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Complexity and Organization–Environment Relations: Revisiting Ashby's Law of Requisite Variety

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INTRODUCTION

It is a commonplace of organization theory that organized systems must adapt to their environment in order to survive (Lawrence and Lorsch, 1967; Aldrich, 1979). The cybernetician, W. Ross Ashby (1956) is perhaps best known for his *Law of Requisite Variety*, which framed the internal order generated by a system as its response to impinging environmental forces (Ashby, 1962). In this chapter, we recast Ashby's law as the *Law of Requisite Complexity* (McKelvey and Boisot, 2009). The latter holds that, to be efficaciously adaptive, the internal complexity of a system must match the external complexity it confronts.

Current thinking holds that organizations can invest in adaptation in two ways: (1) simplify the complexity of incoming stimuli so as to economize on the resources that need to be expended in responding; (2) invest more resources in the response than they judge to be strictly necessary so as to ensure some degree of adaptation. The risks associated with the first approach are those of oversimplification – i.e. unfamiliar stimuli merely get assimilated to familiar ones and hence get mis-classified. The risks associated with the second are that resources get depleted by unnecessarily complex responses before adaptation occurs. To explore the trade-offs a system faces between stimulus simplification and response complexification, we draw on complexity theories to develop a conceptual framework, the *Ashby Space*, that can help researchers and practitioners to frame the challenges of adaptation in resource-efficient ways. We first briefly review key aspects of general systems theories, early organization theories, and complexity theories. We then draw on Ashby's *Law* to create the Ashby Space and illustrate its use by applying it to the 2007 liquidity crisis.

SYSTEMS, ORGANIZATIONS, AND COMPLEXITY: A REVIEW

General systems theory

Our point of departure is a living cybernetic system capable of responding to its environment in adaptive ways, defined as the class of systems behaviours that contribute to the maintenance of system identity in the face of external perturbations (Churchman and Ackoff, 1950). Cybernetics was defined by Wiener (1948) as the science of control and communication in the animal and the machine. All living and most mechanical systems are sustained by the presence of positive and negative feedback loops; the first amplifying and the second dampening information-bearing signals of relevance to them. The study of negative feedback in general systems theory (GST) showed how systems acted to preserve themselves under changing external conditions. The distinction between the system's interior and its exterior is essential to the preservation of a system's identity and continued survival under conditions of environmental change. Through the mechanism of *homeostasis* (Ashby, 1956), a system is able to maintain an 'internal' equilibrium in the face of 'external' perturbations. Yet systems are also capable of generating change autonomously by amplifying feedback instead of merely adapting to external contingencies by dampening it – an idea that took root in GST with Maruyama's (1963) classic paper on deviation-amplifying positive feedback processes.

Organizations in environments

The cybernetic systems discussed by Wiener and others (Buckley, 1968), exhibited minimal complexity. They were designed to respond to a limited range of external contingencies, and to do so primarily through negative feedback processes. Human organizations, by contrast, are capable of dealing with a massive range of external contingencies, far exceeding those that an individual human being, let alone a simple cybernetic machine, can handle. Yet for most of the twentieth century human organizations were conceived of as simple machines, tightly controllable by their creators or owners (Taylor, 1911; Fayol, 1916; Koontz and O'Donnell, 1964) and hence predictable in their behaviour. Etzioni (1961) analyses an organization's capacity to secure compliance in carrying out complex tasks through the exercise of *power* expressed via hierarchical authority relations, suggesting that, in the human case, this capacity is what distinguishes internal from external organization – a distinction that was later taken up by the markets and hierarchies framework (Coase, 1937; Williamson, 1975). With internal organization, the exercise of power allows multiple negative feedback loops to be brought under some central control in order to achieve stability and a unitary agency.

The passage from a mechanistic to a more organic conception of human organization (Burns and Stalker, 1961) had taken place by the early 1960s, partly in response to the discovery that human organization was neither as controllable nor as predictable as had been assumed (Trist and Bamforth, 1951; McGregor, 1960). The systemic processes that demarcated a lower-entropy[1] internal organization from a higher-entropy external environment were not all under managerial control. Nevertheless, through evolution, and in contrast to a purely mechanical system, an organic system could *learn* to maintain a distinction between internal and external environment, preserving a boundary and exercising some measure of control over what crossed the boundary (Miller, 1978). Homeostasis could thus be maintained inside the boundary across a wider range of environmental changes than in the case of a purely mechanical system. An *intelligent* organic system could then take this adaptive capacity one step further by generating representations of both its internal and external environment (March and Simon, 1958). These could be manipulated so as to allow it to anticipate and respond to the future states of both.

