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Subscriber Information: *Emergence* is published four times a year by Lawrence Erlbaum Associates, Inc., 10 Industrial Avenue, Mahwah, NJ 07430-2262. Subscriptions are available only on a calendar-year basis.

Printed: Journal subscription rates are US \$45 for individuals, US \$160 for institutions, and US \$20 for students within the United States and Canada; US \$75 for individuals, US \$190 for institutions, and US \$40 for students outside the United States and Canada. Order printed subscriptions through the Journal Subscription Department, Lawrence Erlbaum Associates, Inc., 10 Industrial Avenue, Mahwah, NJ 07430-2262.

Electronic: Full price print subscribers to Volume 2, 2000 are entitled to receive the electronic version free of charge. Electronic only subscriptions are available at a reduced subscription price. Please visit the LEA Web site at <http://www.erlbaum.com> for complete information.

Send information requests and address changes to the Journal Subscription Department. Address changes should include the mailing label or a facsimile. Claims for missing issues cannot be honored beyond 4 months after mailing date. Duplicate copies cannot be sent to replace issues not delivered due to failure to notify publisher of change of address.

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Emergence

*A Journal of Complexity Issues in
Organizations and Management*

a publication of The Institute for the Study of
Coherence and Emergence

Volume #2, Issue #1, 2000

<i>Editor's Note</i>	3
Emergence: A Construct Amid a Thicket of Conceptual Snares <i>Jeffrey Goldstein</i>	5
What Can We Learn From a Theory of Complexity? <i>Paul Cilliers</i>	23
Corporate DNA: Organizational Learning, Corporate Co-Evolution <i>Ken Baskin</i>	34
Moving Beyond Metaphor <i>Ted Fuller and Paul Moran</i>	50
Complex Rhetoric and Simple Games <i>Jeffrey Goldberg and Livia Markóczy</i>	72
Dynamic Strategies: Emergent Journeys <i>Janice A. Black and Gerard Farias</i>	101
Is There a Complexity Beyond the Reach of Strategy? <i>Max Boisot</i>	114

Editor's Note ||

The year 2000 promises to be an invigorating one for those interested in the conjunction of scientific thought and management practice. Complexity as a buzzword has perhaps become too popular. It is used in advertisements and even on the side of a New York City bus. That popularity is one of the greatest risks to the serious development of the field.

In the face of such populist rhetoric, the year has or will see the publication of several of the most promising books on complexity and management. Perhaps the best book I have ever read on complexity (out of more than 100) is Alicia Juarrero's *Dynamics in Action: Intentional Behavior as a Complex System* (MIT Press). While not explicitly dealing with management or organizations, Juarrero writes with great clarity on the thinking and actions underlying the very prospect of managing or organizing. As a companion piece, I recommend Robert Axelrod and Michael D. Cohen's *Harnessing Complexity* (Free Press). Together, these books provide a solid foundation on which both academic research can be built and managerial practice improved.

In that spirit, this issue of *Emergence* aims for the heart of what the topic of this journal is all about. Jeff Goldstein opens by writing of emergence itself, followed by Paul Cilliers on complexity and Ken Baskin on management: Our title recaptured in three articles but for the notion of issues. Ted Fuller, Paul Moran, Jeffrey Goldberg and Livia Markóczy fill that gap by focusing on metaphor and rhetoric—issues at the core of many a debate about what the role of complex systems thinking can be in a managerial and organizational context. The last decade has seen shrill debate among those who believe in complexity as metaphor and those who believe in complexity as structural model. Fuller and Moran approach the question from the pragmatic side. Goldberg and Markóczy approach it from the theoretical side. But all of these authors reach nearly

the same conclusion: there is much that can be learned by thinking about organizations as embodiments of the models used in complex systems theory, but we must recognize the limitations of the models and of the words we use.

It is one thing to use metaphor to inspire thinking, it is another to attempt literal application of strategies that apply in a model world. Finally, Black, Farias and Boisot attempt to provide foundations to link complexity, strategy, and the “real” world faced by managers on a daily basis.

The high peak of research, which Juarrero, Axelrod, and Cohen have created, needs to be filled out if it is to be used as a landing strip for much of the lofty rhetoric the media has used surrounding complexity and management. The remaining issues of *Emergence* for the year aim to provide a significant portion of that landfill. Look for articles regarding the application of complexity thinking, the development of new approaches to marketing and the provision of services, and in-depth examinations of just what can be learned from complexity modeling.

To our old readers, thanks for being part of the family. To our new readers, welcome. *Emergence* is in its second year, our chosen field in its second decade, and the challenges of both await us as the year unfolds.

Michael Lissack
Editor

Emergence: A Construct Amid a Thicket of Conceptual Snares

Jeffrey Goldstein

We see that the intellect, so skillful in dealing with the inert, is awkward the moment it touches the living.

Henri Bergson (1983:165)

The concept of emergence is playing an increasingly critical role in the quickly expanding field of complexity theory. In a previous article in the inaugural issue of this journal (Goldstein, 1999), I discussed the history and development of the construct of emergence from its origin in the movement called Emergent Evolutionism (see Alexander, 1966; Broad, 1925; Morgan, 1923; and Wheeler, 1926) through its current employment in complexity theory. Although emergence may be an intriguing, even revolutionary, notion, the more one tries to get a clear grasp on the concept, the more it can prove to be elusive and murky. The controversy surrounding the concept did not end with Emergent Evolutionism, but continues to ignite debates concerning the implications of emergence for causality, determinism, predictability, the ontological status of emergent phenomena, and so on.

It appears that emergence is not a concept that comes alone but, rather, tends to carry considerable metaphysical freight. This can be seen in remarks from two leading complexity scientists. First, chaos physicist Doyne Farmer (quoted in Waldrop, 1992: 297) places emergence in a grand evolutionary scheme:

EMERGENCE

The key is that there would be a sequence of evolutionary events structuring the matter in the universe in the Spencerian sense, in which each emergence sets the stage and makes it easier for the emergence of the next level.

Second, in similar vein, complexity researcher Stuart Kauffman (Kauffman, 1995: 23) declares:

A theory of emergence would account for the creation of the stunning order out our window as a natural express of some underlying laws. It would tell us if we are at home in the universe, expected in it, rather than present despite overwhelming odds.

Emergence may indeed go on to reveal matters of cosmic significance, yet this same proclivity for speculation can also set up sundry conceptual snares for the unwary in their appeal to emergence for either descriptive or explanatory purposes. In this article I want to discuss these snares in relation to eight broad issues encountered on the route to adopting the idea of emergence:

- ◆ causality
- ◆ spontaneity
- ◆ predictability
- ◆ ontology
- ◆ prevalence
- ◆ levels
- ◆ coherence
- ◆ outcome.

CAUSALITY

DOES EMERGENCE VIOLATE CAUSALITY?

The study of complexity is challenging many established assumptions about the dynamics of systems, including the role of causal explanations in complex systems. Some complexity theorists have gone so far as to propose that complex systems may violate the linkage of cause and effect. For example, Ralph Stacey (1996: 187), a pioneer in applying complexity theory to strategic planning and organizational creativity, has charged:

Causal links between specific actions and specific organisational outcomes over the long term disappear in the complexity of the interaction

between people in an organisation, and between them and people in other organisations that constitute the environment.

Stacey, no doubt, is not averring that complex systems are acausal. So, what exactly is he getting at?

There are indeed features of emergence that do seem to make it a good candidate for causality violation, since emergent patterns, structures, and properties are characterized by a radical novelty in comparison to the properties and patterns of the components out of which emergence arises (for more on the role of causality in emergent systems, see Goldstein, 1996). According to chaos/complexity physicist James Crutchfield (1994:1), emergent structure is:

not directly described by the defining constraints and instantaneous forces that control a system ... not directly specified by the equations of motion ... [and] cannot be explicitly represented in the initial and boundary conditions.

Consequently, the radical novelty of emergent phenomena can appear quite enigmatic.

These recent notions of the implications of emergence for causality were foreshadowed in the philosophical discussions accompanying Emergent Evolutionism, which recognized the novelty of emergents as challenging inherited ideas of causality. For instance, animal behaviorist C. Lloyd Morgan (1923) believed that emergent novelty necessitated a distinction between causality and causation: “causality” would refer to the causal nexus of natural processes; whereas “causation” would allude to a breach in natural processes afforded by emergent novelty—which, in turn, would allow a place for the inclusion of divinity in the natural world. For sure, Morgan’s distinction is not particularly enlightening, but this cannot be blamed solely on his theological preoccupations, since they are not all that dissimilar from current-day speculations on the cosmic, evolutionary significance of emergence, as seen in our quotes in the introduction. However murky Morgan’s distinction appears, it does point to how emergence pushes us up against traditional notions of causality.

To understand more about the impact of the radical novelty of emergents on the causal nexus of a complex system, it can be helpful to take a look at the phenomenon of chaos, another system dynamic that has been challenging conventional understanding of causality. Philosopher David Newman (1996) has made a case for understanding strange attractors in

chaotic systems as instantiations of emergence. Specifically, Newman claims that being in the basin of a strange attractor is an emergent property of a nonlinear dynamical system, since it is a property neither deducible from, predictable from, nor reducible to antecedent conditions or factors. Thus chaos, like emergence, challenges conventional notions of causal connection.

It is crucial to note that chaos is technically termed “deterministic chaos” because, although the outcome is aperiodic and random-like, it can be produced, i.e., “determined,” by simple rules. (Here I am leaving out “stochastic chaos,” which results not only from deterministic rules but from the admixture of stochastic events in the resulting chaos.) Mathematician Ralph Abraham, a mentor of many of today’s leading chaos and complexity scientists, made a very telling observation about chaos that is also pertinent to the causal nexus of emergence:

An attractor functions as a symbol when it is viewed through an output projection map [map of a system by concentration of some variable into a finite dimension state space] by a *slow observer*. If the dynamic along the attractor is too fast to be recorded by the slow-reading observer, he may then recognize the attractor only by its averaged attributes, fractal dimension, power spectrum, and so on, but fail to recognize the trajectory along the attractor as a deterministic system. (Abraham, 1987: 606; his emphasis)

The failure to discern determinism in such a system is thus not because it is indeterminate, but instead is due to limitations of observers, i.e., their “slowness” compared to the much more rapid unfolding of the system’s dynamics. The observer is in an epistemologically deficient position and cannot trace backward from the chaotic attractor the exact sequence of iterations that led to it. But this does not then mean that chaos violates determinism—what it shows, instead, is our incapacity to perceive this determinism. Something like this must be what Stacey means by his remarks that causal links disappear in the complexity of interactions.

Chaos as emergence doesn’t violate causality *per se*. Instead, as a macro or global phenomenon, what is violated is our ability to trace all the micro determinates responsible for it. However, in an important sense, this is really just another way of saying that emergence *is* a global or macro phenomenon. One there needs to understand not only how it is determined by micro events (namely, the interaction of components), but the terms and constructs that are pertinent to the macro level.

Instead of causality, what emergence does indeed tax is the medieval

(and still persisting) presumption of *causa aequat effectum*, or, roughly, “causes and effects are equal.” This refers to the tendency to think that an effect cannot contain more than what was in the cause alone. Since the radical novelty of emergent phenomena in a complex system is not something contained in the components alone, it would seem that emergence does challenge the notion of an equivalence between effects and causes. The good news, though, is that it is precisely the inequality of cause and effect that makes emergent phenomena so interesting in the first place and worth their while for intensive study. Complexity science is finally opening up the “black box” of the radical novelty of emergence, and what is being found inside the box are constructs that themselves are on an emergent level (see Goldstein, 1997a). We shall go into greater detail about the significance of this new qualitative level below.

SPONTANEITY

IS EMERGENT ORDER FOR FREE?

Emergence in complex systems is envisioned to arise from *self-organization*, in contrast to the external or hierarchical imposition of new order on to a system. But another conceptual snare lies in wait here: an overemphasis on the spontaneity associated with the idea of self-organization can lead to a discounting of the conditions that are necessary for these spontaneous processes to occur.

One particularly influential source of this overaccentuation on spontaneity can be found in Stuart Kauffman’s (1995: 25) concept of *order for free*:

Most of the beautiful order seen in ontogeny is spontaneous, a natural expression of the stunning self-organization that abounds in very complex regulatory networks ... Order, vast and generative, arises naturally.

Kauffman’s way of conceptualizing “order for free” is at the basis of his cosmic meditations on emergence of which we saw examples above. “Order for free,” in fact, is not that different than the old idea of spontaneous generation or other candidates for spontaneous processes in nature (discussed more fully in Goldstein, forthcoming).

On a more prosaic level, the phrase “order for free” does seem to be a decent way of rendering how emergent patterns and structures arise out of the dynamics of the systems itself and, therefore, don’t derive from the intrusion of order represented, for example, in how a cookie cutter makes

a shape in dough. However, the phrase also has the unfortunate connotation that there is no cost involved in emergence, which can then lead to neglect of some of the very important determining conditions of emergence.

This kind of “order for free” perspective shows up in allegations on the part of organizational enthusiasts of self-organization that all that is required for self-organization and emergence is simply to interrupt the normal hierarchical command-and-control practices of management. Certainly, there are times when such a strategy can confer tremendous benefits on an organization, but there are other times when this can be a strategy for disaster, a subject to which we will return later. Moreover, this kind of *neo-laissez faire* attitude ignores the fact that one of the sources of the order found in emergent patterns is the containment field or boundaries within which self-organization takes place (see Goldstein, 1999). We can say that emergence is a “qualified” spontaneity, but this qualification points to various and sundry “costs” attached to the bringing about of emergence.

PREDICTABILITY

IS EMERGENCE UNPREDICTABLE?

Along with both of the claims that emergence violates causality and is totally spontaneous is the often-heard insistence that emergence is unpredictable. Indeed, the early emergentists placed unpredictability high on their list of attributes for emergence, along with nondeducibility from and irreducibility to antecedent conditions. Morgan (1923) thought that the same novelty that was supposed to undermine traditional views of causality was at heart unpredictable. As I mentioned in my earlier article (Goldstein, 1999), in complexity theory there is a similar refrain about how the properties, qualities, or patterns of global or macro dynamics are not able to be predicted from knowledge of the components or antecedent conditions alone.

Unpredictability, however, is not the last word on complex systems. First, what is unpredictable in emergent phenomena may not be their most interesting facets. For example, in the famous Benard convection cells studied so exhaustively by Ilya Prigogine and his followers (see Nicolis, 1989), the only thing really unpredictable about the stunning emergent patterns of the hexagonally shaped cells is the direction of their rotation—surely not the main feature of emergence in such systems. What is predictable, however, is that given the right container, and the right liquid, and the right process of heating, the remarkable Benard con-

vection cells will emerge, and their pattern will be quite similar to those observed in previous experiments. This can be seen in the Game of Life (see Poundstone, 1985), where the presence of two emergent patterns called t-tetraminos in close proximity to one another can be used to predict the later emergence of another pattern, the pentadecathelon. At first this relationship was not noticed, so the pentadecathelon was presumed to be an unpredictable emergent; but now that the correlation is established between the t-tetramino and the pentadecathelon, the latter is not nearly as unpredictable. Even in chaotic systems, which are touted as full-blown unpredictability, there is a great deal of predictability due to the attractors of the system that serve to delimit its possible states (Goldstein, 1997b). In the light of such advances in predicting phenomena in complex systems, more and more effort is likely to be put into taxonomies and typologies of emergents. Such classification schemes will be a great help in discovering patterns of sequences and thereby yield even greater predictability.

Moreover, as stated above, much of the order found in emergent phenomena derives from the order inherent in the containers of the self-organizing processes. Knowledge of the order of the containers, therefore, can help in predicting the type of order that will be found in the ensuing emergent processes (see Goldstein, 1999). This, then, adds another measure of predictability to emergence. Furthermore, there is no reason to think that the predictability of emergent patterns in organizations will prove any the less susceptible to increase as careful observation and scrutiny of these patterns deepen over time.

These constraints on the unpredictability of emergence are not meant to suggest that emergent phenomena will yield to total predictability. Instead, my point is that adopting a fatalistic attitude about the supposed total unpredictability of emergence is neither based in fact nor particularly useful in going ahead with studies of emergent phenomena.

ONTOLOGY

IS EMERGENCE MERELY PROVISIONAL?

If the more we learn about complex systems, the more predictable emergence becomes, does this imply that emergent phenomena are merely provisional, epistemological artifacts, lacking an ontological status? Critics of Emergent Evolutionism reached such a conclusion when the theory of quantum bonding came along in the 1930s and demonstrated that the emergent properties of compounds resulting from chemical reactions

were deducible from knowledge of the components alone (McLaughlin, 1992). As a result, these commentators argued that the entire construct should be relegated to the status of an epiphenomenon. Does this mean that, as new and more sufficient theories come along, a similar conclusion should be reached about emergent phenomena in complex systems?

It needs to be pointed out that the study of emergent phenomena in complex systems is of a decidedly different nature than the inquiry into the emergent properties of chemical compounds that the theory of quantum bonding provided. The high point of discoveries in complexity science concerns the emergent level itself, whereas the searching for micro-determinants as in quantum bonding is basically a side issue. The richness of emergent phenomena requires a set of functional laws congruent with their own level (this requirement was pointed out even in Emergent Evolutionism by, *inter alia*, Samuel Alexander; see Gillett, 1998).

A case in point is the very serviceable construct of an order parameter (Haken, 1981). This, an emergent-level construct, greatly simplifies our understanding of the behavior of the component level; Ockham's razor is at work here. Of course, the use of order parameters doesn't obviate the need for inquiry into the conditions resulting in emergence in complex systems. But discerning such conditions is not the same as tracing the micro events leading to emergence.

IS EMERGENCE MERELY SUBJECTIVE?

Another barrage against the ontological status of emergents concerns the role of subjectivity in the discernment of emergent patterns. Of course, the study of emergence is not unique in the involvement of the experimenter's perceptual perspective in observing the object of study. A particularly egregious case is that of certain interpretations of quantum mechanics, for example where an observer is supposed to affect the collapse of the wave function. The insular ontological status of what is being observed, then, becomes subject to doubt.

Complexity science also has its share in the issue of subjectivity versus ontological reality. In my previous article in this journal (Goldstein, 1999), I discussed Crutchfield's (1993) attempts to address the role of subjectivity via his conceptualization of emergence as an *intrinsic* capability for computational and, consequently, evolutionary adaptability of the system. Although subjectivity enters into the identification of emergent phenomena, there is nevertheless something inherent, i.e., ontological, about emergents in the computational capacity they confer on complex systems.

Although computational capacity may not be directly relevant to all instances of emergence in complex systems, e.g., emergence in organizations, the core of what Crutchfield is alluding to still seems to be pertinent in general. This has to do with how emergent patterns, structures, and properties add some kind of potency in the form of greater adaptability than such systems would otherwise contain. If emergence can indeed bequeath this potency, then, from a purely pragmatic perspective, emergent phenomena must have considerable ontological status. Certainly, as the sciences of complex systems advance, better theories will be developed explaining more about how emergent phenomena are constituted out of lower-level components and processes. Crutchfield's own "particle" theory of emergence is an example. Yet enough is being discovered about emergent levels with constructs commensurate with those levels, and micro explanations will not completely supplant their usefulness.

Moreover, one need not go as far as Crutchfield's response, since the issue of subjective bias in studying emergence is not substantially different than that in any other scientifically informed discipline. That is why psychological researchers, for example, spend so much time worrying about inter-rater reliability. Identifying emergent phenomena demands a similar conscientiousness and a similar community of practice. Starting with subjectivity doesn't entail us necessarily ending up there. Otherwise, we would all be condemned to a solipsistic existence. Hence, in my opinion, subjective bias does not ring the death knell for emergence any more than it does for other attempts to find patterns in our environments.

PREVALENCE

HOW UBIQUITOUS IS EMERGENCE?

Emergent Evolutionist C.L. Morgan (quoted in Tully, 1981: 35) once exclaimed, "it is beyond the wit of man to number the instances of emergence." The reference was to all living creatures as instantiations of emergence. This pleroma of emergents has grown even larger with the recent additions of neo-emergentists. Thus, in the study of cellular automata, there are parameter values in which emergence is abundantly prevalent. Of course, it is precisely because of the fascinating systems behavior at these values that so much of the study of complex systems takes place at them. But, we must remember that these values are set by experimenters. So why should we expect the same prevalence outside the laboratory?

Computer scientist and pioneer of complexity theory John Holland (1998) warns about confusing authentically emergent phenomena with instances of “serendipitous novelty” that ubiquitously surround us, for example the play of light on waves. For Holland, if emergence is to be a meaningful construct, it must be more rare than all the multifarious combinations of patterns that we perceive in our environment. Holland’s criterion to distinguish emergence from other such concatenations of patterns is one often heard in complexity circles: “Emergence ... occurs only when the activities of the parts do not simply sum to give activity of the whole” (1998: 14). In another article (Goldstein, 1999), I have described a certain arbitrariness incumbent in defining emergence as “more than the sum of the parts.”

What I want to call attention to here, in contrast to Holland, is how it may indeed be valid to refer to the play of light on waves as an authentic example of emergence, at least from the point of view of novelty, irreducibility, and so on. Emergence, after all, does include novelty, and it is serendipitous in the way that it takes advantage of the confluence of many factors, including random ones. So, operationally, it may be impossible to distinguish emergence from “serendipitous novelty.” However, I don’t think that this amounts to a significant issue, since the crux of the matter is not so much what counts or doesn’t count for emergence as how important the instance of emergence is to the agenda or intention on the part of observers of or participators in emergent phenomena. The play of light on waves may be unimportant for certain purposes or intentions of observers, but I can imagine where it could be quite important for others, such as for Claude Monet.

In terms of organizations, can it not be said that emergence is going on all over the place, since people are continually interacting? Working entirely alone is unquestionably rare. But interaction itself is not enough to lead to emergence. It must be interaction that ushers forth some novel pattern, structure, process, or pattern; moreover, a pattern that exhibits a type of coherence not found among the interactional agents alone. However, even such emergent patterns may be of negligible importance for organizational dynamics. An example might be several employees spontaneously meeting in a restaurant at lunchtime, sitting together, and as a result regularly meeting for Tuesday lunch. How important is such an emergent lunch pattern? It could be an authentically emergent pattern, but it is not immediately obvious how important it would be for organizational functioning (of course, it might prove to be extremely significant if these lunch meetings ended up generating creative ideas that were used back in the workplace).

It seems to me that for emergence to be a useful construct it must be neither rare nor everywhere. If it is too unusual it will have little to do with everyday organizational dynamics. If it is everywhere, then it loses any explanatory power. But once recognized, the more important issue is what it adds to or detracts from the organization.

LEVELS

THE CONFLATION OF LEVELS

Inherent in the very definition of emergence is the notion of a level distinction between the preliminary components (the micro level) and the emergent patterns (the macro level). Thus, the early emergentists conceived of evolution as a series of discontinuous emergences of new qualitative levels of reality (see Blitz, 1992). A paralleling level distinction is made by contemporary complexity theorists. For example, Chris Langton (Lewin, 1992), when referring to a graphic illustration of emergence, points upward to a global, emergent level “up here” and downward to a component, interaction level “down here.” And Bedau (1997) points to the level distinction when he characterizes emergent phenomena as being “autonomous” in respect to the underlying processes.

Some sort of hierarchical stratification seems a necessary component of any doctrine of emergence. In this vein, the dynamicist Diner (Diner, Fargue, and Lochak, 1986: 276) underscored that in the evolution of a dynamical system there is a required “explicit passage from one level to the other ... to disclose the appearance of these [emergent] properties.”

This level distinction can be overlooked by organizational theorists in their fervor about the role that attractors may play in organizational dynamics. Thus, we are hearing about the leaders’ visions as attractors or incentive and other reward systems as attractors. But attractors are a construct whose proper level is the emergent level, not the local interaction level, whereas leadership vision and corporate rewards are more appropriately understood as local, component-level phenomena.

Again, turning to dynamical systems theory can shed some light on what I am getting at concerning the emergent level of attractors. In the period-doubling route to chaos found in the logistic map (to calculate populations at discrete time intervals with a simple nonlinear difference equation), different attractors emerge as the control parameter increases (see Feigenbaum, 1983). When the dynamics become trapped at a fixed point attractor, the population gets stuck at a particular amount and does not change after that. If the parameter is raised, a period 2 attractor emerges,

and this sequence of period doublings occurs all the way to chaos.

At what level are these attractors? Imagine that you are a little being traveling along the parabola. You come to a fixed-point attractor and it is like a wall you can't get beyond. This wall seems to be of the same nature as the parabolic road you are on, so it seems like the attractor is on the same ontological level as the road. But that is only because you are a one-dimensional being. Actually, the attractor is a phenomenon that arises out of the dynamics of the system represented by the logistic equation. As such, attractors "deform" the possibility space of movement along the parabola from their higher-level vantage point: they come from above, so to speak, and constrain the behavior below. This, of course, doesn't make them miraculous—they arise out of the particular dynamics of these non-linear interactions when certain parameter values become critical, i.e., at bifurcation. But they are a higher-level emergent construct.

Similarly, organizational attractors need to be understood as phenomena on the global or emergent level. How this emergent level emerges from organizational dynamics nevertheless needs to be further clarified. The question, then, is what are the underlying dynamics of complex systems that serve to shape the specific emergent phenomena that occur in organizations, and not how lower-level activities function as attractors.

THE INTERACTION OF LEVELS

Although the level distinction between emergents and components needs to be kept in mind to utilize the insights of complexity theory more adequately in organizational research, an opposite snare also lurks: believing that there is some inseparable barrier between the level of the components and the level of emergent patterns. These levels are both distinct and interactive at the same time. As Diner (Diner, Fargue, and Lochak, 1986: 277) pointed out, researchers will not only try to see how the whole is generated by the parts, but also how the parts are generated by the whole: "The local properties get a real meaning only through their relation to the global properties." This is one of the aspects of emergence highlighted by Chris Langton: a bottom-up, top-down feedback going on among the levels. Similarly, Ralph Abraham (1987) has described self-organization in terms of the output of the system influencing the control parameters.

Here, we see what can be termed a *transgression of levels*. This transgression, however, is not a conflation but a maintenance of the level distinction while at the same time trespassing it. This makes the study of emergence in complex systems a much more messy affair, and in organi-

zational applications there will be a great deal of opportunity to get confused about what is happening on what level. But this kind of confusion can be taken as a good sign that one is getting close to the real essence of emergence.

COHERENCE

One of the defining characteristics of emergent phenomena in complex systems is a coordination, correlation, or coherence that is not present in the antecedent conditions of the components alone. An example of this coherence can be seen in the various emergent structures of the Game of Life that travel across the cells of the array, enduring through time. The property of coherence is one of the meanings of the typification of emergents as supposedly being “more than the sum of the parts.”

Applied to organizations, it is often supposed that the coherence of emergent phenomena is a good thing because of its facilitative role, say, in high-performance teams. Certainly, coherence can be an important asset in organizational dynamics, as borne out by numerous studies of team functioning. Very recently, Michael Lissack and Johann Roos (1999: 16) have pointed out the crucial role that coherence must play in effective leadership: “Finding coherence, enabling coherence, and communicating coherence are the critical tasks of leadership.”

