paths change.¹⁶ Three realizations offer a basis for equating Δ with Δ_K : (1) Define network complexity as an inverse U —high complexity = $\Delta @ 0.5$; low complexity = $\Delta @ 0$ or 1 —giving a folded Δ scale running from zero to high complexity; (2) Recognize that the folded Δ scale is isomorphic with the Δ_K scale; and (3) Anticipate that complexity catastrophe starts taking effect midway along the Δ scale, as it does for Kauffman's Δ_K scale (see 1993, p. 260), resulting in an inverse U fitness or network performance relative to, respectively, Δ_K and Δ .

3.4 RESEARCH QUESTIONS

Kauffman's “complexity as cause” theory allows us to ask a number of questions bearing on strategic choices where complexity effects might compromise expected competitive advantages. The questions are posed in language applicable to firms in coevolutionary pockets. I will use the notebook computer industry as an example of a coevolving pocket.¹⁷

1. **Can too many coevolutionary links among a firm's value chain competencies inhibit competitive advantage?** How much internal coevolutionary density K is optimal for achieving maximum fitness? Assume a notebook computer maker has several chain competencies N that could be targets of competitive improvement (Table 1). A number of these might be linked with respect to adaptive action. The firm may or may not be aware of these links. The firm may try to encourage some interconnections and discourage others.

2. **Can too many coevolutionary chain links between a firm and an opponent inhibit its competitive advantage?** How much external coevolutionary density C is optimal for achieving maximum fitness? Considering a notebook firm's competition against an opponent, we might ask, given a fixed budget, should a firm attempt to enter into coevolutionary competition by focusing intensely on just a few of the opponent's competencies or broadly on many?

3. **Do internal and external chain interdependencies interact to inhibit competitive advantage?** Is there an optimal ratio between internal and external coevolutionary density? Complexity grows as a function of internal and external coevolutionary density and their interactive effect. A firm could choose to increase both at the same rate. Should a firm try to keep internal density at levels higher or lower than external coevolutionary density? And supposing that a firm can choose its coevolutionary partners, is it better to pick those where the

¹⁴ As Wasserman and Faust note (1994, p. 23), most of their book focuses on descriptive techniques, with the remainder concerned with statistical methods for testing network theories and assumed structural properties. This is far different from basing models on probabilistically determined agent attributes which then change as a result of changes made by other agents. Interestingly, the sociological network theorists principal use of actor probabilities (Holland and Leinhardt (1981)—in dealing with triad census (Wasserman and Faust 1994, Ch. 14)—has led to the vector T that is in essence a statistical mechanics reduction of the triad variances to one stable indicator. This is not unlike Kauffman's (1993, Ch. 5) development of his Boolean statistical mechanics as a means of simplifying the representation of cellular automata when higher N and K produce unmanageably large combinatorial spaces. The $NK[C]$ model is a simplification of Boolean statistical mechanics and Kauffman's use of Boolean networks. For an illustrative application of this approach to organizational complexity see McKelvey (in press-a).

¹⁵ Various alterations to the NK model that organization scientists might wish to consider before further application are discussed in McKelvey (1997a).

¹⁶ I wish to thank Kathleen Carley (email dated September 11th, 1998) for a helpful insight about how the catastrophe notion might better fit with network sociologists' conception of network density.

¹⁷ To simplify the discussion, I assume that notebooks are made by independent companies or autonomous divisions with all relevant competencies self-contained within the notebook unit. An obvious complication occurs if notebook competencies are spread out among a number of divisions in, say, a larger corporation such as IBM. A complication such as this would add to the internal/external multicoevolutionary complexity problem but does not undermine the essential import of the discussion.

resultant external coevolutionary density would be high or low?

4. **Is there a limit to how many simultaneous innovative advancements a firm should attempt, given its existing internal and external chain interdependencies, before its competitive advantage is weakened?** Thus, a firm could minimize internal densities, but seek competitive advantage by attempting many simultaneous coevolutionary matching games with its opponents. Or a firm could attempt to compete by emphasizing internal chain interdependencies while going head-to-head with an opponent on only a few.

5. **Given constant complexity levels, is there an optimal group size, S , at which firms might expect higher fitness levels?** The size of a coevolutionary pocket may confound the impact internal and external coevolutionary densities have on competitive advantage. Too small an industry group may lead to too little external coevolutionary density to stimulate improved fitness levels. Too large a group, and external coevolutionary density may be so diffused that firms do not have strong direct opponents or there is little focus to coevolutionary activity. Thus, a pocket's overall increase in fitness levels could suffer, leaving the industry to struggle along in a maladaptive state, if not actually collapsing.

6. **Is it possible that there are levels of internal and external integration that are good for both individual firm and the pocket as well?** Here the tension is between strong individual players and a strong set of players. As professional sports teams have discovered, the overall quality of games suffers when there are so many teams that the average quality of play deteriorates, or when there are a few super teams and a large number of losers. Coevolutionary pockets may suffer the same consequence due to complexity effects if firms emphasize internal coevolutionary density at the expense of abandoning external coevolutionary density, or *vice versa*.

7. **Should strategists worry about possible complexity catastrophes?** Kauffman's theory holds that too much complexity has an effect on the competitive advantage of coevolutionary systems that severely limits their adaptive success, whether natural selection forces are strong or weak. Strategists in individual firms may feel that anything thwarting the competitive selection process is good for their firms—so complexity catastrophe might be good for them. On the other hand, a coevolutionary pocket that loses its competitive edge (because complexity dominates selection) may also lose out against an opposing coevolutionary pocket holding more strategically competitive firms whose adaptive improvement is not thwarted by a complexity catastrophe and thus, also holding improved competencies as a collective.

4. METHOD

The NK model derives from physicists' spin-glass models, a well studied set of models used to study the energy landscape created by sets of magnetic dipoles spinning in similar or opposite directions (Fischer and Hertz 1993). While physicists use these binary particle models to understand energy minimization, Kauffman (1993) uses them to understand how organisms, via mutations, take hill climbing "*adaptive walks*" to maximize fitness—though Kauffman, Macready and Dickinson (1994) use the NK model in a cost minimization format. A step in the walk occurs when, for example, an agent in a firm moves to a new point on the landscape by adopting an improvement from an agent in its network. The NK model is an environmentally isolated model. It is useful for answering questions about how many local optima there are, what their fitness levels are, lengths of adaptive walks, rates at which improved fitnesses are found, and so forth.