The organic conception of organizations emerged alongside the new GST being formulated in biology, itself aspiring to the status of 'a general theory of organization' (Bertalanffy, 1968: 34; Kast and Rosenzweig, 1973). A cybernetic system could now be viewed as a special case of a general system, one that was equilibrium-seeking. A subset of these – *autopoietic* systems – exhibited the property of self-organization (Maturana and Varela, 1980), exploiting the dampening and stabilizing effects of negative feedback effects to achieve autopoietic closure. The interior of any autopoietic system will always be characterized by a lower level of entropy than that of its environment. Indeed, for many biologists, this entropy differential actually *defines* organization (Brooks and Wiley, 1988; Weber et al., 1988).

A number of scholars then began to study the way that the structures and behaviours of organized human systems adapt to changes in the environment (Woodward, 1958; Lawrence and Lorsch, 1967; Thompson, 1967). An environment experienced as complex provokes a matching process of differentiation and integration in such structures and behaviours; one experienced as simple, less so. In these contingent responses of an organized system to the characteristics of its environment, we have, in effect, a first social science application of Ashby's *Law of Requisite Variety* (1956): an adaptive system survives to the extent that the variety it generates matches that of the environment it finds itself in. In what could then be seen as a further application of Ashby's law, Perrow (1972) framed the issue of organizational complexity in terms of the *tasks* that human organization has to perform, characterizing task complexity by its resistance to both routinization and understanding. For Perrow, complexity had both an objective and a subjective side, that is, it can be inter-subjectively ascertained to be a property of the environment itself (objective complexity) or it can describe an individual's experience irrespective of the objective properties of the environment (s)he encounters (subjective complexity).

Complex adaptive systems

The foregoing view assumes that organizations are *objects* in an environment that can be treated as a *residual* category – i.e. it comprises everything that the organization is not. Yet *we,* either as external observers or as members of organizations, are the ones who decide where to place boundaries around 'the' organization and hence who define what we will treat as residual. *We* then see the environment as having higher levels of entropy because we ignore the degree to which it is itself organized and capable of exerting force on organizations. The emergence of far-from-equilibrium thermodynamics (Prigogine, 1955; Prigogine and Stengers, 1984), and of the *complex adaptive systems* (CAS) perspective in the 1990s, however, challenged this stability-seeking, 'object-oriented' view of organization.

The first phase in the development of the CAS perspective can be traced back to the physicist Erwin Schrödinger, who, in a small book called *What is Life?* (1944), had suggested that life self-organizes by sucking in low entropy from its environment and spitting out high entropy back into it. Prigogine and his co-workers in Europe, building on Bénard's (1901) study of emergent structures in fluids, then further postulated that new order – and, by implication, organization – emerged from a speeding up of such entropy production (Swenson, 1989). Prigogine labelled the resulting organized entities 'dissipative structures'. In a teapot, for example, the 'rolling boil' familiar to chefs describes a shift from conduction – homogeneous molecules dissipating heat by vibrating faster in place – to convection – molecules circulating around the pot. The shift speeds up heat transfer and in so doing more efficiently reduces an imposed energy differential. This phase transition, which occurs at the so-called '1st critical value' of imposed energy – McKelvey (2001) calls this an *adaptive tension* – defines an 'edge of order' (Haken, 1977; Mainzer, 1994/2007). Living 'dissipative' systems become increasingly efficient and exploitative of their environment, indeed, in some cases so much so that at the 'edge of order', many lose their capacity to adapt and die (Miller, 1990).

A second phase, more focused on living systems, was initiated by Anderson (1972), Gell-Mann (1988), Holland (1988, 1995) and Arthur (1994) at the Santa Fe Institute in New Mexico. These scholars explored the behaviour of heterogeneous agents interacting at the so-called 'edge of chaos', a state that emerges at a '2nd critical value' of adaptive tension. At this value, a second phase transition occurs from the order that appeared at the 1st critical value to chaos. Between the 'edges' of order and chaos lies a region of emergent complexity, or what Kauffman (1993) terms the 'melting' zone. It is a zone in which adaptive capability is at its maximum. Bak (1996) argued that to survive, entities need to maintain themselves near the edge of chaos, i.e. in the melting zone, in a state of 'SELF-ORGANIZED CRITICALITY',[2] one in which the entity achieves and then maintains an efficaciously adaptive state under changing environmental (or even internal) conditions. A process of self-organization is initiated when heterogeneous agents in search of improved fitness interconnect under conditions of exogenously or endogenously imposed adaptive tension. New order is an emergent outcome of this process.

