Self-Organization, Complexity Catastrophe, and Microstate Models at the Edge of Chaos

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INTRODUCTION

Consider General Motors Corporation. GM seems like a giant Sequoia tree rotting slowly from the top. Theories abound as to why: myopic management; hubris; politics, vertical integration, inefficiency, outdated plant and equipment, the Icarus Paradox (Miller 1990), resistance to change; permanently failing organizations (Meyer and Zucker 1989), the unions; and so forth. GM is a dinosaur (Loomis 1993) stuck in a time warp with a "gargantuan bureaucracy" (Kerwin 1998, p. 26) that, as a high cost producer of low quality cars, is well off the efficiency curve. And it is not that there isn't motive. The industry is very competitive and everyone in the industry knows GM is below the curve. Further, GM has spent billions trying to get back on the curve—some say they have spent more than the total asset value of Toyota.

What is not working at GM and can organization science explain it? Like Gaul, organization science is divided into three parts: rational, natural, and open systems (Scott 1998). The rational system view, the visible hand Chandler (1977) calls it, puts the blame on managers. The natural system view—the invisible hand—tells us that the emergent structure is apparently defeating whatever good ideas the managers do come up with. And the open systems view? It focuses on environmental effects and boundary transactions. Paradigm proliferation (Donaldson 1995) further delineates views within Scott's broad framework. Much as one might like some of the newer paradigms, Pfeffer (1997) cautions that much of the paradigm proliferation in organization science results from fads and fashion. He quotes himself 16 years earlier, saying, "If we use relatively simpler processes and models the world will appear to be simpler and more certain…. We overlook the potential for finding simpler models to describe the world" (1981, p. 411). So, in this chapter I reduce Scott's framework to four driving forces: *adaptive tension*, *self-organization* (by managers or nonmanagers), *interdependency effects*, and *multilevel coevolution*.

Ironically Pfeffer (1997) decries the dangerous liaison with economics while simultaneously calling for simplicity. The one thing economists' penchant for mathematical models has created is a constant drive for simplicity. They focus on just a few key variables otherwise the mathematics becomes intractable. Following the direction of current philosophy of science, embodied in ***Campbellian Realism*** (McKelvey this volume), I not only follow Pfeffer and the economists in emphasizing parsimony, but also take a step in the direction of a formal model-centered organization science by framing my complexity theory application to firms in terms of computational models.[1] Campbellian Realism calls, in part, for scientists to coevolve the development of theory and model so as to maximize "*experimental adequacy*" tests—the theory predicts model behavior and the model allows testing of the intricacies of the theory.

Section 2 develops: (1) *Self-Organization Theory*—If the level of adaptive tension falls outside a region defined by the chaos theorists' "*critical values*" (Cramer 1993),[2] the resulting complexity field will not support the emergence of structures necessary for constructive adaptation; and (2) *Complexity Catastrophe Theory*—If the conditions of complexity catastrophe exist, Friedman's (1953) natural selection based constrained maximization or Campbell's blind variation, selection, and retention (BVSR) processes may function properly and yet fail to produce the kinds of intrafirm behavior necessary for survival and growth in a selectionist competitive context. Together these theories state that (1) critical value effects creating emergent structure in the mid range of adaptive tension; and (2) complexity effects on the flat and jagged extremes of rugged landscapes combine to produce a nonlinear inverted U effect on organizational performance relative to adaptive tension and complexity. Section 3 illustrates how to set up the groundwork for testing experimental adequacy. The model frameworks come from Kauffman (1993). I draw on both his Boolean statistical mechanics and his *NK*[*C*] model. I conclude that (1) self-organization and complexity catastrophe theories offer useful insights into the prolonged poor performance of large complex organizations such as GM; and (2) computational modeling approaches offer a basis for testing the

[1] Starbuck (1965), Cohen, March, and Olsen (1972), Carley (1991, 1994), March (1991), and others (Burton and Obel (1984, 1995) are well ahead of me in formally modeling organizational behavior. Carley (1995) gives a review of formal modeling in organization science.

[2] To be defined more fully in Section 2.1, below the 1st critical value no structure emerges and above the 2nd critical value the system becomes chaotic.

experimental adequacy of scientific theories pertaining to complexity theory applications to firms.

COMPLEXITY CATASTROPHE AT THE EDGE OF CHAOS

Self-organization at the edge of chaos and complexity catastrophe involve both downward and upward causality. The interplay between downward and upward causation arises frequently in Campbell's writing (1974a, 1981, 1988a, 1990, 1994). It is also a constant source of debate in biological evolution (Eldredge 1995). Paleontologists and ecologists emphasize downward causation (Stanley 1979, Eldredge 1985, Gould 1983, Pianka, 1994) while the selfish gene folks emphasize upward causation (Williams 1966, Maynard Smith 1975, Dawkins 1976, Kimura 1983). The clash of selectionist causal paths is growing in organization science (McKelvey 1997) and is evident in many chapters in this volume. Is emergent order in an industry—the kinds of firms surviving—due to the ecological selection of firms or due to the competitive selection of individuals and ideas within firms that combine to create successful firms? Though the debate rages on in biology (Eldredge 1995), cooler heads argue that the production of "order" that is favorably selected ecologically (downward causation) is the result of BVSR processes boiling up from within (upward causation) (Kauffman 1993, Depew and Weber 1995). Long ago Lewontin (1974) said that it is the interactive context that counts in biology. Campbell makes the same point for socio-cultural systems and the epistemology of knowledge. Baum and Singh (1994), Van de Ven and Poole (1995), and Hunt and Aldrich (1998) recognize multilevel causation in organizations.

What about the interactive context of GM? Friedman uses selectionist theory to suggest that successful firms behave "…*as if* they were seeking rationally to maximize their expected returns" (1953, p. 22; his italics). Apparently GM is not doing this. What it takes to compete effectively in the automobile business is reasonably transparent these days and the usefulness of performance incentive packages for executives is also well known. Since GM has been failing for two decades, why hasn't it been fixed? Following Friedman, the application of natural selection theory *inside* firms suggests that only those managers who are successful in maximizing rational expectations would survive and move up, and therefore GM *should* have just as many good managers as any other large firm and be just as able to maximize its returns. The implication is instead that the selection process of good individuals and ideas within GM has broken down. Why? Madsen, Mosakowski, and Zaheer (this volume) suggest one reason: internal BVSR has failed.

A second possibility is that BVSR is working but that complexity effects thwart it. Two fundamental ideas from complexity theory may go a long way toward explaining GM's malaise. One idea boils down to the proper management of adaptive tension and the second idea focuses on the proper management of coevolutionary interdependencies. Causality goes like this: By operating on these two basic parameters, managers "seed the clouds" by unleashing the natural forces in firms that produce adaptive self-organization and by inhibiting the build-up of complexity catastrophe. Self-organization is a strong force augmenting BVSR in a rapidly changing competitive context. Complexity catastrophe is a strong force thwarting BVSR. Though risking oversimplification, these two theories let me stay well within Pfeffer's simplicity standard.

Self-Organization Theory, initiated by Prigogine and colleagues (Prigogine 1962, 1980; Prigogine and Stengers 1984, Nicolis and Prigogine 1977, 1989), holds that adaptive tension "critical values" (1) create fundamentally different kinds of complexity fields; (2) give rise to different bases of explaining complexity phenomena; and (3) frame a particular kind of complexity "at the edge of chaos" in which emergent self-organized structures leading to significant adaptive change will occur. This theory implies that adaptive tension within GM must be outside the critical value levels needed to foster self-organized adaptive response. ***Complexity Catastrophe Theory***, promulgated by Kauffman and colleagues (mostly summarized in Kauffman 1993), holds that complex interdependencies within entities may accumulate to thwart selectionist effects by altering the adaptive landscape to produce the conditions of complexity catastrophe. This view implies that BVSR may be working effectively within GM but that complexity effects create conditions in which the selected agents or ideas are little better than those selected against.

Skeptical readers knowing that Prigogine's theory stems from nonlinear thermodynamics and that Kauffman's theory comes from biology may question whether these theories are relevant to firms and organization science. To be sure, the compatibility of underlying assumptions is critical and cannot be dismissed. Nevertheless space precludes discussion of the following points:

1. There is reason to believe that the assumptions of stochastically idiosyncratic microstates (particles in physics, molecules in chemistry, genetic material and cells in biology, actors in economics, and activities in value chains (Porter 1985) or organizational processes (Mackenzie 1986), apply as much in organization science as they do in modern natural sciences—a point, following from the conflation of modern natural science with the ontological assumptions of relativists and postmodernists (Schwartz and Ogilvy 1979, Lincoln 1985, Chia 1996), that I have argued at length elsewhere (McKelvey 1997, 1998b).