A question arises in this context, however, as to whether the type of coherence manifested in emergence in complex system research is necessarily the kind of coherence from which organizations might benefit. This doubt becomes especially troublesome in the light of emergent coherence’s conceptualization by certain pioneers of complexity theory. A particularly strident example can be found in the Synergetics school founded by one of the trailblazers of complexity theory, German physicist Hermann Haken (1981). According to Haken, emergence—for example laser light—represents collective processes that reinforce themselves and eventually gain:

the upper hand over the other forms of motion and, in the technical jargon of synergetics, *enslave* them. These new processes of motion, also called modes, thus imprint a macrostructure on the system ... If several of these collective motions, which we also call order parameters, have the same rates of growth, they may in certain circumstances cooperate with each other and thus produce an entirely new structure ... a new order will occur. (1981: 236; my emphasis)

The obviously poor choice of word in “enslave” points to more than a semantic issue—is this the kind of picture of coherence that is needed in organizations? In fact, I think these connotations of overly rigid coherence also show up in the buzzword “consensus.” In my experience, what most people mean by consensus is premature conformity to some group norm—in which case we could honestly say that it “enslaves” them.

Of course, coherence need not denote such rigid conformity. For example, coherence in the sense of boundaries or containment does seem a good idea, at least some of the time, at least when containment doesn’t simply reinforce nonadaptive organizational “silos.” What is needed is a paradoxically sounding nonconsensus coherence. This points to how much more work is needed in organizational applications of complexity to begin even to recognize and adequately describe the kinds of organizational phenomena on which complexity theory can shed some light.

OUTCOME

HOW BENEFICIAL IS EMERGENCE?

Amid all the hoopla surrounding self-organization and emergence, it is often assumed that they are necessarily a good thing, that systems exhibiting them are significantly better off, or, at least, that something problematic in these systems is markedly ameliorated. To be sure, the tendency to emphasize the beneficial nature of emergence seems to be a taken-for-granted attitude in complexity science. This can be seen in complexity theorist Luc Steele’s (1993, 1994) distinction between first- and second-order emergence: first order is a property not explicitly programmed in; whereas second order is emergent behavior that confers additional functionality generating an “upward spiral of continuing evolution.” A similar bias toward the advantageous status of emergence can be seen in James Crutchfield’s point about intrinsic emergence being an additional computational capacity coming about from emergent patterns in a complex system.

However, this emphasis on the positive value of emergence derives mostly from the computational framework of much of complexity research. Within such a framework, the enhancement of computational capacity does seem to be a good thing and therefore the enthusiasm over it is warranted. What happens next, though, is that complexity theorists jump beyond the immediate computer simulations and speculate further about how such an increase in computational capacity would aid in the evolution of all complex systems. A similar bias for believing that self-

organization and emergence are nothing but advantageous for a complex system can also be seen in organizational applications. I myself have given into this enthusiasm for the salving effect of self-organizational processes for evoking organizational creativity and motivation (see for example Goldstein, 1994, 1997a).

Strong caveats nevertheless seem to be in order here. First, consider the case of the former Yugoslavia. The central hierarchical control mechanism was dismantled and, consequently, the society self-organized, and became fraught with emergent political structures. Unfortunately, a great deal of these emergent structures were formed around pre-existing fault lines of ethnic differentiation and hatred. Dismantling control mechanisms and thereby encouraging self-organization and emergence, therefore, doesn't necessarily mean that you're going to have a better state of affairs than existed before.

Self-organization and emergence are powerful forces that must be channeled appropriately. One of the challenges is how we can constructively create conditions so that they do indeed tend toward a better state of affairs. Here, there is a need for work on the "boundaries" that will contain anxiety and anarchic impulses (see Goldstein, 1994). These "boundaries" are akin to the earlier mentioned "containers" that shape the structure of emergent phenomena taking place within them. These boundaries can be psychological (e.g., a sense of safety), social (e.g., rules of interaction), cultural (e.g., rituals and stories), technological (e.g., computer networks), even physical (e.g., the actual physical attributes of the workplace). Working on the boundary dimension influences the turns that processes of emergence take. Experimenting with changing the boundaries, therefore, is a crucial step in learning how to guide emergence in constructive dimensions. Emergence can certainly be a very powerful advantage to a complex, human system, but much continuing ground work needs to be done to insure that it takes a constructive direction.

CONCLUSION

Charles Sanders Peirce (Taylor, in press) once wrote that in science and mathematics metaphysics leaks in at every joint. I have tried to point to where conceptual snares exhibiting a metaphysical tinge can leak in when it comes to using the construct of emergence. In the face of these snares, I am suggesting that those applying the idea of emergence tread cautiously and try to be aware of the assumptions underlying its application. Are these assumptions getting in the way of or aiding in the pragmatics of application?

Good physics doesn't ensure good metaphysics. And at least one of the first steps toward constructive metaphysics is to recognize where it exists in hidden form, then to surface it, and then to consider if the particular flavor of metaphysics is in congruence with the aims of the applier of emergence. Emergence is a charged concept and as such can obfuscate as much as enlighten. It would be unfortunate if carelessness in using the construct of emergence contaminated future directions before they were even taken.

NOTE

This article is an elaboration and expansion of a presentation at the *Complexity and Organization Conference*, Toronto, Ontario, April 4, 1998.

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What Can We Learn From a Theory of Complexity?

Paul Cilliers

The aim of this article is to investigate the implications of a general theory of complexity for social institutions and organizations, such as business corporations. Complexity theory has implications for the way we conceive of the structure of an organization, as well as for the way in which complex organizations should be managed. However, a preliminary warning is necessary: The lessons to be learned from the study of complexity are somewhat oblique. Any hope that a study of complex systems will uncover *the* way of running an organization is in vain. While we will not come up with a quick fix, the lessons are most certainly important.

The first half of the article will investigate what we can learn from a theory of complexity. Most of these insights are widely accepted, but it is useful to revisit them briefly. This general understanding of complex systems also provides the background to the second half of the article, in which I investigate what we *cannot* learn from complexity theory. The “negative” part of the article is at least as important as the “positive” part. There I will investigate the unavailability of an ethical dimension to all decisions made in a complex environment.

COMPLEXITY IN A NUTSHELL

I will not provide a detailed description of complexity here, but only summarize the general characteristics of complex systems as I see them.¹

- 1 Complex systems consist of a large number of elements that in themselves can be simple.
- 2 The elements interact dynamically by exchanging energy or information. These interactions are rich. Even if specific elements only interact with a few others, the effects of these interactions are propagated throughout the system. The interactions are nonlinear.
- 3 There are many direct and indirect feedback loops.
- 4 Complex systems are open systems—they exchange energy or information with their environment—and operate at conditions far from equilibrium.
- 5 Complex systems have memory, not located at a specific place, but distributed throughout the system. Any complex system thus has a history, and the history is of cardinal importance to the behavior of the system.
- 6 The behavior of the system is determined by the nature of the interactions, not by what is contained within the components. Since the interactions are rich, dynamic, fed back, and, above all, nonlinear, the behavior of the system as a whole cannot be predicted from an inspection of its components. The notion of “emergence” is used to describe this aspect. The presence of emergent properties does not provide an argument against causality, only against deterministic forms of prediction.
- 7 Complex systems are adaptive. They can (re)organize their internal structure without the intervention of an external agent.

Certain systems may display some of these characteristics more prominently than others. These characteristics are not offered as a *definition* of complexity, but rather as a general, low-level, qualitative *description*. If we accept this description (which from the literature on complexity theory appears to be reasonable), we can investigate the implications it would have for social or organizational systems.

COMPLEXITY AND ORGANIZATIONS

The notion of complexity has been applied to organizations in a number of different ways, and with varying degrees of rigor. I would like to emphasize two things. In the first place, the principles discussed here are of a very general nature. The contingent conditions at stake when investigating a specific case will be relevant, and may radically affect the importance of some of the implications. Despite this remark, I wish to

stress, secondly, that this does not mean that the acknowledgment of the complexity of a situation allows us to be vague, nor does it imply a chaotic state of affairs. Complexity theory has important implications for the general framework we use to understand complex organizations, but within that (new) framework we must still be clear, as well as decisive.

- 1 Since the nature of a complex organization is determined by the interaction between its members, relationships are fundamental. This does not mean that everybody must be nice to each other; on the contrary. For example, for self-organization to take place, some form of competition is a requirement (Cilliers, 1998: 94–5). The point is merely that things happen during interaction, not in isolation.
- 2 Complex organizations are open systems. This means that a great deal of energy and information flows through them, and that a stable state is not desirable. More importantly, it means that the boundaries of the organization are not clearly defined. Statements of “mission” and “vision” are often attempts to define the borders, and may work to the detriment of the organization if taken too literally. A vital organization interacts with the environment and other organizations. This may (or may not) lead to big changes in the way the organization understands itself. In short, no organization can be understood independently of its context.
- 3 Along with the context, the history of an organization co-determines its nature. Two similar-looking organizations with different histories are not the same. Such histories do not consist of the recounting of a number of specific, significant events. The history of an organization is contained in all the individual little interactions that take place all the time, distributed throughout the system.
- 4 Unpredictable and novel characteristics may emerge from an organization. These may or may not be desirable, but they are not by definition an indication of malfunctioning. For example, a totally unexpected loss of interest in a well-established product may emerge. Management may not understand what caused it, but it should not be surprising that such things are possible. Novel features can, on the other hand, be extremely beneficial. They should not be suppressed because they were not anticipated.
- 5 Because of the nonlinearity of the interactions, small causes can have large effects. The reverse is, of course, also true. The point is that the magnitude of the outcome is not only determined by the size of the cause, but also by the context and by the history of the system.² This

is another way of saying that we should be prepared for the unexpected. It also implies that we have to be very careful. Something we may think to be insignificant (a casual remark, a joke, a tone of voice) may change everything. Conversely, the grand five-year plan, the result of huge effort, may retrospectively turn out to be meaningless. This is not an argument against proper planning; we have to plan. The point is just that we cannot predict the outcome of a certain cause with absolute clarity.

- 6 We know that organizations can self-organize, but it appears that complex systems also organize themselves toward a *critical* state.³ This not only means that at any given point we can expect the system to respond to external events on all possible scales of magnitude, but also that the system will organize itself to be maximally sensitive to events that are critical to the system's survival. Think of language as a complex system. If there is a desperate need for new terms to describe important events, the system will organize itself to be critically sensitive to those terms specifically, and not necessarily to other novel terms. The "need" is determined by the context and the history of the system, not by a specific "decision" by some component of the system. Similarly, an organization will self-organize to be critically sensitive to specific issues in the environment that may affect its wellbeing. The implications of self-organized criticality for organizational systems seems to be a subject that demands further investigation.
- 7 Complex organizations cannot thrive when there is too much central control. This certainly does not imply that there should be *no* control, but rather that control should be distributed throughout the system. One should not go overboard with the notions of self-organization and distributed control. This can be an excuse not to accept the responsibility for decisions when firm decisions are demanded by the context. A good example here is the fact that managers are often keen to "distribute" the responsibility when there are unpopular decisions to be made—like retrenchments—but keen to centralize decisions when they are popular.
- 8 Complex organizations work best with shallow structures.⁴ This does not mean that they should have *no* structure. This point requires a little elaboration. Complexity and chaos—whether in the technical or the colloquial sense—have little to do with each other. A complex system is not chaotic, it has a rich structure. One would certainly not describe the brain or language, prime examples of complex systems, as "chaotic."⁵ I certainly would not put my trust in a chaotic organization.

A complex system does have structure, but not a strictly hierarchical structure; perhaps not even a shallow structure. Structure can be shallow, but still extremely hierarchical. Perhaps the best way to think of this would be to say that there should be structure on all scales, and much interaction between different structural components. This is another aspect of complex organizations that could be fleshed out with insights from self-organized criticality.

These few implications of complexity theory for organizations are important, and can dramatically affect our understanding of complex organizations. They can be spelled out in much more detail, but as I insisted above, this will have to be done in the context of specific organizations and their contingent conditions. In order to do that, we should also be clear about what we *cannot* learn from a theory of complexity.

WHAT WE CANNOT LEARN FROM A THEORY OF COMPLEXITY

I hope to show that the implications of this negative part of the article are at least as important as those following from the positive part. Acknowledgment of the limitations of our knowledge lies at the root of the whole western tradition of Socratic philosophical reflection, but I am sure that the mere *acknowledgment* of limitations is not enough. On the one hand, it suppresses the challenge to shift the boundaries of our knowledge. On the other hand, it stops short of investigating the ramifications of this limitation. I want to argue that one important consequence is that we are forced to take up an ethical position.

What are the limits of a theory of complexity? Looking at the positive aspects we discussed above, you will notice that none is specific. They are all heuristic, in the sense that they provide a general set of guidelines or constraints. Perhaps the best way of putting it is to say that a theory of complexity cannot help us to take in specific positions, to make accurate predictions. This conclusion follows inevitably from the basic characteristics discussed above.

In order to predict the behavior of a system accurately, we need a detailed understanding of that system, i.e., a model. Since the nature of a complex system is the result of the relationships distributed all over the system, such a model will have to reflect all these relationships. Since they are nonlinear, no set of interactions can be represented by a set smaller than the set itself—superposition does not hold. This is one way

of saying that complexity is not compressible. Moreover, we cannot accurately determine the boundaries of the system, because it is open. In order to model a system precisely, we therefore have to model each and every interaction in the system, each and every interaction with the environment—which is of course also complex—as well as each and every interaction in the history of the system. In short, we will have to model life, the universe and everything. There is no practical way of doing this.

Before I continue, two qualifications are required in order to prevent misunderstanding. The first is to re-emphasize that this is not the same as saying that complex systems are chaotic. Emergence is not a random or statistical phenomenon. Complex systems have structure, and, moreover, this structure is robust. Secondly, this does not imply that there is no point in developing formal models of complex systems. We can develop models on the basis of certain assumptions and limitations, just as with any scientific model.

Let me put the matter in slightly different terms. The prediction of complex behavior is only possible as a form of generalization. However, when we deal with a complex system, we can never escape the necessity of facing the *particular* nature of the system at any given moment. Since we do not know the boundaries of the system, we never know if we have taken enough into consideration. We have to make a selection of all the possible factors involved, but under nonlinear conditions we will never know if something that was left out because it appeared to be insignificant was indeed so.

What does this amount to in practice? It means that we have to make decisions without having a model or a method that can predict the *exact* outcome of those decisions. A theory of complexity cannot provide us with a method to predict the effects of our decisions, nor with a way to predict the future behavior of the system under consideration. Does this mean we should avoid decisions, hoping that they will make themselves? Most definitely not. We cannot avoid them. Without activity in the system, without the energy provided by engaging with the system, it would probably wither away into a state of equilibrium, another word for death. Not to make a decision is of course also a decision. What, then, are the nature of our decisions? Because we cannot base them on calculation only—calculation would eliminate the need for choice—we have to acknowledge that our decisions have an ethical nature.

ETHICS AND COMPLEXITY

I want to make clear how the notion of ethics is used here. I do not take it to mean being nice or being altruistic. It has nothing to do with middle-class values, nor can it be reduced to some interpretation of current social norms. I use the word in a rather lean sense: it refers to the inevitability of choices that cannot be backed up scientifically or objectively.

Why call it ethics? First, because the *nature* of the system or organization in question is determined by the collection of choices made in it. There are, of course, choices to be made on all scales: major ones, as well as all the seemingly insignificant small ones made all the time—and remember that the scale of the effect is not related to the scale of the cause. In a way, the history of the organization is nothing else but the collection of all these decisions. Secondly, since there is no final objective or calculable ground for our decisions, we cannot shift the responsibility for the decision on to something else—“Don’t blame me, the genetic algorithm said we should sell!” We *know* that all of our choices to some extent, even if only in a small way, incorporate a step in the dark. Therefore we cannot but be responsible for them. This may have a pessimistic ring to it, but that need not be the case. An awareness of the contingency and provisionality of things is far better than a false sense of security. Such an awareness is also an integral part of the notion “adaptive.”

Of course, this does ultimately translate into a value system, but this system is not a given, something that is governed by *a priori* notions of good and bad. The system of values is itself a matter of choice. Our decisions are guided by some notion of what we think the organization should be—and it is in this “should” that the ethical dimension is contained. If an organization decides “The bottom line is our first priority,” then that is the kind of organization it would be: nothing comes in the way of money. The central issue here is that a system of values is exactly that. Values are not natural things that we can read off the face of nature; we choose them. It is not written in the stars that the bottom line is vital to the survival of a company, it comes with accepting a certain understanding of what a company should be under, say, capitalist conditions. Of course, it is not only the nature of the organization that is determined by choices, but also our nature as individuals. We are also the result of our choices. Thieves are not thieves when they are caught out, or found guilty under some legal system. Thieves are thieves when they steal.

A further implication of this “ethical” position needs to be spelled out. “Ethics” is part of all the different levels of activities in an organization.

These ethical components, related to the values and preferences of the members of the organization, are often referred to as merely “politics,” something separate to the organization’s real operation and goals. The argument here is that the political aspects of the interactions in an organization are not something extraneous to the workings of that organization. It is not something that has to be dealt with in order to guarantee the proper working of the organization, it is integral to its proper working. The individual and collective values of members of the system cannot be separated from their functional roles. This point is probably instinctively accepted by most good managers. The fact of the matter is that this is the case, whether it is accepted by management as such or not.

To summarize the argument: The ethical position is not something imposed on an organization, something that is expected of it. It is an inevitable result of the inability of a theory of complexity to provide a complete description of all aspects of the system.⁶

MODELING AND CALCULATION

It may appear at this stage as if I am arguing against any kind of calculation, that I am dismissing the importance of modeling complex systems. Nothing is further from the truth. The important point I want to make is that calculation will never be *sufficient*. The last thing this could mean is that calculation is *unnecessary*. On the contrary, we have to do all the calculation we possibly can. That is the first part of our responsibility as scientists and managers. Calculation and modeling will provide us with a great deal of vital information. It will just not provide us with *all* the information. Perhaps I am wrong here: it may become possible for some sophisticated model to provide all the information about a specific system. The problem would remain, however, that this information has to be interpreted.

All the models we construct—whether they are formal, mathematical models, or qualitative, descriptive models—have to be limited. We cannot model life, the universe, and everything. There may not be any explicit ethical component contained within the model itself, but ethics (in the sense in which I use the term) has already played its part when the limits of the model were determined, when the selection was made of what would be included in the frame of the investigation. The results produced by the model can never be interpreted independently of that frame. This is no revelation, it is something every scientist knows, or at least should know. Unfortunately, less scrupulous people, often the pop-

ularizers of some scientific idea or technique, extend the field of applicability of that idea way beyond the framework that gives it sense and meaning.

My position could be interpreted as an argument that contains some mystical or metaphysical component, slipped in under the name “ethics.” In order to forestall such an interpretation, I will digress briefly. It is often useful to distinguish between the notions “complex” and “complicated.” A jumbo jet is complicated, a mayonnaise is complex (at least for the French). A complicated system is something we can model accurately (at least in principle). Following this line of thought, one may argue that the notion “complex” is merely a term we use for something we cannot yet model. I have much sympathy for this argument. If one maintains that there is nothing metaphysical about a complex system, and that the notion of causality has to be retained, then perhaps a complex system is ultimately nothing more than extremely complicated. It should therefore be possible to model complex systems in principle, even though it may not be practical.

Would the advent of adequate models of complex systems relieve us from our ethical responsibility? My contention is that it would not. Here is why: We cannot make simple models of complex systems. Their non-linear nature, or, in other words, their incompressibility, demands that the model of a system be as complex as the system itself. If it is in the nature of the system to behave, at least sometimes, in novel and unpredictable ways, the model must also do so. In any case, how would we be able to determine if the model were indeed an adequate model of the system if we were already in trouble when trying to decide what constitutes the system itself? It would be as difficult to interpret the model as to interpret the system itself.⁷ Good models of complex systems can be extremely useful; I just do not believe that they will allow us to escape the moment of interpretation and decision.

COMPLEXITY AND THE HUMANITIES

Whatever we take the notion of ethics to mean, our analysis of what we can and cannot learn from a theory of complexity has shown that a proper reflection on complex organizations will have to involve the humanities. Perhaps we can describe the humanities as those disciplines that realize that their subject matter cannot be studied only by formal means.

There are, of course, a number of disciplines that immediately come to mind: political science, sociology, psychology, and, of course,

philosophy. Allow me the opinion that philosophy, the mother of all the sciences—but in an instrumental- and outcomes-based world often seen as redundant—may yet prove to be one of our greatest resources. The need to reflect critically on the nature and the limits of our knowledge and understanding is indispensable to a study of complexity.

I do not, however, want to end with that cheer for the home team. I also want to stress the importance of the arts. Artists through the ages have attempted to find new ways of portraying and understanding the complexities of our world. Under certain conditions, a good novel may teach us more about human nature than mathematical models of the brain, or the theories of cognitive psychology. An engagement with the arts should not be a luxury in which we indulge after “work,” it should be intertwined with our work. Faced with the complexities of life, we all have to be artists in some sense of the word. It is to be hoped that this will not only help us to a better understanding of our organizations, it will also make us better human beings.

NOTES

This article is based on a paper delivered at *Managing the Complex*, the Third Annual Symposium of the New England Complex Systems Institute, held in Boston, March 1999.

- 1 This summary is based on an extended analysis of complex systems in Cilliers (1998).
- 2 In this regard I have to stress that the butterfly metaphor borrowed from deterministic chaos is very misleading. There is no way in which the statement “a butterfly flapping its wings in Borneo could ‘cause’ a hurricane in Florida” can have any sense. The notion of causality loses all its meaning. There are many better ways of talking about a hurricane in Florida, despite the fact that we cannot be sure about exactly what caused it. Causes can be investigated, even if at best retrospectively.
- 3 For an introduction to self-organized criticality, see Bak (1997). For a discussion of some implications, see Cilliers (1998: 96–8).
- 4 The notion of “structure” here refers to the relationships among the various components of the system. Some of these relationships can be fairly fixed and static, others fairly fluid.
- 5 I am not implying that there are no lessons to be learned from chaos theory, but that they are more limited than is often believed. The notion of the “edge of chaos” is often useful, but even here I think we are better served by using the idea of *critical* organization.
- 6 This argument can also be made from a strictly philosophical position, particularly from the perspective of deconstruction. Despite the resistance to Derrida’s poststructural insistence on undecidability, it is a strongly argued position that does not imply indecision or relativism. For a good philosophical introduction to this perspective, see Caputo (1997).
- 7 The problem of interpretation is one of the central issues in the history of philosophy, so much so that it has its own name: hermeneutics.

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Corporate DNA: Organizational Learning, Corporate Co-Evolution

Ken Baskin

Over the last 30 years, the Law of Life—learn and adapt or die—has become the Law of Markets. When Digital Equipment Corp. didn't adapt to the personal computer because its CEO, Ken Olsen, couldn't learn that this was the future, the company began to die. When General Motors couldn't learn about either customers' changing tastes or how to create a more cooperative style with its unions, the company's market share began falling from nearly 50 percent of American cars to just above 30 percent. As long as Xerox was unable to learn how the Japanese could sell copying machines for less than it took Xerox to make them, the company continued in a downward spiral. Having learned that management technology—quality improvement—the company bounced back. Because this Law of Markets has become unmistakable, it's no surprise that the idea of the learning organization, which Peter Senge introduced less than a decade ago in *The Fifth Discipline* (1990), has become so popular. Today, Amazon.com lists more than 100 titles under “the learning organization,” and the idea has been reincarnated in the trendy new management technology, knowledge management.

What is surprising is that no one has gone back to the Law of Life for guidelines on how to design organizations that learn. Life has been able to learn and adapt to shifts in the environment for 3.5 billion years. Those shifts have been as extreme as the transformation of the atmosphere from

a methane to an oxygen base and five major extinctions, where at least half of all species disappeared. What, then, can managers learn about designing organizations that take advantage of life's record?

The best way to answer that question is to explore a series of other questions about the purpose and processes by which organizations learn:

- ◆ What does this organic way of thinking suggest about the term “organizational learning”? What is learning's purpose in nature? Is it similar in organizations?
- ◆ What does organic organizational learning look like, compared with the learning that occurs in more traditional, more mechanical organizations?
- ◆ To what extent does the choice of a mechanical or organic model determine an organization's style of learning?
- ◆ What examples do we have of corporations already built on this model?

AN ORGANIC DEFINITION OF ORGANIZATIONAL LEARNING

In order to define organizational learning organically, it is important to state three assumptions that indicate why such learning is important and why it's becoming more so:

- ◆ First, *time is how we experience change*. Life is an ongoing, irreversible flow of shifting conditions to which we must adapt. Because the rate of this change is accelerating, it's becoming more and more difficult to predict what those shifts will be, except in the short term. For example, current studies expect that, by 2025, as many as 80 technologies now in the lab, representing breakthroughs in virtually every field—from computing with light to the use of fuel cells for transportation—will be fully competitive (Halal, Kull, and Leffman, 1997). How those technologies will combine with existing technologies and each other is impossible to know. As a result, the most sustainable strategies are likely to be those in which organizations develop the capacity to learn quickly about new market developments, and then encourage products and services that take advantage of them to emerge from their interaction with customers.
- ◆ Second, as Gregory Bateson pointed out a quarter century ago, evolution and learning are similar processes, in which a stream of events,

mutations, and ideas, respectively, are chosen from by a selective process so that some of those events survive (Bateson, 1979). Evolution is the process by which living things develop emergent adaptations to change over many generations. Learning is the process by which they develop emergent adaptations within a single generation. Organizations, however, blur this distinction. While it took dinosaurs hundreds of thousands of generations to evolve into birds, Mercedes-Benz Credit Corporation was able to evolve from a mechanical hierarchy to a much more organic form in only five years, in a single organizational generation. As a result, we can define organizational learning as *the process by which organizations evolve emergent adaptations*.

- ◆ Third, *all organizations are complex adaptive systems (CAS)*. CAS are complex, composed of many autonomous agents whose interaction creates behavior on the scale of the whole that would be impossible at their individual level. One such behavior is the need to adapt as its surroundings shift over time. The important distinction that will be noted in this article is whether management wants to direct/control the behavior of the organization as a CAS, with a mechanical model of organization, or to free it to find its own direction through self-organization. For this reason, mechanical and organic models lead to radically different styles of organizational learning.

TWO STYLES OF LEARNING

Most readers of this article will be familiar with the way traditional organizations learn in their markets. Essentially, their leaders act as chief learning officers who use the organization to pursue a vision, operating it by command and control, much the way you operate your car. For example, in the late 1940s and early 1950s, Tom Watson, Jr. urged his father, IBM CEO Tom Watson, Sr., to push the company into the emerging market for digital computers. That required a powerful vision, because, at the time, even the most knowledgeable experts couldn't imagine a market for more than 100 computers worldwide.