A third phase, driven by the new discipline of econophysics, is now underway, focusing on the *outcomes* of self-organization and emergent new order. According to Thietart and Forgues (this volume), Prietula (this volume) and Tracy (this volume), emergent phenomena appear in the nonlinear, intra- and inter-level causal processes of multi-level hierarchies. Nonlinearities are a source of *butterfly-effects*[3] and *scalability*, extending across multiple hierarchical levels within organisms and other organized entities. Butterfly effects, which are tiny initiating events (i.e. Holland's 'lever points' (1995: 5)) that can produce extreme outcomes such as hurricanes, stock market crashes, giant firms, etc., can be expressed in power law form (Zipf, 1949; Newman, 2005). Scalability (Brock, 2000) and scale-free causes (West and Deering, 1995; Andriani and McKelvey, 2009) are best understood by considering a cauliflower. First cut off a 'floret' and then cut a smaller floret from the first; keep cutting successively smaller florets in this way. Each will be smaller than the former, but each will exhibit the same shape, structure, and genesis. Scalability reproduces the same 'fractal' structure[4] at different scales (Mandelbrot, 1982); which is to say that scale-free causes generate the same dynamic, effect, or characteristic at multiple levels of a system.

In what follows we take organizing to be an emergent far-from-equilibrium phenomenon that neither entails nor precludes the existence of 'organizations' as stable objects. The latter occupy one end of a continuum along which a range of organizational phenomena can be located. Order-creation via the amplification of positive feedback at one level of an organization becomes as important as equilibrium-seeking via the damping effects of negative feedback at another. When working in tandem, both contribute to the 'organizing' process; hence both can be adaptive. We now explore this point further by means of the Ashby Space.

ASHBY'S LAW AND THE ASHBY SPACE

Ross Ashby, one of the founders of GST, was interested in the range or variety of situations that an animal or a machine could respond and adapt to. His *Law of Requisite Variety* states that 'only variety can destroy variety' (Ashby, 1956: 207): a system survives to the extent that the range of responses it is able to marshal – as it attempts to adapt to imposing tensions – successfully matches the range of situations – threats and opportunities – confronting it. In the case of a living system, the response might be wholly behavioural and often outside a system's cognitive control – as in the case of a hormonal response or a reflex. Alternatively the response might be a blend of behaviour and cognition that is contingent on the system classifying a stimulus as foreshadowing, say, the presence of a foe and requiring a fight-or-flight decision. It will then respond to *representations* of its environment that are constructed out of such classification activity rather than to its environment directly (Plotkin, 1993). Gell-Mann (2002: 16–17; see also Maguire this volume) sees representations as *effectively complex* 'schemas' – structured descriptions of an objective external world which incorporate neither too few nor too many degrees of freedom. What advantage do schemas confer?

If it is not to waste its energy responding to every will-o'-the-wisp, a system must build schemas in ways that distinguish meaningful information (stimuli conveying 'important' real-world regularities) from noise (meaningless stimuli). In other words, it must distinguish between what Gell-Mann has labelled 'effective' and 'crude' complexity (Gell-Mann, 1994). Note that what constitutes information or noise for a system is partly a function of the system's own expectations and judgments about what is important (Gell-Mann, 2002) – as well as of its motivations – and hence, of its models of the world and its intents (Dennett, 1987). Valid and timely representations (schemas) economize on organism's scarce energy resources (Ball, 2004; Vermeij, 2004). This can even be seen in how we use language. Zipf (1949) showed how the frequency of word use inversely correlates with word length. The resulting power law distribution established a PRINCIPLE OF LEAST EFFORT as defined in Table 16.1.

The Ashby Space

We illustrate the functioning of Ashby's law with a simple diagram we call the *Ashby Space* (Figure 16.1). On the vertical axis we place the real-world stimuli that impinge on an organism. These range in variety from low to high. A low-variety stimulus might be an image of the moon; a high-variety stimulus might be the trajectory of an insect in a swarm.[5] On the horizontal axis, we place the variety of a system's responses to the stimuli. These also range from low to high. A low-variety response to the moon-as-stimulus would simply be to stare at it, meditate, and otherwise do nothing. Here, it is the absence of a response that is adaptive. A high-variety response to the insect swarm, by contrast, might be to chase after each individual insect flying past. This could prove exhausting and time consuming. The first type of response