2. There is a growing body of relevant literature describing the microstate basis of complexity theory and justifying the application of complexity and chaos theory to organization science (see for example treatments by Stacey 1992, 1995; Zimmerman and Hurst 1993, Levy 1994, Merry 1995, Thiétart and Forgues 1995, McKelvey 1997, 1998a, in press, Baum and Silverman in press), the forthcoming special issue of *Organization Science* on complexity theory applications to organizations, not to mention supportive arguments in a host of new books appearing in 1998–1999 such as Eisenhardt (1998), Lissack and Gunz (in press).

3. Arguments supporting formal models in organization science are already well established. These models further develop the implications of complexity theory, or other subjects such as organizational learning and adaptation, in organization science and have sound epistemological

and scientific basis (McKelvey 1998a, this volume, in press). Computational models are also increasingly used to further theory development in organization science (March 1991, Carley 1994, 1995; forthcoming; Prietula and Carley 1994, Carley and Svoboda 1996, Bruderer and Singh 1996, Levinthal 1997a,b; Levinthal and Warglien 1997, Rivkin 1997, Lomi and Larsen this volume). Empirical testing of model behavior is beginning in experimental organizations (Carley 1996) and real world firms (Cheng and Van de Ven 1996, Sorenson 1997).

1.1 COMPLEXITY THEORY

Over the past thirty-five years complexity theory has become a broad ranging interdisciplinary subject, as demonstrated in the books by Anderson, Arrow, and Pines (1988), Nicolis and Prigogine (1989), Kaye (1993), Mainzer (1994), Favre et al. (1995), Nadel and Stein (1995), Belew and Mitchell (1996), and Arthur, Durlauf, and Lane (1997). The study of "*complex adaptive systems*" (Cowan, Pines, and Meltzer, 1994) focuses its modeling activities on how stochastic idiosyncratic microstate events, whether particles, molecules, genes, neurons, human agents, or firms, self-organize into emergent aggregate structure. My rather narrow treatment here focuses on emergent dissipative structures, adaptive landscapes, critical values, complexity catastrophe, and agent-based computational modeling. The traditional way sciences have dealt with the stochastic microstate assumption is with statistical mechanics (Gibbs 1902; Tolman 1938, Weidlich and Haag 1983; Aoki 1996). In the second half of the 20th century complexity theory has emerged as an alternative method of explaining phenomena given a stochastic microstate assumption (McKelvey 1997). Instead of using the statistical mechanics artifice of taking an average (of stochastic idiosyncratic microstate movements) so as to then continue in the manner of an exact science, complexity theory accepts and builds on random idiosyncratic nonlinear behavior. In the following subsections I divide complexity theory into, (1) emergent dissipative structures; (2) critical value effects; and (3) complexity effects on adaptive landscapes.

Emergent Dissipative Structures. Complexity theory departs from classical Newtonian deterministic laws about the conservation of motion and conservation of energy as represented by the 1st law of thermodynamics. Given the 2nd law of thermodynamics, that all ordered states eventually dissipate (via entropy) into disordered states, complexity theory emphasizes dissipative dynamical systems created or maintained by negentropy and eroded by entropy (Nicolis and Prigogine 1989, Mainzer 1994). Negentropic effects that create or maintain order in the form of new structure, and entropic (energy dissipation) order destroying effects within any structure, form the heart of complexity theory.[3]

"[Newtonian] physics deals with an invented, simplified world. This is how it derives its strength, this is why it works so well" (Cohen and Stewart 1994, p. 12). This idealized view of physics mirrors the "semantic conception of theories" in modern philosophy of science (see Suppe 1977, 1989; Thompson 1989). It is predicated on the belief that the Universe is "algorithmically compressible" into simple rule explanations (Barrow 1991, p. 15). But how do phenomena appear, absent the invented, idealized, simplified world of 19th century physics? Offering a view based on Kolmogorov's '*K*-complexity' theory (Kolmogorov 1965), Cramer (1993, p. 210) defines complexity "as the logarithm of the number of ways that a system can manifest itself or as the logarithm of the number of possible states of the system: $K = \log N$, where K is the complexity and N is the number of possible, distinguishable states." For a parallel view of the "algorithmic information content" of complex bit strings see Gell-Mann (1994, Ch. 2). Cramer then identifies three levels of complexity, depending on how much information is necessary to describe the complexity. These are defined in Table 1a.

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Complexity theorists define systems in the critical complexity category as being in a state "*far from equilibrium*" (Prigogine and Stengers 1984). The key question becomes, What keeps emergent structures in states of equilibrium far above entropy, that is, in states counter to the 2nd law of thermodynamics? Prigogine and colleagues observe that energy importing, self-organizing, open systems create structures that in the first instance increase negentropy, but nevertheless ever after become sites of energy or order dissipation, thereby accounting to the 2nd law. Consequently they are labeled "*dissipative structures*" because they are the sites where imported energy is dissipated. If energy ceases to be imported, the dissipative structures themselves eventually cease to exist. Negentropy may occur from adding energy or simply by dividing (finite) structures (Cohen and Stewart 1994, Eigen and Winkler 1981). Entropy occurs simply from the merging of structures. Thus, despite the wishful aspirations of Wall Street gurus and CEOs to add energy from synergy, mergers and acquisitions are mostly entropic, a classic example being the assimilation of Getty Oil into Texaco.

Self-organized dissipative structures may exhibit two key behaviors: persistence and nonlinearity. As to persistence, following Eigen's work on autocatalytic hypercycles (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; their italics) wherein some agent 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). As to nonlinearity, Depew and Weber note further that the behavior of dissipative structures is nonlinear and tending to create marked explosions or crashes of structure, a situation far from the gradualism of Darwin.

3 Schrödinger (1944) coined negentropy to refer to energy importation.

They also observe that when "…a system is constrained far from equilibrium [because of imported energy], macroscopic order arises not as a violation of the second law of thermodynamics but as a consequence of it" (1995, p. 464). This kind of order may appear as Cramer's subcritical complexity. Thus self-organizing systems may come to stasis at any of the several levels of complexity. Complexity caused self-organizing structures with autocatalytic tendencies are now seen as a ubiquitous natural phenomenon (Cramer 1993, Kaye 1993, Mainzer 1994, Favre *et al*. 1995), and hypothesized as broadly applicable to firms (Stacey 1992, 1995; Zimmerman and Hurst 1993, Levy 1994, Thiétart and Forgues 1995).

If such emergent structures are in some way opposed to each other, they may themselves become tension creators giving rise to still other emergent self-organized structures, or possibly chaotic behavior. Thus, as the energy gradient increases (between a more entropic equilibrium state and the "far from equilibrium" state), and the stress of maintaining the negentropic state increases, there is a likelihood that the system will oscillate between the different states, thereby creating chaotic behavior. Oscillations that traditionally were taken as variance around an equilibrium point, now may be discovered to be oscillating around a strange attractor, or as bifurcated oscillations around two attractors, or if the stress increases beyond some additional limit, the chaotic behavior will change to pure random behavior—no deterministic structure at all, possibly not even probability distributions. Definitions of *point*, *periodic*, and *strange* attractors are given in Table 1b. By this line of reasoning, Nicolis and Prigogine (1989), Ulanowicz (1989), and Depew and Weber use thermodynamic energy differentials to explain how the various states of complexity come to exist (see also Beck and Schlögl 1993).

Critical Value Dynamics. "Critical values" determine when a system shifts from being explainable by the simple rules of Newtonian science, to having self-organizing capability, to behaving chaotically (Cramer, 1993). Nicolis and Prigogine (1989, Ch. 1) offer an overview of the function of critical values in natural science. As an example, consider the life-cycle of an atmospheric storm cell. The level of adaptive tension setting up the heat convection dynamics in a weather system is defined by the difference between the warm-to-hot surface of the earth and the cold upper atmosphere. At a low level of adaptive tension heat is slowly transferred from air molecule to air molecule via conduction. Energetic (heated) molecules at the surface more rapidly collide with molecules just above the surface and thereby transfer their heat energy collision-by-collision to the less energetic molecules—but the molecules stay in their local area just banging around at each other. If the adaptive tension increases sufficiently, to the *1st critical value*, some mass of air molecules, having become collectively "lighter" than other molecules, will start rising toward the upper atmosphere in bulk, thus setting up a convection current. At this critical value clear air turbulence appears and if the rising bulk of air is sufficiently moist, it will appear visible as clouds as it reaches the cooler upper atmosphere. The "bulk air current" is classed as an emergent structure by complexity theorists. If the adaptive tension between surface and upper atmosphere increases still further, the structures quite predictably develop as thunderstorms. Examples of other kinds of emergent structures appear in physics, chemistry, biology, and other natural sciences. Thunderstorms may be treated as isolated physical structures and are scientifically studied via scientific realist epistemology and the analytical mechanics of Newtonian science. In Prigogine's terminology (Nicolis and Prigogine (1989, Ch. 2), the storm cells are dissipative structures occurring as the result of negentropy—they are created by the energy differential between hot and cold air and they serve to dissipate the energy of the hot surface air into the cold upper atmosphere. This accomplished, they dissipate to the point of disappearance.