Then, after Watson, Jr. became IBM's CEO in 1956, he risked the company in a \$5 billion effort—that would be valued at about \$200 billion in 1998—to recreate the computer industry. At the time, major computer makers produced a line of computers with increasing computing power. However, each computer in the line was developed separately and so required its own software. As a result, it was impossible to upgrade. If

your business was ready for a more powerful computer, you had to buy an entire new system. Watson, Jr. set out to create a family of computers, all using the same software, so that customers could upgrade their machines as their computing needs grew. Under his direction, IBM succeeded in creating its “360” family of computers in the early 1960s, and was catapulted into a dominant position in the industry, with a 70 percent market share. Tom Watson, Jr.’s vision of emerging trends in the computer industry, and his ability to direct IBM to realize that vision in the market, demonstrate exactly how powerful the mechanical model of organizational learning can be (Carroll, 1994).

Organic organizational learning, on the other hand, is less an issue of any one person’s learning. It involves people throughout the organization building on each other so that the most significant learning occurs at the level of the organization itself, as we can see from 3M’s Integrated Solutions program. In 1995, managers at the company began noticing a pattern of complaints from some of their largest customers. Because 3M sells its products through some 40 semi-autonomous product divisions, each with its own sales department, these customers were receiving calls from three, four, even five 3M salespeople, each from a different division. The team of managers charged with solving this problem developed Integrated Solutions, demonstrating how 3M’s processes of corporate learning not only meet its customers’ current needs, but actually increase its ability to meet new needs as they emerge.

With Integrated Solutions, if a 3M customer buys from four product divisions, the company trains a team of four salespeople, one from each division, and has them ask if they can map the customer’s workflows. In return, they promise recommendations for reducing costs and increasing productivity. If the customer agrees, the sales team maps its workflows and, later, examines them with members of their divisions’ marketing and R&D departments, looking for three things:

- ◆ *Existing 3M products* that the customer can use. While no one salesperson can know all 50,000 3M products, the team of eight or ten working on the customer workflows might know most of them.
- ◆ *New products* that 3M can develop to solve customer problems.
- ◆ *Process improvements* that 3Mers had learned in working with their other customers.

When the recommendations are ready, 3M brings in the customer, usually one of its senior managers, for a full report. According to Dominic

Tallarico, a member of the management team that heads Integrated Solutions, these reports are often eye-openers for customers, suggesting opportunities they'd never even imagined. In his words:

We had one customer that manufactured buses. By the time we made our report, we were able to offer them material and process science solutions that gave them the opportunity to do things they didn't think would be possible. The company now wants 3M in on the design and specification stage of its development process.

In another case, a team making recommendations to the vice-president of an airline suggested a productivity increase of as much as 300 percent to a process the airline thought was already highly efficient. Tallarico noted:

When he saw the improvements we were suggesting, the vice-president got so excited that he offered us one of the company's planes for a year, so we'd have a model to work from.

With Integrated Solutions, 3M does more than learn about immediate customer needs. The program blurs the company's boundaries from its customers. As its customers implement its recommendations, 3M managers can watch for new needs that customers develop as a result. When those needs develop, it will be prepared to find ways to meet them, *even before its competitors know those needs exist*. By contributing to its customers' success, 3M can encourage a mutual dependency that will enable both the company and its customers to operate more successfully. In the process, it will also continue to learn about its customers and their markets in the most intimate possible way.

This organic learning process is co-evolutionary. That is, 3M is optimizing its ability to behave like a living thing, evolving in ways that enable it to cultivate mutually beneficial relationships with other living things in its environment. In one striking example of co-evolution in nature, certain acacia trees have evolved hollow thorns and small food packets at the base of their leaves. A species of ant lives in the thorns and eats the food packets. In return, the ants protect the trees from small mammals that would damage them. What makes this arrangement appear co-evolutionary, rather than merely accidental, is a curious fact: Researchers have found this arrangement in the Americas, Europe and Africa, but not in Australia, where there are no small mammals to threaten the acacias (Grant, 1984).

Just as this arrangement between acacias and ants increases the ability of both to survive, Integrated Solutions increases the ability of both 3M and its customers to prosper in their markets. This market co-evolution is the purpose of organic organizational learning. To develop such an organic learning process, managers can model an organization on living things, rather than machines—that is, they can apply the dynamic principles by which living things learn and adapt, freeing the organization to function as a self-organizing CAS.

MODELS OF ORGANIZATION

One warning: It's tempting to think of organizational models as either metaphors that enable managers to translate whatever they find attractive in a model to their organization, or literal renderings that translate every detail of the model into their organization. This article uses the idea differently. On one hand, a literal rendering ends up seeming ridiculous because organizations are significantly different from both machines and living things. With a mechanical model, for example, managers may think of workers as replaceable parts. But it's impossible to control a human being as fully as we control machine parts. On the other hand, organizational models operate much more specifically than metaphors. With them, managers apply the design principles of a model to help answer a critical question.

That question is: "How can managers integrate the very different interests, skills, and desires of 100 or 100,000 people to pursue a common goal?" Traditionally, managers used a mechanical model. By thinking of their organizations *as if* they were machines and applying the design principles of machines to those organizations, managers could consider their workers as replaceable, pre-programmed human parts. Such employee/parts would need to know only how to do their jobs, just as the spark plugs in your car only "know" how to ignite gasoline in the engine. Managers must then be responsible for connecting workers in cause-and-effect chains to perform complex tasks, as an engineer must put the parts of an engine together in a design, if your car is to run. In such an organization, the formal structure should also be mechanical, composed of many mechanically distinct subunits with impermeable boundaries. This structure functions as a prison, keeping workers focused on their tasks and those of their units, avoiding distraction by limiting connection. If you've ever worked in a bureaucracy, you'll recognize how extensively these principles are translated into such organizations' operations.

Finally, machines are tools of human purpose. As we saw in the story of Tom Watson, Jr. at IBM, organizations built on a mechanical model need someone to exercise purpose—a visionary leader whose job is to operate the corporate machine. Such a leader will use their vision to navigate the organization through shifting market conditions, just as your vision enables you to drive your car through shifting road conditions. In the end, the visionary leader acts as chief learning officer, testing their vision in the market and making necessary adjustments through a command-and-control management style.

As long as such organizations have capable visionary leaders, they can remain highly successful. This style of organizational learning, however, has two problems. First, a leader's vision sometimes fails. When Henry Ford's vision of the auto industry failed in the 1920s, his insistence on producing just one model, at a time when General Motors recognized the public's desire for more product differentiation, severely damaged Ford Motor Co., which had dominated the industry for some 20 years. Similarly, Ken Olsen's refusal to recognize the growing demand for personal computers in the late 1970s and early 1980s would eventually kill off Digital Equipment Corp., which had been one of the leading computer companies from that market's beginnings. Second, when a visionary leader leaves the company without a visionary successor, it can easily lose its way, as IBM did after Watson, Jr. left in 1970. In both these cases, deprived of their chief learning officers, mechanically modeled organizations lose their ability to remain connected to their markets, stop evolving, and face extinction.

AN ORGANIC MODEL

The alternative to a mechanical model is an organic one. What happens if managers put their people together *as if* they were members of a living thing, rather than parts of a machine? What organic design principles are critical for ensuring that our organizations are able to learn and adapt as living things must?

CORPORATE DNA

For our purposes, the key organic design principle is DNA. Functionally, DNA is a *flexible database of procedures and structures, all aligned to an organism's identity, with which the information of the whole is encoded in all the parts*. In Bateson's words, it provides "storage of available alternative pathways of adaptation" (Bateson, 1979). Notice how each part of this description contributes to DNA's value as the vehicle for evolution:

- ◆ As a *database of procedures and structures*, DNA enables living things to replicate in a way that maintains their integrity.
- ◆ Because the database is *flexible*, DNA enables living things to experiment with new procedures and structures, a capability that becomes especially important when their environment shifts.
- ◆ With procedures and structures *aligned to identity*, DNA ensures that surviving experiments will enhance its ability to survive. This alignment is maintained by two mechanisms—an internal one that filters out most mutations, and natural selection, which operates externally. Because the information of the whole is encoded in all nucleated cells, living things can develop from a single fertilized cell with one set of directions.

When we apply DNA to our organization, not as a specific structure (a literal translation) but as a set of operating principles, the resulting corporate DNA has enormous power to help our organizations learn and adapt. *Corporate DNA would then be a flexible database of all an organization's procedures and structures, aligned to its corporate identity, and made available to everyone in it.* Consider how these qualities enable organizations built on an organic model to learn:

- ◆ As a *database of procedures and structures*, corporate DNA documents the best ways that any organization has currently found to perform any task. Some organizations document it in hard copy, as with the Ritz-Carlton's Skills Mastery Manuals (a binder of each department's procedures); some in electronic form, as much of Mercedes-Benz Credit Corporation's is; others in a mix, as at Federal Express. What is most important is that it can act as the repository of alternative approaches to evolution that Bateson suggested.
- ◆ Corporate DNA's *flexibility* enables people to experiment with it continually. When combined with its universal availability, corporate DNA drives the process of organizational learning. For example, people at the Ritz-Carlton's Philadelphia hotel were working to reduce cycle time for room cleaning. When they got stuck in this effort, one person working in housecleaning told a friend at the front desk about the impasse. The friend at the front desk wondered what would happen if housecleaning used the same software the front desk used to track customer preferences. After checking housekeeping's Skills Mastery Manual, this person suggested what would become the breakthrough procedure for speeding room cleaning. As opposed to a

more mechanical organization, where procedures belong only to the people who use them, the universal availability and flexibility of the Ritz-Carlton's corporate DNA invited everyone to take ownership for all the organization's procedures and improving them.

- ◆ Finally, because all procedures and structures are *aligned to corporate identity*, such improvement efforts have an internal guidance that allows managers to encourage their people to work in a self-organizing manner. Rather than need the external direction that management provides in a bureaucracy, people can operate autonomously. At 3M, for example, almost all procedures and structures are aligned with its corporate identity, Innovation. Its practice of having R&D people visit customer premises; its 15 Percent Rule, by which most people have 15 percent of their time to explore their own ideas; its "bootlegging" policy, through which people can beg and borrow the resources they need to pilot new ideas—all these, and many more, provide the incentives that keep 3M people focused on finding new ways to use its technologies to meet developing customer needs, without managers having to tell them what to do.

In short, corporate DNA provides the flexible documentation of alternative paths of evolution/learning on which anyone can build, so long as their contribution moves the organization in the direction of its identity. The result is ongoing, accelerated organizational learning. At St. Luke's Stroke Center in St. Louis, MO, use of a critical path for stroke patients, treated as part of its corporate DNA, enabled healthcare providers to reduce the average length of stay for stroke patients from 7.5 days in 1993 to 5.5 days in 1997. The critical path maps all the procedures through which stroke patients must go, from the time they're admitted until they're released. Because the path was considered both flexible and universally available, team members—including physicians, nurses, rehabilitation therapists, and dieticians—were all invited to suggested ways to improve care and reduce length of stay. The more than 25 percent reduction over less than four years occurred, not as the result of individual learning, but through the combined contributions of many team members. The organization was learning, rather than merely one or two of its individuals.

In addition to the way it enhances organic organizational learning, corporate DNA can produce other benefits for organizations that treat their procedural and structural information this way. For one thing, it speeds customer service. Unlike bureaucracies, where customers often

have to speak with a series of people before finding the one employee who can answer a specific question, universal availability of procedural information means that even when employees can't answer a customer's question, they can quickly and easily find out who can. And that, in turn, makes it easier to learn about those customers' emerging needs. For another, having information universally available creates a sense of common ownership. As with the front desk clerk at the Philadelphia Ritz-Carlton, a job isn't limited to its procedures, which in a bureaucracy are owned by the person who performs them. Rather, every employee's responsibility is to the company as a whole, and with corporate DNA available, those employees have the information they need to make contributions anywhere in the organization.

CORPORATE NERVOUS SYSTEM

A second critical organic design principle is the nervous system's ability to gather information, integrate it into a picture of the world outside, and then coordinate the activities responding to the events it senses. (The nervous system also works with the endocrine system to communicate what's happening within the body. For the sake of simplicity, we'll consider endocrine functions as part of the nervous system.) The nervous system has two components: the *peripheral nervous system*, the network of nerve cells that connects almost every cell in the body, communicates sense impressions from all parts of the body to the *central nervous system*, the brain and spinal chord, and then carries messages back to the body. We'll return to the central nervous system when we look at how an organic corporation governs itself. Right now, let's turn to what happens when an organization applies the principle of communication available to all its parts performed by the peripheral nervous system.

When organizations apply the principle embodied in this system, they come up with a corporate equivalent of the peripheral nervous system. I've elsewhere called it a "corporate nervous system." Such a corporate nervous system enables everyone in the organization to learn what's happening inside or outside so that they can react by drawing on its corporate DNA. Not only that: It also allows people to learn how effective their actions have been so that they can modify them to be more effective next time. In this way, every person in the organization becomes its eyes and ears, the sense organs by which it gathers information about its markets.

Some examples of corporate nervous systems are extremely well known. Wal-Mart, for example, transformed retailing by using barcode scanners to create a company-wide information network. Because its

people could learn what was being purchased at the point of sale, Wal-Mart was not only able to manage inventory on a moment-to-moment basis. It was also able to identify hot new items earlier than any of its competitors. With the information from its corporate nervous system, Wal-Mart began buying directly from its suppliers and stocking its stores through regional distribution centers. In addition, because it could amass this information much more rapidly than its suppliers, Wal-Mart was able to develop strategic alliances with suppliers, such as Procter & Gamble, which now has employees dedicated to working with Wal-Mart in its Bentonville, Arkansas headquarters. According to George Stalk and Thomas Hout (1990), this use of barcode information enabled Wal-Mart to grow three times faster and earn a return on capital twice that of its competitors.

Federal Express uses its corporate nervous system, including a barcode-scanning network, for very different purposes. Because every package is repeatedly scanned on its voyage to the person who will receive it, FedEx's computer system enables customers to learn exactly where their packages are at any moment. You don't even have to call a FedEx service rep to find out: You can check for yourself on the company's website. In this way, Federal Express has extended its corporate nervous system out to its customers. In addition, there is a company-wide television network so that people can learn what they need to know. If jets in Nome, Alaska, are having trouble taking off, people who will have to process them in Memphis, Tennessee, can find out so that they can rearrange their work schedule to avoid disruption.

3M's Integrated Solutions demonstrates a less technological, but still highly sophisticated use of corporate nervous system. On one hand, the work process mapping brings in extensive amounts of information about customers. On the other, when the sales/marketing/R&D team sits down to look for business opportunities in that mapping, those team members can draw on information from another area of 3M's corporate nervous system—the network of technical information by which 3Mers can learn about new technologies that are being developed within the company. It was, for instance, through this extended network that Art Fry learned about the adhesive he would use to invent Post-it Notes. These two elements of 3M's corporate nervous system ensure that its people working in Integrated Solutions have enormous amounts of information to enhance the quality of learning they do to meet their customers' needs.

It is important to note here that, in living things as well as organizations, learning occurs in the interaction between the nervous system and

DNA. For organizations, the corporate nervous system brings in information about its customers in its markets, and corporate DNA gives their people the information on their options for responding. The clearer the information from the corporate nervous system, the more employees know about how to respond. The more effective the procedures and structures in corporate DNA, the more effectively they can respond.

NESTED NETWORKS

While it is essential to have these types of information available, living things also must be structured in such a way that enables them to respond in an emergent fashion—that is, they must be able to respond appropriately to the specific circumstances around them, no matter how different they are from what happened yesterday or the day before. To do so, living things are structured as nested networks. Molecules are nested in organelles, such as mitochondria or the nucleus; organelles, in cells; cells, in organs; organs, in organ systems; and organ systems, in the body as a whole. The boundaries of all these structures are semi-permeable so that all of them can be connected, either by the nervous system, the circulatory system, or both.

With this structure and their distributed information systems, living things can attack complex tasks very differently from the way machines do. Machine parts must be programmed and then arranged to perform complex tasks in a cause-and-effect manner. Living things, on the other hand, bring together units from each nested level to perform such tasks. As I write these words, hemoglobin molecules in my bloodstream are bringing oxygen, picked up in the alveoli of my lungs, to my brain cells so that they can choose the words and send messages to muscles in my arms and fingers, to type the words, and to muscles in my eyes to scan the words and ensure that they are put together and spelled (mostly) correctly. In this one activity, my body uses structures at the level of molecules, cells, organs, and organ systems, combining activities in my nervous, circulatory, respiratory, and muscle systems. Our bodies are the ultimate in teamwork.

3M structures itself exactly this way. To oversimplify only a little, individuals are networked in functional departments (sales, marketing, R&D); departments, in product divisions; divisions, in market groups; market groups, in sectors; and sectors, in the company as a whole. And like living things, the boundaries of each of these units are semi-permeable so that information can flow in and out. The key structure is the product divisions, which are semi-autonomous to the point of each

having somewhat different cultures. To ensure a strong sense of inter-connection, people in any functional department are cross-trained in other areas of their divisions. Salespeople, for example, learn about key divisional technologies, and those in R&D are expected to visit customer premises to learn how they use the division's products. Look at how this structure enhances organizational learning in Integrated Solutions:

- ◆ Individual salespeople from different divisions, sometimes representing different market groups, work together to map a customer's work-flows.
- ◆ Salespeople work with others in their divisions representing marketing and R&D to identify customer needs.
- ◆ Each of those people draws on their personal network of connections within 3M, so that 10 people sitting together can be connected to most of the people in the company.

With the ability to draw on the knowledge of people company wide, regardless of the formal structures to which they belong, 3Mers can learn in a way that is truly organizational, rather than individual.

Moreover, this organic structure makes teamwork an expected standard of behavior. Because of the mechanical separation of subunits in more traditional organizations, cross-functional teamwork often creates problems. At one Baldrige National Quality Award winner, senior management demanded that such cross-functional teams start looking at a variety of problems. When the quality managers in charge of this effort reported back, they told the senior managers that these teams had made some advances but that, to make them most effective, the company would have to change its reward system. As long as rewards were solely tied to team members' units, they would represent the interests of their bosses, not the team. However, because those senior managers' relied on the reward system to maintain their power, they never made the changes that would have produced more effective cross-functional teamwork.

3M's nested network structure, however, facilitates teamwork by suggesting a reward structure based on organic teamwork, rather than mechanical separation.

CORPORATE CENTRAL NERVOUS SYSTEM

Where machines need an external intelligence to control and direct them, living things are self-governing. That self-government is provided by the central nervous system, which performs four key functions:

- ◆ To integrate impressions from the peripheral system into a unified picture. The world you see when you open your eyes combines thousands and thousands of nerve messages from the outside world with even more messages from your brain on how to interpret it all (Maturana and Varela, 1992).
- ◆ To make high-level decisions for the whole body. Parts of your brain are responsible for helping you decide everything from your body as a whole, from what to eat for breakfast to whether you will marry someone you're seeing or how to spend your lottery winnings.
- ◆ To coordinate the activities of the various parts of the body. As I write these words, the motor area of my brain is sending messages to the muscles in my hands and fingers, and to my eyes, so that their activities can be coordinated and I can string together on the page the words I've chosen.
- ◆ To monitor the body's subsystems so that the whole can remain healthy. Various centers in the brain monitor everything from temperature (the hypothalamus) to carbon dioxide levels in the blood (the vasomotor center) so that it can send chemical messages to keep the whole system healthy enough for all parts to do their jobs.

Two differences between mechanical government and organic self-government are key. First, with machines the governing intelligence is external; with living things it is internal. Second, while the governing intelligence in both is responsible for maintaining a picture of the outside world, making high-level decisions, and coordinating activities, the governing intelligence must *control* mechanical systems to give them direction; on the other hand, it must *monitor* organic systems so that they can self-organize and find their own ways.

As a result, an organic model suggests that senior management must act much like a corporate central nervous system. That is, while senior managers are still responsible for maintaining the corporate picture of the outside world, for coordinating activity, and for making high-level corporate decisions, they do not control the organization, as they would with a mechanical model. Rather, they monitor corporate systems to maintain the health of the organization as a whole.

At 3M, for example, as part of their responsibility for monitoring corporate systems, senior managers:

- ◆ gathered the information they needed to recognize the large customer sales problems that would lead to Integrated Solutions;

- ◆ decided to create a team-based sales program to take advantage of the opportunities those problems represented; and
- ◆ coordinated the activities needed to get it underway.

Having done all that, they could stand back and give people autonomy to run the program. They retained responsibility for monitoring the success of Integrated Solutions, but did not control it, as would probably happen in a more mechanical organization. The result is that people across the organization learn from their experiences in the program and build on each other's learning to create true organizational learning.

One other excellent example of how this process of organizational learning works at 3M is the spread of microreplication technology. Microreplication enables manufacturers to create specific product effects by covering surfaces with thousands of tiny structures. Researchers at 3M first used microreplication to create the first affordable overhead projectors in the mid-1960s. Then, without any dictate from senior management, this technology became a topic of discussion in the company's technical information network, and other researchers in a variety of product divisions began to use it. In the early 1970s, researchers used it to improve the reflective properties of traffic lights; by the late 1970s, for solar concentrators. By the mid-1980s senior managers had recognized, through their ongoing monitoring efforts, how useful the technology could be, so they created a center to speed the process of applying this technology. Today, products developed in one out of four of 3M's 40 product divisions use it, together accounting for about \$1 billion in sales annually.

Yet, because the company is largely designed along organic principles, there was no need for a chief learning officer to recognize the opportunity and push its development. As Roger Appledorn, one of the 3M researchers who first applied microreplication, puts it:

We didn't sit down and say, 'Microreplication is the next thing to do; let's go do it.' It doesn't work this way. It evolved. It reached a critical mass. And it suddenly proliferated.

At 3M product development can evolve like this because the company is largely based on an organic model. That is, it behaves *as if it were a living thing*: It treats internal information as flexible, universally available corporate DNA, makes current events available through a corporate nervous system, is structured in interconnected nested networks, and is governed by senior managers acting as a corporate central nervous sys-

tem. By thus taking advantage of these organic design principles, 3M can function as a true learning organization, where contributing to the corporate store of knowledge and applying that knowledge to meet customer needs in new and exciting ways becomes the most important part of every person's job. Freed of the controls of a mechanical model, 3M's people work together as the autonomous agents of a self-organizing complex adaptive system, learning and adapting because that is the basic nature of their organization.

NOTE

Much of this article's discussion—from its theory of organizational models to its analysis of corporate DNA, corporate nervous system, nested network structure, and corporate central nervous system, as well as most of the corporate illustrations—are taken from the author's book, *Corporate DNA*. A briefer discussion of the difference between organic and mechanical models can be found on the internet, in the first issue of *Thresholds* at <http://www.thresholds.com>.

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Moving Beyond Metaphor

Ted Fuller and Paul Moran

The proposal that the metaphors associated with complexity theory can inform the business world is made by several writers (Wheatley, 1992; Stacey, 1996; McMaster, 1996, Merry, 1995), but is open to critique that the metaphors are not grounded in the field of study, but in other domains that may or may not be analogous. In previous articles, the authors (Fuller, 1998, 1999; Fuller and Moran, 1999) have illustrated the apparent analogies between complex adaptive systems and the world of small firms. However, because there is no grounding of these analogies in that domain, there is no evidence that complexity theory has validity in describing or explaining empirical observation. For example, a new firm starting up may be associated with the metaphor of emergence, but whether theories of emergence as developed in thermodynamic systems have any analogous properties with a business start-up is problematic.

This article investigates how complexity theory can inform an understanding of small firms, which we posit as an example of socioeconomic systems, in a more rigorous and scientific way than metaphor. Our approach to this is to investigate the possibility of a methodology that is plausible in its relationship to small firms, and developed from the conceptions and literature of complexity.

Methodology is about how we conceptualize, theorize, and abstract (e.g., Sayer, 1992): our modes of explanation, understanding, research design, and methods of analysis. In this article, a methodological position is developed, grounded in the literature of complexity theory and in substantive small business research literature. The methodology embodies philosophical principles, concepts, ontology, questions, methods, and

ethics. The purpose of the article is to open discussion on these methodological aspects. The purpose of the methodology is for application to real-world problems and issues in small business.

HOW COMPLEXITY INFORMS METHODOLOGY

Complexity is a science concerned with nonlinear dynamics and open, dissipative systems. Central to the enterprise would seem to be analogy, with dynamic modeling as a mode through which descriptions of dynamic behavior are made; for example dynamics as changes in patterns of relationships, in the emergence of events or conjunctions through time phases, and of the emergence of forms that display apparently different characteristics from their constituent parts. Approaches to modeling are varied, and include computer simulation (Hiebeler, 1994) and tracing of historic evolutionary paths (Gould, 1989). Models, too, provide a mode of explanation in terms of the results of unpredictable effects of multiple causal powers (e.g., codified as “rules” of behavior or inheritance). The effect on the researcher of such modeling is to create explanatory frames of reference that guide further abstraction and modeling.

In assimilating a systemic approach into a study of the social world, there is an explicit acceptance of what Cohen argues as the “insight that organisms are systems” (Cohen, 1998). For example, in a rubric to students, Axelrod (1998) suggests that a research goal is to “discover new principles about the dynamics of complex systems, especially complex adaptive systems which are typical of social processes.” Protagonists have assimilated the scientific metaphors. For example:

The evolution of dissipative social systems is chaotically driven and is sensitive to initial conditions. The structure is generated by symmetry breaking mechanisms and is consequently ontologically layered ... These evolutionary properties establish the foundations for the historicity of the entities and the events under consideration. (Harvey and Reed, 1996: 306)

And, according to Byrne (1998), these systemic ideas transcend the limitations of the homeostatic systems model basic to Parsonian structural-functionalism. Complexity enables us to reflect the character of the social world as consisting of complex nested systems with a two-way system of determinant interrelationships among the levels. Also, it:

enables us to deal with both of the crucial problems identified for any sociological theory by Mouzelis (1995). It provides a way of relating the macro and the micro which is not inherently aggregative and reductionist and it provides a way of describing the relationship between agency and structure which takes account of Elias's assertion of the fifth dimension of reflexive human consciousness. (Byrne, 1998, Chapter 2)

Those searching for "science" in their research of society, including the domain of business, are attracted to complexity because of its scientific antecedents. Complexity studies provide the social scientist with many metaphors of dynamical systemic behavior. Are these metaphors analogous with social "systems"? Rosenhead (1998) and Fuller (1999) both critique the elevation of metaphors, grounded in nonanalogous phenomena, to the status of causal reasoning in social systems. The approach is open to a fallacy that metaphors are the same as reality.

The mistake here is directly to link metaphors of complexity with empirical experience. At issue is the extent to which patterns identified empirically, or modeled theoretically in the physical and natural sciences, provide ontological adequacy. Is it plausible to use metaphors of fitness, of attractors, of emergent properties, of rules and conditions, and to have adequate grounding of meaning in the business domain?

We suggest that these metaphors do not provide ontological adequacy *per se*, but have a role in informing the design of models or abstractions that may have such adequacy. From an evolutionary perspective, this kind of methodological positioning can legitimately be developed as potentially fallible, and from a scientific perspective it requires substantive reasoning or evidence for its claims. One issue arising from this is, therefore, how we test the adequacy of this work at a level of meaning. What is its instrumental reliability? We posit methods for this later in the article, attempting to find a starting point, with links to the empirical domain, for an investigation of the value of complexity science to the understanding of certain characteristics observed in small businesses.