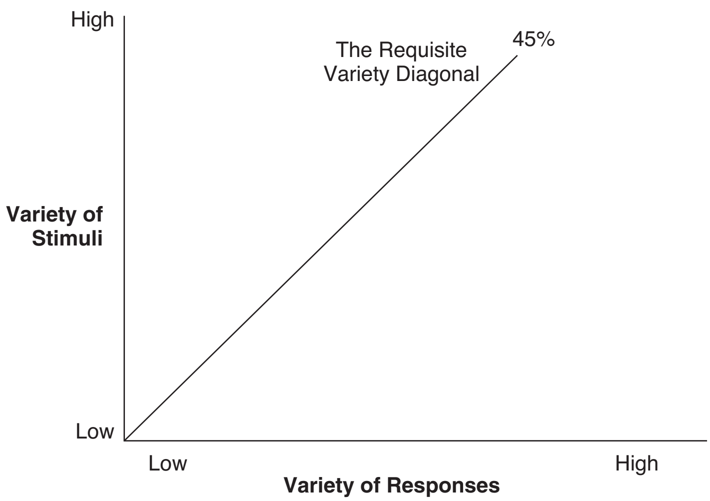

Figure 16.1 The Ashby Space

saves on scarce resources of energy and time; the second wastes them. The diagonal in the diagram indicates the set of points at which variety can be considered 'requisite', that is, where the variety of a system's response matches that of incoming stimuli in an adaptive way – it facilitates survival whether or not it does so with an efficient use of resources.

Ashby stressed the need to reduce the flow of some forms of variety from the external environment to certain essential processes in a living system. This was the role of regulation, and, as Ashby pointed out, the amount of regulation that can be achieved is bounded by the amount of information that can be transmitted and processed by a system (Ashby, 1956). The variety that the system then has to respond to depends in part on its internal schema development and transmission capacities and in part on the operation of tuneable filters, controlled by the system's cognitive apparatus, and used by the system to separate out regularities from noise (Clark, 1997) – i.e. Gell-Mann's effective complexity from its crude complexity. The more intelligent a system, the higher will be the cognitive component in its response relative to the purely behavioural one. Birds mostly act according to genetically derived behavioural instincts; monkeys produce both behavioural and cognitive responses; humans exhibit higher-level cognitive skills. There is, thus, a trade-off between the behavioural and the cognitive resources that a living system has to marshal to be adaptive.

The matching of stimulus and response variety on the diagonal can only be considered functionally adaptive, however, if it occurs inside the region of the schematic diagram labelled ***OAB*** in Figure 16.2 which describes a response budget available to a living system defined in terms of energetic, temporal and spatial resources. The curve ***AB*** constitutes the system's *adaptive frontier*, i.e. the region in which it reaches the limit of the budget it can draw on for the purposes of adaptation. To the right of this region, the mix of cognitive and behavioural variety required to respond to incoming stimuli is too high for adaptive purposes, causing the system to spend too much of its resource budget and, thus, eventually leading to its physical disintegration. Above this region, the resources consumed by the data processing required to register incoming stimuli, to interpret them, and to formulate adaptive responses also exceed the system's resource budget, eventually leading to errors and to adaptive failure – in the language of decision theory, the system's rationality is 'bounded' (Simon, 1947).

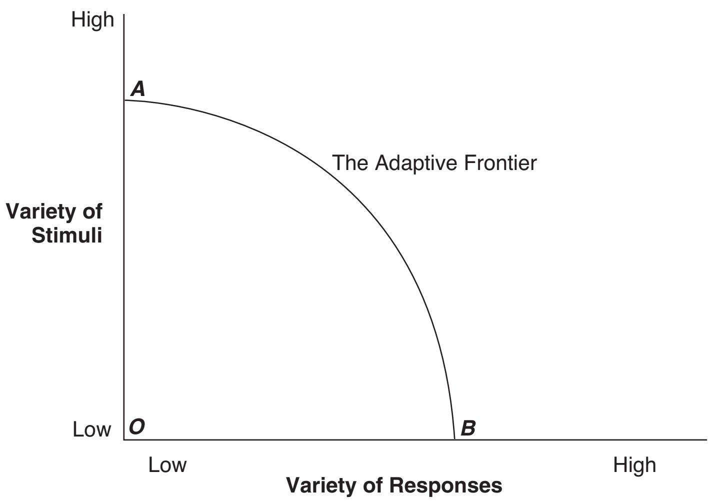

Figure 16.2 The adaptive frontier

Cognitive and physical disintegration, however, are not mutually exclusive alternatives: the first will sooner or later lead to the second and vice versa. And even when it is operating within its resource budget, at any point above the diagonal of Figure 16.1, the system is still under-adapting – cognitively or behaviourally – relative to what is actually required. Likewise, at any point below the diagonal it is using up its budget wastefully or ineffectively relative to what is required (Thaler, 1992). The challenge for an adaptive system, then, is to locate itself at some point on the diagonal in Figure 16.1 while remaining within the budget area ***OAB*** in Figure 16.2.