To add the dynamics of complexity theorists' emergent

structure at the edge of chaos (that is, dynamics in the region of Cramer's *critical complexity*), Kauffman shifts from spin glasses to the computer scientists' cellular automata, focusing on Boolean network dynamics.¹⁸ They allow the modeling of coevolutionary dynamics wherein an opponent's strategy toward complexity alters the landscape of the focal firm. Spin glass models, are *single change "bit-flipping"* functions in which the outcome state is based on a single randomly chosen input. Automata are *mutational functions* having 2^N inputs, each of which has some probabilistic effect on the Boolean outcome state (Jones 1995). Given a Boolean output of two states, on or off, the total number of different outcomes in an *autonomous* (closed to inputs outside the automata elements in the network) Boolean network is 2^{2^N} . Since this could be a truly vast number (over 33 million for $N = 24$), Kauffman creates a "*Boolean statistical mechanics*" in which fairly "exact" outcomes are created by sampling from the total system of elements (Kauffman 1974, Gelfand and Walker 1984).

For $K = 2$ inputs there are 16 Boolean functions—Figure 1. In this "tabular" depiction the on-off inputs are on the edges and the outcome disposition (the cell *function*), is inside the box.¹⁹ For game theorists one input is a "feedback element" showing the current state of the automata element itself, but for Kauffman inputs are determined only by the existing states of other elements in the network. The stability of a Boolean network may be upset by "*minimal*" or "*structural*" perturbations: (1) minimal ones are caused by a state flip in an input, say from on to off; (2) structural perturbations come from changing the outcome state of one or more Boolean function elements. In Kauffman's models only minimal perturbations create network instability.

Emergent structure in Kauffman's models could derive from two sources: (1) "*forcing functions*;" and (2) "*homogeneity bias*." Forcing functions occur when only one input can force the outcome state. In the "OR" function any input with a 1 forces an outcome state of 1. With the "AND" function any input with a 0 forces an outcome state of 0. In Figure 1, only the "XOR" and "IFF" functions are not forcing functions—on one or both inputs.²⁰ As the number of inputs K increases, the relative number of forcing functions decreases rapidly—

¹⁸ There is no way I can attempt to replicate Kauffman's development here. Recourse to Kauffman (1993, Ch. 5) is highly recommended for the more interested reader.

¹⁹ A very accessible description of automata is given in Westhoff, Yarbrough, and Yarbrough (1996). A more advanced introduction is Weisbuch (1991). Considerably more advanced are Toffoli and Margolus (1987) and Garzon (1995).

²⁰ Weisbuch (1991, p. 11) says only functions numbered 1, 4, 7, 8, 11, and 13 are truly forcing. Other authors such as Gelfand and Walker (1984) and Westhoff *et al.* (1996) consider all but functions 6 and 9 as forcing since for these two the outcome state depends on knowing both input states—some functions are a little more "forcing" than others.

dropping from 87.5% for $K = 2$ to less than 5% for $K = 4$ (Gelfand and Walker 1984, p. 128).

Homogeneity bias is created by altering the number of forcing functions. Thus, if the ratio of “OR” functions is increased (“OR” has 3 out of 4 values = 1) the probability of homogeneity increases. If the ratio of the “IFF” or “XOR” functions is increased, homogeneity stays the same since for them the ratio of 1’s and 0’s is 50/50. In Kauffman’s models automata elements are randomly selected, meaning that both forcing and homogeneity impacts are fully randomized.

>>> **Figure 1 about here** <<<

In Boolean network models emergent structure is predictable at $K = 2$, is highly unlikely at $K > 3$, but can be “encouraged” by increasing forcing functions and homogeneity bias (Stauffer, 1987a,b, Weisbuch 1991). Kauffman argues that his “ $NK[C]$ Boolean game” model behaves like Boolean networks when agent outcomes are limited to 0 or 1, the K number of interdependencies is taken as the number of inputs, and Nash (1951) equilibria²¹ in N person games are taken as equivalent to agents being trapped on local optima. In the NK Boolean game, fitness yields are assigned to the 0 or 1 actions by drawing from a uniform distribution ranging from 0.0 to 1.0. The K epistatic interdependencies that inhibit fitness yields from an agent’s actions are drawn from a fitness table in which fitness levels of each “one-change” nearest-neighbor are assigned by drawing from a uniform distribution also ranging from 0.0 to 1.0. Kauffman points out that the complexity “*tuning*” effect occurs when increasing K reduces the height of local optima while also increasing their number. Thus, high K leads to complexity catastrophe.

In describing how K and C effects enter into the model, Kauffman says:

...[F]or each of the N traits in species 2, the model will assign a random fitness between 0.0 and 1.0 for each combination of the K traits internal to species 2, together with all combinations of C traits in species 1. In short, we expand the random fitness table for each trait in species 2 such that the trait looks at its K internal epistatic inputs and also at the C external epistatic inputs from species 1 (Kauffman 1993, p. 244).

One might conclude from this that K and C are combined into one overall moderating effect on the fitness yield from an agent’s choice to adopt a higher fitness from a nearest-neighbor. Results of the models indicate otherwise. As Kauffman points out (pp. 249, 254), the speed at which agents encounter Nash equilibria increases with K , and decreases as C and S increase. Thus, in these models K acts as a complexity “forcing” effect in speeding up the process of reaching stable Nash equilibria, whereas C acts as an “antiforcing” effect, as does S . Presumably K effects are averaged as per the basic NK model, leaving C and S effects (S multiplies the

C effects) to modify fitness yields on an agent’s actions independently of K effects. The consequence is that increasing K tunes the landscape toward more ruggedness (increased numbers of less fit local optima), and increased likelihood of agents being marooned on local optima, but increasing C and/or S prevents achieving Nash equilibrium by prolonging the “*coupled dancing*” as Kauffman calls it in which opponents keep altering each other’s landscapes, keep the fitness search going, and thereby prevent stability—the more opponents there are, the more the instability persists.

As Kauffman has designed the $NK[C]$ model, K acts as a force toward increased complexity and complexity catastrophe whereas C acts as a force away from catastrophe, that is, internal complexity leads to complexity catastrophe but external complexity leads away from catastrophe. The results in his Figure 6.3 (reproduced here as Figure 2) show that a high C considerably prolongs oscillation or coupled dancing, unless K is larger than C . This behavior of the model is significant since from Kauffman’s theory and the quote above we might easily conclude with reason that—holding S constant—external complexity C should lead to complexity catastrophe just as much as internal complexity K does. But Kauffman’s Figure 6.4 (p. 248; not shown here) clearly shows this not to be true. Bottom line: high K leads to catastrophe; high C prolongs coupled dancing; increasing S independent of C also leads to prolonged oscillation or instability.

>>> **Figures 2 and 3 about here** <<<

5. SIMULATION OUTCOMES

Can the ruggedness of landscapes be more optimally tuned by varying N , K , and C ? If the computer model has reasonable representational validity with respect to real world phenomena, the simulations could be quite instructive, and at relatively low cost compared, say, to experimenting with a real firm. Though Kauffman’s $NK[C]$ model has some questionable aspects (McKelvey 1997a), and is only just being applied to firms (Levinthal 1997, Rivkin 1997, Baum in press, McKelvey in press-a, Kauffman, Macready and Dickinson 1994), an early result suggests that the basic idea of “complexity thwarting selective improvement” does hold in the computer workstation industry (Sorenson 1997). So, while the simulations reported below are preliminary and novel to organization science, they offer some response to the foregoing questions.