A number of authors—e.g., McKelvey (1998); Reed and Harvey (1992)—have noted the proximity of complexity to the epistemology of scientific realism (Aronson, Harré, and Way, 1994; Suppe, 1989), and in social sciences to critical realism (Bhaskar, 1978; Outhwaite, 1987; Sayer, 1992). Realism provides philosophical principles on which dynamical nonlinear characteristics can be understood. For example, the appearance of novel structures and patterns can be explained by a conception of contingent or latent powers inherent in the interrelationships, rather than by

the external imposition of order. One epistemological implication is that causality is not identified from the observation of empirical regularities *per se*. Causality in a specific context may be traced by theory building using concrete, intensive methods (Harré, 1979), but does not carry the same construct of being generalizable that the notion of causality carries in social positivism. Complexity is itself a scientific ontology

which fits Bhaskar's philosophical framework: one which treats nature and society as if they were ontologically open and historically constituted; hierarchically structured, yet interactively complex; non-reductive and indeterminate, yet amenable to rational explanation; capable of seeing nature as a "self-organising" enterprise without succumbing to anthropomorphism or mystifying animism. (Reed and Harvey, 1992: 359)

THE CASE FOR LINKING COMPLEXITY TO SMALL BUSINESS AND ENTREPRENEURSHIP RESEARCH

Small firms may lend themselves particularly well to a complexity-based research paradigm, possibly more so than large corporations, since the latter may be "overcomplex" ("complicated"?) in the sense of Kauffman's notion of "complexity catastrophe" (see Kauffman, 1993, 1995). This is because of the tendencies toward excessive (imposed) order, centralization, overengineering etc., which can result in a reduction of the overall fitness of the system and a thwarting of the selectionist process. As McKelvey (1999) puts it, "internal complexity leads to complexity catastrophe but external complexity leads away from catastrophe," thus pointing up the importance of decentralized, disaggregated structures, following the logic of autonomous but co-evolving "patches" (Kauffman, 1995), which is resonant with our understanding of how small firms behave. Organizational theorists have not been able to mount a convincing case so far that modern corporate organizations can be adequately studied from within the paradigm of complexity, apart from in a purely metaphorical sense. As Rosenhead points out in a critique of "complexity" management texts:

It hardly needs saying that there is no formally validated evidence demonstrating that the complexity theory-based prescriptions for management style, structure and process do produce the results claimed for them. (1998: 10)

A small firm, by contrast, is relatively simple as an entity, although with possibilities of complex behavior arising because of the influence of the human agent (usually one person, i.e., the owner-manager/entrepreneur), and the high degree of interaction with other firms/agents that can lead to the evolution of new forms of structure. Such structures may be perceived, for example, as networks or clustering. The small firm can thus be viewed as a (relatively) simple system and as part of a more dynamic, complex whole, where multiple agents and interactions take place, giving rise to phenomena such as “swarming” and other emergent behavior.

Empirically, populations of small firms resemble the characteristics that Holland ascribes to a complex adaptive system, that is,

[an] evolving perpetually novel world where there are many niches with no universal optimum of competitor, where innovation is a regular feature and equilibrium rare and temporary and where anticipations change the course of the system, even when they are not realised. (1995)

Evolutionary and ecological metaphors of emergence, fitness, and mimicry resonate with observations of the large number of smaller firms in the economy. Small businesses are not a homogeneous population. They vary considerably in size and sector activity, in their ownership, their location, the markets served, and so on. Each business is different. Each has its own “initial conditions,” and each incurs a number of “accidents” in its temporal path. Given that entrepreneurs are “innovative,” many businesses will operate with their own “rules,” as well as complying (more or less) to more general rules. Business strategies explicitly operationalize the metaphor of “niche specialization.”

Some of the features of businesses’ domain are common or shared. They all interact with key economic stakeholders, such as banks and government agencies. Businesses operate in a regulated environment, providing at least some of the “rules” of behavior. The mimicry of doing business, i.e., copycat methods and the diffusion of information through benchmarking and best-practice guides, is ubiquitous. Swarming is commonplace, for example physically in business districts and clusters (e.g., Gillies *et al.*, 1998), or in the use of particular technologies (e.g., North *et al.*, 1991). And energy, in the form of cash and perhaps technological innovation, flows within the system, with those firms that do not maintain cashflow or adopt new ideas ceasing to operate.

COMPLEXITY DYNAMICAL CONCEPTS IN THE WORLD
OF SMALL BUSINESS

In its assimilation into the small business domain, complexity theory may become trapped in its own metaphors, but there are at least four areas in which it can move beyond the metaphor as a surface description of observed behavior. These areas are interlinked, but conceptually different.

Take first the notion of the small firm, or some attribute of the small firm, as an adaptive agent; see, for example, Rydal, 1996; Casti, 1997. The notion of an adaptive agent is highly resonant with Schumpeterian notions of entrepreneurial innovation. Indeed, Schumpeter's work stimulated Nelson and Winter's (1982) contribution to evolutionary economics. The "adaptive" (entrepreneurial) actions—"the capacity of seeing things in a way which afterwards proves to be true, even though it cannot be established at the moment" (Schumpeter, 1934: 85)—appear reflexive, taking into account the existing perspectives and external stimulus (Lewis and Fuller, 1998). This reflexivity is perhaps more likely to be understood through the investigation of learning and social processes, rather than a two-dimensional, systemic concept of adaptation. The articulation of rule-like, reflexive behavior or the nature of the learning that gives rise to changes in reflexive responses has not yet been adequately codified. Adaptation is conceptualized herein as a reflexive process, one in which the adapter exercises agency.

Second, the notion of the firm as being part of a wider system, "ecology," or nexus of stakeholder relationships and actions (Fuller, 1997) is significant in theorizing the small firm. Small firms are not individual entities *per se*, but part of interrelated structures of relationships. The nature of these relationships is not well articulated in the literature. For example its representation in agency theory (Williamson, 1991) as a nexus of contracts does not adequately take account of qualitative or non-economic factors. Small firms are theorized as operating in "networks" by a number of authors (e.g., Johannisson, 1987; Jarillo, 1988; Lorenzoni and Ornati, 1988; Larson, 1992; Castells, 1996). These studies stress the importance of both social and economic rationales for the relationships. However, the nature of the relations and "coupling" between small firms and their environment is not well enough understood to have yet produced plausible complex adaptive models. In the complexity literature, relationships between the individual agent and others are often definitionally implicit, yet crucial. For example, in the "Ant" rules—Coveney

and Highfield, 1995: 250, if you find food, take it home and mark a trail; if you cross a trail and have no food, follow the trail to the food etc.—the crucial relationship between the ant colony, the behavior of individual ants and food is axiomatic, and the necessary relationship between ants and food for survival is implicit. Relationships are conceptualized herein as interdependent powers between firms, individuals, other agencies, and other objects or mechanisms.

Third, the notion of fitness, and the maintenance of fitness, are synonymous with “competitiveness,” but also with growth or survival. Life is short for most small firms and the rate of new firm formation alters in different conditions. Maintaining fitness in complex adaptive systems is said to be informed by what Holland calls “look ahead.” Lane and Maxfield (1995) address this with regard to strategy in organizations, arguing that only those “inside” the system can have any sense of prediction of strategies. The concept of fitness and emergence in alternative conditions is also to be found in the work of Fuller *et al.* (Fuller, 1999) on foresighting. Their approach uses the idea of structural coupling to simulate the emergence of typical new firms and innovation from scenarios of alternative (future) initial conditions.

In small business research, links between conditions and systemic fitness are largely empirical and judgmental, with little theoretical explanation. This leads to a critique of empirical discovery of regularities associated with “success” at any point in time. Most positivist research in the small business field makes claims with regard to the association of hypothesized factors and some form of success. There is no evidence that this has any predictive capability, nor any explanatory value. There have been some classic errors, such as Peters and Waterman (1988). From a complexity perspective, the reason that such empirical evidence is unreliable as a guide to behavior is that the systemic interdependencies or reflexive linkages between the firm and the environment are not adequately understood from an external perspective. More fundamentally, in open systems fitness is a highly dynamic and unpredictable state.

Fitness is conceptualized herein as a state of relative performance, which may be the result of reflexive adaptation. It may be articulated or described partly in terms of relationships, but is inherent to a firm within its context, i.e., it is relative.

Fourth, the causal concept of structural emergence through self-organization or autopoiesis provides a powerful methodological construct for the investigation of change in the small firm domain. The production of results from the Prigogine and Lefever experiments (Prigogine and

Stengers, 1984) showed that nonlinearity occurs in a chemical reaction if a product catalyzes its own production, a feedback process known as autocatalysis. Prigogine introduced the term “dissipative structures” (the dissipation of introduced energy) to emphasize the origins of self-organization in far-from-equilibrium thermodynamic processes.

This idea of a system retaining energy through the formation of additional structure resonates with Anderson’s ideas of “symmetry breaking” (Anderson, 1972). This implies that dynamical systems do not become ever more complex, in a “flat” sense of more features, although they do create new structures, new ontological levels. If the systems were entropic, then they would become more chaotic. Dissipative structures do not necessarily become more chaotic, but dissipate entropy to outside the system. According to Harvey and Reed (1996:306), sustainable dissipative systems:

- ◆ convert free energy into more elaborate forms of internal construction;
- ◆ transport thermal disorder (positive entropy) out of the “system” (into the environment);
- ◆ the resulting net negative entropy gives rise to evolution;
- ◆ the system is far from equilibrium.

Luhmann’s work (e.g., 1986) is seminal in linking autopoiesis to social systems. Open systems are dynamic: energy flows within them and in and out. The precise circumstances that give rise to an ordering property are unique, unlikely to exist more than once. The existence of novel form creates novel conditions and vice versa. The authors’ guide to theorizing, abstracting, or conceptualizing is a sense of what Allen (1997) calls an “evolutionary tree of successive structures.” In this context, the arrow of time is one way, not reversible—events cannot be undone, nor ever repeated exactly.

Such a central concept as autopoiesis we believe is significant in developing a methodology for researching small firms in a complexity paradigm. This is developed in the next section of the article through the idea of ontological layers. An example of linking the analytical ontological perspective of interrelationships with model-centered theory is in the work of Gillies *et al.* (1998). However, autopoiesis may also inform an understanding of other creative processes, for example innovation and generative relations (Lane, 1996).

Emergence is conceptualized herein as the concrete result of a reflexive or self-organized, creative or generative process, whose form may be

empirically observed, or whose presence empirically sensed.

These four main concepts—reflexivity and learning, relationship with the environment and other agents, fitness and innovation, and autopoietic structural emergence—may perhaps be understood as interlinked facets of a process of contingent adaptation and survival in a population of small firms. The concepts inform a methodology with surface validity for investigating the dynamics of small firms. The claim for validity is that the dynamical characteristics that the concepts label in experimental fields of complexity have analogical or metaphorical resonance with observations in the small firm domain.

SMALL FIRM ONTOLOGY

The central property of dynamical systems of symmetry breaking and the creation of novel ontological layers provides a theoretical dimension to investigate multiple layers of firm characteristics and dynamics. The firm may need to be understood to exist simultaneously on many layers, possibly unconnected, and each having different meaning and different characteristics. This is partly why it is so difficult to operationalize interdisciplinary research work: each discipline is concerned with different, epistemologically or ethically separated, ontology, not just different perspectives on the same phenomenon.

A challenge for small firm research is to define the relevant “ontological layers” of the small firm “domain” and how these may interrelate and possibly give rise to emergent behavior and structures. Clearly, some ontological layers are outwith the scope of small firm research, but are nevertheless important as influences on “micro states.” As McKelvey (1999) points out, modeling of complex adaptive systems is focused on how micro-state events (including human agents or firms) “self-organize into emergent aggregate structure.” The division of structures is important here as a means of maintaining emergent structure far from equilibrium (i.e., “negentropy”) and therefore a networked form of structure is potentially more stable and adaptive over time than one based on merging structures (i.e., a large corporation) (see for example Kelly, 1995; Castells, 1996). The latter requires large amounts of energy to sustain it and will be incapable of rapid change; whereas the former is dynamic, adaptive, and, because of the very nature of its structure, does not require large overall amounts of energy to sustain it (the energy inputs are in effect “localized” due to the independent actions of adaptive agents).

Figure 1 illustrates six theorized ontological layers, derived from the

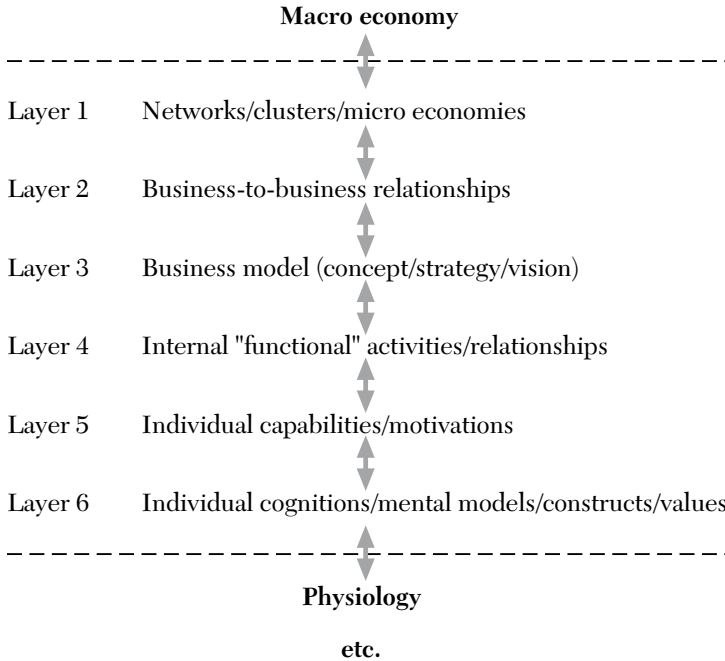


Figure 1 Posited ontological layers in the small firm domain

canon of research literature within the small firm domain, and the “boundaries” at each end. For small firms, the relevant layers are posited to range from “micro economies” to individual mental models and cognition (e.g., of the entrepreneur). The layers are intended to reflect key areas of research and debate in the small business field, i.e., networks/clusters (e.g., Chaston, 1996; Curran *et al.*, 1992; Hansen, 1995; Johannisson, 1987, 1995); external relationships in the value chain (e.g., Hall and Andriani, 1998; Lewis and Fuller, 1998; Mitchell and Agle, 1995); business model/strategy/vision etc. (e.g., Atherton and Hannon, 1997; Gibb and Scott, 1986; Miller and Toulouse, 1986); internal resources/processes (e.g., Garnsey, 1998; Hendry *et al.*, 1995); capabilities and motivations (e.g., Bellu and Sherman, 1995; Carsrud *et al.*, 1989; Harrison and Leitch, 1994; Miner, 1997); individual cognitions etc. (e.g., Chell *et al.*, 1991; Gatewood *et al.*, 1995; McGaffey and Christy, 1975; Moran, 1998). Beyond the “top” boundary is where aggregations become superordinate structures such as the macro or global economy. Below the “bottom” boundary is where physiology, biochemistry, and so on down to the quantum level influence individual cognitions, mental models etc.

These are also ontologies but of different “domains,” albeit impinging on the small firm “domain,” which is about how ways of seeing, thinking, and so forth are manifested through successive ontological layers to result in micro-economies of small firms existing in interrelationship with each other. In effect, the diagram reflects how small firm “ecologies” are built up from particular “micro states,” including individual personal characteristics and attributes of human psychology, through successive emergent realities.

The question arising from the above is to what extent these ontologies (or “perspectives”) reflect real-world mechanisms with causal properties, and how they might be operationalized in real experiments or studies. There is an issue here about the “permeability” of the “layers” in terms of the tendency among researchers to stay within tightly prescribed disciplinary boundaries. This is particularly important in this context in exploring the interactions between layers or how emergent properties arise from the lower-level micro-state interactions. Focusing solely within one layer may result in a limited view of the overall phenomenon and of how the “reality” of one layer is due to behavior or events at the layer below reaching some critical threshold (or “phase transition”) sufficient to create new, emergent structure or form. Thus, while the “business model” within the small firm domain (layer 4) may be legitimately studied in its own right, only a partial understanding (in the widest sense) will be achieved if the forces and influences that give rise to it at lower ontological layers are ignored or “assumed away” as not being germane. However, from an existential perspective, it must be remembered that a phenomenological entity termed “a business” can only exist because of a particular nexus of human activities and relationships, influenced themselves by particular competencies, drives, cognitions, and sense-making mechanisms. This reinforces the importance of the “bottom-up” nature of complexity science (Epstein and Axtell, 1996).

An example of research reaching down through several layers is currently in progress by one of the authors (see Moran, 1998). This research originated in the personality profiling of owner-managers (level 6) and how these relate to “growth orientation” (level 5). This is now being developed through in-depth interviews to explore issues such as the future shape and direction of the business (level 3), and key external relationships and their impact on the business (level 2). For completeness, the internal processes and relationships should also be explored (level 4). Being able to make connections between findings from different “layers” for the same cohort of firms may enable the construction of systemic

models reflecting the complex, dynamical nature of small firms arising from particular micro-state realities, which can be tested within the “model-based science” paradigm using simulations (see Casti, 1997).

RESEARCH QUESTIONS IN A FIELD OF STUDY

From the above analysis—i.e., four significant complexity concepts and six small firm ontological levels that can be posited as having a hierarchical or nested relationship—a potential field of study emerges. Drawing on the previously discussed concepts of autopoiesis and symmetry breaking, conceptually we would expect that the dynamics associated with complex adaptive systems would be related to the linking of hierarchical (emergent) ontological structures. Thus we can generate a plausible field of study by the simple cross-tabulation of these two sets of characteristics, shown in Figure 2. The range of research questions generated in this conceptual space requires further work. Some examples of substantive issues, still largely understood only in atheoretical (empirical or heuristic) terms in the domain of small firms, are given below (see Table 1).

	Adaption	Relationships	Fitness	Emergence
L1 Networks/clusters/ micro economies				
L2 Business-to-business relationships	1	1, 5	2	3
L3 Business model (concept/strategy/vision)		8	8	4
L4 Internal "functional" activities/relationships			7	
L5 Individual capabilities/motivations	6			
L6 Individual cognitions/ mental models/constructs/ values				10
		9		

Figure 2 *Ontological levels tabulated with complexity dynamical concepts (numbers refer to Table 1)*

Table 1 *Some research questions relevant to the field of study generated*

- 1 In what sense do small firms co-evolve with one another/other stakeholders?
 - 2 What is the result of this co-evolution?
 - 3 To what extent do small firms aggregate and create self-sustaining systems (e.g., “clusters”)? What evolutionary characteristics emerge within these higher-order systems?
 - 4 Why do firms network? Why do these relationships continue or discontinue?
 - 5 What are relevant boundaries to the firm?
 - 6 What is the role of the owner-manager in the process of adaptation in a small firm?
 - 7 How are firms deemed to be fitter or less fit over time?
 - 8 Does a firm’s fitness co-evolve with stakeholders?
 - 9 What sense-making and schema-building strategies do owner-managers use to improve the positioning of the business and thereby increase the chances of survival?
 - 10 What new concepts do owner-managers develop from their experiences?
-

Dynamical processes can only be understood through a time dimension. This might be historical or “real time.” We suggest that there is little or no historic evidence available that has been gathered through the conceptual framework developed in Figure 2. This requires further investigation, but it is likely that a longitudinal study is required if an empirical grounding is sought.

METHODS

The authors propose an iterative modeling/grounding approach to operationalize this research. They take the view that knowledge of the workings of any social system (of which the small firm is posited as being part) requires deep insight that is normally only available to its experienced actors. The common sense that such insights might generate may be shown ultimately to be “wrong,” but insights are, we suggest, closest to making sense of experienced dynamical processes at the relevant ontological layer. In such a case, the methodology demands the participation of system actors.

We further propose that in order to operationalize a methodology that takes account of dynamical properties, some form of simulation model is

required. The construction of this model should be informed by grounded theory or propositions of salient features identified initially by inspection of the literature and by intensive (Harré, 1979) reasoning from empirical evidence. This in itself may require considerable fieldwork, or can draw on existing research.

Simulations may help to clarify interactions and emergent patterns that might be fed back to assist in strategic decision making and executive action. In other words, the research enterprise would not merely be a way of creating new knowledge and models, but of adding practical value to the small firm community (i.e., create a “fitter” ecology from an evolutionary perspective). This requires that results of simulations are validated through field testing over time. The schema for this is illustrated in Figure 3, a Mandala or loop of modeling and testing, implying a learning or theory-building process.

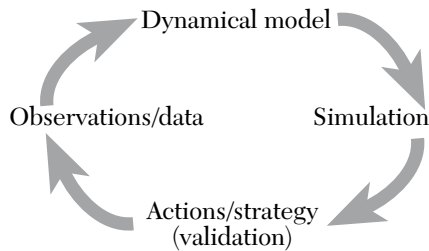


Figure 3 *Generic research cycle*

We therefore propose a method that iterates between everyday practice and analogous modeling. The method is guided by the concept shown in Figure 4, which places interpretation centrally, communicated through language and shared theory in practice between researchers and actors in the domain. Modeling provides an experimental form for scientific analysis (McKelvey, 1998); practice provides a grounding and testing of the emergent or evolving theories. In a sense this is a closely coupled microcosm of social theoretical evolution.

It is important to note from Figure 3 that the intermediate step of model building is required to “convert” observations and data into something that can be simulated in order to facilitate more in-depth understanding of the phenomenon. The simulation is thus only as good as the dynamical model from which it is derived. The loop is then closed by the testing of the outcomes of the simulation in relation to the real-world agents from which further observations/data would continue to be

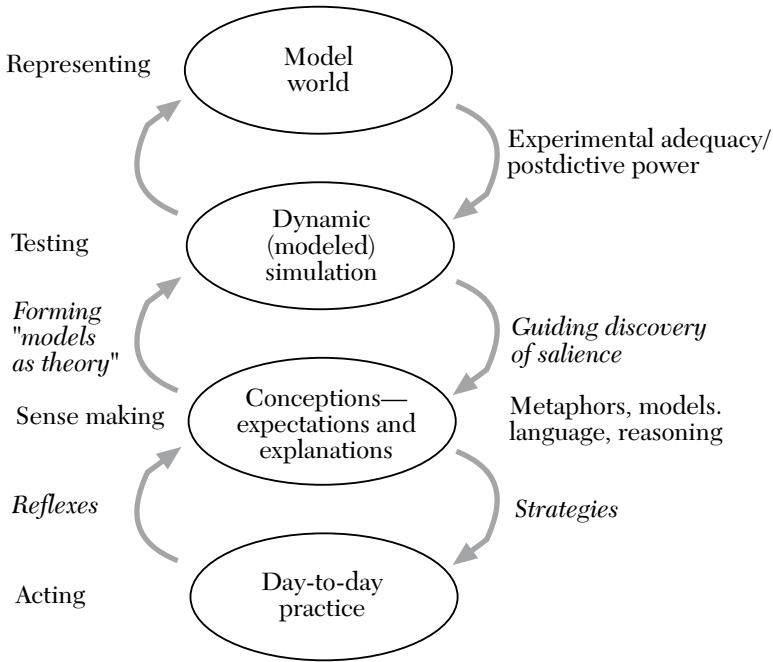


Figure 4 *Model of evolutionary theory building through modeling, insight, and practice*

collected, and the dynamical model refined accordingly for further iterations of the simulation. Any such model would abstract features from the experience of the observers, but its linkage in this process could ground the features in the day-to-day experiences of actors, providing a sense of salience.

We propose to use this simulation with actors (i.e., owners of small firms) as a way of helping them understand and articulate their worlds (i.e., the systems of which they are a part). We conceptualize that such an action will lead to a reconceptualizing of the individual or shared “theory” of the system, which in turn may lead to new strategies or behavior. The degree of utility and resonance that the models have for these actors will act as a test of instrumental reliability. The models themselves can be independently tested for robustness, for example by the use of counterfactual tests (see example below).

*THE ETHICAL CONSIDERATIONS OF THE
PROPOSED METHODS*

This approach has ethical and practical issues associated with it. A particular perspective here emphasizes the utility of research within the human systems domain, particularly focusing on the researcher/client relationship. In small firm research there is the possibility of intervention to the benefit or detriment of the firm, particularly if the researcher appears to be a “credible” source. Being wholly detached/objective is difficult if the work involves working inside the small firm with the owner-manager and/or other members of the company. There is certainly scope for researcher and owner-manager (practitioner) to influence and learn from each other through a positive feedback cycle. This is resonant with Schon’s (1991) notion of “reflective research,” where the researcher uses both observation and intervention to help the practitioner develop insight and capability (“reflection-in-action”). Of course, it is also important that the researcher recognizes when not to intervene and understands the importance of using experimentally valid methods within the research inquiry.

The challenge therefore is to develop a research methodology in the small firm domain that seeks to build productive relationships with owner-managers as clients/practitioners in order to acquire a deep(er) understanding of systemic processes, relationships, and dynamics in small firms. This understanding can then inform the building of improved models, which can lead via testing to better interventions and improved capability in the small firm domain and thus, potentially, “better” (i.e., fitter) small firms.

OPERATIONALIZING THE RESEARCH

The research paradigm suggested here might be interpreted either as a whole methodology, or as a method. From a methodological perspective, the model could help to position and make coherent discrete research activities. As a method, interactive modeling between researcher and small business owner (as decision maker) is relatively novel.

Three examples of the authors’ current research are given below, showing how the metaphors of complexity contribute to the *post hoc* interpretation of present findings (rather than the framing of the original research).

EXAMPLE 1

The longitudinal research with owner-managers described above (Moran, 1998) is intended to explore research questions as detailed in Figure 2 (particularly 6, 7, 9, 10) concerned with the interaction of individual agent (owner-manager) and the business “system.” The research conducted to date has focused on developing insight into the “psychology” of a cohort of owner-managers and linking this to an independent (quasi-performance) measure of “growth orientation” (GO). Thus, relationships can be explored between personal characteristics and orientation toward the business (ontological levels 5 and 6) in such a way that “rules” for adaptation and learning linked to the fitness of the business entity (system) may be derived and tested further. The research is currently entering a “grounding” phase in which actual performance and development of the businesses can be related to the assessments of the individual owner-managers from the initial study. This will help to ascertain the degree of predictive validity of the previous measures and deepen our understanding of the processes of change and the influence of the individual agent on them. This move takes the research to ontological level 3, with a continuing linkage through to levels 5 and 6.

EXAMPLE 2

A study of small firm stakeholder relationships (Lewis and Fuller, 1998) grounded a typology of relationships, through a qualitative analysis of in-depth interviews with about 40 small firms. Some five separate approaches to relationships were identified, which can be used to categorize individual firms in the sample. This work provides insights into the nature of the firms’ responses to changes in the stakeholder environment, in particular to new uses of information and communications technology. As such, it helps to identify reflexivity, which can be conceived as agency (causing change) in a dynamical system. Further ethnographic studies were also carried out to discover whether an owner-manager’s perspective or relationship style was carried through in the whole business. Conceptually, this links level 2 with level 6 in Figure 2, which may itself present a healthy critique for the ontology *per se*.