Suppose the adaptive tension between hot lower air and cold upper air were to increase further, perhaps by the conflation of warm moist air from the Gulf of Mexico and a cold air front coming down from Alaska, say over Kansas. At some point a *2nd critical value* is reached that defines "the edge of chaos." At this point the point attractor, or the limit cycle (pendulum) attractor of a conservative reversible deterministic system, is replaced by (1) two attractors causing the system to oscillate between the two; (2) possibly several attractors; or (3) a strange attractor in which the system is confined to a limited space by forces defining behavioral extremes (limits) rather than by the attraction of a central point. In a weather system chaotic emergent structures are things like tornadoes—the system oscillates between tornadic and nontornadic behavior.

The key propositions are:

2. The sun's energy causes an adaptive tension (energy differential) between hot surface and upper atmosphere.
3. Below the 1st critical value, energy will dissipate via conduction among the kinetic gas particles (microstates).
4. Above the 1st critical value of adaptive tension, one or more convection currents or dissipative structures (storm cells) will emerge to exist in a state far from equilibrium—at the edge of chaos.
5. Above the 2nd critical value the dissipative structures will pass from a state "at the edge of chaos" to a state governed by deterministic chaos and multiple basins of attraction—occasional tornadoes.

Complexity Catastrophe. The notion of an adaptive landscape is attributed to Sewall Wright (1931, 1932). The landscape metaphor has subsequently retained considerable popularity among biologists, though in other disciplines *sequence*, *configuration*, or *search space* is preferred. An adaptive landscape has three elements: (1) A configuration space; (2) fitness functions; and (3) move rules which define the steps of the *adaptive walk*. As one approaches explanation from a "micro" level, the landscape or search space becomes central. As Macken and Stadler (1995) observe, Maynard Smith (1970) uses it to study protein evolution; Eigen (1971), Spiegelman (1971), and coworkers (Kramer et al. 1974) use it to investigate the *in vitro* evolution of RNA molecules; the Vienna group also uses it to study RNA adaptation (Fontana and Schuster 1987, Fontana, Schnabl, and Schuster 1989); and Kauffman and Weinberger (1989) introduce the idea of a tunable landscape in which complex interdependencies are allowed to affect fitness yields.

Kauffman's (1993, pp. 33–34) new wrinkle in *fitness landscapes* is that his 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 shows 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 more numerous statistically typical central tendencies of other properties comprising the broader population. 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).

Given a tunable landscape, Kauffman (1993) identifies two conditions when complexity effects may thwart selectionist effects as the root cause of order in biology:

1. In a "correlated" landscape containing some clearly advantageous fitness peaks, 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. In a "rugged" landscape, given that (a) as peaks proliferate they become less differentiated from the general landscape; (b) in precipitous rugged landscapes adaptive progression is trapped on the many suboptimal "local" peaks; and (c) even in the face of strong selection forces, the fittest members of the population exhibit characteristics little different from the entire population.

Kauffman labels these conditions *"complexity catastrophes"* because one or the other inevitably happens 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). The "catastrophe" is designated as such because complexity acts to thwart the selectionist process, thereby stopping progression toward improved fitness.

The bullets defining the catastrophe conditions introduce two concepts central to Kauffman's thesis, *"correlated"* and *"rugged"* landscapes, which are also key determinants of his notion of tunable landscapes, and which form the key elements of the *NK* model. N represents the number of significant components comprising an adapting entity, such as a gene, chromosome, trait, or species, or in our case, number of process events, units, actors, firms, or generally the number of agents attempting to achieve higher fitness. K stands for the number of interdependencies among the agents; K can range from 0 to N–1. Thus, K is a measure of the complexity of interdependencies. Kauffman argues that K causes the landscape to buckle and deform with the result that it changes from a single dominant fitness peak at the $K = 0$ extreme to many low level peaks at the $K = N$–1 extreme. Kauffman defines the $K = 0$ landscape as highly correlated whereas the $K = N$–1 landscape is highly rugged. Rugged landscapes contain many peaks and valleys, steep slopes, many suboptimal peaks, and offer a greater chance of an agent being trapped on a suboptimal peak. Note that suboptimal in a land of many low peaks may not be much less than a considerably flattened global optimum, nor much higher that the surrounding plain.

Kauffman uses the *NK* model to investigate the *rate of adaptation* and *level of success* likely on a particular landscape. With tunable landscapes one may ask how levels of complexity affect rates and levels of adaptation by altering the ruggedness of the landscape. Kauffman uses the *NK* model to answer questions pertaining to adaptive evolutionary rates in protein evolution, the crystallization theory of the origin of life, the origin of a connected metabolism, the formation of autocatalytic sets of RNA catalysts, and the evolution of genetic regulatory circuits. With the *NK*[*C*] model he uses cellular automata models to explore the distortion of landscapes due to micro level complexity effects on the coevolutionary dynamics between opponents, the complexity induced percolation[4] of emergent ecological structures, and complexity induced alterations of the landscape affecting the relative height of Nash equilibrium levels.

5.1 COMPLEXITY EFFECTS IN FIRMS

Critical Value Dynamics Translated to Firms. To apply the critical value idea to firms, consider a small firm recently acquired by a larger firm. With a low level of adaptive tension—below the *1st critical value*—in which existing management stays in place and little change is imposed by the acquiring firm, there would be little reason for people in the acquired firm to create new structures, though there might be "conduction" type changes in the sense that new ideas from the acquiring firm percolate slowly from one person to another person adjacent in a network. If the acquiring firm raises adaptive tension by setting performance objectives calling for increasing returns on investment, more market share, etc., perhaps changing the top manager, but keeps the tension below the *2nd critical value*, complexity theory predicts new structures will emerge that will lead more quickly to better performance.

Above the *2nd critical value* complexity theory predicts chaotic behavior. Suppose the acquiring firm changes several of the acquired firm's top managers and sends in "MBA terrorists" to change the management systems "over-night"—new budgeting approaches, new information systems, new personnel procedures, promotion approaches and benefits packages, new production and marketing systems—and the acquired firm's culture and day-to-day interaction patterns. In this circumstance two bifurcating attractors could emerge: one being an attractor for people trying to respond to the demands of the MBA terrorists and the other an attractor for people trying to resist change and hang onto the comfortable pre-acquisition ways of doing business.

In between the 1st and 2nd critical values is the region complexity theorists refer to as at *the edge of chaos*—Cramer's critical complexity field. It is also the region where Cohen and Stewart's *"emergent simplicity"* concept prevails. Here, structures emerge to solve a firm's adaptive tension problems. To use the storm cell metaphor, in this region the "heat conduction" of interpersonal dynamics between communicating individuals in a value chain network is insufficient to resolve the observed adaptive tension. As a result, the equivalent of organizational storm cells consisting of "bulk" adaptive work (heat energy) flows starts in the form of formal or informal emergent structures—new network formations, new informal or formal group activities, new departments, new entrepreneurial ventures, importation of new technologies and competencies then embedded within the new social or formal organizational structures, and so forth. These organizational structures are the emergent *"simple rule"* governed structures Cohen and Stewart discuss. Their emergence is caused by the contextual dynamics of adaptive response to changing environmental conditions. Having emerged, they generate work flows of a probabilistically predictable nature. For epistemological purposes, these structures may be explained using the simple rule epistemology of traditional normal science—prediction, generalization, falsification, nomic necessity,[5] experiments, and so forth. As one may see, in this region there is the confluence of both contextual (downward) and reductionist (upward) forms of causal explanation.

Besides defining the critical value concept in nature and in firms, it is important to understand how the state of a critical value might be defined by the adaptive tension experienced by a firm or one of its subunits. Though critical values in organization science are unlikely to have the precise value they appear to have in some natural sciences (Johnson and Burton 1994), it seems likely that a probability distribution of such values will exist for individual firms and each of their subunits. I assume here that adaptive tension may not be uniform for a firm as a whole or across its SBUs.