The shape of the resource budget, schematically represented by the curve ***OAB*** varies with the intelligence of the system. Figure 16.3 illustrates the point by comparing the resource budget of a human being with that of a hummingbird. Given its larger brain size, a human being can readily apply its resource budget to the data processing and transmission tasks that convert high-variety stimuli into low-variety ones, or vice versa. It does this by *interpreting* the stimulus, distinguishing which part of the variety associated with it is information bearing and which part is noise. In doing so, it can use its resource budget to move either down or up the vertical dimension of the Ashby Space. Hummingbirds, by contrast are better off deploying their 'flatter' resource budgets towards the right in Figure 16.3, i.e. towards more energetic responses. But human beings go further. As indicated in Figure 16.4, their capacity for social collaboration and for creating technological artefacts extends their resource budget along both the vertical and the horizontal axis of the diagram, thus significantly increasing the level of environmental variety that they can adapt to. We no longer just walk, we can fly at several times the speed of sound. And the stimuli that we process and respond to no longer originate in our immediate environment; CNN collects them from around the globe. The human case thus calls for a more dynamic formulation of Ashby's law: *The rate at which a human system's adaptation budget increases variety – i.e. at which the adaptive frontier expands – must at least match the rate at which environmental variety increases.*

What are the different response strategies available to intelligent agents in the face of variety? Consider an agent located at point ***Q*** in Figure 16.5 corresponding to some prior background activity shown as level *X* along the horizontal axis. The agent now registers a high-variety stimulus at point *Y* along the

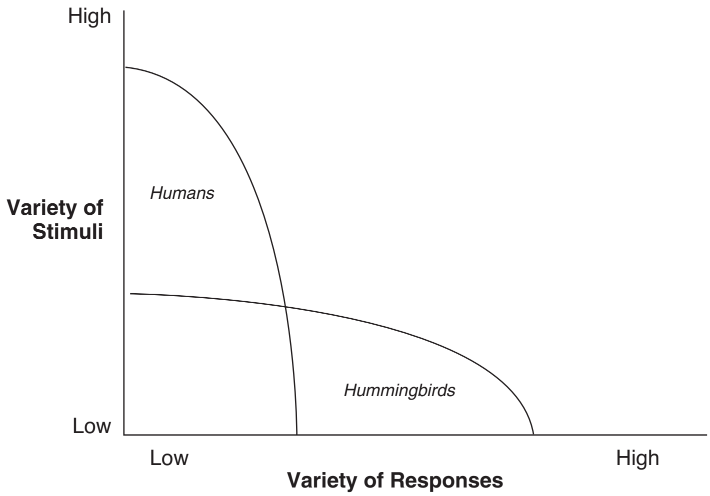

Figure 16.3 The adaptive frontier of hummingbirds and humans

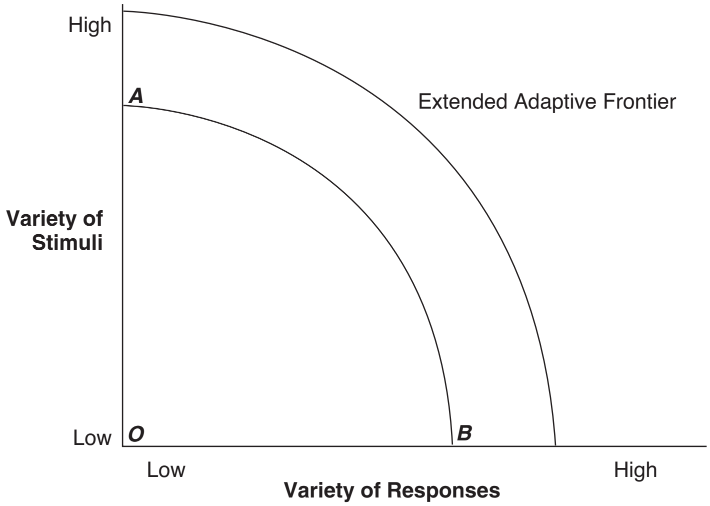

Figure 16.4 The socio-technical expansion of the adaptive frontier

vertical axis. It could respond to the variety associated with point *Y* directly in a 'mindless' behaviourist fashion either by waiting to see what happens, or by generating responses that move it horizontally to the right by trial and error until it hits the diagonal at ***C*** – i.e. one of the responses proves to be adaptive. No cognitively-driven simplification of the stimulus is involved here; its response – a mixture of cognition and behaviour – is thus costly in terms of resources consumed. In adopting this *headless chicken response*, however, the agent might well move outside its budget area ***OAB*** in Figure 16.2 thus depleting its resource budget. When the sheer variety of the stimuli allows neither prediction nor anticipation – the first specifies with precision some future event whereas the second can only orient to general classes of events – the agent would then do better to adopt the *wait-and-see* option and let nature show its hand. Alternatively, if the agent