EXAMPLE 3

In the development of foresight among groups of businesspeople and their stakeholders, it is common to develop scenarios of future possible worlds and to extrapolate from these the nature of business opportunities and innovations. The process involves explicit “soft” modeling of the

landscape, i.e., making assumptions about the interconnections between different actors and the relative strengths of forces and relationships. From the process of describing and constructing these mental landscapes, the actors intuitively create possible strategies and rationale for these. The soft models can be subject to some counterfactual examination of “what ifs” (Fuller, 1999; Carrier *et al.*, 1999).

Each of these examples informs an interpretation from a complexity perspective, but none employs the complete methodology in the sense outlined here. However, these research activities have between them many of the methodological characteristics. For example:

- ◆ Longitudinal and able thus to provide a descriptive sense of change in the case of these businesses and owner-managers (Example 1).
- ◆ An objective assessment of “initial conditions” through the employment of the GO criterion (Example 1).
- ◆ Concerned with the “trajectory” of development and how this is perceived and influenced by key agents in the system (Examples 1, 3).
- ◆ Concerned with the agents’ perspective of the “system” in which they operate and to what extent this perspective influences or guides their “strategy” (adaptive moves) (Examples 1, 2, 3).
- ◆ Attempts to uncover some of the “intrapersonal” influences on the dynamics of small business development and how these inform the owner-manager’s perspectives and actions (Examples 1, 2).

The complexity perspective is important here in introducing a theoretical framework concerning the behavior of agent-based systems that are open, dynamic, evolving, and sufficiently complex to be capable of “emergent” behavior. This framework directs attention to particular aspects of the phenomenon and provides a language for describing what is observed. This language is in terms of dynamical systems and seems to fit intuitively with what we know about small businesses (e.g., they are many, varied, interconnected, and subject to rapid change, including growth, decline, or “death”). The involvement of the human agent (i.e., the owner-manager) entails a concern with “reflexivity” (i.e., conscious intention can be a significant factor in the making of “adaptive moves” and these are not wholly dependent on environmental stimuli). In principle, models can be developed that take account of reflexivity in explaining how particular developments and outcomes occur.

The way in which this research can be developed to further the

methodology is of considerable interest to the authors. The aim would not be to describe the “whole” small business system, but to focus on understanding the dynamics of adaptation, learning, and change at both the individual and business level, and how they interact to produce particular outcomes. The role of adaptive agents (owner-managers) is critical here, as are their connections (relationships) with other adaptive agents within a networked “community.”

The selection of salient modeling features from the process of grounding attributes such as personality types, typologies of rule such as reflexive behavior, actor descriptions, and soft models of the relevant landscapes provide a rich basis for abstraction and modeling and the possibility of scientific approaches to theory testing.

The practical output from this research could be particular “sense-making” tools that could be used by owner-managers themselves or their advisers to understand their situation better and improve their ability to make better adaptive moves. There might also be the opportunity afforded by the building of dynamical models to explore alternative “trajectories” of business growth/development at particular critical junctures in order to aid decision making. The opportunity to test out models/processes via simulation studies might also be explored.

NOTE

The authors gratefully acknowledge the feedback on an earlier draft of this article from participants in the EIASM Workshop on Complexity and Organisation in Brussels, Belgium, June 25–26, 1999.

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Complex Rhetoric and Simple Games

Jeffrey Goldberg and Livia Markóczy

Disorder, unintended consequences of actions, and turbulence followed by calmer periods are part of the everyday experience of individuals in organizations as a consequence of the many small interactions among individuals and organizations. Organizational scholars have long been fascinated by this dynamism and unpredictability and have sought theories capable of capturing these.

Complexity theory and chaos theory now seem to fill the role. They have been presented in scholarly and practitioner-oriented journals as comprising a revolutionary new paradigm (e.g., Johnston, 1996; McKergow, 1996; Brown and Eisenhardt, 1997) that is not only capable of modeling dynamism and unpredictability, but does so while eliminating the perceived evils in social sciences: reductionism, predictability, and the assumption of rational individuals (e.g., Stacey, 1995; McKergow, 1996). In that discussion, the distinction between complexity theory and chaos theory is often blurred. As we comment on the literature that fails to make the necessary distinction, we will use the term “complexity/chaos theory” as a cover term. We will reserve “complexity theory” or “the study of complex systems” and “chaos” or “chaotic systems” or “nonlinear dynamic systems” for things that more closely resemble the notions as they have come from mathematical physics and modeling.

Complexity/chaos theorists pride themselves in drawing from recent scientific developments in physics, biology, and mathematics.

Complexity/chaos theory, however, has also accumulated a rich rhetoric that distorts the picture of what it can do for us. Before we can evaluate complexity/chaos, we need to strip away the rhetoric that surrounds it. Only then can we see how it really contributes.

When we separate chaos from complexity, we will see that most of the actual work in chaos/complexity in management has been with complexity theory (although muddled by some of the rhetoric of chaos) and so we will focus mainly on complexity, but will have something to say about chaos as well.

WHAT PEOPLE SAY COMPLEXITY/CHAOS DOES FOR US

In the management literature, complexity/chaos theory is presented as a theory that, unlike traditional theories, is able to demonstrate how the interaction of agents following simple rules can lead to complicated macroscopic effects in the long run (McKergow, 1996; Levy, 1994).¹ The interaction of the agents is said to follow a nonlinear dynamic, and differences in the initial state of a system lead to different interaction patterns among the agents, which lead to unpredictable, often unintended, consequences on the system level (McKergow, 1996; Stacey, 1995). Unforeseen consequences are assumed to be the result of the existence of both negative and positive feedback loops in the system (Cheng and Van de Ven, 1996; Ginsberg *et al.*, 1996). Negative feedback loops by themselves lead to the stabilization of the system, but the positive feedback loops make the system unpredictable and unbalanced as they amplify the effects of certain interactions (Van de Ven and Poole, 1995). Some management scholars consider organizations to be good candidates for the nonlinear dynamic feedback system described by complexity/chaos theory (Brown and Eisenhardt, 1997; Stacey, 1991; Parker and Stacey, 1994). Stacey (1995: 480–81), for example, writes:

Organizations are clearly feedback systems because every time two humans interact with each other the actions of one person have consequences for the other, leading that other to react in ways that have consequences for the first, requiring in turn a response from the first and so on through time. In this way an action taken by a person in one period of time feeds back to determine, in part at least, the next action of that person ... Furthermore, the feedback loops that people set up when they interact with each other, when they form network, are nonlinear. This is because: the choices of agents in human systems are based on perceptions

which lead to non-proportional over- and under-reaction ... and without doubt small changes often escalate into major outcomes. These are all defining features of nonlinear as opposed to linear systems and, therefore, all human systems are nonlinear feedback networks.

Complexity/chaos theory is often presented as superior to existing theories that are concerned with equilibria (McKergow, 1996; Brown and Eisenhardt, 1997). Interest in equilibrium is often equated with “stability, regularity and predictability” (Stacey, 1995: 477), while complexity/chaos theory is claimed to be able to model systems that “operate far from equilibrium” and are at the “paradoxical states of stability and instability, predictability and unpredictability” (Stacey, 1995: 478). Given the occurrence of both positive and negative feedbacks, a complex system might never reach equilibrium.

Complexity/chaos allegedly has a number properties that are claimed to characterize human systems and interactions. Some of these are listed below. These are discussed in more depth later.

- ◆ *Dynamic feedback* Complex/chaotic systems involve dynamic feedback; both positive (reinforcing) and negative (damping).
- ◆ *Initial state dependence* The butterfly effect that small differences in the initial state of a system can lead to very large differences in the final outcome.
- ◆ *Complex output* Many simple interactions between things following simple “rules” can lead to complicated macroscopic effects in the long run.
- ◆ *Nonlinearity* Nonlinear systems lead to unpredictability.
- ◆ *Antireductionism* Complex/chaotic systems are “holistic.”
- ◆ *Self-reflection* This is often (mis)taken as a synonym for dynamic feedback.
- ◆ *Unstable or no equilibrium* Complex/chaotic systems might never reach an equilibrium, which is why they are thought to be highly suitable to model both stability, and instability, predictability and unpredictability.

THE THEORIES

COMPLEXITY VS CHAOS

Chaos and complexity are often discussed together, but are quite different. There are many characterizations of the differences. Cohen and

Stewart (1994: 2), for example, claim that complexity is about how simple things arise from complex systems, and chaos is about how complex things arise from simple systems.² It is generally true to say that the study of chaos generally involves the study of extremely simple nonlinear systems that lead to extremely complicated behavior, and complexity is generally about the (simple) interactions of many things (often repeated) leading to higher level patterns.

To give an example of a nonlinear dynamical system (which we will come back to later), we will look at one famous and simple system. The discussion here is based on Sigmund's (1993) description. This work is also well described by Gleick (1996: 70–73).

PARABLE 1

Imagine a simple species whose population in one generation depends only on its population in the previous generation in two ways. If there are more potential parents there will be more offspring in the next generation, but if there are too many in one generation they each may not get enough nourishment to reproduce. Also to make things simple, let's set the units that we use for talking about the population so that 1 is the absolute maximum that the particular environment can hold. So, in the i th generation the population x_i depends on the population of the preceding generation x_{i-1} according to some equation. Probably the simplest function that fits the description is an inverted parabola

$$x_i = kx_{i-1}(1 - x_{i-1})$$

where k is some constant.

That equation is very simple, but it is nonlinear (when multiplied out it is $x_i = kx_{i-1} - kx_{i-1}^2$). For some values of k , most starting values for the population, x_0 , will eventually lead to a single point (depending on k and not on x_0). For other values of k , most starting values for the the population will lead to oscillating or cyclical values for the population (and the cycles can be quite long). But for other values of k , starting values for x_0 don't necessarily converge on any repeating cycle and the population fluctuates in a way that is neither cyclical nor random. When this happens, no difference in starting x is so small that it might not make a big difference when a system behaves that way it is chaotic.

Chaos theory as used in biology, physics, and mathematics is about how to recognize, describe, and make meaningful predictions from systems that exhibit that property.

Complexity theory (or the study of complex systems) is really about how a system that is complicated (usually by having many interactions) can lead to surprising patterns when the system is looked at as a whole.

For example, each of the billions of water molecules does its own thing when it joins up with others as it freezes to others, given some constraints on what each of them can do, and something recognizably snowflake shaped can emerge. Complexity theory is about how the interaction of billions of individual entities can lead to something that appears designed or displaying an overall systems-level pattern.

There is actually a relation between complexity and chaos that we have been ignoring, but an actual relation is something we have not seen mentioned in the management literature. Some complex systems with entirely linear interactions between agents can be approximated at the macroscopic level with nonlinear relations. However, the fact that some systems have such a relationship doesn't mean that they all do. The relationship must be justified in each and every case.³

GAME THEORY

There are some excellent introductions to game theory suitable for students of management (e.g., Dixit and Nalebuff, 1991; Gibbons, 1992; McMillan, 1992), as well as others that are better suited to those with some undergraduate training in economics (e.g., Binmore, 1982; Kreps, 1990); there are also shorter introductions, designed for economists, that can help provide an introduction (e.g., Gibbons, 1997). Those are all excellent sources for developing an understanding of game theory.

One difficulty we face here is overcoming some management scholars' preconceptions of game theory. We have seen more than a couple of (unpublished) manuscripts that equated all of game theory with one very particular game, the Prisoner's Dilemma. Game theory is far broader. Basically, there are two kinds of decision (or action) situations involving several agents or decision makers. A situation is *parametric* if the decisions of the agents are independent of each other (although the outcomes may be an effect of interaction), while a situation is *strategic* if the actions or decisions of the agents depend on each other. In a perfect market, setting the price for a product is a parametric decision because no single individual decision can affect the overall market. In a duopoly, price setting is a strategic decision. Game theory is about strategic decision making in this sense. Dixit and Nalebuff (1991) provide a series of cases where game theoretic, or strategic, thinking is important.

A rough typology of games that game theorists talk about is as follows:

- 1 *Static games with complete information* (e.g., one-shot Prisoner's Dilemma, Chicken) These are games where all of the decisions to be

made by all of the players are made simultaneously. However, because players can think about what the other players will think about what they will do, these do—despite the name—involve a certain amount of feedback and self-reflection.

- 2 *Dynamic games with complete information* (e.g., *repeated Prisoner's Dilemma*, *Ultimatum Game*) In these games, players take turns.
- 3 *Static games with incomplete or asymmetric information* These are just like the static games, except that not all players have full knowledge of the parameters of the games, or they have limited (bounded) rationality.
- 4 *Dynamic games with incomplete information* (e.g., “*auctions*” and “*signaling games*”) These are just like the dynamic games except that not all players have full knowledge of the parameters of the games or they have limited (bounded) rationality.

For all of the above there are both cooperative and noncooperative games leading to a typology of eight types of games. Additionally, all of these types can include two-player games, two-player games, or games involving any finite number of players. When we talk about game theory in general, we mean to include the theory that describes all of these types of games, and not just the two-person static games with complete information that are so often used in examples for simplicity.

There is a special kind of game theory, *evolutionary game theory*, which is largely indistinguishable from much of the better work done under the name of complexity. Sigmund (1993) provides a very accessible introduction to some of the concepts of evolutionary game theory (as well as discussing complexity and chaos). Schelling (1978) provides an enjoyable and accessible discussion of some game theoretic problems and solutions that have a very strong “emergent properties” feel to them.

More interestingly, there is also what has become known as *behavioral game theory*, which is described in an outstanding review of the topic by Camerer (1997). Behavioral game theory takes as its agents real humans with their sense of fairness, cognitive limitations, and decision biases. Some of our recent work on understanding cooperation has been in this area (e.g., Goldberg and Markóczy, 1997).

THE COMPARISON GAME

We can most effectively discuss the particular properties attributed to chaos/complexity— and in doing so clarify and demystify them as well as

evaluate their desirability and novelty—by making a comparison with game theory.

SIMILARITIES

Dynamics and feedback

Probably one of the most attractive features of complexity/chaos theory is that it uses a system of dynamic feedback (e.g., Cheng and Van de Ven, 1996; Ginsberg *et al.*, 1996; Van de Ven and Poole, 1995). The value of some variables at any given time is (partially) a function of the values of the same variables at an earlier time. How an organization works today is a function of (among other things) how it worked yesterday.

Game theory may at first appear to lack this dynamism because static games don't involve time. Yet even in static games, game theory, through its recursive awareness, incorporates dynamics. A typical game might first involve reasoning of the form: "I know that she knows that he knows that I know that she knows..." Game theory explicitly provides the tools for managing such a loop and determining (for many cases) what decisions the infinite expansion of such a loop would yield. The self-reflection of even static games gives them a dynamism and a feedback all their own.⁴

The dynamism and feedback of chaos/complexity require iterations over time, and they are often based on trial and error. Sometimes it is the dynamism of the game theoretic type that matters, where trial and error is just too slow or ruled out for other reasons. We provide a somewhat extreme (and grossly simplified) example. See Kavka (1987: Chapter 8) and especially Schelling (1980: Part IV) for discussions that are not so grossly simplified.

PARABLE 2

Roughly speaking, the strategic policy during much of the Cold War between the US and the USSR was based on Mutually Assured Destruction (MAD). If a war were to start, both participants would be devastated. Although there would be an advantage to whoever started first, neither side would have "first strike capability." This made it in the interest of both parties to avoid a war.

Suppose, however, that one side started to develop technology that might make it able to survive such a nuclear exchange (e.g., President Reagan's "Star Wars" proposal). Once a working missile defense system is in place, there is no longer Mutually Assured Destruction. The US might then have first strike capability. When one side has first strike capability, it is in its interest to strike first. It has a strong incentive to strike before the other develops first strike capability in its turn. It is also in the interest

of the side without first strike capability to strike first, since by doing so it can at least reduce the damage it would suffer if the other struck first. Both know this about each other, and so both know that the other knows that they know that it is best to strike first; so the first strike is bound to come soon, so push the button now!

This is not a very healthy situation. And it gets even worse. If one side is *developing* first strike capability, it is in the interest of the other to strike before the missile defense system is deployed. Naturally, since the first side knows this... Furthermore, it doesn't even matter if the defense system isn't technologically feasible. If at least one side believes that the other believes that it believes that it might be feasible, then it is in the interest of both sides to strike first.

What can be done to prevent such an unstable and dangerous situation? The answer is the Antiballistic Missile (ABM) treaty of 1972 (and its predecessors). The ABM treaty paradoxically—but correctly—placed no limit on offensive missiles, but strictly limited the deployment of missile defense systems (and then only to missile bases) to ensure that no side would have first strike capability.⁵

The ABM treaty did not evolve out of many iterations of generations of learning what strategy works best. It had to work the first time (and thankfully it did). The paradoxical treaty that might have saved the world required thinking about feedback loops, and it required thinking about thinking. That is, it involved both feedback and self-reflection. While self-aware actors are able to reach solutions the first time just by thinking about feedback loops, most complexity models require many iterations before the shape of any equilibrium becomes clear.

Even with nominally static games, there can be a sense of dynamism. Game theory also explicitly incorporates dynamic games that include repetitions or turn taking. While we have illustrated a similarity (feedback and dynamics), we have also highlighted a difference (self-reflection), to which we will return later.

Initial state dependence

Many people find an attraction in complexity/chaos theory that it allows very small differences in the initial conditions to lead to very large differences in later outcome (e.g., Johnston, 1996; McKergow, 1996). This, they argue, helps us explain the unpredictability of aggregate outcomes from the interactions among individuals or organizations. The above is often called the *butterfly effect*. A butterfly flapping a wing in Brazil can be the difference that means there is a blizzard two weeks later in New York. McKergow (1996: 722) describes this effect:

There are some attributes which are associated with complex systems. Such systems are self-referential ... They are non-linear, so that a small change can lead to much larger effects in other parts of the system and at other times.

People often associate this feature of complexity/chaos theory with its reliance on nonlinear models and do not consider alternative theories that rely on linear models (e.g., Johnston, 1996; McKergow, 1996). Nonlinearity, however, is neither necessary nor sufficient for one kind of butterfly effect.

An article in *The Economist* (1998) on public misunderstanding of science mentions the butterfly effect:

Reading a book rich with subtle and unfamiliar ideas is a bit like having a custard pie thrown at you: the few bits that stick may not resemble the original very closely. James Gleick's book *Chaos* was clear and well-told, yet many readers came away with little more than the notion that a butterfly flapping its wings in Miami can cause a storm months later in New York. (*Economist*, 1998: 129)

The often discussed cases of standards battles⁶ provide a good example of perfectly linear and simple systems leading to butterfly effects.

PARABLE 3

Imagine a world with two kinds of people, those who produce keyboards and those who type or learn how to type. Let's suppose that a producer of keyboards can produce a "qwerty" keyboard arrangement or a "dvorak" keyboard arrangement. Let's also suppose that all other things being equal, the dvorak arrangement is better for typing.⁷ It is in the typist's interest to learn the system to which most keyboards will be produced, and it is in the manufacturer's interest to produce the kind of keyboard that most people use.

This is a situation with two stable evolutionary equilibria. In one everyone is using or producing dvorak keyboards, and in the other everyone is using or producing qwerty keyboards. If everybody had perfect information and started from a position where there was no prior commitment to either of the two types, all would choose to use and produce dvorak keyboards. However, if there are initially a few consumers who prefer qwerty or manufacturers who overestimate the number of people who prefer qwerty, the less optimal qwerty equilibrium may be reached instead.

In fact, very small differences in the numbers of initial consumers preferring qwerty (or just in the estimate of these numbers from some of the manufacturers) can

lead to one equilibrium being reached instead of the other. Depending on the initial conditions and the amount of imperfection of knowledge in the system, something as small as a butterfly's wing could tip the balance one way or another.

The basic model has only to list people with their preferences. Those preferences can be on a linear, or even ordinal scale. Yet still a small difference in the initial conditions can lead to large differences in the final state. So *nonlinearity is not a necessary condition for the butterfly effect*.

Another example might be a somewhat simplified pool table that can be modeled with linear relations only. Yet small differences in a shot can lead to winning the game or losing.

If we return to the nonlinear dynamical population model discussed earlier, $x_i = kx_{i-1}(1 - x_{i-1})$, we will find that for some values of k , the initial population, x_0 , has no effect on the final outcome. For example, if $k = 3.2$, the population will end up alternating between 0.513 and 0.799 no matter what x_0 was initially picked. This goes to show that *nonlinear dynamic feedback is not a sufficient condition for the butterfly effect*.

The lesson here is that nonlinear dynamics is neither necessary nor sufficient for the small initial differences leading to large differences in output. However, it is commonly thought to be necessary, and it is not accidental that people believe in a special relationship between chaos and the butterfly effect. That is because there is a very peculiar and fascinating type of butterfly effect that is unique to some parts of some nonlinear dynamical systems. If we return to that population model, we can illustrate the special, or chaotic type of butterfly effect. If we set $k = 4.0$, then the initial values for x_0 matter greatly. Not only will small differences in x_0 lead to different results, but *there is no difference so small that it won't make a difference*. But remember that not all nonlinear dynamical systems behave in this way, and those that do, only do so for certain ranges of initial conditions.

The stranger kind of butterfly effect is interesting in its own right, but we do not see that it says anything about the sorts of models that management scholars should or shouldn't be exploring. Since our ability to measure initial conditions is so limited, it hardly matters which sort of butterfly effect is in place. But if we keep our models linear, we can more easily use them to examine what does occur.

Predictability

It appears that some people are attracted to the notion of the weird sort of butterfly effect because they think that it rules out predictions (e.g., McKergow, 1996; Johnston, 1996). Fortunately, they are wrong.

PARABLE 4

The earth, the moon and the sun form a nonlinear dynamical system in exactly the way that leads to the weird sort of butterfly effect. No matter how precisely we measured the mass and velocities of the earth, moon, and sun (short of truly perfect measures, which are impossible), we could not predict their ultimate positions in the far future. We are not able to say when moonrise will be in London one million years from today. But we still can predict quite accurately when it will be a few years from today based on today's measures.

The unpredictability that is inherent in some nonlinear dynamic models may take time to settle in. One cannot simply declare a model useless for predication without making some calculation of how long it takes it to diverge. Predictions of moonrise, tides, and the weather all rely on nonlinear dynamical models, and they do get it right most of the time.⁸

Furthermore, even the behavior of a system that becomes chaotic very quickly is “constrained” in a way that does allow for some interesting and useful predictions. Chaos theory allows us to make predictions about systems that may at first appear random, but can, in fact, be described by simple models.

Determinism

Along with unpredictability, many of those looking at complexity/chaos (and particularly chaos) claim that these systems are nondeterministic. Usually that claim is bolstered by pointing out the butterfly effect and problems of predictability. Chaos does have something interesting to say about determinism, but it is quite the opposite of how some people have taken it. Chaotic systems are deterministic. If we go back to May's example in Parable 1, the equation is entirely deterministic. The state of the system at one stage is completely and entirely determined by the state at a previous time. These are deterministic systems, based on deterministic equations. What is interesting about chaos is that it shows how *apparently random behavior can be described by completely deterministic systems*. One of the founding papers in the chaos literature is entitled “Deterministic nonperiodic flow” (Lorenz, 1963). Gleick's account of that work includes:

His colleagues were astonished that Lorenz had mimicked both aperiodicity and sensitive dependence on initial conditions in his toy version of the weather: twelve equations, calculated over and over again with ruthless mechanical efficiency. How could such richness, such unpredictability—such chaos—arise from a simple deterministic system? (Gleick, 1996: 23)

The FAQ (list of answers to “frequently asked questions”) for the internet newsgroup news:sci.nonlinear also makes it clear that these systems are deterministic:

Dynamical systems are “deterministic” if there is a unique consequent to every state, and “stochastic” or “random” if there is more than one consequent chosen from some probability distribution (the “perfect” coin toss has two consequents with equal probability for each initial state). Most of nonlinear science—and everything in this FAQ—deals with deterministic systems. (Meiss, 1998: §2.9)

A very useful essay on chaos and complexity for management also correctly points this out:

Chaos theory models are deterministic and simple, usually involving fewer than five evolution equations ... That is, system behavior can be described using few equations that include no stochastic inputs. These two features highlight one of the least intuitive aspects of chaos theory: complex ... outcomes can be generated using very simple deterministic equations. (Johnson and Burton, 1994: 321)

What attracts attention is not that these systems aren’t deterministic (they are), but instead that these deterministic systems behave in ways that superficially resemble some nondeterministic systems.

If everything there is to know is known about the initial state of a system, then it is in principle possible to predict later states with perfect precision, assuming perfect computation. But it is not possible to know everything there is to know about a system, nor is it practical to compute things with perfect precision. These practical limits on determinism have been known for centuries, and are not new discoveries at all.⁹

Complex output

One of the appeals of the complexity approach is its ability to generate surprising (or at least nontrivial) macroscopic effects from the iterated interactions of many microscopic agents (Brown and Eisenhardt, 1997). Often complex structures (from which the approach derives its name) are visible at the macro level. These structures appear to emerge from the lower-level interactions.

This emergent complexity is fascinating. But is it new or unique to the new paradigm of complexity? No, it is old hat. In the natural sciences, the

laws of gases, black body radiation, the shapes of galaxies are all old examples. Economists have been looking at exactly these sorts of emergent phenomena. Game theorists have delighted in showing how some very simple games can lead to very complex-looking behavior. Game theorist Schelling (1978) has a delightful book that lists many such examples, from the way that an auditorium can fill up to the pattern of people switching on headlights as it gets darker.

Equilibria

Some claim that game theory and complexity theory deal with equilibria in very different ways:

Even the most complex game theoretic models, however, are only considered useful if they predict an equilibrium outcome. By contrast, chaotic systems do not reach a stable equilibrium; indeed they can never pass through the same exact state more than once. (Levy, 1994: 170)

But contrary to popular belief, game theory, complexity theory, and chaos theory say more or less the same about equilibria. There are some differences, but those differences don't matter a great deal in light of the similarities. First, however, it is crucial to clarify a few concepts.

An equilibrium can have any degree of stability. Some equilibria are very unstable (see Figure 1a), others can be very stable (Figure 1b), while yet others can be moderately unstable (Figure 1c). A very small amount of noise or turbulence can take a system out of an unstable equilibrium; only a large disruption or shock will take a system out of a very stable equilibrium, and a moderate disruption can take a system out of a moderately stable equilibrium. What is important to note here is that all of the theories under consideration share this. Some games can have moderately stable equilibria; some complex systems can have moderately stable equilibria; some nonlinear dynamic systems can have moderately stable equilibria.

Another point in which the perspectives don't disagree is that all allow for multiple equilibria. Some games will have multiple equilibria; some complex systems will have multiple equilibria; some nonlinear dynamic systems will have multiple equilibria. These multiple equilibria will each have their own degree of stability. The tender trap discussed above has three equilibria, two of which are evolutionarily stable (Figure 1d).