Complexity Catastrophe Translated to Firms. Suppose a notebook computer firm and an opponent exist in a coevolutionary pocket (Porter 1990) and that they coevolve in terms of a number of technologies (departments), *N*, in charge of, for example: processor and bus speed, motherboard, hard drive capacity and speed, weight, battery life, display, multimedia capability, upgradability, reliability, and service—each in the charge of, or treated as, an agent. Each firm has a level of interdependency among its agents, *K*, and between its agents and those in its opponent, *C*. *Within a firm* each agent could be a source of a good idea (a fitness improvement) or an impediment (for example, yield on processor speed could be inhibited by a slow bus and poor heat sink). *Between firms* coevolution could push a technology ahead because the opponent is more advanced (leading to fitness improvement) or slow it down because the opponent is lagging.

Supposing an agent gets a good idea from another agent within the firm, as *K* increases the likely yield from the idea diminishes because of the increased probability of impediments from the increasing number of interdependencies. Eventually the high probability of

[4] An emergent structure is said to "percolate" when it stretches from one edge of a network lattice to another—top to bottom, left to right, etc. (Stauffer 1987b)

[5] Nomic necessity is a requirement imposed by philosophers to protect against explanations responding to "accidental regularities" by insisting that all explanations be based on theories that include at least some laws of the "counterfactual conditional" kind, that is, "If *A* then *B*." For example, a theory purporting to offer a culture-based explanation why Japanese firms have no-layoff policies is based on the accidental regularity that "all Japanese firms have no-layoff policies." Since exceptions exist the regularity, as stated here, is mistaken.

impediments from epistatic interdependencies[6] thwarts the yield from the BVSR process, leading, in Kauffman's terms, to complexity catastrophe. Increasing the number of coevolving technologies between a firm and its opponent leads to increased instability, what Kauffman terms "coupled dancing" (1993, p. 249). Though the interaction between *K* and *C* is complicated, according to Kauffman's modeling a higher *C* generally allows a higher *K* before catastrophe hits.[7] Further details about the translation of the *NK*[*C*] model to firms are given in Section 3.

A Stylized Complexity Theory of Firms. Over the course of this discussion I have applied a few key principles from complexity theory to firms. They are restated below:

Critical value dynamics from Prigogine:

1. A corporation's performance demands cause an adaptive tension (energy differential) between an SBU's current practices and what is required by the acquiring firm—or the market.
2. Below the 1st critical value, adaptive change may occur at some minimal level within the constraints of the existing SBU process (microstates) governed by its existing organizational culture and structure.
3. Above the 1st critical value of adaptive tension, one or more dissipative structures (informal or formal groups or other organizing units) will emerge to exist in a state far from equilibrium.
4. Above the 2nd critical value the dissipative structures will pass from a region "at the edge of chaos" to a region governed by deterministic chaos and multiple basins of attraction—possibly bifurcated basins of attraction, one being the existing practices and the other being attempts to conform to the demands of the MBA terrorists sent down from corporate headquarters, or multiple basins of attraction as people oscillate among various short-lived attempts to deal with the tension.

Complexity catastrophe from Kauffman:

1. BVSR forces are too weak in the face of industry competition for a subset of firms to hold a unique attribute, hence typical properties pervading the industry prevail. That is, systems facing high innovation opportunities exhibit order not so much because of competitive selection but because complexity effects offer no resistance. That is, *some* complexity, by offering resistance, strengthens the BVSR process. Thus, if selection had dominated, Apple Computer's superior operating system would have prevailed. As it happened the prevailing "typical" system of the PCs won out—not because the best was selected nor because complexity effects thwarted Apple more than any other firm.
2. Even with strong selection forces, an industry may be characterized by many suboptimal innovation opportunities which do not differ substantially from the average properties of the industry. That is, given that (a) as peaks proliferate they become less differentiated from the general landscape; (b) in precipitous rugged landscapes adaptive progression is trapped on the many suboptimal "local" peaks; and (c) even in the face of strong selection forces, the fittest members of the industry exhibit characteristics little different from the entire industry. Therefore even though selection is strong, complexity effects thwart selection effects. For example, gasoline may be very competitive but the minimal improvements from different additives do not give any particular firm an advantage.

These six propositions reduce complexity theory to: (1) Emergent dissipative structures appear between the 1st and 2nd critical values of adaptive tension; and (2) As complexity increases, selection effects are initially enhanced because the landscape has some fairly high suboptimal fitness peaks, and then thwarted as too much complexity lowers the multiplying peaks to minimal levels. Adaptive success, thus, appears as a two dimensional Gaussian distribution of likely performance—a single rounded hill when plotted against adaptive tension and complexity.

AN ILLUSTRATIVE EXPERIMENTAL ADEQUACY TEST

Campbellian realism, as further developed by McKelvey (this volume) defines a model-centered epistemology in which science is divided into two independent activities. In this late 1990s interpretation of effective scientific activity, Campbell (Campbell 1988b, Paller and Campbell 1989) and scientific realists such as Bhaskar (1975/1997), Boyd (1991), de Regt (1994), Aronson, Harré, and Way (1994) join semantic conception theorists (Beth 1961, van Fraassen 1970, 1980, Suppes 1962, Suppe 1977, 1989, Lloyd 1988, Thompson 1989), to replace the axiomatic basis of theory[8] with a "*theory-model*" link in which axioms may or may not be essential. The difference is illustrated in Figure 1. In this view the theory–model link is "coevolutionarally" improved as theory and model are developed toward increased predictive isomorphism—"*experimental adequacy*." More or less in parallel, the "*model–phenomena*" link is also coevolutionarally developed, leading to improved "*ontological adequacy*"—fit with real world phenomena. In contrast to this modern interpretation of science, organization science still attempts to develop a link directly between theory and the complex reality of the real world, also illustrated in Figure 1.

>>> Insert Figure 1 about here<<<

To conform to Campbellian realism and the thrust of the semantic conception, in what follows I show that both self-organization and complexity catastrophe theories may be formally modeled. To illustrate, I take only the first step of suggesting that computational models exist with which to develop the theory–model link. Their origin is jointly from biology, physics, and computer science.

5.2 MODELING EMERGENT STRUCTURE

Kauffman's *NK* model derives from physicists' spin-glass models (Weinberger 1991), a 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

[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.

[7] Implications of Kauffman's *NK*[*C*] model for firms is spelled out in more detail in McKelvey (in press).

[8] Thompson (1989) gives a good review of the reasons why philosophers shifted from the syntactic/axiomatic view to the semantic conception of theories.

(1993) uses them to understand how organisms, via mutations, take hill climbing *"adaptive walks"* to maximize fitness. A step in the walk occurs when, for example, a gene moves to a new point on the landscape by adopting a mutant form from a neighboring gene. The *NK* model is a "static" 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 (see Kauffman Ch. 2).

To model emergent structure phenomena I draw on a series of studies by Kauffman and Derrida and colleagues[9] in which they discovered parameters controlling the emergence of structure in random Boolean (binary) networks. In this modeling approach Kauffman shifts from spin glasses to the computer scientists' *cellular automata*, focusing on **Boolean network dynamics**.[10] 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^K inputs, that is *K* binary inputs, each of which has some probabilistic effect on the Boolean outcome state (Jones 1995). Given a binary cell function, 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^k} . Since this could be a truly vast number (2.8×10^{14} for $K = 24$), Kauffman creates a "*Boolean statistical mechanics*" in which fairly "exact" outcomes are created by sampling and averaging to describe the total system of elements (Kauffman 1974, Gelfand and Walker 1984).

For $K = 2$ inputs there are 16 Boolean functions, shown in Figure 2. In this "tabular" depiction the on-off inputs are on the edges and the outcome disposition is inside the box.[11] For game theorists one of the inputs 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 perturbations 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 2, only the 'XOR' and 'IFF' functions are not forcing functions—on one or both inputs.[12] As the number of inputs *K* increases, the relative number of forcing functions decreases rapidly—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 functions that are forcing. 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.

> > > Insert Figure 2 about here < < <

A substantial body of research bearing on random Boolean networks identifies several parameters that shift the systems from *ordered* to *complex* to *chaotic* behavior, as reviewed by Kauffman (1993, Ch. 5). These networks are termed *"annealed"* because at each time period the connections from other automata cells and the cell functions are randomly reassigned. As a result there is no reason to expect them to revisit some prior state, that is, act as a limit cycle. This is in contrast to "*quenched"* networks, in which connections and cell functions are randomly assigned only once at the outset (Kauffman 1993, p. 198). In either case there are *N* vertices or binary variables), *K* input connections from other cells, and *P* (the forcing bias of the cells). As *N*, *K*, and *P* increase, random Boolean networks shift from *order* to *chaos*. At $K = 2$ with $P = 0.5$ (meaning no imposed forcing bias), networks show a phase shift separating order from chaos. Depending on the size of *K*, there is also a generalized phase shift parameter, P_c, also separating *order* from *chaos*. In the region of $K = 2$ with $P = 0.5$ or approximately at P_c there exists *a "boundary region"* in which *complex emergent structure* appears.