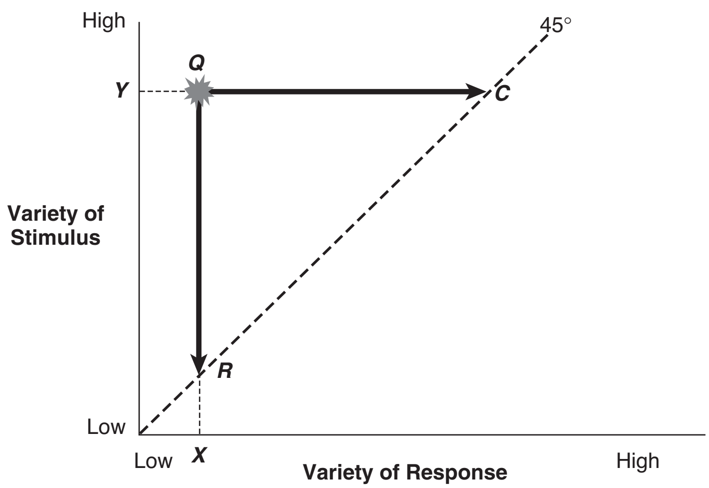

Figure 16.5 An agent at point *Q* in the Ashby space

believes that the variety of stimuli conceals some structure, it could attempt to respond in a purely cognitive fashion by moving vertically down the diagram until it approaches the horizontal axis at point ***R***. In this case, the agent treats *all* incoming stimuli either as familiar regularities or as noise and thus not in need of any *new* response. This is the strategy of agents who have 'seen it all before' and – possibly overconfidently – feel no need to actually *do* anything different. Call this a *routinizing response*. But since any downward movement calls for an interpretation and classification of incoming stimuli, whether this strategy is adaptive or not will depend on how well the resulting schema matches the real-world variety-reducing regularities confronting the agent – i.e. how *effectively complex* they are.

Intelligent adaptive agents are best off locating on the diagonal in the Ashby Space, somewhere between ***O*** and a point before which the diagonal of Figure 16.1 would intersect the budget line ***AB*** of Figure 16.2. That is, an intelligent agent first needs to *interpret* the stimuli impinging upon it. This requires a cognitive move either up or down the diagram's vertical scale that extracts information about relevant regularities from noisy incoming stimuli. The agent then needs to develop a relevant schema and respond with some *action* to regularities so extracted – a behavioural move horizontally across the diagram towards the right that is only adaptive if it stops when it meets the diagonal and does so before exhausting its budget. A cognitive move up the Ashby Space, effectively expands the range and variety of stimuli that an agent will need to process before responding – as a result, as Gell-Mann would put it, its schemas will become more complex. Such an upward move delivers *exploratory learning* (Holland, 1975; March, 1991). A cognitive move down the Ashby Space, by contrast, draws on prior learning to reduce both the range and variety of stimuli and simplify the schemas required – it delivers *exploitative learning* (Holland, 1975; March, 1991). Clearly, the further down towards ***O*** an intelligent agent can move before having to turn right and respond with a physical (behavioural) action, the more easily it can secure a quiet life for itself by achieving adaptation within its resource budget. Conversely, the further up the vertical scale towards ***A*** the rightward move occurs, the more turbulent life becomes for the agent and the more resources it has to expend in order to adapt.

The trajectory of any living system (i.e. agent) through the Ashby Space reflects its 'intelligence' – its capacity to discern meaningful regularities, develop adaptive schemas, and generate effectively complex responses. Given the limited number of stimuli that a hummingbird's brain can 'make sense' of, for example, any trade-off that the bird is required to make between its energy and data-processing resources favours drawing predominantly on its energy resources. The variety of stimuli that a human being can respond to adaptively, by contrast, is much greater so that the trade-off favours drawing predominantly on its data-processing resources. A living system's trajectory through the space thus also tells us something about its physiology. Not only are there *physiological* limits as to what may count as a stimulus, and hence as data, for a given type of system – a frog, for instance, can only detect and process peripheral movement (Lettvin et al., 1959) and a bat's movements are guided by sound, not sight – but there are also *cognitive* limits on the system's capacity to process the data contained in the stimulus. It thus confronts a problem of bounded rationality (Simon, 1986). Above the budget line the variety of stimuli may be such that a system cannot even register them. Yet, as indicated by Figure 16.4, for many living systems and especially for human beings, the budget area ***OAB*** is constantly being expanded outward from the origin by means of artefacts (Clark, 1997), cultural transmission (Gregory, 1981; Boyd and Richerson, 1985) and organized collective action (Corning, 2003). These simultaneously increase the variety of interpretive schemas available to a system on the vertical axis and that of the responses available to it on the horizontal one – its effective complexity – and thus its adaptive capacity.[6]