Kauffman runs the $NK[C]$ model with various combinations of parameters, as described in Table 5. To help readers connect these models back to Kauffman’s book, I label the models by their Figure or Table numbers in his book. Outcomes bearing on the research questions are:

>>> **Insert Table 5 about here** <<<

1. Can too many coevolutionary links among a firm’s value chain competencies inhibit competitive

²¹ A Nash equilibrium occurs when “no player has incentive to deviate from his strategy given that the other players do not deviate” (Rasmusen 1994, p. 23).

advantage? For firms comprising a coevolutionary group, is there an optimum level of internal coevolutionary density, K , to achieve high fitness? The findings (models F6.3 and F6.4; Kauffman 1993, pp. 247–249) are:

1. As K increases, the proportion of firms reaching Nash equilibria increases, independent of C .
2. Under high C conditions, during the oscillatory period before Nash equilibrium, and if the opponent does not change its K , a firm that increases its K will improve its fitness level.
3. Under high C conditions, a low K firm will improve its fitness most during the preNash oscillatory period if it chooses opponents having the highest K values, and also raises its own K .
4. When Nash equilibria are encountered, fitness levels of low K firms are higher than fitness levels of high K firms, independent of the values of C .

Increasing K is not good, unless the opponent has a high K or a high C . But if Nash equilibria are encountered, low K is better than high K , because low K means higher fitness peaks. So, as the probability of encountering Nash equilibria goes up, say because of an opponent's actions to raise its K or C , the better it is to have a low K . But if the opponent does not raise K or C , and therefore Nash equilibria do not occur quickly, the low K firm will lose its advantage. A firm's strategy with respect to number of internal coevolutionary links among value chain competencies, K , seems to hinge on whether Nash equilibria can be anticipated; that is, on whether an opponent will raise its K or C . In general the simulations indicate that keeping one's internal and external

coevolutionary interdependencies just below that of opponents is the best strategy. Thus, a little more coevolutionary prioritizing compared to one's opponent seems a good idea.

2. Can too many coevolutionary chain links between a firm and an opponent inhibit its competitive advantage? Does external coevolutionary density (measured by C) affect fitness? These findings (F6.3, F6.4; Kauffman 1993, pp. 247–249) are:

1. When $C > 1$, firms reaching Nash equilibrium have fitness levels higher than firms still oscillating.
2. For high values of C , and during the preNash oscillation period, any single move by one partner sharply lowers the expected fitness of the other partner.
3. For high C s, a firm that keeps its K smaller than C , but larger than the K s of opponents fares best.
4. Overall average fitness of all firms in a coevolving system is highest when C and K themselves coevolve toward similarity; that is, when C and K equal each other, whether both are high or low—but a pocket with high C s and high K s fares best.

Firms having dense external coevolutionary ties with opponents (that is, high C s) are best off if they achieve Nash equilibria before the opponent. During preNash oscillation, rapid moves by a firm are likely to have significant detrimental effects on its opponents. A “maxi-min” strategy suggests a firm should target coevolutionary opponents whose C s match its own K . That is, absent any more pointedly aggressive strategy

toward a specific opponent, a firm should attempt to equalize internal and external coevolutionary densities. For a more targeted strategy, a firm is best off if it attacks opponents who have moderate C s and low K s, while keeping its K slightly higher than the K of its opponents, till its K reaches the C of its opponents (see simulation #7).

3. Do internal and external chain interdependencies interact to inhibit competitive advantage?

Concerning the interaction between internal and external coevolutionary density, what are the advantages to firms in considering the interactive effect? Kauffman finds:

1. Average fitness across coevolutionary groups is highest when internal and external coevolutionary densities are matched, that is K and C are the same (F6.4; 1993, p. 249).
2. In a coevolving group, firms having K and/or C values distinctly at odds with most of the group are selected out, with the effect that the system tunes itself toward the optimal $K = 8$ to 10 (F6.8; 1993, pp. 259–260).

It is clear that in coevolutionary pockets there is an advantage to stronger firms if K and C are similar and if the system will tune itself toward the optimum. In the organizational world, this tuning effect could result from the “visible hand” of strategic choice theorists (Child 1972, Chandler 1977) or the “invisible hand” of the evolutionists (Aldrich 1979, McKelvey 1982, 1994). Firms aiming for external and internal interdependency levels at odds with most other firms in the coevolutionary pocket are selected against, thereby leaving the competitive advantage to, and the system populated mostly by, the $K \approx C$ firms—whether they get that way by visible or invisible hands. This effect could be helped along by firms taking more aggressive attacking approaches toward firms with high C s and low K s, coupled with raising their own K s.

4. Is there a limit to how many simultaneous innovative advancements a firm should attempt, given its existing internal and external chain interdependencies? What is the complexity effect if a firm allows simultaneous competence changes by agents at more than one site per timing cycle? The findings (F6.5; Kauffman 1993, pp. 250–251) are:

1. Fitness decreases as the number of simultaneous moves increases, for low, medium and high C conditions, and for all K values except $K = 16$.
2. Fitness levels for all K values peak at two to four simultaneous moves, and then decrease, except for $K = 16$. The latter does not decrease except when C exceeds K .
3. As K values increase, the decreases in fitness due to simultaneous moves are less pronounced, except that when C exceeds K .
4. The highest fitness levels come when C , K , and the number of simultaneous changes are all low.

At almost any level of internal and external coevolutionary density, firms are best off if they hold simultaneous moves to only a few. An exception occurs when $K = 16$, that is, when $C < K$ (there is no decrease). These findings indicate that on balance, firms gain little strategic advantage from pursuing more than just a few simultaneous changes.

5. Given constant complexity levels, is there an optimal group size? If firms can have some affect on pocket size by merging or divesting, are there fitness advantages stemming from pocket size effects? Kauffman's findings (F6.6; 1993, pp. 253–255) are:

1. When $K > S \times C$, all coevolving firms reach Nash equilibria rapidly.
2. When $K < S \times C$, coevolving firms do not reach Nash equilibria.
3. As S increases, the preNash oscillation period increases.
4. As S increases, the amplitudes of the preNash oscillations increase considerably.

As the number of coevolving firms increases, the likelihood of achieving a high fitness equilibrium around a widely accepted set of chain competencies diminishes. Also, because of the increased amplitude of fitness oscillations for high S levels, there is increased likelihood that the high oscillation could lead to mass extinctions during an economic downturn. Kauffman uses this finding to suggest an additional explanation to the “Alvarez cataclysmic event hypothesis” for the mass extinction of dinosaurs and many other species over the last 600 million years (1993, pp. 263–269). Randle's (1990) findings of the “extinction” of over one hundred microcomputer firms, as the 1983 shake-out period approached, might be an organizational equivalent. Thus, the most stable and high performing coevolutionary pockets tend to be those having relatively few firms. Overlapping a moderate sized strategic group with a coevolutionary pocket might produce highest national advantage—a finding compatible with Caves/Porter (1977) strategic group and Porter's (1990) coevolutionary pocket theories.