Figure 3a presents a lattice coming from Weisbuch (1991) showing two kinds of emergent structure: (1) *"islands"* of structure (non 1's); separated by (2) a larger *"percolating frozen structure"* of forced cell functions, all of which have a value of 1. In this lattice $K = 4$ and $P = 0.2$. Though the frozen structure has been forced to a value of 1, the cells in the islands still are able to oscillate between 1 and 0. In this *"ordered regime"* the control parameters produce ordered behavior in the percolated structure—the "forcing" behavior at some initial cell percolates throughout the system resulting in uniform behavior and cells in the percolated structure are all in one state. That is, a small change in one cell ripples through the frozen

[9] Some key contributors are: Kauffman 1974, Gelfand and Walker 1984, Derrida and Flyvbjerg 1986, Derrida and Pomeau 1986, Derrida and Stauffer 1986, Derrida and Weisbuch 1987.

[10] I cannot replicate Kauffman's development here. Recourse to Kauffman (1993, Ch. 5) is highly recommended.

[11] A very accessible description of automata is given in Westhoff, Yarbrough, and Yarbrough (1996). A more advanced introduction is given by Weisbuch (1991).

[12] 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, Yarbrough and Yarbrough (1996) consider all but functions 6 and 9 as forcing since for these two the outcome state depends on knowing both input states.

component producing wholesale forcing into one basin of attraction—the value 1 in this particular lattice. Alternatively, one could also see a *chaotic regime* (shown in Figure 3b) in which the larger *"percolating chaotic structure"* oscillates around long to possibly limitless limit cycles and islands are frozen on a single value where $K = 4$ and $P > P_c$ ($P_c = 0.28$). This would also result if $K > 3$ with $P > P_c$. In this circumstance the major component would continue oscillating on the 1 and 0 values with *order* appearing as small isolated islands frozen on one value. In terms of the *NK* model, ordered networks adapt more readily on less rugged landscapes, whereas chaotic systems adapt more successfully on rugged landscapes, according to Kauffman's results (1993, p. 215–217).

> > > Insert Figure 3 about here < < <

Kauffman argues that at the point of the $K = 2$ with $P = 0.5$, or $K > 2$ with $P \approx P_c$, *"phase shift"* transitions there exists a *"liquid region"* in which complex adaptive systems emerge "at the edge of chaos"—the small isolated frozen islands in the Boolean network model. Thus, these network systems may lie in three states: (1) the ordered regime of small isolated frozen islands; (2) the chaotic regime of one large frozen state with a few oscillating islands remaining; or (3) the liquid region of the phase transition state where the large frozen component *"melts"* into some number of oscillating islands. This model, thus, behaves consistently with complexity theory in that it shows emergent structure when the critical values take on the instigating values.

Needless to say, complexity theory applied to biology is quite new. Using random Boolean networks to model biological behavior is even more novel. Little of either has been applied to developing a model-centered organization science, except for a brief example given by Gelfand and Walker (1984, p 230) in which they apply this modeling approach to managerial control systems focused on repetitive routines. Consider the following rudimentary illustration.

Imagine a firm with 20 agents (line managers, staff, and engineers) responsible for various parts of a value chain. At any given time for any specific activity an agent has two alternatives: make an adaptive improvement (value 1) or do nothing (value 0). In making this decision an agent may consider a variety of inputs, from one other person or from many other people. For modeling purposes an agent can only make a binary decision at any given time period, but obviously over many time periods an agent can make rather complicated adaptive moves. And for modeling purposes we limit an agent to a fixed number of input connections from other individuals, though of course in the real world he or she could have varying inputs on any given day for any specific activity. But given the cost of time and effort to communicate, and boundedly rational abilities to process information, Simon's (1957) satisficing theory suggests that agents might typically settle for a small fixed number of information inputs for any given decision. Given that we have narrowed managerial decision making down to micro sequences of decisions on specific micro aspects of their responsibilities at any given time, the 20 agents in the model are not unreasonably simplified from real agents. With this model, then, we can alter the number of agents, alter the number of decision (cell) outcomes, alter the number of input connections they consider at any given instant. In addition we can randomly assign each agent one from a range of cell input configurations and cell functions or rules—from the lattice defined as 2^{2^K}.

Supposing agents were limited to two inputs, the range of possible cell functions is given in Figure 2—sixteen in all. Agents could have many more inputs—they could value or weight each input differently, or they could wait until input information from other agents accumulates to some level deserving their attention, the range of cell functions may become limitlessly more complicated. To cope with a potentially vast number of cell inputs and functions, Kauffman (1974) introduces his *"statistical mechanics ensemble modeling*" approach. Instead of working through an entire lattice containing potentially billions of elements, he assumes that the samples drawn and averaged in the manner of statistical mechanics fairly accurately represent the mix of cell functions distributed in the entire multidimensional $2 \times 2 \times K \times N$ lattice. For now, let's stay with the simple $2 \times 2 \times (K = 2)$ lattice, with the parameter P ranging from 0.5 to 1.0. We may delete N because, as Stauffer (1987a, p. 791) observes, the forcing dynamic is independent of N, varying only by K and P.

Now imagine that at the time a corporation acquires a new division (SBU), each SBU value chain agent responds to two inputs from fellow agents—represented as $K = 2$. Suppose further that the acquiring corporation imposes up to two additional inputs—represented as $K = 3$ or 4. And suppose as well that the adaptive tension imposed by the acquiring firm ranges from MBA terrorist type demands to the mildest of suggestions—represented as P. Given Prigogine's theory, consider the following question: *How many corporate interdependencies (cell inputs) governing the agents of an existing SBU value chain should the acquiring firm impose and how much forcing should they impose so as to assure the level of emergent structure likely to optimize SBU adaptation?* Below the 1st critical value little change results. Above the 2nd critical value chaos results. In the middle are the emergent dissipative structures at the edge of chaos. Three critical value scenarios are possible:

First, a preliminary response to this question rests on some analytic results produced by Stauffer (1987a), shown in Table 2. The left hand column shows P ranging from 0 to 0.5—since the probabilities are symmetric the results for P are the same as for $1 - P$. At $P = 0.5$ (no bias toward either 1 or 0 values) and $K = 2$ these results mirror Kauffman's simulation results—the incidence of forcing cells is at a high enough probability ($\pi = 0.8750$) that forcing results. A phase transition occurs at $K = 2$. The model generates a dominant component of cells percolating throughout the network showing short oscillating cycles around a repeating state (limit cycle) attractor with a few isolated frozen islands here and there in which cells oscillate through long, if not limitless, cycles. This is the *ordered* regime where cells in the dominant component oscillate around a quickly repeating limit cycle not unlike a negative feedback process in a goal directed control (machine bureaucracy) system. In terms of our acquiring firm this means that, absent inputs from the corporate level, most of the behavior in the SBU is retained at a steady-state by the governing routines and information inputs. Since forcing is independent of *N*, a model of SBU behavior would appear similar to the lattice shown in Figure 3a—there would be a minimal number of islands of emergent adaptive structure "oscillating" in attempts to improve adaptation, but most agents in the lattice would be frozen in an ordered regime continuing mostly unchanged.

> > > Insert Table 2 about here < < <

Second, suppose the MBA terrorists enter the SBU and create so much adaptive tension that chaos results. This is represented in Table 2 by $K = 4$ (the right hand column)—now four inputs to each agent or cell instead of two. One may can see right away that if P remains at 0.5, π quickly reduces well below the phase transition level (which is 0.59275 (Stauffer 1987a, p. 792)) at which a network becomes ordered. As a result the network consists of a dominant *chaotic* regime in which a small perturbation starting in a cell having lengthy, or limitless, cycles between repeating states percolates throughout the system, except for a few frozen stable (low limit cycle) islands. In this case it is oscillation that percolates. This is opposite to the stable percolation structure of the ordered regime in which cells oscillate around a quickly repeating limit cycle. This means that absent any "forcing" by corporate, three things happen that foster chaos: (1) A few SBU agents abandon the negative feedback process in favor of freewheeling change (oscillation) of a nonlinear positive feedback kind (that is, the limit cycle has lengthy or limitless repetition); (2) This tendency among a few agents percolates throughout the value chain to become the dominant chaotic component, though with a few isolated frozen islands showing ordered regimes; and (3) Each agent responds to the four inputs with an independent idiosyncratic possibly limitless change process (oscillation cycle) in his or her attempt to respond to the adaptive tension raised by the MBA terrorists—or to attempt revert to behavior existing before acquisition. The latter situation represents bifurcated chaos between two attractors—maintain the status quo or try to please the MBA terrorists. A model of SBU behavior would appear similar to the lattice in Figure 3b.[13]

[13] This model does not discriminate between deterministic chaos (bifurcation into two or a few attractors) and an even less structured totally random kind of complexity where no algorithmic compression is possible.