A third point of agreement is that each of these theories allow for systems that have no equilibrium. While it is true that the simplest kinds of

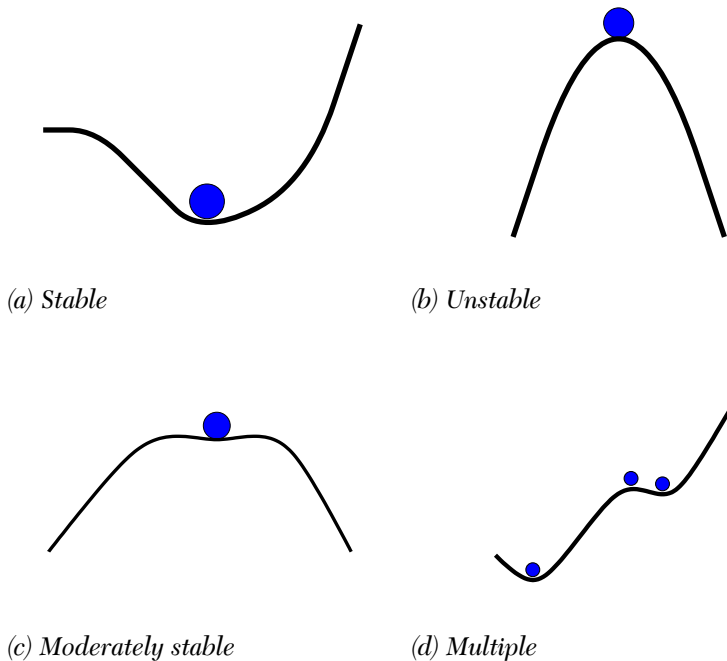


Figure 1 Types of static equilibria

games (two-player complete information static games) are guaranteed to have at least one equilibrium, that does not always hold of other types of games (e.g., the “Dollar auction” has no equilibrium; Poundstone, 1992). Moreover, even for these simplest types of games, the equilibrium might involve a “mixed strategy” that behaves probabilistically (e.g., with a rule like “pick action A with 70 percent probability”).

A fourth similarity is that all of these views accommodate dynamic equilibria. A system can be in a *cyclical equilibrium* if it goes from, say, state s_i to state s_j and eventually back to s_i . So if it ever gets into one of the states in that cycle it will cycle around forever if the equilibrium is sufficiently stable.

Nonlinear dynamic systems can, uniquely, have a type of equilibrium called a *strange attractor*, which resembles a cyclical equilibrium with the important exception that the system doesn’t actually ever repeat itself. As the system goes from state to state it stays (depending on how stable the attractor is) within a set of possible states. So, while a particular path or state is unpredictable, the set of states to which the system can go is not arbitrary and can be predicted.¹⁰ In addition to the strange attractor,

which is unique to nonlinear dynamical systems, there are two differences in the ways that equilibria are dealt with. The first difference is that most of the people who are involved with game theory think that it is worthwhile to calculate the equilibria of a system and show how stable those equilibria are if they exist; many people involved in complexity theory think that it is not worthwhile to calculate the equilibria, but instead that it is best to run computer simulations until the system arrives at a reasonably stable equilibrium. Note that this is not an actual difference in the theories, but a difference in the people who use them. One can take identical models and either calculate the equilibria or run simulations or both.

There are some advantages to both methods. In calculating equilibria, if it is done correctly, one knows that all of them have been found, while with the computer simulation, you only know that one reasonably stable one has been found, but may miss others.¹¹ Additionally, other properties of the equilibria can be made clearer through a game theoretic analysis that may not be available through a simulation. The advantage of a simulation is that it is easier. Sometimes the model is so complicated that it is extremely difficult to do anything else; at other times it can be an aid to the calculation, since the simulation can often tell us what one equilibrium is.

Robert Axelrod, an important and clear-thinking developer of complexity, describes complexity simulations (“agent-based modeling” in his terms) extremely modestly:

Agent-based modeling is a third way of doing science. Like deduction, it starts with a set of explicit assumptions. But unlike deduction, it does not prove theorems. Instead, an agent-based model generates simulated data that can be analyzed inductively. Unlike typical induction, however, the simulated data come from a rigorously specified set of rules rather than direct measurement of the real world. Whereas the purpose of induction is to find patterns in data and that of deduction is to find consequences of assumptions, the purpose of agent-based modeling is to aid intuition. (Axelrod, 1997: 4–5)

Axelrod may be being a bit too hard on the approach he is advocating, in that if he is correct it abandons the best of deduction (theorem proving) and the best of induction (inference from the real world) and combines what remains in a technique for aiding intuition. However, the use of explicit models is what makes this approach more valuable than many other means of aiding intuition.¹²

Returning to the one new factor in complexity/chaos with regard to equilibria—strange attractors—we have yet to see how this particular entity is useful for the study of social sciences, however.

Path dependence: You can't get there from here

Any one of the types of systems might have several (or no) equilibria. Some equilibria might be stable, but without there being a path from some particular state to that equilibrium. This property is not unique to chaos/complexity, but arises in some of the relatively simple games discussed by game theorists. The tender trap with partial information is one of these. Once you get stuck with one standard, it is difficult to move to a more desirable equilibrium because the intermediate steps are unavailable (see also Figure 1d). So, again, complexity/chaos offers us nothing new here, except that it may have served to introduce people to these concepts if they were unfamiliar with them.

DIFFERENCES

Linearity

As we have suggested above, the attractiveness of nonlinearity seems to be the desire to produce models that exhibit the butterfly effect. We have already argued that nonlinearity is neither necessary nor sufficient to achieve the simple form of this effect. Furthermore, it is not enough to show that nonlinearity exists in the world to add it to a model; this complication must be individually and specifically motivated. Its proponents must show that it is necessary to get a useful model. People promoting something that makes models so much harder to handle need to do two things:

- ◆ They need to provide good theoretical reasons for the basic nonlinear equations they wish to add. Plausibility arguments for those equations are not enough if one can also provide a plausibility argument for a linear alternative.
- ◆ They must show that after their modification from linear to nonlinear they can achieve some solid result that would not otherwise be available.

We don't feel that even the first of these has been done for the case of nonlinearity in the social sciences, much less the second. The situation has not changed since Elster (1989: 3) made this point:

I am not sure, however, that [nonlinearity] is the right direction in which to look for sources of unpredictability [in the social sciences]. The nonlinear difference or differential equations that generate chaos rarely have good microfoundational credentials. The fact that the analyst's model implies a chaotic regime is of little interest if there are no prior theoretical reasons to believe in the model in the first place. If, in addition, one implication of the theory is that it cannot be econometrically tested there are no posterior reasons to take it seriously either.

To our knowledge, there have only been two arguments in the management literature for introducing nonlinear equations into models. One is that nonlinear dynamic systems involve both positive and negative feedback loops (e.g., Cheng and Van de Ven, 1996; McKergow, 1996). People correctly want models with feedback loops and seem to think that if there are feedback loops there must be a nonlinear dynamical system. In some unpublished manuscripts we have seen, authors have explicitly insisted on nonlinearity for the sake of feedback loops, and yet gone on to work with models that are entirely linear.

The other reason that is given to motivate nonlinearity is unpredictability (McKergow, 1996). We have argued that nonlinearity is neither necessary nor sufficient for unpredictability. Even if it were, it could only be used as a motivation for the existence, somewhere in the interactions, of nonlinearity. It cannot be used to motivate a particular nonlinear interaction that must be either theoretically or empirically motivated.

The better studies (Richards, 1990; Cheng and Van de Ven, 1996), which actually looked for and found the very specific sort of unpredictability that comes with some parts of some nonlinear dynamical systems, did so by filtering out every linear relationship available from the data. Once all linearity was filtered out, all that could remain were true randomness and nonlinear variation. The researchers found that there was a nonrandom nonlinear-type component to the variation. But it must be recalled that this was done after filtering out all linearity. If you filter out everything except for what you are looking for, then no matter how small the object of your search turns out to be you will find it. Furthermore, we have no reason to believe that the nonlinearity is a fact about the system under observation. Like the randomness, it could have been introduced at any stage in the process from data collection onward. These are interesting studies, but until some difficult follow-up work is done, the best that can be concluded is that some of the apparent randomness in the data analyzed may be the result of simple interactions. A

prior “critique” of the approach used by these better studies is given by Johnson and Burton (1994), and readers are referred there for discussion of the applicability of chaos to the study of management in those cases where the chaos theory is used with understanding.

Self-reflexivity

In the standard complexity examples that have been used, agents are simple-minded entities that follow simple-minded rules. In game theory, agents can anticipate the future and the consequences of their actions and the actions of others. To ignore the ability to reflect may be ignoring exactly the sorts of factors that make human systems interesting. Systems without the ability to reflect or anticipate may be extremely interesting, for after all evolution cannot look to the future. However, evolution can build agents that do look into the future. When we talk about human systems, it seems reasonable to leave open the possibility, as game theory does, that the agents think about their situation and what they are doing.

Game theory, like complexity theory, works on the interactions between fairly simple and abstract agents. The core ontologies of both theories are very simple. In fact, the only real difference in the ontologies of the theories is that in game theory agents can make conscious decisions aware, to some extent, of their own predicament and that of others.

Is it important to consider the reasoning of self and others in interaction when trying to model system with many interactions?

PARABLE 5

Suppose that you and someone else (let's call her Alice) are to meet at 12 noon on a particular day on Manhattan Island, but you forgot to arrange a meeting place. Neither of you lives there or has an office on the island. Neither of you carries a mobile phone. Where would you go?

Before reading what studies show the most common answer to be, you should stop and think about the options yourself. Write down an ordered list of locations.

In a series of studies of questions like this (Schelling, 1980), it appears that the overwhelming first choice is Grand Central Station. While an impressive piece of architecture, it is not really many people's favorite place to wait for other people. Very few of us would actually arrange to meet someone there, but it is where we would go when the meeting place wasn't arranged. When you thought about this problem, you must have thought about what Alice would think about what you thought. That is reflection on others reflecting on your own state of mind.

By self-reflection, humans are able to exclude early on some highly unlikely options from their decisions and substantially reduce the number of possible outcomes. But the agents described by complexity/chaos theory would just move all around New York and the chance that they would meet be very small indeed. Self-reflection and reflection on others clearly play an important role in this example, reducing the set of possible outcomes by excluding highly unlikely options.

Some might argue, however, that although in certain situations self-reflection might be necessary, most organizational activities are routine and do not require self-awareness and foresight. Some people might feel that they are “just a cog in a wheel of a big machine,” but even that makes them profoundly different from a cog in a wheel of a big machine. Real cogs in real wheels never think of themselves as such.

Even where an organization is designed to minimize its members’ understanding of it, people will try to figure out what their place is, as the following example suggests.

PARABLE 6

Bletchley Park (BP) was the site of UK code-breaking activities during the Second World War. At various times it employed more than 12,000 people. The code breaking (and particularly its substantial successes) had to be kept strictly secret. To a very large extent, BP was an information-processing center. Some of the steps in processing the information involved people, and some involved machines. It seems that here is the perfect setting to have people act as mindless agents playing their small part and not thinking about the whole picture or even where they fit in.

While this may have been more true of BP than of any other organization, it appears that it didn’t work that way. Reports from people who worked there indicate that while they were not really supposed to know what was going on outside of their own narrow activities, they did have a sense of what was going on. In fact, it appears that in order to maintain commitment, people were even deliberately shown where their work fitted in. The operators of the Turing bombes performed “soul-destroying but vital work on the monster deciphering machines” (Payne, 1993: 132) used in some steps of Enigma decoding. The operators were specifically taken to the British Tabulating Machine Company at Letchworth “to watch [the machines] being made and to encourage the workers, although we thought their conditions were better than ours. It was a surprise to see the large number of machines in production” (Payne, 1993: 135). Apparently it was felt that various people needed to see other bits of the operation (or at least some of the other people involved) to be encouraged. Also for the operators to have been surprised by the number of machines being built, they must have had a sense (even if incorrect) of the scale of the whole operation.

The Bletchley Park example illustrates that even where it might appear to be good (and possible through secrecy regulations) for an organization to have people unaware of the big picture and their place in it, people in organizations just aren't that way. Awareness is ever present.

There will, of course, be some models in which individual decision rules can be simple and mindless instead of complicated and mindful. Game theory, and in particular evolutionary game theory, has exactly the ability to model simple agents where that is called for. Game theory, however, is uniquely positioned to model mindfulness and self-awareness in decision making and the systems that emerge from that in the many cases where it is appropriate.

The epitome of reductionism

It appears that one of the appeals of complexity/chaos is that it somehow rejects reductionism:

These results [of complexity] are rather counter-intuitive to those of us brought up on the reductionist assumption that knowing all about the parts will enable us to understand the whole. In complex systems the whole shows behaviors which cannot be gleaned by examining the parts alone. (McKergow, 1996: 722)

One widely distributed version of the call for papers for a special issue on complexity for the journal *Organization Science* stated:

Complexity theorists share a dissatisfaction with the “reductionist” science of the past, and a belief in the power of mathematics and computer modeling to transcend the limits of conventional science.

Unfortunately for those who seek antireductionism in complexity/chaos, it just isn't there in any interesting sense. But without digressing too far, we do need to clarify what is actually meant by “reductionism.” Richard Dawkins (1986: 13) has described the use of the word well:

If you read trendy intellectual magazines, you may have noticed that “reductionism” is one of those things, like sin, that is only mentioned by people who are against it. To call oneself a reductionist will sound, in some circles, a little like admitting to eating babies. But, just as nobody actually eats babies, so nobody is really a reductionist in any sense worth being against. The nonexistent reductionist—the sort that everybody is

against, but who exists only in their imaginations—tries to explain complicated things directly in terms of the *smallest* parts, even, in some extreme versions of the myth, as the *sum* of the parts! [emphasis in original]

Elaborating on Dawkins and also on Dennett (1995: 80–83), we distinguish among three uses of the word “reductionism” as either a philosophy or a pejorative:

Type I Reductionism is the belief that one can offer an explanation of phenomena in terms of simpler entities or things already explained *and the interactions between them*.

Type II A system or theory is reductionist if the components are additive, but there are no interactions between the parts.

Type III A theory or explanation is reductionist if it seeks to explain macro-level phenomena directly in terms of the most basic elements without recourse to intermediate levels.

In much of our discussion of reductionism, we are following Dennett (1995: 80–83). We agree with Dennett that reductionism Type I is a good thing. Any theory or explanation that is not reductionistic in that sense is simply question begging or mystical. An explanation that is not in terms of simpler things or things already explained and the interactions between them fails to be an explanation.

Reductionism Type II is simply not very interesting. While there are some systems that are reductionistic in that sense and many more that aren't, it does not present any interesting or disputed boundary between different ways of investigating the world. By this type of definition an analysis that uses linear regression would be reductionist, while one that uses ANOVA would be nonreductionist. We suspect that this notion of reductionism is little more than a straw man. Neither game theory, complexity theory, nor chaos is reductionist in this sense. They all deal with interactions.

Reductionism Type III is what Dennett (1995: 82) calls “greedy reductionism.” It is the attempt to explain things without recourse to intermediate levels. A meteorologist who tried to explain the weather directly in terms of the motions of billions of molecules instead of talking about the intermediate levels of air masses, humidity, and the like might be guilty of greedy reductionism. A slightly less pejorative term for this might be “eliminative reductionism.”

In the rest of this discussion we will ignore the straw man of reductionism Type II and just consider the two other types.

Here we do need to examine chaos and complexity separately. First, we will look at the easy case: chaos. Before developments in chaos theory, certain nonlinear systems were simply not studied because they were too hard. Chaos theory has allowed researchers to make some sorts of predictions about the attractors and equilibria of these difficult systems. Chaos does not represent a retreat from the domain of Newtonian determinism, but an advance. It does not say that there are fewer things that we can talk about and make predictions about; instead, it gives us tools to talk about things that previously were too difficult to consider. Chaos theory expands the domain of reductionist (Type I) analysis:

When one observes collective behavior that exhibits instability over slight variations one typically assumes that an explanation must be equally complex. Traditionally, one expects simple behavioral outcomes from simple processes, and complex outcomes from complex processes. However, recent developments in chaotic dynamics show that a *simple deterministic system* [emphasis added] that is nonlinear can produce extremely complex and varied outcomes over time. (Richards, 1990: 219)

Chaos, then, is about finding simple underlying models for complicated phenomena. It expands the domain of what can be explained by simple models.

What about complexity? One contrast between game theory and complexity theory is that the latter usually relies on very simple agents with no self-reflection, as discussed earlier. Game theory allows for more sophisticated agents. Complexity is very specifically about generating macroscopic-level phenomena directly in terms of the many interactions of simple parts, often with little concern for developing theories about intermediate constructs. Clearly, complexity is more reductionistic in the sense of Type III. It appears that Dawkins may have been mistaken when he said that nobody really is reductionistic in the sense of trying “to explain complicated things *directly* in terms of the *smallest* parts” (Dawkins, 1986: 13); complexity theorists may be real examples of Type III reductionists!

Anyone who seeks antireductionism in chaos or complexity is bound to be disappointed. For us, however, their reductionism is appealing.

CONCLUSION

Our critique of complexity/chaos has been concerned with the rhetoric and with incorrect claims about what they entail. Once the rhetoric has

been removed and the real tools are seen for what they are, we see true value in applying them to the study of management. Using complexity/chaos means constructing explicit models of the systems in question. In another domain, theoretical biology, Maynard Smith (1989) describes the utility of formal models (as opposed to what Saloner (1991: 127) calls the “boxes-and-arrows variety”):

There are two reasons why simple mathematical models are helpful in answering such questions. First, in constructing such a model, you are forced to make your assumptions explicit—or, at the very least, it is possible for others to discover what you assumed, even if you are not aware of it. Second, you can find out what is the simplest set of assumptions that will give rise to the phenomenon that you are trying to explain.

Saloner (1991) points out additional benefits of formal models, including that they can be built on and that they can lead to novel insights through surprising results.

We suspect, however, that many management scholars who currently find complexity/chaos appealing will find it less appealing, and even distasteful, if we do manage to persuade them that complexity/chaos is not a challenge to traditional science, but instead constitutes analytical tools allowing traditional science and modeling to be extended to domains that were previously too difficult.

If the explicit modeling of complexity is removed, it is disturbing to imagine what will actually remain.

FEAR OF GAMES

It may seem puzzling that a field is willing to embrace complexity theory and makes little use of its near equivalent, game theory. We have neither the data nor the space to provide a detailed argument as to why this discrepancy exists, but that won't prevent us from engaging in some brief speculation.

The expanding domain of economics

Many social sciences are under “threat” from the expansion of the economists’ way of thinking and analysis into their domains. While the expansion has been going on for a while, it has been described explicitly by Hirshleifer (1985). At a recent workshop (ELSE, 1997) on the evolution of utility functions involving economists, biologists, some cognitive psychologists and anthropologists, and three management scholars,

economist John Hey expressed some disappointment. He had expected to learn some methods and perspectives from the biologists, but instead discovered that they were just doing some (dated) economics.

Fear of this expansion can lead to management scholars trying to build walls around their domain by exaggerating the differences, which “incites a level of fear” (Hesterley and Zenger, 1993: 497). This would include demonizing the encroaching forces. Markóczy and Goldberg (1997: 409) argue that management scholars should be doing exactly the opposite:

We will have to learn how to enter into dialogue with scholars from other social sciences. Even if we ultimately reject the assumptions and approaches of those fields, we need to understand why those approaches are attractive to other scholars instead of merely searching for ways to dismiss them quickly.

This will be a difficult transition and it will meet with much internal resistance. But it is necessary. As soon as this interdisciplinary group extends their study of cooperation to organizations, they will develop theories of organizations and behavior within them which will be attractive to anthropologists, biologists, cognitive scientists, economists, philosophers, and psychologists. As they are making great gains in discovering the nature of cooperation, management scholars ought to be working with them.

We believe that a renewed interest among management scholars in modeling human systems provides a step toward that interdisciplinary integration. Those who resist the encroachment of economics (or fields that have adopted many of their methods) will be reluctant to build explicit models, or will try to call them by other names when they do.

The snake swallows its own tail

Everyone loves a self-referential paradox: a rule or a system that turns in on itself or proves its own impossibility. If that system is thought to be cold, cruel, an authority, and a power, then it is even better if it contains the seeds of its own destruction. Those who maintain this view of traditional science will naturally delight in the claims of complexity/chaos.

From a theoretical perspective, chaos theory is congruous with the post-modern paradigm, which questions deterministic positivism as it acknowledges the complexity and diversity of experience. (Levy, 1994: 168)

We accept neither their view of science nor those claims of complexity/chaos. Chaos and complexity do not pose a serious challenge to science and prediction; and science has always been concerned with the interactions of parts.

Abuse of science

Some of the attraction of (mis)using chaos and complexity theory in the study of management has little to do with particular details of the theories, but may be part of a broader pattern of abuse of physical and mathematical sciences in the humanities and social sciences. Sokal and Bricmont (1998: 4) describe that sort of abuse and make an attempt at defining it:

The word “abuse” here denotes one or more of the following characteristics:

- 1 Holding forth at length on scientific theories about which one has, at best, an exceedingly hazy idea. The most common tactic is to use scientific (or pseudo-scientific) terminology without bothering much about what the words actually *mean*.
- 2 Importing concepts from the natural sciences into the humanities or social sciences without giving the slightest conceptual or empirical justification. If a biologist wanted to apply, in her research, elementary notions of mathematical topology, set theory or differential geometry, she would be asked to give some explanation. A vague analogy would not be taken very seriously by her colleagues...
- 3 Displaying a superficial erudition by shamelessly throwing around technical terms in a context where they are completely irrelevant. The goal is, no doubt, to impress and, above all, to intimidate the non-scientific reader...
- 4 Manipulating phrases and sentences that are, in fact, meaningless. Some of these authors exhibit a veritable intoxication with words, combined with a superb indifference to their meaning.

While Sokal and Bricmont (1998) were largely discussing other abuses, they do include a chapter (Chapter 7) on “chaos theory and ‘postmodern science,’” which covers some of the same material and misunderstandings we discuss above.

Rational concerns

Some of the objections that are occasionally raised in relation to game theory are that it requires absurd assumptions of rationality. This simply isn't true. The introductory exercises and examples given usually do

involve very strong rationality assumptions, but once one understands how to use game theory, it is possible to relax those assumptions substantially (Camerer, 1991). Evolutionary game theory involves agents, such as bees and trees, with exceedingly limited rationality; and behavioral game theory specifically seeks to work with agents that have empirically verified types of human rationality (Camerer, 1997).

*IT'S NOT WHETHER YOU WIN OR LOSE
BUT HOW YOU LAY THE BLAME*

In looking at some of the literature on chaos/complexity we find misleading and incorrect statements. But we also find that many of those arise not from the misinterpretations of management scholars, but from the popularizations of complexity/chaos itself. When complexity proponents make statements suggesting a radical new paradigm for all sciences including the social sciences, it is no wonder that some of those in search of a radical new paradigm will follow.

Some complexity workers very strongly exaggerate the difference between what they do and what evolutionary game theorists do. At a seminar organized by the Research Centre for Economic Learning and Social Evolution (March, 1997), John Holland argued forcefully that the model he presented could not be treated game theoretically because "the rules changed." However, a superficial glance at his model showed that what he called "rules" map into what game theory calls "strategies," which can and do change.

In other cases, popularizers have been more careful, but have still left areas open for misunderstanding. For example, most of the discussion by Gleick (1996) treats the issues of determinism and nondeterminism correctly. However, Gleick does indeed quote people whose statements do suggest that chaos overturns determinism. He does not appear to notice the contradiction and takes no corrective action. People seeking a radical challenge to traditional science will pick up on those few quotes and entirely ignore most of the rest of the book's insistence that those systems are deterministic.

It is natural for any stream of research to overstate the differences between it and its rivals, but it is also the responsibility of the rest of the academic community to look through the rhetoric and examine the real claims and identify what is of real value. We hope we have helped fulfill that responsibility.

To add one more paradox to this article, we note that our challenge to complexity and chaos as reported in the management literature is par-

tially motivated by our sympathy with chaos and some parts of complexity in general. The benefits to fields outside of the social sciences of the study of nonlinear dynamical systems are too numerous to mention. Some of the best work in complexity (e.g., Axelrod, 1997; Sigmund, 1993; Schelling, 1978) eschews the worst of the rhetoric and has helped raise the awareness of what can be reached with very simple agents. It is our appreciation of the better parts of this work that drives us to discourage management scholars from using misunderstood slogans from these fields and to encourage people to show these areas due respect by either really learning about them or remaining silent.

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Dynamic Strategies: Emergent Journeys

Janice A. Black and Gerard Farias

Many business environments today can be described as chaotic or complex systems characterized by nonlinearity, aperiodicity, and unpredictability (Johnson and Burton, 1994; D'Aveni, 1994; Ilinitch, D'Aveni, and Lewin, 1996). However, much of our current understanding of business strategy arises from traditional economic models that are largely linear, periodic, and predictable (Peteraf, 1993). These models assume that marketplaces move toward equilibrium, unless barriers to competition (i.e., imperfect information) make supranormal returns possible (Peteraf, 1993). Beyond barriers restricting movement toward equilibrium, there are also events of discontinuous change (Nadler and Tushman, 1995) that often move the market toward higher dynamism and complexity (D'Aveni, 1994; Ilinitch *et al.*, 1996). Such movement away from equilibrium is not rare.

Strategy researchers began to seek dynamic strategies that would be able to incorporate conditions of nonlinearity, ambiguity, and uncertainty in the 1970s (Cohen, March, and Olsen, 1972; Mintzberg, 1979) and recently have attacked problems associated with complex dynamic systems (Liebeskind *et al.*, 1996; Hanssen-Bauer Snow, Smith, and Zeithaml, 1996). Still, many important research issues are only now being articulated. The lack of a well-defined conceptual framework that can explain the simultaneous presence of both equilibria-oriented markets and attendant strategies, as well as disequilibria-oriented markets and strategies, is one such issue.

This article utilizes the theoretical bases of disequilibrium-based Austrian economic theory (Scarath, 1988; Jacobsen, 1997, Stacey, 1995; Young, 1995; Smith and Grim, 1996) and complexity theory (Senge, 1990; Wheatley, 1992; Waldorf, 1992; Stacey, 1995; McKelvey, 1997). Both of these theoretical bases propose movement between structured and unstructured states (Stacey, 1995; Young, 1995). We propose to link the information processing and organization design literature with Austrian economics and, by utilizing complexity theory, create a model that explains the simultaneous presence of both equilibrium and disequilibrium characteristics in marketplaces.

*LITERATURE REVIEW:
THE AUSTRIAN SCHOOL OF ECONOMICS*

Several authors have presented basic premises of Austrian economics to management researchers (Jacobsen, 1992; Young, 1995; Stacey, 1994; Hunt, 1995; McWilliams and Smart, 1995). This school of economics assumes that causal links are nonlinear and that relative firm performance is only partially the outcome of plans and managerial intentions—making specific predictions of outcomes problematic. Such assumptions mirror market realities and allow us to explore market complexity and hyper-competition as something other than aberrations (Stacey, 1995; Young *et al.*, 1996).