6. Is it possible that there are levels of internal and external integration that are good for both individual firm and the group as well? In Kauffman's findings there is some evidence of collective good, but how might an individual firm act to achieve a collective good if such an action were to its advantage? Kauffman's findings (F6.3 and F6.4; 1993, p. 252) are:

1. In an externally dense (high C) coevolutionary group it is advantageous to an individual firm, and to the group, for any firm to increase its internal coevolutionary density, that is, increase K .
2. Given a high C , if a firm tunes its K to match C , preNash oscillations shorten considerably, and Nash equilibria are more fit than fitness levels achieved during the prior oscillation phase.
3. Under these conditions, average fitness levels during the oscillation period are optimized, Nash equilibria are, on average, attained rapidly and, on average, are of maximum fitness across the group.
4. Under these conditions, a unilateral decision by a firm to add a new K (that is, a new tie between the adaptive progression events of two of its N chain competencies), helps the collective good.

These findings indicate that a firm can help itself in two ways: (1) Sometimes it can best help itself by acting to help the entire coevolutionary pocket; and (2) Other times it best helps itself by acting to increase its own fitness at the expense of a specific opponent, an action that may not help the pocket—but being competitive in a strong pocket wins over being competitive in a weak

pocket. When C is high, the first alternative is more likely to work. When C is low, the second alternative makes more sense, but is still a second best solution. Acting to improve collective good (without hurting one's own firm) works best when the level of coevolutionary interdependence with an opponent is high. Compare the outcome of the open PC computer architecture of IBM, Intel, and Microsoft with the closed proprietary approach of Apple.

7. Should strategists worry about possible complexity catastrophe? One of Kauffman's basic insights is the complexity catastrophe. I would like to use his findings to consider how complexity catastrophes might affect firms. The underlying question is, what is the effect of landscape ruggedness on firms? Since the findings indicate that N and K are the dominant effects (1993, p. 55), I focus on them. The findings (T2.1, T2.2; Kauffman 1993, pp. 55–67) are:

1. If N increases while K remains fixed, fitness levels of local optima hold steady.
2. If K increases while N remains fixed, fitness levels of local optima decrease.
3. Fitness levels of local optima are highest for values of K ranging between 1 and 8.
4. If K increases linearly with N , fitnesses of local optima decrease and the complexity catastrophe occurs.
5. Low levels of K , relative to N , create rugged landscapes in which a few local optima peaks are high and precipitous and complexity catastrophes are averted.

Lower levels of K (relative to N) create moderately rugged landscapes composed of a few high and precipitous local optima peaks. As levels of K increase, the number of peaks increases but their height diminishes, with the result that the landscape appears less rugged, with less differentiation between the plains and the local optima peaks. The lesson for a notebook computer firm, for example, seems to be, “Create a rugged landscape to heighten access to local optima having higher fitness peaks, by keeping internal coevolutionary interdependencies relatively small ($K = 2$ to 8) even though the number of value chain competencies, N , in your coevolutionary pocket, is rising.” But if C is increased then the upper bound on K also increases.

6. CONCLUSION AND DISCUSSION

Findings. Is there an optimal level of cross-functional interdependency within a firm? What happens if there is too much interdependency among coevolutionary firms? What happens if there is coevolution among value chains of competing firms? In terms of Kauffman's $NK[C]$ model, these questions translate into: (1) What are the strategic consequences for firms, of internal, K , and external, C , coevolutionary densities? and (2) To what extent does complexity play a part in the nature and fitness of coevolutionary pockets of firms? In broad

terms, outcomes from Kauffman's models, as applied to firms, suggest the following points:

1. Firms should keep their internal value chain coevolutionary interdependencies, K , and external coevolutionary value chain match-up attempts, C , to levels just below the K and C values of opponents, with the proviso that if stability in competitive advantage is reached, low K firms beat high K firms.
2. Firms keeping internal coevolutionary value chain levels, K , similar to their external coevolutionary value chain match-ups with an opponent's C , have a competitive advantage over firms having disparate values.
3. Coevolutionary systems automatically gravitate toward firms having K and C values similar to the pocket average, because of the competitive disadvantage of firms holding K and C values at odds with the group.
4. Firms considering simultaneous advancements or innovations on multiple value chain competencies have greater competitive advantage if they hold the number of simultaneous changes to just a few.
5. As the number of firms, S , in a coevolutionary pocket increases, the likelihood of the pocket achieving high competitive advantage declines, because the overall selective rigor within the pocket is diminished and the increase in the amplitude of the oscillations raises the likelihood that oscillation troughs will spur the failure of many members of the pocket if coupled with an exogenous event such as a recession.
6. When external coevolutionary match-up attempts, C , are high, a firm's increase of internal coevolutionary advancement by introducing a new advantageous interdependency, K , that becomes diffused throughout the pocket, will increase the fitness of the entire group. This is not true if C is less than K .
7. In the face of an increasing number of significant components of the value chain, N , throughout a coevolutionary pocket, a firm is best off if it attempts to keep its internal coevolutionary interdependencies, K , small relative to N —this assures that the competencies that it stakes its competitive advantage on, though limited in number, will nevertheless allow movement toward higher fitness levels.

These findings suggest that **a firm should focus on opponents who are themselves keeping C at moderate levels—around eight by Kauffman's findings—so it can match its opponents C s but still keep a rugged landscape (i.e., a moderate K), thus assuring that “coupled dancing” will be prolonged and Nash equilibria, should they occur, will do so at high fitness levels.**

Explanation. Why is it that having too much or too little complexity relative to competitors in a coevolutionary pocket is a disadvantage? The computational experiments suggest that more or less complexity than opponents offers little competitive

advantage—being “idiosyncratic” with respect to complexity is a disadvantage. One explanation is that with too little complexity the loss of the adaptive improvements gained from interdependencies outweighs the cost savings; and too much complexity just slows down adaptive efforts while also adding interdependency management costs. Another explanation is that firms focusing on coevolutionarily improving a “challenging but manageable” number of value chain competencies are more likely to achieve success than those working on too few or too many. Why should the number of external coevolutionary interdependencies set the upper bound on internal interdependency levels? An explanation could be that in a coevolutionary pocket characterized by uncertainty and cognitive ambiguity (Mosakowski 1997) the *certainty* of sluggishness and cost imposed by trying to compete simultaneously on too many internal value chain competencies quickly outweighs the *probability* of gaining positive effects by coevolving on too many links with competitors.