Finally, consider the "edge of chaos" region between the 1st and 2nd critical values. In the random Boolean network model the region between the two critical values is compressed down to a very narrow slice at the phase transition. Studies (Stauffer 1987a,b; Weisbuch 1991) show that for the $K = 3$ column the phase transition occurs at 0.278 (within Kauffman's (1974) limits of 0.26 ± 0.02). For the $K = 4$ column there is some disparity between the analytic method of Stauffer and the numerical method of Kauffman, depending on the kinds of automata rules used (see Hartman and Vichniac 1986). For consistency I will stay with Kauffman's computational number—0.26 ± 0.02—for the $K = 4$ column. The results are that the 1st and 2nd critical values are compressed nearly to the same point and that P has to be lowered to 0.26 ± 0.02 to reach the threshold. Thus, the complexity theorists' "edge of chaos" kind of complexity is what Kauffman calls a liquid region at the transition point. So, let's assume we are starting with $P = 0.5$ and the frozen dominant component is chaotic. Then, as P is lowered nearly to the 0.26 level, the frozen percolated *chaotic* component "melts" and the model creates numerous substructures of the more ordered kind—shorter limit cycle oscillations. Oppositely, if we started with an ordered regime (P near 0) and were to raise P toward 0.26, the frozen percolated *ordered* component would melt, creating numerous substructures of the more chaotic less ordered kind—longer limit cycles.

Ideally one would want to expand the melting zone of the model. Critical values in firms are likely fuzzy and, given that the most interesting "action" is in the melting zone, the larger the zone is the more one can develop the model to represent the nuances of emergent structuration in firms. Further, specific automata cells may be identified that more easily represent aspects of the corporate/SBU governance relationship. Thus, cell functions could be designed to represent **U**, **M**, and **H** form corporate/SBU governance relationships (Williamson, 1975). Or cells could be designed to represent other governance and communication interdependencies between corporate general office and SBU or among different parts and levels of a value chain. Following this line of reasoning it seems possible that a model from statistical physics, via biology, could be developed to study the liquid region of adaptive tension where critical complexity emerges and with it emergent structures. Though I am not aware of studies already doing this, it seems logical that one could also take a "fractal" approach with the model. Thus, one could bring the main model into the "melting" zone and then as substructures appear they also could be forced into their own melting zones. In this way the model would have a widened melting zone and could more subtly represent firms showing emergent dissipative structures.

5.3 MODELING COMPLEXITY CATASTROPHE

Kauffman (1993, p. 239) argues that his "*NK*[*C*] Boolean game" model behaves like Boolean networks, if agent outcomes are limited to 0 or 1, the *K* number of interdependencies is taken as the number of inputs, and Nash equilibria in *N* person games are equivalent to agents being trapped on local optima. 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. In the *NK*[*C*] 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* interdependencies that might serve to modify 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. Complexity catastrophe occurs as *K* is increased. An explanation of Kauffman's modeling approach is given in Westhoff, Yarbrough and Yarbrough and an illustration of their application to firms in McKelvey (1998a, in press).

> > Insert Tables 3 and 4 about here < < <

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 as *K* increases, 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 at low fitness peaks, thereby bringing on complexity catastrophe. In contrast, *C* acts as a destabilizing effect, as does *S*. *K* effects are averaged as per the static single agent *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 stabilization. And the more opponents there are, the more the instability persists.

In the *NK*[*C*] model, *K* acts as a force toward increased complexity and complexity catastrophe whereas *C* appears to act as a force away from catastrophe, that is, internal complexity leads to complexity catastrophe but external complexity leads away from catastrophe. The experiments in his Figure 6.3 (reproduced here as Figure 4a,b) show that increasing *C* prolongs instability (the fraction of coupled dances not reaching Nash equilibrium). This behavior of the model is significant since from Kauffman's theory and the quote above one 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 (1993, p. 248; not shown here) clearly shows this not to be true.

> > > Figure 4 about here < < <

Kauffman experiments with the *NK*[*C*] model using various combinations of parameters, as described in the "computational experiments" below. To help readers connect these models back to Kauffman's book, I label the models by their **F**igure or **T**able numbers in his book. Outcomes from some of the experiments are described briefly.

1. Can too many coevolutionary links among a firm's value chain competencies inhibit competitive advantage? The experiments[14] show that 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. But, as the probability of encountering Nash equilibria decreases, say because of an opponent's actions to raise its *K* or *C*, the better it is to have a high *K*. But if the opponent does not raise *C*, and therefore Nash equilibria occur quickly, the high *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 the search for Nash equilibria is prolonged; that is, on whether an opponent will raise *C*.

Proposition 1: In general keeping one's internal coevolutionary interdependencies just below those of an opponent's is the best strategy.

2. Can too many coevolutionary chain links between a firm and an opponent inhibit its competitive advantage? The simulations[15] show that firms having dense external coevolutionary ties with opponents (that is, high *C*s prevail), benefit from a higher upper bound on their *K* before catastrophe sets in. However, during the preNash oscillation period, rapid moves by a firm are

[14] Experiments F6.3 & F6.4 (Kauffman 1993, p. 247–249). Set $N = 24$; $C = 1, 8, 20$; $K = 2, 4, 8, 12, 16$. Allow only one random change per time period at only one (randomly selected) of the *N* sites (competencies); each agent chooses a new one-change neighbor if it contributes to an improved overall chain fitness. The experiments draw 100 to 200 pairs over 250+ time periods.

[15] Also based on experiments F6.3 and F6.4.

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*.

Proposition 2a: That is, absent any more pointedly aggressive strategy toward a specific opponent, a firm should attempt to equalize internal and external coevolutionary interdependencies.

Proposition 2b: 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.

Why? High *C*s allow higher *K*s—true—but lower *K*s tune the landscape toward higher fitness peaks. This produces the inverted U relation between performance and complexity.

3. Should strategists worry about possible complexity catastrophes? 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? The experiments[16] show that lower levels of *K* create moderately rugged landscapes composed of a few high and somewhat 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:

Proposition 3: "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."

In this section I have shown how the second principle of complexity theory applied to firms may be appropriately modeled using Kauffman's *NK*[*C*] model. I have emphasized the effects of *C* in raising the upper bound allowed for increasing *K* before complexity catastrophe sets in.[17] Raising C has the effect of moderating the slopes of the inverted U "hill" when performance is plotted against adaptive tension and complexity.

CONCLUSION

Two aspects of complexity theory are emphasized: **First**, I identify four propositions from Prigogine's (Nicolis and Prigogine 1989) *self-organization theory* that relate the chaos theorists' critical values to different kinds of complexity. The region between the 1st and 2nd critical values is identified as the complexity field "at the edge of chaos" in which emergent structures will occur. These structures are analogous to the bulk air currents that most effectively reduce the tension between a hot earth and a cold upper atmosphere. From this analogy, I argue that there is a region between the critical values of adaptive tension corporations may impose on acquired SBUs in which SBU adaptation and performance in a rapidly changing competitive context may be maximized as a result of emerging structures (the equivalent of bulk air currents). This complexity theory application emphasizes adaptive tension, governance, and emergent self-organized structure in SBUs. It argues that too much or too little adaptive tension diminishes the likelihood of effective adaptation.

Second, using the notebook computer industry, I translate Kauffman's (1993) *complexity catastrophe theory* to firms. This theory argues that the BVSR process may be thwarted if a firm tries to coevolve on too many interdependent value chain elements or technologies. In this theory *K*, the number of interdependencies "tunes" a firm's adaptive landscape such that too low or too high a *K* depresses adaptive effectiveness. Complexity catastrophe occurs when, even though the BVSR process is functioning effectively, the value chain elements favorably selected are not really any more effective than those not selected.