Complexity in the Ashby Space – three ontological regimes

Computational theory teaches us that problems whose size grows much faster than their inputs may require what effectively amounts to an infinite amount of data processing for their solution (Chaitin, 1974; Sipser, 1997). This will happen when the inputs – which here we take to be stimuli – cannot be made sense of. From the computational perspective, an intelligent agent grappling with such vast problems will then experience input stimuli as being unfathomably complex. No regularities or structure can be extracted from them and no sense can, therefore, be made of them. Even problems whose size only grows moderately faster than their inputs will be experienced as very complex to an intelligent agent. Only problems whose size is in some linear relationship with their inputs will come across as ordered. If we now take variety to be the phenomenological manifestation of complexity at work and further assume that problem-input size correlates with stimulus variety for an intelligent agent such as a human being (Grünwald et al., 2005), we can map the different input sizes of various threats and opportunities to which an agent has to adapt onto the vertical axis of Figure 16.1 to give us three distinct *ontological regimes*: the *Chaotic*, the *Complex*, and the *Ordered*. We show these in Figure 16.6.[7]

Mixing two regularities

Stimuli appearing in the *chaotic regime*[8] at the top of the diagram are hard to extract useful information from and may be judged computationally intractable, not just because of the size problem but because they are also experienced as chaotic. Unless luck intervenes, an intelligent agent drawing on conventional representations and unaware of chaos dynamics can typically make no sense of such stimuli within an adaptive time frame – i.e. before depleting its energy budget. Here, phenomena cannot even be anticipated, let alone predicted. As suggested earlier, an intelligent agent must then either wait for nature to show its hand in order to respond or it must proceed by trial and error. How it will experience the *adaptive tension* that it confronts under either option will be a function of the resources available

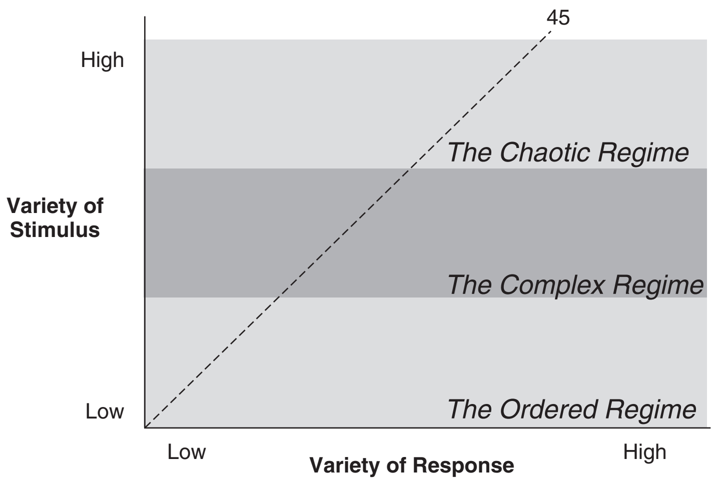

Figure 16.6 Ashby's law in three regimes

to it since a lack of resource can itself be a source of tension.

Stimuli appearing in the *ordered regime* at the bottom of the diagram, by contrast, are mostly linear in nature and are experienced as relatively unproblematic by an intelligent agent – the resulting linear regularities and noise are the stuff of everyday experience and in the human case, the products of 'normal science' (Kuhn, 1962).

In his discussion of the processes that underpin the three regimes, Gell-Mann (2002; Maguire, this volume) distinguishes between regularities produced by two fundamentally different *generative processes* (Bhaskar, 1975):

Type 1. *Reductionist Regularities:* The causal processes that are well captured through reductionist normal science, which are predictable and easily represented by equations; the focus of classical physics and neoclassical economics (Gell-Mann, 2002: 19). These characterize the Ordered Regime. They may be confidently schematized to yield predictions that then become the basis of prescriptive solutions.

Type 2. *Scale-free Regularities:* Outcomes resulting from an accumulation of random tiny initiating events amplified by positive feedback effects that generate unpredictable, seldom repeated nonlinear – and possibly extreme – outcomes that have lasting effects; what Gell-Mann calls *frozen accidents* (2002: 20). Scale-free regularities are at best problematic and beyond the reach of the explanatory traditions of normal science.