Contribution. Use of the $NK[C]$ model could take strategic analysis in several new directions:

1. Application of natural selection and ecological theory to value chain *parts* of firms rather than just wholes. This gives us a look at firm and industry development that turns our attention to the relative importance of reductionist vs. contextualist explanations.
2. Reductionist analysis of value chains inside coevolutionary pockets to look at the concepts of internal and external coevolutionary interdependencies (densities), both underdeveloped ideas for the strategy/organization design fields. We can now get closer to the underlying causal processes.
3. Looking at the relative size of these densities and their possible affect on a firm's competitive advantage.
4. Looking at the interaction between benefits to individual firms vs. benefits to the collective pocket.
5. Introduction of the possible effects of Kauffman's complexity catastrophe to strategic organizing.
6. $NK[C]$ computational experiments allow us to go beyond the loose insights of natural history case studies, to pursue questions about intricate complexities impossible to study in real world analyses.
7. Agent-based models offer network sociology an alternative to its static descriptive algebraic models.

The outcomes I itemize offer intriguing messages for strategists, strategy implementers, or organization designers. At a broad level they achieve some credibility since they replicate what makes intuitive sense—zero chain interdependency seems mistaken, but too much complexity may be equally injurious to the competitive advantage of firms. Yet at the “detail” level, the findings about the relative balance of internal and external coevolutionary density seem quite unexpected. As such they are surely worthy of further study, both as to their validity, and as to further analysis of how the N , K , C , S ,

and A parameters affect firm fitness levels.

Limitations. Some specific limitations to these outcomes are as follows:

1. It is a bit of a stretch for Kauffman to assume that the $NK[C]$ game model mirrors Boolean network models. No comparative test is given.
2. The “moves” at a given clocking cycle in Kauffman’s model are randomly distributed and their adaptive value is also randomly determined. It is possible that in real firms, these events are less random. However, there seems to be little solid evidence that, in any given real firm, coevolutionarily adaptive advances are not random arrivals, a view reminiscent of the “garbage can” model (Cohen, March and Olsen 1972).
3. A model, no matter how carefully contrived, is never the real world. Every parameter of the $NK[C]$ model is a much simplified approximation of a real world event in a firm. Thus the validity of the model leaves much to be desired. Nevertheless, the $NK[C]$ and other agent-based models may offer useful insights about adaptive progression in coevolutionary groups of firms as the models are reformulated to improve their validity.
4. The C and K effects in Kauffman’s models hit competence sites rather indiscriminately. In real firms not all sites are equally likely to suffer the effects of internal or external coevolutionary density. It is not clear that the overall complexity results are affected by this—there is no information one way or the other.
5. A more detailed discussion of possible limitations of the $NK[C]$ model for organizational applications appears in McKelvey (1997a).

Camerer (1994) suggests that the biologists’ evolutionary game-theoretic models seem inappropriate for studying business strategy. On the other hand: (1) The models are, after all, not much more than assumptions, 0s, 1s, and stochastic events—they may very well be better idealizations of firms than of genes or proteins. (2) The models “look” biological but they are not—they are from physics and computer science. (3) Camerer’s more fundamental complaint against biological evolutionary models hinges on the pace of evolution (1994, p. 207). He says, “evolutionary equilibration seems like an inappropriate justification for equilibrium analysis of business strategies, because the process of evolution is probably far too slow to produce convergence before a game’s equilibrium changes.” How fast evolutionary generations pass by an observer depends entirely on how “micro” we define a generation. A model’s “generation” is really just a clocking period. (4) Barney (1994, p. 60) argues that game theorists and strategists tend focus on “big” decisions, like Walmart’s choice to be a low-cost leader. He contends that strategists and game theorists might better focus on the “hundreds of thousands of smaller decisions that make the big decision real.” Clearly, a focus on many small decisions and many incremental fitness improvements

justifies many “micro” clocking periods, perhaps hundreds or thousands in the span of one big decision. Thus, while an automobile has a model year, incremental coevolutionary design changes “on paper” occur throughout the year.

Rugged Landscapes. One over-riding message for strategists is that it seems preferable to steer firms toward rugged landscapes rather than the single fitness peak amongst gently rolling coevolutionary hills or the opposite, jagged landscapes created by high complexity. Rugged landscapes occur only when internal coevolutionary density (K) is held to smaller numbers (but greater than zero), even though value chain lengths (number of agents N) may be increasing. In this circumstance there are fewer fitness peaks available, but they have high fitness levels. If a firm shifts toward landscapes having many peaks, the likelihood of reaching a peak is higher, but firms will be trapped on peaks having lower fitness levels—the reward is smaller. The ruggedness message and the Lippman/Rumelt (1982) effect join here. Undoubtedly, coevolutionary competition in rugged landscapes is more difficult and risky. Consequently the Lippman/Rumelt effect applies—rents go to firms reaching the high peaks in the rugged landscape, but the failure rate of firms to reach high peaks also rises, as Rivkin (1997) notes; trying for, but missing Mt. Everest does not mean we land on Kangchenjunga—it could be a deep valley in between. In contrast, in a jagged landscape, it is much easier to reach the peaks, but economic rents are unlikely since many firms can reach the peaks.

Complexity. Individual and multiple firm failures in coevolutionary pockets may be as much the result of complexity as exogenous selection. Kauffman’s (1993) argument to biologists is that *internal* and *external* coevolutionary densities (K and C respectively) create a level of complexity that offers an alternative explanation to natural selection for explaining order in the biological world. Given that economists make the same fundamental argument, that external factors “select” firms and that only firms following the rules of constrained maximization are those that survive (Friedman 1953) it appears that Kauffman’s thesis might apply equally well to both firm *and* aggregate economic levels of analysis. It suggests that aggregate economic order could be at least as much determined by intrafirm and interfirm complexity as it might stem from external selection. This line of reasoning seems fundamental and quite novel to economics.

Dino’-Complexity. A persistent question about firms is, Why do so many large complex firms, having vast power, technology, resources, and experience, consistently fail to adapt to new technology or other significant economic events (Meyer and Zucker 1989, Loomis 1993, Baden-Fuller and Stopford 1994, Kerwin 1998)? Why is it that Rommel, *et al.*, find that *Simplicity Wins*, as they title their 1995 book? One of

the best chronicled failures of giant firms is the story of the rise of the semiconductor industry on the doorsteps of the large powerful resource-rich vacuum-tube electronics firms (Brittain and Freeman 1980). The textbook answer until recently, is that managers are myopic, make mistakes, resist change, can not make the needed implementation changes, can not retain key people, and so on. Kauffman's complexity thesis suggests an alternative story-line: The K and C levels in dinosauric firms are so high that, absent concerted managerial action to turn the extant jagged coevolutionary landscape into a moderately rugged one, the failure may be more the result of "dino'-complexity" than anything else. Interestingly, the Kauffman simulation results, though biological in theory, predicted the Baden-Fuller and Stopford and Rommel, *et al.*, findings that complexity greatly undermines firms' competitive advantage and adaptive capabilities in changing times. The turnaround of a current dinosaur, Sears, Roebuck & Co., also started with a "decomplexifying" phase (Martinez 1997). Outcomes such as these should give the simulation findings, as I have translated and reported them, some reasonable credibility for being relevant to firms, strategy, and organization design. While the qualifications are many, nevertheless an unmistakable message now lies on the desks of strategists: *Optimum levels of complexity are key elements of competitive advantage and organization design.*