While traditional economics assumes that changes in market structure are exogenous to the model, the process of structural change in markets is integral to the Austrian economic model (Young, 1995; Kirzner, 1979; Hayek, 1945, among others). The market order or structure is the by-product of each entrepreneur's actions (Mises, 1949; Kirzner, 1979). For instance, imperfect information is an example of "market failure" in traditional economic analysis, whereas imperfect information flows are a core process characteristic in the Austrian view. For our purposes, an entrepreneur can represent either an individual or a collective of individuals who make market interaction choices (i.e., a firm). Our definitions of market-structuring actions include the identification of opportunities and linkages of the main elements in the market supply or value chain (i.e., input or supply choices, production choices, customer choices, etc.; see Lawler, 1996, among others).

While the overall order emerges from all actions taken, following both Kirzner (1982) and Lachmann (1978), we have found it useful to focus on two types of entrepreneurial actions: structuring and refining.

Structuring actions relate to setting boundaries for what it means to compete in a particular industry or market. Refining actions pinpoint the most effective and efficient ways to operate in that newly defined or redefined market. First and early movers in a market therefore create structure in that market and in the process set standards. Followers, attracted by the high returns, follow the beaten path and adopt the structure and standards set. Note that the structuring process may involve a completely new marketplace (a new product or service) or redefine an existing marketplace. For example, Amazon.com pioneered a restructuring of the already existing retail book market. Barnesandnoble.com and others have adopted this structure.

One recent observation is that many markets have not wound down to a stable equilibrium but have rather kicked into a “hyper” phase (D’Aveni, 1994; special issue of *Organization Science*, 1997). The Austrian economics perspective allows for this type of market change to occur as the direct result of the competitive actions taken by firms within the marketplace. For example, a hypercompetitive shift can occur when a change in technology makes the industry more dynamically resourceful (i.e., able to produce new strategic assets; Thomas, 1996). Alternatively, such a shift may occur when the economic acts in the focal marketplace increase in number and rate to an information overload stage (Black and Farias, 1996). In information overload, ambiguity in the marketplace increases and its boundaries become indeterminable. Disequilibria conditions again exist, but the increased ambiguity is a result of a complex market system problem (hypercompetition or information overload), rather than a simple market system problem (lack of market structure). The market has moved from one patterned period into a “chaotic” session where opportunities for redefinition abound. When new patterns emerge, they may be different in specifics but will be recognizable.

It is not only the market structure or lack thereof that provides the potential for rent creation. Austrian economics supports the idea that efforts to refine or shape market structure and/or market interactions are also potential sources of rent creation (Coyne and Subramaniam, 1996). From this perspective, a state of equilibrium is not the main characteristic of the marketplace. Rather, markets are characterized by a series of disequilibria that, as this fitting dynamic occurs and information is shared, move closer to states of equilibria (Kirzner, 1982), unless the earlier mentioned shift to hypercompetition occurs (D’Aveni, 1994).

The term “complexity” is not new to the management literature. Senge (1990) distinguishes between detail complexity and dynamic complexity. Most of the literature focuses on detail complexity, which essentially is concerned with the number of variables: the more the number of variables, the more complex the problem. However, a complex system is not the same thing as a complicated system (Devaney, 1993). A complicated system meets Senge’s definition of detail complexity and is one with many parts and subparts with a wide range of linear relationships. It can look very intricate, but it has a static pattern. Dynamic complexity refers to the nonlinearity and low predictability in a system.

Dynamic nonlinear systems are being addressed by a number of system researchers (Lichtenstein, 1998a, 1998b) and have been gathered together under the heading of complexity theory. In this framework, a complex system can look very simple but will have nonlinear relationships among its constituent elements (e.g., a feedback loop). A system with embedded nonlinear relationships becomes dynamic until it reaches a state of equilibrium (Devaney, 1993; Cramer, 1993). At equilibrium, the system neither uses nor produces anything. Most complex systems are in a far-from-equilibrium state and so are dynamic (Cramer, 1993).

Complex systems have the characteristic of having nonlinear relationships between system elements that may interact, creating an unpredictable reoccurrence of a patterned result (Johnson and Burton, 1994; D’Aveni, 1994; Waldorf, 1992; Stacey, 1995; Wheatley, 1992; Senge, 1990; McKelvey, 1997). Most applications of complexity theory include dynamism in the system over time, with the reoccurring patterns being recognizable to earlier iterations but not identical to those earlier patterns. Common examples of such dynamic complex systems include those from meteorology. One can certainly recognize a cloud when one sees it, but the specific water droplet formation is never the same. A static version of this is the snowflake (no one flake is identical to any other).

Recall that dynamic systems are predictable only over the short term (Hunt, 1995; Cramer, 1993) and retain an ordered stability typically when in close proximity to an attractor variable. These strange attractors act as order coalescent points for the complex system (Devaney, 1993; Hunt, 1995). Patterns emerge at these spots after much iteration. Such patterns imply not only the presence of an attractor but a particular attractor, which comes in many types (Favre *et al.*, 1995). These range from attractors that are independent of time and or are in a stationary state to those

that have a regular repeating pattern over time, to those whose pattern changes slightly as it repeats irregularly.

An interesting type of attractor is one whose revealing pattern includes a bifurcation point. The point represents a critical value where equally viable alternatives exist, but which then contribute to the forming of a new attractor with a different order pattern. In other words, there is a qualitative change in the system (Favre *et al.*, 1995). While recognizable, the nature of the order in the system is different from its earlier state. The bifurcation point occurs even when one follows the existing “rules of order.” Such a bifurcation point can result in the system being poised on the edge of entering chaotic behavior (Cramer, 1993). It only takes three bifurcations before the system becomes unpredictable and turbulent (i.e., change and multiple possibilities are prevalent; Favre *et al.*, 1995). The area of time during these iterations (while a system is moving toward a chaotic state but before it reaches true chaos) has been termed “the edge of chaos” (Cramer, 1993; Brown and Eisenhardt, 1998).

INTEGRATION OF AUSTRIAN ECONOMICS AND COMPLEXITY THEORY

The edge of chaos, where data generated from deep underlying nonlinear rules appears chaotic, has been targeted as an area where a great deal of organizational activity occurs, metaphorically speaking (among others Brown and Eisenhardt, 1998; Stacey, 1995). Yet further application of complexity theory is predicated on a better translation into organizational and economic literatures of complexity theory assumptions. Bryan (1988, 1994) has begun transferring some of the concepts in his positive feedback economics. We suggest that Austrian economics also provides a linking mechanism between complexity theory and organizational activity, specifically entrepreneurial actions and attendant strategies for a full range of actions. This linkage is possible because the deep underlying rules guiding the system are the two main “drivers” of Austrian economics: the creation and diffusion of market information (Black and Farias, 1998).

The tension between these two drivers is revealed in the fitting dynamic and results in market growth. Although Austrian economics includes in the framework all market participants (i.e., suppliers, customers, regulators, etc.) as contributing to the level of market information available, for simplicity these participants’ contributions are implicitly added in the revealed data portion of the model. These two driving forces

result in entrepreneurial market-organizing efforts of market structuring or refining.

These separate activities have been identified as enterprising and honing activities respectively (Black, Farias and Mandel, 1996; Black, 1997, 1998; Black and Farias, 1998). The enterprising orientation is defined as market structuring; the inclination to put together the elements of a market and thereby enact a definition of the market (whether an initial definition or a revised definition). The second, honing orientation is defined as market refining; the inclination to refine the details of the activities within a defined market structure by acquiring and using the information available from all relevant economic agents in the market.

With these two orientations acting as the deep mathematical rules for the system, we can see how the organizing efforts of entrepreneurs result in two simultaneous drivers: the enactment of market structure and the revealing of information to all market participants.

The existence of a market structure pattern also provides information about a particular market. When the market boundaries are either not yet defined or are being defined, there is a feedback loop reinforcing the enterprising orientation market-organizing efforts. Participants in the economic activity of this market will loop through these steps until a stable pattern results (i.e., industry standards are set). We anticipate that the setting of industry standards is the equivalent of a bifurcation point in a complex system. At this bifurcation point, many organizing actions are switched from an enterprising orientation to a honing orientation based on those acceptable industry standards. A new organizing logic is in place. Enterprising activities done in this market context are now done with the logic and intent to destabilize this market pattern.

Thus we now have an expanded model that shows how the economic environment moves from one ordered state to another. We would expect the honing cycle to repeat again and again until the next critical bifurcation point is reached. That bifurcation point is evidenced in one of two scenarios:

Scenario 1 The market will stabilize into the reduced returns associated with the perfect competition model of traditional neoclassical economics, with the attendant generic strategies suggest by Porter (1980).

Scenario 2 It will transition into a hypercompetitive state with strategies associated with a market in transition and rapid change (among others D'Aveni, 1994; Eisenhardt and Brown, 1997).

At this hypercompetitive state, the market has again entered the edge of chaos but with a twist: There is now organizational history regarding a successful pattern. There is organizational inertia (Kelly and Amburgey, 1989). Learning and change literatures suggest that organizations will be tempted to reuse the exact pattern of resources and processes that have previously brought them success (Tushman and Romanelli, 1985; Gresov, Haveman and Oliva, 1992; Levitt and March, 1988).

Thus in this more complex, edge-of-chaos environment, we expect that there will continue to be some resources expended on honing organizing efforts. These efforts may even be a rational approach to reducing the complexity and chaos by tightening and simplifying relationships of their particular supply or value chain subsystem. Alternatively, when faced with chaotic market patterns, others may choose to re-emphasize their enterprising activities. These entrepreneurs again choose to set the definitions of the market structure in a more directed fashion.

To illustrate, we will use an example discussed earlier. Amazon.com introduced a major change in the retail book market. Its success revealed the existence of a market for internet-based book retailing. This information is not available to Amazon.com alone. Any entrepreneur wishing to enter this market now has information revealed by the success of Amazon.com. Other book retailers (e.g., Barnesandnoble.com) use this information and structure the market further. Several other companies selling a variety of products (e.g., Buy.com) recognize the value of the market and the potential for rent. Further structuring takes place. Firms have two choices. They might choose to compete by destabilizing the market through the introduction of changes that induce new market restructuring. On the other hand, they might choose to compete by developing more efficient ways to deliver the product or service. As discussed earlier, the former strategy reflects the enterprising orientation and the latter the honing orientation. Enterprising actors interpret and enact their environments in unique ways. Honing actors adopt the interpretations of the enterprising actors.

However, two distinct but intertwined loops operate. As long as the actors in a particular market continue to earn rents, both the actors and the market grow. Eventually, however, these rents are eroded and a new tension created. The enterprising rent seekers seek to destabilize the market and redefine it, or move to create new markets. The honing organizations seek to stabilize and further structure the market. Note, however, that the availability of information increases as characteristics of a market are revealed through the structuring process. In other words,

the market has become less equivocal or ambiguous. Actors have to deal with the relatively tame problem of uncertainty. However, as the number of actors increases, conditions of information overload are created and present opportunities for redefining the marketplace. The market has reached conditions of equivocality once more. The interpretation and enactment of this environment generate a new cycle of marketplace dynamics.

DYNAMIC IMPLICATIONS

Recall that the primary orientation in use before the first bifurcation point (which occurred when industry standards and norms coalesced) was the enterprising orientation. These market activities occurred at the very beginning of a market and hence under conditions of high ambiguity. These conditions imply that firms that act will be those that have a bias of high levels of enterprising orientation.

The first bifurcation point occurs when an industry norm or standard coalesces. There is then a shift in the logic of order in the market. The shift is toward refining the now defined market. This implies that there will be a shift toward an emphasis on a honing orientation rather than an enterprising orientation. Firms will then focus their resources on developing their efficiency or uncertainty-reduction skills. This increase in uncertainty-reduction skills enables them able to move to higher honing levels. However, they typically have few or no slack resources available to develop their enterprising capabilities. The combination of the need to focus their attention on uncertainty-reduction skills and inattention to or lack of development of their equivocality-reduction skills (due to no immediate need for such skills) increases the tendency of firms' orientations to drift toward only reinforcing their uncertainty-reduction skills. Once a high level of honing orientation is reached, a firm is able to keep pace with the efficiency pressures of a complex market. Furthermore, by being able to keep pace, these high-honing firms now generate or have the slack available to utilize and/or develop greater amounts of their enterprising-fitting dynamic orientation.

As market information is dispersed and firms reach high levels of honing, there is a potential shakeout of firms that have not been able to develop the necessary skills to move to higher honing levels. If the market continues to develop better and better honing skills, it may become mature and continue to develop as predicted by traditional economic models. If, however, in their competition for better fit firms begin to take

incremental steps in increasing their enterprising skills, another bifurcation point may be reached. As firms increase their use of an enterprising-fitting orientation and associated equivocality-reduction skills, they finetune their ability to handle ambiguity and may ultimately be able to attain high levels of both honing and enterprising. While this may be due to the available slack as indicated above, if there are a number of high-honing firms their proactive efforts may spark a hypercompetitive environment.

This movement to a hypercompetitive environment is the second bifurcation point. When this happens (which can be simply due to the proactive tendency involved in a high honing orientation), firms may choose to engage in economic activities resulting in increased information density and an increased pace in response to others' actions. This "more to consider and respond to with less response time" is typical of hypercompetitive environments (D'Aveni, 1994). If a firm has no enterprising skills, then the act of engaging in ambiguity reduction will probably be forced on externally as the result of the hypercompetitive actions and/or complex markets that are leading to the change. At this point, firms may choose to stir up the water by introducing destabilizing actions that will cause greater levels of ambiguity to occur, creating opportunities for the firm to earn returns from market-structuring activities as well as from its market-refining efforts from the honing orientation. An alternative scenario is one where firms actually leave the previous market and create a new market, which would be a third bifurcation.

However, once the density of firms in new markets increases, enterprising firms will face pressure to create efficiencies in their operations or move on to other new markets with lower densities. In making the choice of whether or not to invest in "honing skills," some firms will also need to be aware of an additional pressure. Specifically, the pressure to remain in their markets and develop honing skills may emanate from stakeholders in a firm who value the more certain returns available from honing existing markets. Movement into and out of enterprising activities may be part of an overall strategy of planned cycling. A firm may choose to cycle between the two dynamic choices in such a way as to move into a new market, hone its position there until a certain floor level of returns is obtained, and then expand into another market.

Note that if the firm neglects to invest in either skill base, those skills may languish and it may drift to a strategic orientation that is below the level of its current orientation. These tendencies suggest that firms' strategies will be forced to move eventually in some direction (by choice, market pressure, or drift). Thus, changes in a firm's strategy should be

more the norm than the exception, regardless of its starting orientation. This implies that changes in a firm's business-level strategy may be more prevalent than previously implied. This also implies that such changes may be the result of strategic thought that is not a "stuck in the middle," waffling perspective, but a deliberative effort to receive the rents associated with the level of market complexity.

It is evident that the drivers of the dynamism in a disequilibrium-based economy are found in the high-enterprising and high-honing orientations. As discussed, an enterprising orientation is associated with the preference and ability to use equivocality-reduction information-processing skills, while a honing orientation is associated with the preference and ability to use uncertainty-reduction information-processing skills. Those firms that utilize the skills of either orientation thus fine-tune a specific set of skills. When equivocality-reduction skills are enhanced, they reinforce further enterprising activities. When uncertainty-reduction skills are enhanced, they reinforce further honing activities. Although the exact relationship is an empirical question, it is reasonable to assume that a learning curve (a nonlinear relationship) of some sort is present. This implies that further uses of complexity theory in interpreting market and firm actions are likely.

In addition to providing an explanation of the deep underlying rules of our economic marketplace, the model also provides firms, entrepreneurs, and managers with insight into when to expect the next critical point at which a bifurcation might occur, reordering the definition of competition in a market. While both the explanatory and predictive powers of the model have yet to be determined empirically, it does provide us with a base from which to test. Enterprising and honing actions can be coded from descriptions of actions in the marketplace. Changes from a predominance of one type to that of another can be determined. The timing and results of changes in predominance can be studied, as can the ability of a firm to handle both types of skills simultaneously or sequentially.

DISCUSSION AND FUTURE RESEARCH DIRECTIONS

This model provides an explanation for the simultaneous existence of both equilibrium and disequilibrium tendencies in a marketplace. We believe that it helps to enhance our understanding of the dynamics of the marketplace, focusing both on environmental and organizational factors. The model is testable through longitudinal studies of industries as they

have evolved and changed over time. It may also be tested in the context of innovations within an industry. For example, Southwest Airlines redefined the airline market in many ways. Nevertheless, many of the traditional airlines did not choose to change. Yet many of Southwest's innovations are being copied by these traditional airline companies. For instance, the idea of ticketless travel has now been adopted by most airlines in the US. This may be an example of imitation of the innovator to at least maintain competitive parity.

Because of the current timeliness of many of the issues addressed by our model, empirical work is just beginning to be published that addresses these or similar issues (Ilinitch *et al.*, 1996). Additionally, much empirical work remains to be done to test the basic propositions of Austrian economics (Jacobson, 1991) from which this model has been developed. There has been some recent work by Young, Smith and Grimm (1996) that does provide support for some of the critical propositions used in the model. They confirmed some of the assertions of the dynamic fitting process by finding that overall industry profitability declines with increased industry competition. They also found that firms that introduce new competitive elements raise their own performance and lower others (implied support for the high-honing and high-enterprising orientations). Yet even with this encouraging study, and while the suggestions of the fitting dynamic in organization studies are derived logically from previous research and theories, much empirical testing remains to be done.

NOTE

The authors would like to thank Jack Brittain, Dennis Duchon, Amy Hillman, Stan Mandel, Will Mitchell, Dan Schendel, and Scott Sherman for their thoughtful and insightful comments. Any errors remain ours. This paper was originally presented at the 1999 Annual Academy of Management meeting in Chicago.

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Is There a Complexity Beyond the Reach of Strategy?

Max Boisot

A quick overview of the development of strategy over the past three decades suggests that it has been getting steadily more complex (Stacey, 1993; Garratt, 1987). This is both a subjective and an objective phenomenon. Objectively speaking, causal empiricism points to a world that is increasingly interconnected and in which the pace of technological change has been accelerating. The arrival of the internet is evidence of increasing connectivity—some managers find upward of 200 emails waiting for them each morning when they arrive at the office. The persistence and replication of Moore’s Law are evidence of accelerating technical change. The spirit of Moore’s Law—which stated that the speed of computer chips would double every 18 months and that their costs would halve in the same period—has now spread out beyond the microprocessors and memory chips to which it was first applied (Gilder, 1989) and has started to invade a growing number of industries (Kelly, 1998). As a result, corporate and business strategists are today expected to deal with ever more variables and ever more elusive, nonlinear interaction between the variables. What is worse, in a regime of “time-based competition,” they are expected to do so faster than ever before. This often amounts to a formidable increase in the objective complexity of a firm’s strategic agenda.

Complexity as a subjectively experienced phenomenon has also been on the increase among senior managers responsible for strategy. While lower-level employees are working shorter hours, senior managers are working longer hours. Having to deal with a larger and more varied num-

ber of players, they travel more. They meet each other for breakfast, for lunch, and for dinner. And in New York, busy managers now balkanize their lunch, with the first course being devoted to one meeting in one restaurant, the second course being reserved for a second meeting in a second restaurant, and so on. They come out of their meals with more things to think about and with less time to think about them in. Can such growing complexity be tamed by some intelligible ordering principle of the firm's own devising, i.e., is it what mathematicians refer to as "algorithmically compressible" (Chaitin, 1974; Kolmogorov, 1965)? Or does it simply have to be endured and dealt with on its own terms? In other words, can complexity be *reduced* or must it be *absorbed*? Adapting a certain number of simple concepts drawn from both computational and complexity theory, and applying them within a conceptual framework that deals with information flows (Boisot, 1995, 1998), this is the issue addressed in this article.

The claims of neoclassical economic theory to the contrary notwithstanding, we have come to realize that human economic agents are boundedly rational creatures. There is a limit to the complexity that they can handle over a given time period (Simon, 1957). Organizations are devices for economizing on bounded rationality. They create routines for the purpose of reducing the volume of data-processing activities with which they have to deal (March and Simon, 1958). Routines, in a sense, embody working hypotheses concerning both the way that selected portions of the world function and how they can be mastered. Routines, therefore, carry a strong cognitive component that reflects individual or collective sense making and understanding (Weick, 1995).

Nelson and Winter, writing in an evolutionary vein, see such routines as units of selection (Nelson and Winter, 1982). Firms that fail to evolve new and adapted routines in response to changing circumstances sooner or later get selected out—they are penalized if they fail to revise their working hypotheses in a timely manner in the face of disconfirming evidence. Obviously, timeliness is a relative concept, and some environments will be more munificent with respect to the availability of time than others. Yet it is equally obvious that the faster and the more extensively circumstances change, the less time will be available for adaptation to take place and the more likely it is that any given firm will be selected out, to be replaced by new, better-adapted competitors. In such a case, a failure of learning and adaptation at the level of the individual firm is compensated for by learning at the level of a population of firms.

But are cognitive strategies that aim at sense making and the creation

of new routines the only option open to firms for coping with the boundedness of rationality when confronted with complexity and change? Is understanding a prerequisite for effective adaptation? In answering these questions, it is worth recalling the relationship that has been posited between task or task environment and organization (Woodward, 1965; Lawrence and Lorsch, 1967). Simply put, the evidence is that task shapes organization structure. The relationship had originally been established at the level of individual organization units within a firm, but it is in effect a fractal one—that is to say, self-similar at different levels of analysis (Mandelbrot, 1982). It operates wherever we find agency, action, and structure working together. Narrowly construed and embedded deep within the firm, tasks are operational, e.g., assembling a vehicle, writing a marketing report, etc. At the broadest and highest level, however, tasks become strategic so that strategy shapes structure (Chandler, 1962), and aims either to align the firm as a whole with the requirements of its environment or to shape the environment so as to render it hospitable to the firm and its possibilities (Weick, 1979).

We can now phrase the issue before us as follows: Do increases in the complexity of a firm's strategic task of themselves call for changes in the way that the strategy process is organized within the firm? And should these changes be primarily cognitive, i.e., should they aim to accelerate and facilitate the sense-making process among senior managers so that these can initiate the creation of new and better-adapted routines?

The fit between task and organization turns out to be one variant of Ross Ashby's (1954) Law of Requisite Variety (LRV). Adaptive learning requires that the range and variety of stimuli that impinge on a system from its environment be in some way reflected in the range and variety of the system's repertoire of responses. For variety read complexity—or at least one variant of it (see below). Thus, another way of stating Ross Ashby's law is to say that the complexity of a system must be adequate to the complexity of the environment in which it finds itself.

Note that we do not necessarily require an exact match between the complexity of the environment and the complexity of the system. After all, the complexity of the environment might turn out to be either irrelevant to the survival of the system or amenable to important simplifications. Here, the distinction between complexity as subjectively experienced and complexity as objectively given is useful. For it is only where complexity is in fact refractory to cognitive efforts at interpretation and structuring that it will resist simplification and have to be dealt with on its own terms. In short, only where complexity and variety cannot be

meaningfully *reduced* do they have to be *absorbed*.

So an interesting way of reformulating the issue that we shall be dealing with in this article is to ask whether the increase in complexity that confronts firms today has not, in effect, become irreducible or “algorithmically incompressible”? And if it has, what are the implications for the way that firms strategize?

In tackling these two questions, we shall take strategic thinking to be a socially distributed data-processing activity involving a limited number of agents within a population of agents that make up a firm. Strategic thinking involves the sharing of diverse yet partially overlapping representations between agents, with a firm’s strategy being an emergent outcome of the way that such representations are shared (Eden and Ackermann, 1998). The structuring and sharing of knowledge between agents lie at the heart of the approach that we propose to adopt.

A CONCEPTUAL FRAMEWORK: THE I-SPACE

Organizations are data-processing and data-sharing entities. They are made up of agents who successfully coordinate their actions by structuring and sharing information both with insiders—i.e., in hierarchies—and with outsiders—i.e., in markets (Williamson, 1975). Because agents are often subject to information overload, however, they are generally concerned to minimize both the amount of data they need to process and the amount they need to transmit in any time period (March and Simon, 1958; Boisot, 1998). For this reason, organizational agents, when acting purposefully and under some constraint of time and resources, exhibit a general preference for data that already has a high degree of structure and is therefore easy to transmit.

But how does data get processed into meaningful structures in the first place? Data processing has two dimensions: codification and abstraction. Codification can be thought of as the creation of categories to which phenomena can be assigned, together with rules of assignment. Well-codified categories are clear categories and well-codified assignment rules are clear rules. Thus the less the amount of data processing required to assign a phenomenon to a category, the faster and the less problematic the assignment will be. We then say that both the phenomenon and the category to which it is assigned are well codified. Uncodified categories and rules of assignment, by contrast, are characterized by fuzziness and ambiguity. Assigning phenomena to categories will then be slow and costly in terms of data processing. Where no assignment can be made at

all, the amount of data processing required to perform an act of categorization may well go to infinity.

If codification is about minimizing the amount of data processing required to assign phenomena to categories, abstraction establishes the minimum number of categories required to make such assignments meaningful. Where few categories are required, the more abstract our treatment of the phenomenon can be and the larger become the data processing economies on offer. By contrast, the larger the number of categories required to perform a meaningful assignment, the closer we are to the concrete realities of the natural world. At the extreme, when no abstraction is possible, the number of potential categories available to us runs to infinity and we find ourselves dealing with concrete data in its full complexity.

Codification and abstraction are cognitive strategies that any intelligent agent deploys in order to economize on data-processing costs. The two strategies mutually reinforce each other and help the agent make sense of its world by giving it a meaningful structure. They form two of the three dimensions of our conceptual framework. The sharing of data between agents is captured by a third dimension that describes data-diffusion processes. We can think of diffusion as the percentage of data-processing agents within a given population of these that can be reached by an item of data per unit of time. Agents may, but need not, be human. A population of firms, for example, could be located along the diffusion dimension, in which case one might well be dealing with an industry. Or, more fancifully perhaps, the population of agents could be neurons. All that is required for the purposes of I-Space analysis is that agents be capable of receiving, processing, and transmitting data. The agents that are to be located on the diffusion scale, however, have to be chosen with care to avoid mixing apples with oranges. Firms, for example, cannot jostle with individuals on the scale without undermining the analysis. A second issue is that agents have to be placed there for a reason. That is, they must share some interest with respect to the data that flows in the I-Space.

The structuring and sharing of data are related. The more one can codify and abstract the data of experience, the more rapidly and extensively it can be transmitted to a given population of agents. The relationship is indicated by the curve of Figure 1. At point A on the curve one is in the world of Zen Buddhism, a world in which knowledge is highly personal and hard to articulate. It must be transmitted by example rather than by prescription. But examples are often ambiguous and open to different interpretations. Zen knowledge, therefore, can only be effectively

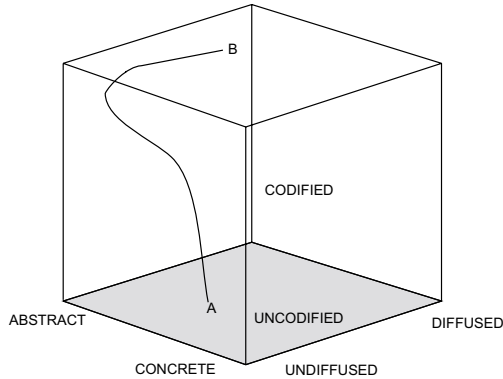


Figure 1 *The diffusion curve in the I-Space*

shared on a face-to-face basis with trusted disciples over extended periods of time (Suzuki, 1956).