Both theories are then computationally modeled in an illustrative fashion. As far back as 1969 Kauffman (1969, 1974, 1993) began using random Boolean network models to explore the dynamics of emergent structure. His early studies have subsequently been pursued by Gelfand and Walker (1984), Derrida (1987) and a number of colleagues in statistical physics, particularly Stauffer (1987a,b) and Weisbuch (1991). Using as an example the various levels of adaptive tension that could be imposed by an acquiring firm in governing a new SBU acquisition, I demonstrate how the parameters of the random Boolean network model fit the organizational world. While at a primitive state of application, these models show how one could use them to develop the complexity theory of emergent structure in firms, depending on the critical values of adaptive tension. Using the example of coevolutionary adaptation in the notebook computer industry, I then use Kauffman's (1993) *NK*[*C*] model to show how one might explore the dynamics of complexity effects on the adaptive BVSR capabilities of firms. These effects may be modeled in terms of intrafirm complexity as well as interfirm complexity. Taken together these theory–model links suggest that firms adapt best under conditions of moderate adaptive tension and value chain complexity.

Of course, much remains to be accomplished. Not since the early exploration by Gelfand and Walker (1984) has anyone tried to apply random Boolean networks to the study of organizational adaptation, so my use of this approach is surely primitive. Kauffman's *NK* model is seeing some application to firms on adaptive landscapes (Levinthal 1997a,b, Levinthal and Warglien 1997, Rivkin 1997, Sorenson 1997). Baum (this volume) applies the

[16] Experiments T2.1-T2.2 (Kauffman 1993, pp. 55, 56). Set N = 8, 16, 24, 48, 96; K = 0 to 95. Starting from a randomly selected firm, allow only one random change per time period at only one (randomly selected) of the N sites; each firm chooses a one-change neighbor if one of its sites is an improvement. Walks occur on 100 randomly selected landscapes with average fitness levels reported.

[17] Additional experimental results from Kauffman's *NK*[*C*] model that are relevant to strategy in coevolutionary pockets appear in McKelvey (in press).

NK[*C*] model at the group level within firms. McKelvey (1998a, in press) also applies the *NK*[*C*] at the agent level within firms The use of the random Boolean network model is novel in my application here and undoubtedly needs further development to more readily fit complexity theory applications to firms.

Most articles in present day organization science do not begin or end with a formal model. Perhaps not all of them should, but in top drawer sciences like physics, biology, and economics *many* published reports of scientific activity are centered around formal models. As developed elsewhere (McKelvey this volume) *Campbellian Realism* is very clear in the model-centeredness of its view of current epistemology. There is no doubt that current philosophy of science strongly supports Campbellian realism from three epistemological perspectives: (1) *scientific realism* (Bhaskar 1975/1997, Boyd 1991, de Regt 1994, Aronson, Harré, and Way 1994); (2) the *semantic conception* (Beth 1961, Suppes 1962, van Fraassen 1970, Suppe 1977, 1989), and *evolutionary epistemology* (Popper 1963, Campbell 1974b, 1990, Churchland and Hooker 1985, Rescher 1990). In the language of scientific and Campbellian realism, effective science requires tests of *experimental adequacy*. I have taken space to present the two illustrative modeling approaches to demonstrate my concern that organization science in general, and complexity applications in particular, be shifted in the direction of model-centered science.

Because of the tractability requirements of formal models, whether mathematical or computational, advanced sciences move forward in terms of theories far more parsimonious than the norm in organization science. Model-centeredness automatically drives parsimony—often more than validity concerns appear to justify. Be this as it may, parsimony characterizes sciences having far more external status, influence, and funding than organization science. Pfeffer was right on target 16 years ago in calling for “simpler models” (1981, p. 411). Given the dictates of models and Pfeffer’s good judgment, this chapter reduces Scott’s (1998) “rational, natural, and open systems” framework to four fundamental forces: *adaptive tension*, *self-organization* (both managerial and nonmanagerial), *interdependency effects*, and *multilevel coevolution*.

My approach has several important limitations. That complexity theory, via Prigogine’s self-organization and Kauffman’s catastrophe propositions, applies to firms is surely preliminary. Given the variety of agent-based models available, *spin-glass* (Mézard, Parisi, and Virasoro, 1987; Fischer and Hertz, 1993), *simulated annealing* (Arts and Korst, 1989), *cellular automata* (Toffoli and Margolus 1987, Weisbuch, 1991), *neural network* (Wasserman, 1989, 1993; Müller and Reinhardt, 1990; Freeman and Skapura, 1993), *genetic algorithm* (Goldberg, 1989; Holland, 1975, 1995; Mitchell, 1996), and most recently, *population games* (Blume, 1995), there is little reason to rush into acceptance of Kauffman’s Boolean statistical mechanics, Boolean network, and *NK*[*C*] models. Further, the four fundamental forces I emphasize may not offer the best framing for 21st century organization science. And of course, the approach described here may never pass any kind of reasonable *ontological adequacy* test, the other primary requirement of Campbellian realism.

I started with the question, Do adaptive tension, self-organization, interdependency, and coevolution contribute in any way toward explaining why dinosauric firms like General Motors languish in a state of seeming permanent failure (Meyer and Zucker 1989)? We can come up with a long list of reasons, from unions to myopic management. For a specific firm any and all of these reasons could be true. This is similar to why a plant on the side of Pikes Peak might die—no water, blown away, washed away, eaten, buried by a landslide, poisoned, hit by lightning, and so on. But to form an organization science around case studies of why a GM lives or dies is like a botanist trying to draw scientific generalizations from a study of the Pikes Peak plant. It doesn’t work! According to Campbellian realism, what does work is nomic necessity and model-centeredness accompanied by effective tests of experimental and ontological adequacy. And there is Pfeffer’s (1981, 1997) continued request for parsimony. With these views in mind, I zero in on just a few underlying forces, suggest a theory based on laws of the counterfactual conditional kind, and illustrate how a couple of computational models might allow experimental adequacy tests. Needless to say, the coevolution of the theory–model link is in its infancy.

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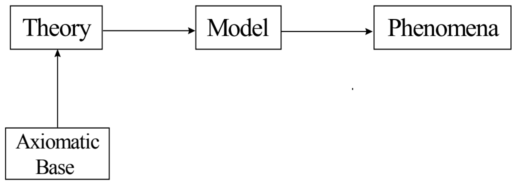
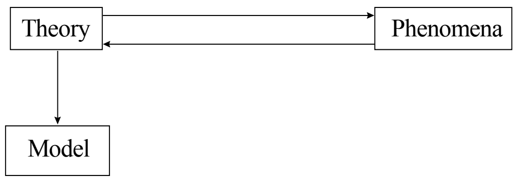
Figure 1 Conceptions of the Axiom–Theory–Model–Phenomena Relationship

1*a* *Axiomatic Conception*



1*b* *Organization Science Conception*



1*c* *Semantic Conception*

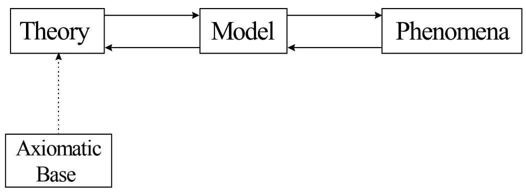
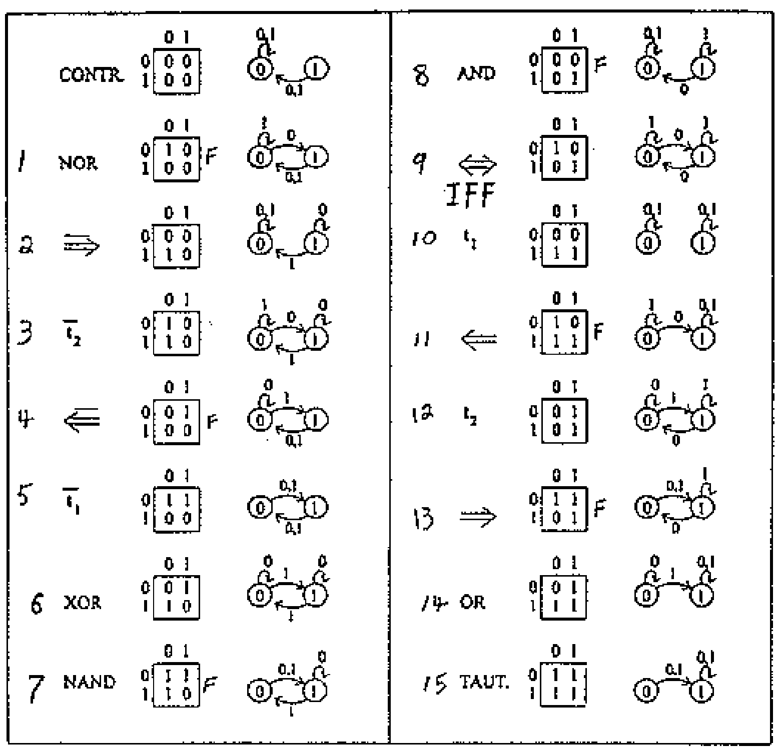