Network Sociology. Kauffman's $NK[C]$ model offers a new wrinkle to network sociology. It cannot be construed as just another network density approach, given its roots in models of stochastic nonlinear agent-based adaptive learning capability. Nor is it related to studies of, say, the effect of external intercorporate alliance network effects on the density of intrafirm networks. As defined earlier, Kauffman's approach appears to fit with network theory only if Δ is defined as in an inverse U relationship with complexity—complexity peaks when network analysts' $\Delta = 0.5$ and tails off when $\Delta = 0$ or 1. Given this, conflation of the two current literatures is problematic.

Furthermore, Δ_C , the measure of the complexity of interdependencies between agents within one firm and agents within a competing firm—that is, links between their two internal networks—seems outside network sociology—whether Δ is folded or not. Kauffman's complexity effects take place *below* CEO level strategies about alliance configurations. And it is at this level that one of Kauffman's most salient findings appears—that a higher density of cross-boundary ties between competing firms actually holds off the impending catastrophe of too much intrafirm network density. The more a firm's agents keep checking in with agent adaptations inside a competing firm, thereby maintaining the "coupled dancing" effect, the less likely density effects will shut down a firm's adaptive progress. Assuming Kauffman's

S (number of competitors) is very large, Liebeskind et al. (1996) offer oblique confirmation of Kauffman's $NK[C]$ findings from the bio-tech industry. Links with outside scientists (Δ_C) enhance the innovation and flexibility of intrafirm networks. This finding is, at least, not inconsistent with the possibility that a higher Δ_C has prevented complexity catastrophe from interfering with "enhanced innovation and flexibility." If the Kauffman/Liebeskind et al. effect holds up, and supposing that agents (outside experts) in competing firms have low innovation (meaning that the coupled dancing effect disappears), we have reason to understand why Porter's (1990) emphasis of coevolutionary pockets is so critical—a collectively innovative coevolutionary pocket thwarts complexity catastrophe within firms. Thus, though lively coevolutionary pockets confront firms with stiff competition they also can raise the level of innovation within firms—resulting in a mutual causal adaptive progression.

Two parallels between complexity and sociological network studies are worth noting. *First, structural holes.* Kauffman finds that under conditions of adaptive tension—the selectionist processing behavior of the system is under adaptive stress—increased interdependencies inhibit the emergence of adaptive structures. This is to say that increased intrafirm complexity or network density puts firms at a strategic disadvantage because of the complexity catastrophe effect. Burt (1992) essentially makes the inverse of this point. Firms in which internal network-wide density is fractured by "structural holes"—places where agents are less encumbered by network interdependencies—set up conditions making it easier for innovative entrepreneurial behavior to flourish. Kauffman shows that too much complexity thwarts learning (via selectionist trial-and-error learning) whereas Burt shows that holes in dense networks foster novelty.

Second, emergent behavior. In Section 4.4 I noted in passing that complexity theory explains how energy imported into a system, coupled with adaptive tension, creates emergent behavior in the form of dissipative structures "at the edge of chaos" (Nicolis and Prigogine 1989). This aspect of complexity theory has been applied to firms by Stacey (1996) and McKelvey (in press-a). As long as the level of adaptive tension exists, that creates Cramer's (1993) "critical complexity," conditions enabling emergent structure apply. Though details of the computational models differ, this aspect of complexity theory is quite similar to the conditions and processes thought to give rise to emergent collective behavior. Given adaptive stress levels imposed on members of a "social movement" and sufficient network density, Kim and Bearman (1997) show that collective behavior emerges, as do some of Kauffman's emergent structure findings. And, in line with Kauffman's catastrophe theory, Macy (1991) finds that dense networks tend to inhibit emergent structure. But

contrasting with this, Gould (1993) and Marwell and Oliver (1993) find an inverted U-shape under some conditions. These parallels and both corroborating and conflicting findings beg for additional formal and computational modeling research.

A Beginning. The new directions and possible lessons outlined in this essay are, at best, a beginning. We might easily discount them simply because the $NK[C]$ models were originated by a biologist for studying complexity at protein and trait coevolution levels of analysis. Before rushing to discount, however, consider the possibility that the larger message, namely that complexity may compete with natural selection theory as an alternative explanation of coevolutionary “order,” is not so easily disposed of. A more instructive avenue might be further research to better fit the $NK[C]$ models to coevolutionary settings more obviously characteristic of industries. Thus, models designed to more closely fit the coevolution of, say, notebook, health care, or auto firms, would be in order and tests of these models by comparison with real-world coevolutionary adaptive progressions would also be a logical next step—one already taken by Sorenson (1997) in his test of the NK model in the computer workstation industry.²²

Is there any indication that any of these projections actually hold in real-world coevolutionary pockets? If results from Kauffman’s models do not pan out, are there other complexity effects in coevolutionary systems? Kauffman’s main thesis may well apply even though the specifics of the current $NK[C]$ models may be found wanting. Several tasks remain: (1) Extending network sociology to coevolutionary cross-boundary networks among lower level agents in the value chains of competing firms in the specific manner of the $NK[C]$ model; (2) Working toward empirical validation of agent-based models such as the $NK[C]$ as idealized representations of complex real-world phenomena; (3) Augmenting existing static linear network investigations to include stochastic nonlinear adaptive learning approaches; and (4) Developing theories explaining the dynamic behavior of outcome behaviors generated by the models. Until these steps are closer to completion, specific findings from models such as those run by Kauffman and brought into this essay are surely preliminary and serve primarily illustrative purposes.

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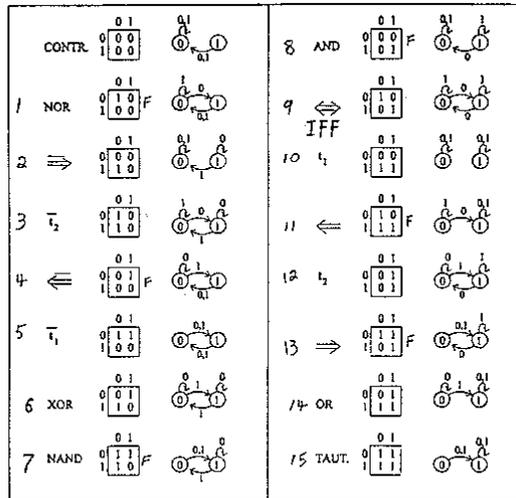
²² After defining “Campbellian Realism” as a current reading on philosophy of science and its emphasis of “model-centered science,” McKelvey (in press-b) sets up the test of the fit between organization theory and models such as the $NK[C]$ as the test of “*experimental adequacy*” and tests such as Sorenson’s, that test a model’s ability to represent real world phenomena, as tests of “*ontological adequacy*.” Both tests are essential to an effective science.