Point B on the curve, by contrast, describes the world of bond traders. This is a world where all knowledge relevant to trading has been codified and abstracted into prices and quantities. This knowledge, in contrast to that held by Zen masters, can diffuse from screen to screen instantaneously and on a global scale. Face-to-face relationships and interpersonal trust are not necessary. Only the technical and legal systems that support transactions need to be trusted, not transacting agents themselves.

Our Zen Buddhists and bond traders are, of course, caricatures. In the real world, some Zen masters trade in bonds and some bond traders practice Zen meditation. What our example is intended to highlight is how different the information environments that confront agents can be, as they go about their business. The fact that certain agents will be exposed to a greater variety of information environments than others does not fundamentally alter the picture.

TRANSACTIONAL STRATEGIES IN THE I-SPACE

The possibilities available to agents for structuring and sharing data, then, create different information environments. Think, for example, of what happens when information is readily structured—and hence diffusible—but its actual diffusion is under some kind of central control. It is then often only made available to agents on a “need-to-know” basis. In such an information environment, the possession of well-structured knowledge

will be treated as a source of organizational power over others and thus carefully hoarded. At the other extreme, we can think of situations in which knowledge is freely available to agents but in fact only diffuses in a limited way—and this by interpersonal means—on account of its being relatively uncodified and concrete. Knowledge will then become the property of small groups of agents whose size is limited by the possibilities of entertaining trust-based face-to-face relationships.

Differences in the possibilities for structuring and sharing data can bring forth distinctive cultural practices and institutional arrangements. We identify four of these in the I-Space (Figure 2) and outline their essential characteristics in Table 1. The features distinguishing such institutional arrangements from each other are:

- ◆ the extent to which exchange relationships need to be personalized and the degree of interpersonal trust that they require;
- ◆ the extent to which data is asymmetrically held and hence constitutes a source of either personal or formal power;
- ◆ the degree to which specific types of exchange are recurrent and hence allow for emergent processes to operate.

Trust requires some ability by agents to get on to the same wavelength and implies some sharing of values. Power relationships require acquiescence. In this way, and drawing on Giddens's Structuration Theory (Giddens, 1984), we move beyond purely cognitive issues of signification to address problems of legitimation and dominance (Boisot, 1995).

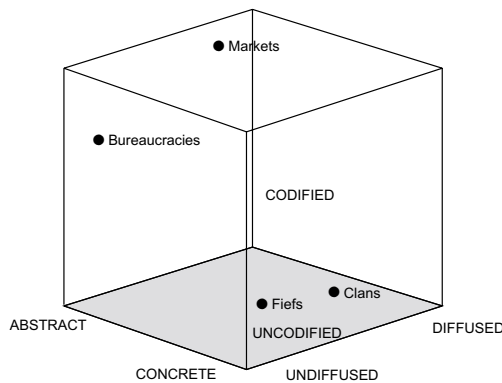


Figure 2 Institutions in the I-Space

Table 1 Institutions in the I-Space

CODIFIED INFORMATION	2 BUREAUCRACIES	3 MARKETS
	<ul style="list-style-type: none"> • Information diffusion limited and under central control • Relationships impersonal and hierarchical • Submission to superordinate goals • Hierarchical coordination • No necessity to share values and beliefs 	<ul style="list-style-type: none"> • Information widely diffused, no control • Relationships impersonal and competitive • No superordinate goals – each for himself • Hierarchical coordination through self-regulation • No necessity to share values and beliefs
UNCODIFIED INFORMATION	1 FIEFS	4 CLANS
	<ul style="list-style-type: none"> • Information diffusion limited by lack of codification to face-to-face relationship • Relationships personal and hierarchical (feudal/charismatic) • Submission to superordinate goals • Hierarchical coordination • Necessity to share values and beliefs 	<ul style="list-style-type: none"> • Information diffusion but still limited by lack of codification to face-to-face relationship • Relationships personal but nonhierarchical • Goals are shared through a process of negotiation • Horizontal coordination through negotiation • Necessity to share values and beliefs
	UNDIFFUSED INFORMATION	DIFFUSED INFORMATION

The institutional structures located in the different regions of the I-Space lower the costs of processing and sharing data and hence of transacting in those regions. They can be thought of as a set of emergent Nash equilibria in iterated games between varying numbers of agents, equilibria that are partly shaped by the characteristics of the information environment in which the games take place. In effect, then, agents face two options when seeking data processing and transmission economies:

- ◆ Where data is amenable to codification and abstraction, move out along the codification and abstraction dimensions.
- ◆ Where it is not, foster the emergence of institutional structures appropriate to the information environment in which they find themselves.

These structures, as Nash equilibria, then act as what mathematicians call attractors in the I-Space, pulling in and shaping any transactions located in their neighborhood or “basin of attraction.”

The institutional structures depicted in Figure 2 can work individually or in combination. And as we have already indicated, they can also be adapted to the needs of different types of data-processing agents. Figure 3, for example, locates a population of organizational employees along the diffusion dimension of the I-Space, i.e., it represents a firm. The diagram also assigns some of the key functions of the firm respectively to those regions of the I-Space that best describe their information environments. Where such an assignment is valid—and whether it is or not is ultimately an empirical matter that will depend on firm and industry characteristics—we

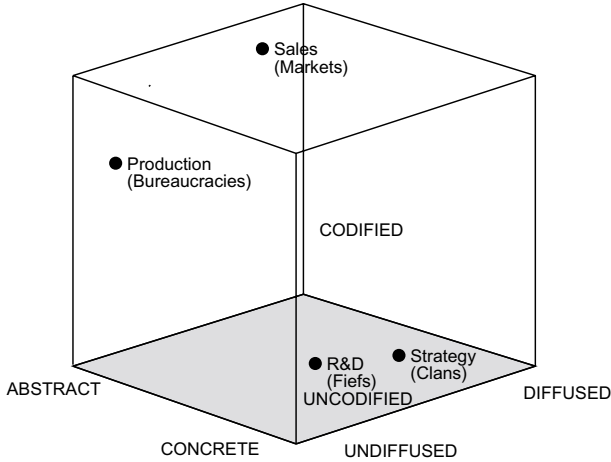


Figure 3 Some firm-level functions in the I-Space

would expect such functions to exhibit the cultural traits predicted respectively for each of these regions. The firm itself, therefore, would accommodate a variety of institutional cultures that then need to be integrated. Where one of these cultures predominates—i.e., acts as a strong attractor—at the expense of the others, dysfunctional behaviors are likely to appear. Thus, for example, a strong sales department driven by well-defined customer needs in a competitive environment operates within a timeframe that could undermine the more long-term and “blue skies” approach of an R&D department, should this be unable to defend its organizational interests.

Figure 4 treats the firm itself as a data-processing agent in its own right and depicts a population of firms in an industry. Here, the I-Space allows us to explore industry-level structures and cultures. We see from the diagram that monopolistic and oligopolistic industries may have quite distinct cultures, and that these, in turn, are likely to differ significantly from industries characterized as either competitive or emergent.

COMPLEXITY IN THE I-SPACE

The issue we are addressing is whether the growing complexity that the firm confronts remains accessible to strategic processes. We therefore now ask: Do any of the concepts coming out of the new sciences of complexity have anything to contribute to strategic thinking, and do they lend themselves to treatment in the I-Space?

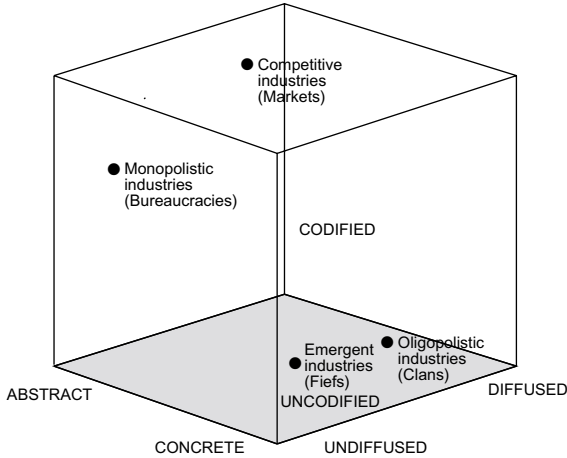


Figure 4 Industry structures in the I-Space

The first point to note is that some of the measures of complexity that have been put forward find echoes in our codification and abstraction dimensions. Gregory Chaitin (1974) and Andrei Kolmogorov (1965), for example, have each separately developed the concept of Algorithmic Information Content (AIC). AIC is measured by the shortest program that will describe a phenomenon such that it can be faithfully reproduced; our own definition of codification is the minimum number of bits of information that will allow us adequately to describe a phenomenon. Murray Gell-Man has pointed out, however, that such “crude” complexity, as defined by AIC, is indistinguishable from randomness (Gell-Man, 1994). He proposes a measure of what he terms “effective complexity” to complement AIC, which he defines as the shortest program that will describe the regularities that characterize a phenomenon; our own definition of abstraction is the minimum number of categories that will allow us adequately to capture a phenomenon. Clearly, if we adopt and adapt the definition offered by Chaitin, Kolmogorov, and Gell-Man, what we mean by information structuring can now be interpreted as an instance of algorithmic compressibility, a reduction in data-processing complexity. Equally clearly, the carrying out of such a reduction is a cognitive process.

To deal with the diffusion dimension of the I-Space, we must turn to the work of Stuart Kauffman (1993, 1995). Kauffman has been investigating the process of self-organization from a theoretical biologist’s perspective. His random Boolean networks—he calls them NK networks—

consist of nodes and linkages that switch on and off in a binary fashion, where N stands for the number of nodes in the network and K measures the density of connections between the nodes. Again, with some adaptation, NK networks allow us to examine the emergence of complex interactions in a population of agents. All we require is that the nodes exhibit some minimal data-processing capacity and that the linkages be treated as communication channels between nodes. Treating each node as an agent, we can then establish measures of data-processing complexity for each one. With increasing data-processing complexity, Kauffman's model comes to look increasingly either like a neural net—where nodes can extend their communicative reach beyond their immediate neighbors (Aleksander and Morton, 1993)—or like a cellular automaton—where they cannot (Wolfram, 1994).

Following Kauffman, we shall let N represent the number of agents in our target population— N thus corresponds to the length of our diffusion dimension—and K the degree of agent interconnectedness. Thus an agent with a high K enjoys extensive interactions with other agents, whereas one with a low K may be feeling pretty lonely. Kauffman then offers us a tuning parameter P —developed by two of his colleagues, Bernard Derrida and Gerard Weisbuch of the Ecole Normale Supérieure in Paris—to represent any switching bias present in the network; that is, the probability that the link between any two nodes will be activated. Where P has the value of 0.5, for example, no switching bias is present. Linkages between nodes are equally likely to be activated and to stay dormant so that the network behaves chaotically. As P approaches the value of 1, however, the network behaves in an increasingly orderly fashion, until at 1 it reaches a frozen or steady state, either fully “on” or fully “off.”

Kauffman's P bears a striking resemblance to Shannon's H , his measure of entropy or information in a channel (Shannon and Weaver, 1949). In Shannon's scheme, H reached its maximum value when symbols in a sequence were equally likely to follow each other. Where the symbol sequence exhibited bias, this could be exploited by a suitable coding scheme to reduce the length of the sequence, i.e., it could be structured and its complexity reduced. We shall use P as a rough measure of data-processing complexity, with a low value of P (at or close to 0.5) corresponding to low levels of codification and abstraction, and a high value of P (at or close to 1) corresponding to high levels of codification and abstraction. Clearly, in our interpretation of P , we are once more combining Gell-Mann's crude and effective complexity in a single measure. The I-Space itself, however—like Gell-Man—keeps the two concepts distinct.

By varying K and N and appropriately tuning P, Kauffman establishes phase transitions between ordered, complex, and chaotic regimes in random Boolean networks. In a similar fashion, by tuning P and varying K for a given N—in our own analysis, to keep things simple, we shall hold the number of agents located along the diffusion dimension constant, even though in real life agents are constantly coming and going along it—we can create phase transitions in the I-Space that reflect ordered, complex, and chaotic social processes. Thus, for example, where the value of P is high—i.e., close to the value 1—and the value of K is low—i.e., the density of interaction among agents is low—we are in an ordered regime where things are stable and predictable. Where, by contrast, the value of P is close to 0.5 and the value of K is high, we find ourselves in a chaotic regime where nothing is stable and valid predictions are hard to come by. In between these values for P and K, we operate in a complex regime exhibiting varying degrees of stability and, hence, predictability.

What are we in fact doing? Nothing more than varying either the amount of data processing that agents are required to carry out or the density of social interaction in which they are expected to engage. Although we are not yet in a position to present empirical results for this exercise—a research project is just getting under way at the Wharton Business School to test out the idea—we can offer an indication of what kinds of hypotheses might be tested by it.

COMPLEXITY REDUCTION (ANALYSIS) VERSUS COMPLEXITY ABSORPTION (EMERGENCE)

The term “culture” has been defined in many ways (Kroeber and Kluckhohn, 1952), but nearly all of them involve the structuring and sharing of data within or across groups. How effectively it is done is a function of the volume of data that is to be shared, the size of the group or groups with which it has to be shared, and the density of social interaction within or between such groups. Figure 2 locates institutional structures in the I-Space as a function of these three variables, and the way in turn that such structures combine in the real world impart to a given culture a unique configuration or “signature” in the Space. In effect, the location and nature of institutional structures in the I-Space reflect both the complexity of the data-processing environment in which they find themselves as well as that of the social interactions to which they give rise. Data-processing activities and social interaction thus place these structures in a phase space as indicated in Figure 5, and according to the

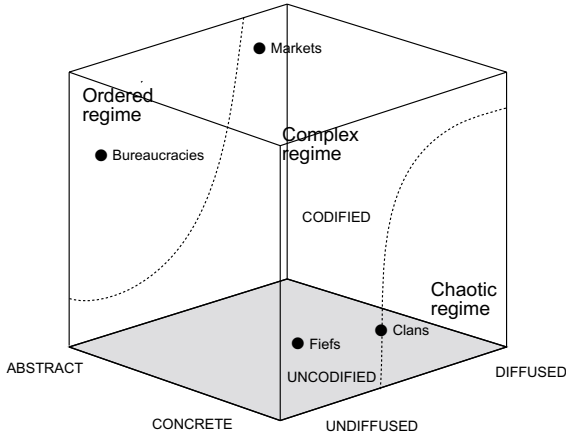


Figure 5 *Institutions in phase spaces*

criteria outlined in Table 2. As we can see from the figure, bureaucracies clearly sit in the ordered regime, whereas markets and fiefs occupy the complex regime. Note, however, that the complexity of markets is due to the number of agents that need to be coordinated, whereas that of fiefs is attributable to the fuzziness of the information environment. Thus, whereas markets operate with a P value closer to 1—i.e., with prices that codify and diffuse all the relevant information—fiefs operate with a P value closer to 0.5. How close is an empirical question that cannot be addressed here. Clans, although also characterized by complexity, seem to be located close to the chaotic regime—with low values for P and medium values for K, they sit on the “edge of chaos” (Langton, 1992).

Over time, cultural and organizational evolution moves us from one set of institutional arrangements to another (North, 1990). As we move, we shall sometimes experience phase transitions reflecting the extra expenditures of cognitive and social energy required both to overcome

Table 2 *The complexity of transactional structures*

	Relational complexity	Cognitive complexity	Overall transactional complexity
Markets	High (High K)	Low (High P)	Medium
Bureaucracies	Low (Low K)	Low (High P)	Low
Fiefs	Low (Low K)	High (Low P)	Medium
Clans	Medium (Medium K)	High (Low P)	High

the attractive forces of a given institutional arrangement acting as a Nash equilibrium, and to adapt to a new institutional regime. Whether it is worth moving or not depends on how far the benefits of doing so counterbalance the costs incurred in doing so. The benefits are measured in savings on energy expenditures, i.e., economies achieved either in the processing of data or in the coordination of agent interaction. The costs are the converse of the benefits: energy expended in learning how to process data in a new region of the I-Space and to coordinate new kinds of interactions between agents. We find ourselves, in effect, confronting the same kind of choices as those identified in the literature on transaction cost economics (Coase, 1937; Williamson, 1975, 1985; Eggertsson, 1990), except that, given our broader treatment of data processing and cognitive issues, our options extend beyond those of markets and hierarchies *tout court* (Boisot, 1986).

This is just as well. For we still have to cope with the effects of entropy in the I-Space, the tendency for data-processing activities and interactions between agents to lose their structure and become increasingly disordered over time. As might be imagined, the rate of entropy production is at its minimum in the ordered regime and at its maximum in the chaotic regime. We know from the second law of thermodynamics that in a closed system, entropy can never decrease. In the I-Space, we can effectively attempt to “close” the system by holding N , the number of agents, constant. That is to say, we can try to limit the entry and exit of agents into the I-Space by controlling access to the diffusion scale.

If we succeed, entropy will then increase in the system in two distinct ways. First, data, is always undergoing diffusion in the Space and hence tending to move transactions toward the right—toward the complexity of markets in the upper regions of the Space, and toward the chaos that lies beyond clans in its lower regions. Second, data that has been highly structured by moves along the codification and abstraction dimensions, becomes subject to the action of time, i.e., to institutional forgetting. Although with structured data the loss of institutional memory will operate more slowly than in the case of unstructured data, over time, unless maintained by further expenditures of energy, the structures created to preserve data gradually erode, thus pulling data-processing activities back into the lower regions of the I-Space, where they become uncodified and concrete.

We can think of our institutional structures as emergent mechanisms that have the effect of minimizing the rate of entropy production in the type of information environment in which they find themselves. They capture and stabilize transactions, temporarily blocking—or at least

slowing down—their movement either downward or toward the right in the I-Space. In the absence of such structures, all transactions sooner or later drift into the chaotic regime and, unless they are “open” to new inputs of energy and information—usually provided by new agents entering the I-Space—organizations disintegrate in a Hobbesian “war of all against all.”

Generally speaking, wherever they can do so, we see entropy-minimizing firms seeking out the ordered regime, one in which the value of P is high and the value of K is low. Firms prefer stability to instability and will simplify and routinize wherever they can. When is that? Whenever they have enough understanding of the tasks they face to reduce their data-processing load, as well as enough power to manage directly the coordination of agent interactions. Firms, then, *pace* Tom Peters (Peters, 1992), do not thrive on chaos if they can possibly help it. Some degree of chaos may be a precondition for creativity and renewal, but chaos is also destructive of identity (Schumpeter, 1934) and firms, like most of us, typically prefer what already exists (us) over what could exist (others). Under most circumstances, therefore, they shun the chaotic regime in the I-Space—one that is unsustainably high in energy expenditures—and, more often than not, they also seek to escape from the complex regime into the stability and security of the ordered regime, of simple and predictable routines, and of uncomplicated, hierarchical relationships. In short, wherever possible, firms will economize on transaction costs by opting for bureaucracies in the I-Space, an institutional form that offers stability and order to firms experiencing their first significant growth (Boisot and Child, 1988, 1996).

Yet what happens when the cognitive understanding required to move up the I-Space into bureaucracies is absent? Or when the power to coordinate agent interaction—a move to the left in the I-Space—is lacking? Is a gradual drift into the chaotic region of the Space the only option?

We argue that a firm has available two quite distinctive strategies for countering the action of entropy in the I-space. Assuming that it is not yet in the chaotic regime and hence disintegrating as an organized entity, it can either seek to *reduce* whatever complexity it confronts through cognitive and relational strategies that will move it toward the ordered regime, i.e., by increasing the value of P and decreasing the value of K or of N or of both. Or it can seek to *absorb* such complexity by first allowing some drift toward the right and then settling down in a location that stops short of the chaotic regime, a strategy that requires the firm to invest in

institutional and cultural arrangements appropriate to that location. Given that they lie outside the ordered regime, markets, fiefs, and clans must be considered as much complexity-absorbing institutions as they are complexity-reducing ones.

One feature that distinguishes bureaucracies from these other institutional forms is the tight degree of coupling between agents. Fiefs, markets, and clans are all characterized by varying degrees of loose coupling between agents. Bureaucracies are bound into rigid hierarchical structures by well-structured roles and routines and a well-defined and accepted set of unitary goals. Fiefs also exhibit hierarchy, but the cement that binds agents together is much weaker: personal loyalty, and to transient agents, not to institutionalized roles. Markets bring agents together in well-structured and legally enforceable transactions, but typically, when we are dealing with markets that are “efficient” (Roberts, 1987), these are “spot” exchanges or at least time-limited ones. Only labor-market relationships are more durable, but then, once contracted, these take the transacting parties out of the market and often place them in bureaucracies. Outside the employment relationship, market players remain atomized, each free to pursue their own interests through a sequence of spot market transactions. Coupling is thus well structured but highly transient and episodic.

Finally, clans are flexible structures that work through personal negotiation and mutual adjustment. Participants in clan transactions share the gain and the pain. Here the binding of agents to each other is achieved through mutual trust. Personal trust is necessary precisely because the nature of the coupling is so uncertain and contingent and because, in contrast to markets, legal enforcement mechanisms are so weak. The looser the coupling between agents, the larger the degrees of freedom they enjoy in what they think and how they behave, and the greater the variety that they can draw on when dealing with increasingly complex tasks. Loose coupling between agents is more difficult to manage than tight coupling. But loose coupling, by increasing requisite variety, allows the firm to manage (i.e., absorb) irreducible complexity over a wider range of states than tight coupling.

The decision by a firm to absorb rather than reduce complexity can be interpreted as a decision to develop a cultural and institutional capacity in the fief, market, and clan regions of the I-Space. The firm can then either develop that capacity internally—in which case it faces the challenge of managing the resulting complexity within its own corporate boundaries by fostering a corporate culture appropriate to the operational

needs of fiefs, markets, or clans taken singly or in combination—or it can develop it through a judicious choice of the kinds of organizations with which it collaborates. It must then manage the complexity taking place at the interorganizational interface through transactional arrangements appropriate to the institutional needs of fiefs, markets, and clans.

Sometimes, the main challenge facing firms pursuing complexity-absorption strategies is to manage the tensions that result when they find themselves in an institutional environment that requires the location of interface-management arrangements in one part of the I-Space while their corporate culture is located in another. Such tensions often surface in strategic alliances, joint ventures, or operations in foreign countries whose cultural and institutional structures differ radically from those found at home (Boisot and Child, 1999).

IMPLICATIONS FOR STRATEGIC PROCESSES

Chandler has traced the evolution of the giant US corporations in the last decades of the nineteenth century (Chandler, 1977) and shown how the adoption of well-articulated functional structures allowed them to manage their growth. He also studied how, following continued growth, such firms were later led to decentralize their operations by creating divisional structures in the first decades of the twentieth century (Chandler, 1962). Both the moves to the functional structure and then to the divisional structure were a response to the pressures of information overload. In the I-Space, the moves corresponded to a trajectory first up the Space toward bureaucracies, where tasks could be structured and assigned to functions, and then horizontally along the Space toward markets, where tasks could be decentralized toward divisions that were made to compete with each other for critical resources such as capital, labor, and managerial talent. The strategy, then, was first to reduce complexity through the creation of articulate structures, and secondly, as it kept on growing, to absorb it through a process of decentralization that reduced the intensity and extent of organizational coupling required between players. Both moves, taken together, however, amounted to a cultural commitment to the upper regions of the I-Space.

The strategy remained serviceable until the 1980s. Firms grew, and also grew richer. But with the globalization of markets and the acceleration of technological competition, the complexity with which firms had to deal kept on increasing. Today, we may be reaching the limit of what the upper regions of the I-Space have to offer in terms of either complexity

reduction or absorption. Both the culture of command and control that characterizes bureaucracies, and that of market-driven SBUs held to well-structured short-term performance objectives, entail a long-term loss of entrepreneurship and a consequent inability to handle fuzziness and uncertainty.

Many firms have sensed this intuitively and have started experimenting with clan-like organizational forms such as networks (Nohria and Eccles, 1992). They have therefore started building cultural and institutional capacity once more in the lower regions of the I-space. In those regions, they encounter regimes that go from the moderately complex (fiefs) to the complex (clans) to the chaotic (no institutionalization possible). A fief culture is typically that of the small firm, the family business, or the start-up. Loyalty to an idea or to an individual predominates. As numbers grow, however, and interactions between agents become more extensive—with the rapid growth of the internet, for example, N and K have both been getting bigger—either the personal power that characterizes this culture needs to be formalized in a move up the I-Space toward bureaucracies, or a decentralization toward clan forms of governance needs to take place. We have characterized clans as an edge-of-chaos phenomenon. If, as we have argued, firms cannot thrive on chaos, might they do so on the edge of chaos?

Mintzberg and Waters have distinguished between deliberate and emergent strategies. They suggested that strategy walks on two legs (Mintzberg and Waters, 1985), one oriented toward analysis and plans, the other toward intuition and responsiveness to the unexpected. If they are right, then strategy has a need for a variety of distinct cultures inside the firm, some to handle the predictable and the routinizable—the deliberate—others to handle the uncertain and the complex—the emergent. In short, if one accepts the Mintzberg and Waters model of the strategy process, then, in an extension of the Chandlerian thesis, if structure follows strategy, the appropriate cultures must be also developed to manage the structure as it grows in diversity and complexity.

Take, for example, managing in clans, on the edge of chaos. This requires an ability to handle much higher levels of uncertainty and anxiety than analytically trained executives are used to. Clans are typically volatile and unstable forms of social organization (Macinnes, 1996). They tend to generate more social entropy than do well-structured bureaucracies. In an unforgiving selection environment, the extra organizational energy that they burn up has to be compensated for by higher levels of creativity and innovation. Yet it is the very need for greater

entrepreneurship and innovation—brought about by hypercompetition (D’Aveni, 1995), by globalization, and by accelerating technical change—that is dragging many firms into the lower regions of the I-space in the first place. Unfortunately, they often bring with them an administrative heritage (Bartlett and Ghoshal, 1989) that is ill suited to the challenge that they face; namely, to foster a culture capable of absorbing complexity as well as reducing it.

Thus in so far as the business environment is becoming more complex, firms will need to shift from the complexity-reducing strategies that secured their success from the end of the nineteenth until the end of the twentieth century and place more stress on complexity-absorbing ones—a shift away from bureaucracies and toward fiefs, markets, and clans in the I-Space. Much of the popular management literature has picked this up. It stresses internal competition (markets), the need for the large firm to behave like a small one (fiefs), and the importance of interpersonal networking (clans). Yet without an appropriate theoretical perspective on what is happening to firms, the insights emanating from this literature will remain underpowered. As we have indicated in this article, the burgeoning sciences of complexity can help put this right.

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EMERGENCE

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