Figure 2 Sixteen Boolean Functions for *K* = 2 inputs



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

Figure 3a. Weisbuch's Lattice Showing an Ordered Regime †

1	1	4	4	8	8	8	1	1	4	4	1	1	1	1	1
1	1	1	1	8	8	4	1	1	1	1	1	1	4	1	1
4	1	1	1	8	72	4	1	1	1	1	1	1	4	1	4
4	1	1	72	72	36	4	1	2	1	1	1	1	1	1	1
4	4	1	18	1	18	36	2	2	2	1	1	1	1	6	1
4	1	1	18	18	18	36	1	1	1	1	1	1	12	6	12
12	1	18	18	18	18	18	1	1	1	1	1	12	12	1	1
1	1	18	18	18	1	18	1	1	1	1	1	1	12	12	12
1	1	1	1	1	1	1	1	1	4	4	1	12	12	1	1
1	1	1	1	1	1	1	1	1	1	4	4	4	12	1	1
1	4	4	1	1	1	1	1	1	1	4	4	1	4	1	4
1	1	1	1	1	1	1	1	1	1	1	4	1	4	4	4
1	1	1	1	2	2	1	1	1	1	1	1	1	1	4	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	4	1
1	1	1	8	8	1	1	1	1	1	1	4	4	1	1	1
1	1	8	8	8	8	1	1	1	1	4	1	1	4	4	1

$K = 4$, $P < P_c$. Percolated ordered regime shown as 1's.

† Reproduced from Weisbuch 1991, Figure 10.9, p. 139.

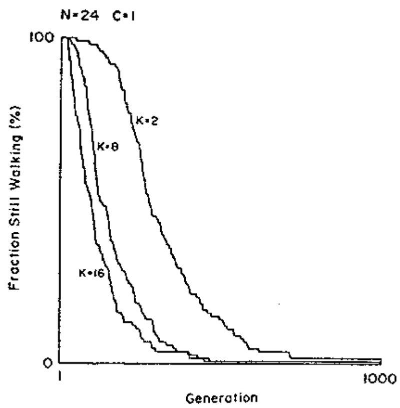
Figure 3b Weisbuch's Lattice Showing a Chaotic Regime †

```
  1+++++++++  1  1  1  1  1  1  1  1  1  6  6  1
  1++++++++++++++++++  1  1  1  1+++++++++++++++
++++++++++++++++++++++++  1  1  1  1+++++++++  1
++++++++++++++++++  1  1+++  1  1  1  1++++++  1
++++++++++++++++++  1+++++++++++++++  1+++++++++
+++++++++++++++  2  2  2  2+++  4+++  1+++++++++
++++++++++++  1  1  1  2  1  1++++++++++++++++++
+++++++++  1  1  1  1  1  1  1++++++++++++++++++
+++++++++  1  1  1  1  1  1+++++++++++++++++++++
+++++++++++++++  1  1  1++++++++++++++++++  1+++
++++++++++++  1  1  1  1++++++++++++++++++++++++
+++  1  1+++++++++++++++++++++++++++  1+++++++++
+++  1  1+++++++++++++++++++++++++++  1+++  1  1
  1  1  1+++++++++++++++++++++++++++ 12+++ 12  1
  1  1++++++++++++++++++++++++  1  1 12  6  6  1
  1  1++++++  1  1++++++  1  1  1  1  1  2  6  1
```

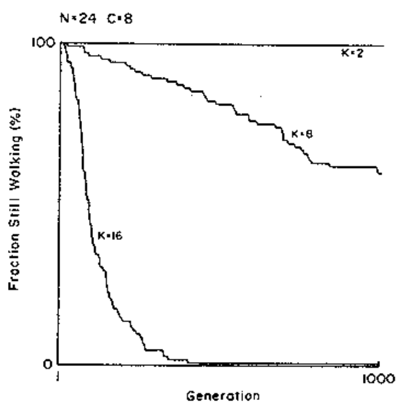
$K = 4$, $P > P_c$. Percolated chaotic regime shows as groups of three asterisks in which *** signifies cells with limit cycles too long to be measured.

† Reproduced from Weisbuch 1991, Figure 10.10, p. 139.

Figure 4 Size of *K* and *C* Related to Time to Reach Nash Equilibrium



4a When C = 1, K varying
(reproduced from Kauffman 1993, Fig. 6.3, p. 247)



4b When C = 8, K = varying
(reproduced from Kauffman 1993, Fig. 6.3, p. 247)

Table 1 Some Complexity Theory Definitions

1a—Definition of Kinds of Complexity by Cramer (1993)

'***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: 213) They are also 'reversible' (allowing retrodiction as well as prediction), thus making the 'arrow of time' irrelevant (Eddington, 1930; Prigogine and Stengers, 1984).

At the opposite extreme is Cramer's '***fundamental complexity***' where the description of a system is as complex as the system itself—the minimum number of information bits necessary to describe the states is equal to the complexity of the system. 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, and stochastic systems are random, though varying in their stochasticity.

In between Cramer puts '***critical complexity***'. The defining aspect of this category is the possibility of emergent simple deterministic structures fitting subcritical complexity criteria, even though the underlying phenomena remain in the fundamentally complex category. It is here that natural forces ease the investigator's problem by offering intervening objects as 'simplicity targets' the behavior of which lends itself to simple rule explanation. Cramer (1993: 215-217) has a long table categorizing all kinds of phenomena according to his scheme.

1b—Definitions of Attractors by Gleick (1987)

'***Point attractors***' act as equilibrium points around which forces cause the system to oscillate away from these points, but eventually the system returns to equilibrium—traditional control style management decision structures may act in this manner (appearing as subcritical complexity);

'***Periodic attractors***' or '*limit cycles*' (pendulum behavior) foster oscillation predictably from one extreme to another—recurrent shifts in the centralization and decentralization of decision making, or functional specialization vs. cross-functional integration fit here (also appearing as subcritical complexity);

If adaptive tension is raised beyond some critical value, systems may be subject to '***strange attractors***' in that, if plotted, they show never intersecting, stable, low-dimensional, nonperiodic spirals and loops, that are not attracted by some central equilibrium point, but nevertheless appear constrained not to breach the confines of what might appear as an imaginary bottle. If they intersected the system would be in equilibrium (Gleick, 1987: p. 140), following a point attractor. The attractor is 'strange' because it "looks" like the system is oscillating around a central equilibrium point, but it isn't. Instead, as an energy importing and dissipating structure, it is responding with unpredictable self-organized structure to tensions created by imposed external conditions, such as tension between different heat gradients in the atmosphere caught between a cold ocean and a hot sun, or constraints in a fluid flow at the junction of two pipes, or tension created by newly created dissipative structures, such as eddies in a turbulent fluid flow in a canyon below a waterfall, or "MBA terrorist" structural changes imposed in an attempt to make-over an acquired firm.

As a metaphor, think of a point attractor as a rabbit on an elastic tether—the rabbit moves in all directions but as it tires it is drawn toward the middle where it lies down to rest. Think of a strange attractor as a rabbit in a pen with a dog on the outside—the rabbit keeps running to the side of the pen opposite from the dog but as it tires it comes to rest in the middle of the pen. The rabbit ends up in the "middle" in either case. With the tether the cause is the *pull* of the elastic. In the pen the cause is *repulsion* from the dog attacking from all sides.

Table 2. Stauffer's Table Showing the Probability π given p and K †

p	K = 2	K = 3	K = 4
0	1	1	1
0.05	0.995	0.9892	0.9718
0.10	0.9838	0.9554	0.8770
0.15	0.9675	0.8997	0.7313
0.20	0.9488	0.8268	0.5655
0.25	0.9297	0.7440	0.4072
0.30	0.9118	0.6599	0.2739
0.35	0.8965	0.5832	0.1730
0.40	0.8848	0.5219	0.1048
0.45	0.8775	0.4824	0.0661
0.5	0.8750	0.46875	0.0536

† Reproduced from Stuaffer (1987a) p.792.

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 *in turn*, 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 <u>*internal*</u> *coevolutionary density* 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 *epistatic links* (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 <u>*external*</u> *coevolutionary density* among parts between a pair of competing firms. The *other* member of a coevolving pair (gene or species) has a number of proteins or traits, *C*, which are *interdependent* 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.
$\boldsymbol{W}, \boldsymbol{w_i}$	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 *microstates* seen in a neighboring agent, there are A^N "one-change neighbor" *microagents*, 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 *next* to $(\boldsymbol{A}-1)\times(\boldsymbol{N}-1)$ 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.