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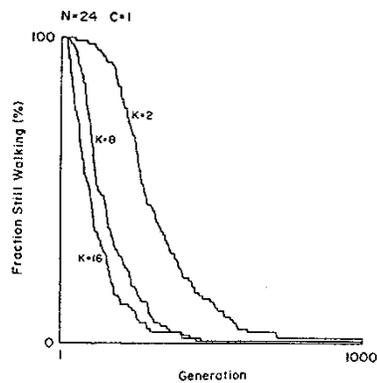
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Figure 1. Sixteen Boolean Functions for $K = 2$ inputs

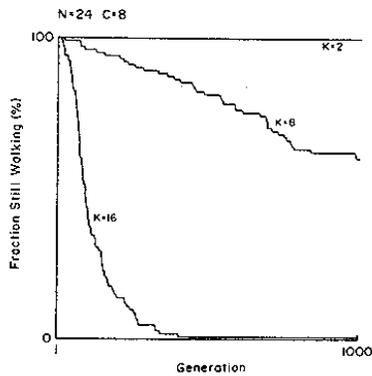


Reproduced from Westhoff, Yarbrough and Yarbrough 1996, p. 12.

Figure 2 Size of K and C Related to Time to Reach Nash Equilibrium



2a When $C = 1$ and K varying (reproduced from Kauffman 1993, p. 247)



2b When $C = 8$ and K varying (reproduced from Kauffman 1993, p. 247)

Table 1. Some Value Chain Competencies of Notebook Manufacturers

<i>Primary Chain¹</i>	<i>Support Chain</i>
Efficient chip utilization	Service & technical repair
Disk technology	Call response time
Battery technology	Shipping
Mouse technology	Purchasing
Heat dissipation	Employee experience
Upgradability	R & D capability
Motherboard	Management/governance structure
Weight minimization	Incentive/compensation package
Size minimization	Product life cycle management
Screen technology	Reliability/warranty management
Docking station capability	Etc, etc, etc.
CD ROM technology	
Optional card slot availability	
Multimedia capability	
Etc, etc, etc. ²	

¹ My focus is not on the hardware item, *per se*, but rather on the underlying competence for assuring that the item is competitive and works as expected. If the item is subcontracted out, then the competence of finding and working with a vendor to assure leading edge technology and product reliability becomes an important substitute competence for in-house technical capability.

² I have listed a possible 24 competencies for a single firm. Each firm in the population, *S*, could have a different set of *N* competencies, drawing from, say, a total pool of 50 competencies. The list is illustrative, not exhaustive.

Table 2. Sources of Organizational Tension Gradients

1. Thompson's (1967) multiple organizational actors with diverse agendas, in and outside the firms, in various interdependency relationships, interacting in a dynamic manner;
2. Actors having different frames of reference (Kahneman, Slovic, and Tversky, 1982);
3. Firms having emergent strategies (Mintzberg and Waters, 1985);
4. Structured and unstructured processes (Mintzberg, Raisinghani, and Théorêt, 1976);
5. Induced and autonomous approaches (Burgelman, 1983);
6. 'Garbage can' decision processes (Cohen, March, and Olsen, 1972).

Table 3. Defining an Adaptive Chainscape to Fit Kauffman’s $NK[C]$ Simulations

S	A species, S , which is a population, is treated as a single homogeneous entity. “Simulations of coevolving systems are carried out under the assumption that each species acts <i>in turn</i> , in the context of the current state of the other species.” (Kauffman 1993, p. 245; his italics). Kauffman’s simplification of species down to a single acting entity is what makes his model applicable to my analysis of firms. Thus, S = number of firms.
N	The NK model consists of N sites, where each site is interpreted as an independent “part” or “agent.” A site for Kauffman is a protein or trait, that is, a “part.” For firms, N could equal the number subunits, production stations, value chain units, process events, competencies, teams, employees, and so forth.
K	Measures <i>internal coevolutionary density</i> among parts within a firm. Thus K is a measure of the interdependencies among the various potentially changing parts or agents. Kauffman terms K a measure of <i>epistatic links</i> (1993, p. 41), that is, links that inhibit change. Because of the interdependencies, the fitness improvement (yield) from a particular change may be diminished because of fitness limitations posed by other parts. He takes a much broader view of their definition than the narrow “allele suppresser effect” typical in biology. In fact, he views the effects of multiple alleles so complex that he relies on a random fitness function. My definition of K as interdependencies having suppressing effects seems well within Kauffman’s usage.
C	Measures <i>external coevolutionary density</i> among parts between a pair of competing firms. The <i>other</i> member of a coevolving pair (gene or species) has a number of proteins or traits, C , which are <i>interdependent</i> with any mutation behavior (or lack of it) of a given focal part (protein or trait). For me, C represents interdependent agents/microagents between a pair of competing coevolving firms. Some number of the opponent’s parts might coevolve with a given part of the focal firm.
A	The Boolean network attribute of Kauffman’s model is retained by assuming that any adaptive walk an agent might make in attempting to improve its fitness is limited to a “2 alternative” action, A —remain unchanged or adopt a change. Any more complicated decision may be reduced to a sequence of binary choices.
D	The dimensionality, D , of a search space/landscape/chainscape is, therefore, defined as $N(A-1)$.
w_j	Because the interdependency effects w_j are complex and unpredictable, Kauffman assigns random values between 0.0 to 1.0. Given K competencies w_j that are epistatically linked to w_i , the A^K fitness contributions w_j are averaged together with w_i at period $t-1$ to create a modified value of w_i at time t .
W, w_i	The total fitness value W of a chain vector is the average of all its N agents, $W = \frac{1}{N} \sum_{i=1}^N w_i$
Agent Fitness	Kauffman interprets each “site” as an independent “agent”. The fitness contribution of each of any particular agent’s two options, $A = 0$ or 1 , is randomly assigned a value ranging from 0.0 to 1.0.
One-Change Neighbor	For a given firm’s value chain of length N , and given a rule of only “one-change” allowed per time period for any agent trying to change toward improved <i>microstates</i> seen in a neighboring agent, there are A^N “one-change neighbor” <i>microagents</i> , each of which is different from a given microagent at only one competence point or locus, that is, in my case 2^N neighbor microagents. Instead of a firm having <u>one</u> alternative value chain that is better on, say, 10 out of 24 competencies, each agent is defined to have 23 neighboring microagents—10 of which are better—each differing by only one competence, and each microagent can adopt only one improvement per period. This is what creates the combinatorial search space/chainscape.
Chainscape	A “chainscape” is, thus, a multidimensional landscape consisting of a total of A^N one-change neighbor microagents—for Kauffman, 2^N . If $A = 2$ and $N = 24$, the landscape is a multidimensional lattice comprising 16,777,216 microstates. Within this ‘scape each agent is <i>next</i> to $(A-1) \times (N-1)$ microagents, each of which may change from one time period to the next depending on changes at other microstate sites (microagents).
Adaptive Walk	Evolution is defined as an adaptive walk through a chainscape where a firm improves the parts of its chain at each time period by surveying all the one-change neighboring microagents and randomly selecting one from those offering improved fitness. If none offer an improvement the agent stays unchanged.
Epistatic Links	Agents may have one or more interdependencies (epistatic links) to other agents which may inhibit the fitness value of a changed competence. For example, a notebook firm’s chances of improving performance reliability may be inhibited by adoption of a leading edge (unreliable) experimental competence conserving battery power, or enhanced by staying with an older highly reliable competence in active matrix screen technology.

Table 4. Additional Notes on the Iteration Dynamics of Kauffman's $NK[C]$ Simulations[†]

1. One item that may seem awkward for my use is Kauffman's "generation", that is time period. When Kauffman the biologist lets a model run 8000 generations or so, it seems reasonable. For organizations, even 2000 clocking cycles may seem long. Length here depends on how "micro" an adaptive walk takes place at each time period. Following Barney (1994) I focus on "micro" decisions rather than "big" decisions.
2. The distribution from which fitness values are randomly drawn could affect the outcome. Kauffman (1993: 44) draws his values "from the uniform interval between 0.0 and 1.0." He could have used peaked Gaussian or U-shaped distributions. Kauffman concludes that the statistical features of his landscape models are "largely insensitive to the choice made for the underlying distribution" (1993, pp. 44–45).
3. In *coevolutionary* simulations, at each time period, the actions of an agent are moderated by the effects of actions by the C agents/parts in the opposing firm, as well as the actions of the given firm's K agents.
4. In Kauffman's *coevolutionary* games, at each time period an agent assesses its current fitness, the fitness of K other internal agents, and picks a "one-change" neighbor (defined in Table 3) offering higher fitness, assuming that the K other agents do not change their action, A . In this game, no foresight is allowed.
5. Since there is no foresight, "in this limit of *pure strategies*, the dynamics of the myopic *coevolutionary* game is [sic] identical to that of a random Boolean network" (Kauffman 1993, p. 240; his italics). A "steady state in this game corresponds to a *pure strategy Nash equilibrium* (Nash 1951)" (1993, p. 240; his italics).
6. In Kauffman's model it is possible for Nash equilibria to occur at less than optimum fitness levels for individual agents and for the entire system. Kauffman also allows for the possibility that subgroups of agents might become "frozen" in a particular Nash equilibrium fitness level, while other agents continue to *coevolve*, though not necessarily to Nash equilibria at improved fitness levels.
7. Given that how each competence interacts with all the $N(A-1)$ other competencies is very complex and unpredictable, the simulations model their statistical features by using a fitness function where a value between 0.0 and 1.0 is randomly selected and assigned to each competence alternative.
8. Given two *coevolving* firms A and B, randomly selected values 0.0 to 1.0 are assigned to represent the effect on firm A that competencies, C , from firm B might have (that are epistatically linked to firm A).
9. In these models, during the course of a simulation run, the values of both K and C remain the same for all chain loci and their effects may inhibit or enhance fitness values at any chain locus.
10. The effect of C is that the chainscapes of both firms 1 and 2 are mutually causal.

[†] Kauffman 1993, pp. 33–45.

Table 5. Description of the Various Model Parameters from Kauffman 1993

1. *Model F6.3.* $N = 24$; $C = 1, 8$; $K = 2, 8, 16$. Only one random change per clock cycle at only one (randomly selected) of the N agents (competencies); each agent in each chooses a new one-change neighbor's fitness if it contributes the agent's improved fitness. The results show the fraction of 100 competing (partnered) firms which have not reached Nash equilibrium, and how long it takes the others to reach equilibrium. (p. 247; Figure 3 in this essay)
2. *Model F6.4.* $N = 24$; $C = 1, 8, 20$; $K = 2, 4, 8, 12, 16$. The values of C are set at below, in the middle, and above K . Only one random change per clock cycle at only one (randomly selected) of the N agents; each agent in each partnered firm chooses a new one-change neighbor's fitness if it contributes to an improvement. The simulation looks at 200 pairs over 250 time periods. The results show the fitness levels of each partner and when Nash equilibria occur, given the various C and K conditions. (p. 248)
3. *Model F6.5.* $N = 24$; $C = 1, 8, 20$; $K = 2, 4, 8, 12, 16$. The number of randomly selected changes per agent (N), per clock cycle, is more than one, going from 2 to 24, thereby making the landscapes increasingly jagged as the change rate increases. It looks at 200 pairs over 250 time periods. The results show the changes in fitness levels of the *coevolving* firms as jaggedness increases. (p. 250)
4. *Model F6.6.* $N = 24$; $C = 2$; $K = 10$; $S = 4, 8, 16$. Pairs are replaced by larger *coevolving* groups of 4, 8, and 16 firms, holding N , K , and C constant. Only one random change per clock cycle at only one (randomly selected) of the N agents; each agent chooses a new one-change neighbor's fitness if it contributes to the agent's improved fitness. The number of time periods ranges up to 8000 (not shown). The results show the level of fitness of the firms, and if and when they reach Nash equilibrium. (pp. 254–255)
5. *Model F6.8.* $N = 24$; $C = 1$; K varies from 0 to 22; This simulation models "square" 5×5 ecosystems containing 25 firms where corner firms *coevolve* with 2 other firms (2 links); edge firms *coevolve* with 3 other firms (3 links); and center firms *coevolve* with 4 other firms (4 links). Firms *coevolve* with other firms on only one competence ($C = 1$), but each firm varies in internal *coevolutionary* density ($K = 0$ to 22). Fifty ecosystems are studied over 200 clock cycles. At each time period, each agent in each of the 25 firms, in turn, chooses a one-change neighboring firm's agent's fitness level if it offers an improvement. Finally, two interior firms are "experimentally" given K s different from the K s of the remaining firms. The results show that firms deviating from the optimal level of K are pulled back toward the optimal level. (p. 260)
6. *Model T2.1-T2.2.* $N = 8, 16, 24, 48, 96$; $K = 0$ to 95. Starting from a randomly selected firm, only one random change per clock cycle at only one (randomly selected) of the N agents; each firm chooses a one-change neighbor's fitness if it offers an improvement. Walks occur on 100 randomly selected landscapes with average fitness levels reported. Results show that fitness levels of accessible local optima start high (at low values of N and K) and decrease toward the mean fitness for a particular landscape, as K increases relative to an increasing N . (pp. 55, 56)