Stimuli appearing in the *complex regime* of Figure 16.2 are experienced as a blend of Gell-Mann's two types of regularities – a partly law-like and partly unpredictable mix of tiny initiating events (TIEs), frozen accidents, and power-law phenomena bathed in noise. Schema development in this regime is challenging to be sure, but computationally tractable once methods for separating out the two kinds of regularities from noise are available.

The more phenomena intelligent agents can classify unproblematically as ordered, the more they can economize on scarce data processing and energetic resources, holding these in reserve for more challenging phenomena – i.e. in responding, they will attempt to minimize the distance that they have to travel up and to the right in Figure 16.1. Human beings have a historically validated interest in steering phenomena downward in the figure towards the ordered regime if they possibly can, in order to economize on the resources needed to respond – this is the origin of their preference for simple mechanical representations identified in the opening section and, of course, of Gell-Mann's reductionist regularities. But they can overdo it. If too many of their 'interpreted' experiences end up in the ordered regime – i.e. if they all 'make sense' and can be taken for granted – human beings lose their sense of the essentially contingent nature of things and either maladapt or fossilize. When human organizations overdo it, they encounter Miller's (1990) *Icarus Paradox*, and unwittingly end up placing themselves in situations that turn out to be beyond their capacity to adapt to – e.g. they become so good at being efficient they lose their capacity to change.

Clearly, the first step in schema development with respect to some impinging real-world phenomenon is to identify the ontology appropriate for dealing with it. We outline three possibilities in Figure 16.7. If, for example, an agent interprets a phenomenon as being ordered, it will pursue the cognitively-routinizing response. This puts the agent on the least-cost trajectory of moving down the ***Q***-to-***R*** path in Figure 16.5 so as to stay within its budget area ***OAB*** – i.e. the data-information-schema-development process underlying the regularities is well understood. If, by contrast, the agent views the phenomenon as chaotic, it will either do nothing and wait or pursue the largely behavioural headless chicken response of moving from ***Q*** to ***C*** in Figure 16.5 – i.e. it could quite possibly move outside its budget area. On this trajectory the agent, knowing nothing of scalability, power laws, and scale-free theories, cannot make sense of anything. Latent regularities completely escape it, leading it to respond mindlessly. It may then expend so much undirected energy that it ends up disintegrating outside its budget area.

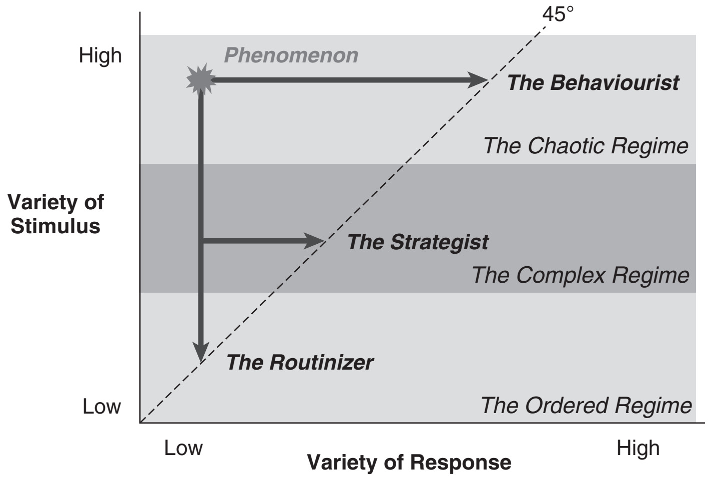

Figure 16.7 Three responses in three regimes

If an agent takes the phenomenon to be complex – i.e. neither so ordered that it can mobilize a least-cost response, nor so chaotic that it can mobilize no meaningful schema at all – it is on a scalability trajectory, one defined both by butterfly-events, frozen accidents, and nonlinearities as well as by many other attributes characterizing the Complex Regime. Here an adaptive response is feasible but more expensive than in the Ordered Regime since schema development combines both law-like *and* scalable TIEs. However, the agent can now more successfully move up the diagonal and still remain within its budget frontier.

Which ontology is adaptive for an agent may depend on how it experiences the level of adaptive tension that it confronts. Increasing tension often increases the level and strength of connectivity between hitherto unconnected phenomena, thus transforming what would ordinarily appear to be reductionist regularities into scale-free ones. TIEs will then propagate more rapidly and easily through a system, getting amplified in the process to produce magnified, nonlinear, and possibly extreme, outcomes. To illustrate: imagine a fishing net lying loosely crumpled up in a pile. Cut the net between any two nodes and the rest of the net will remain undisturbed and the effects of the cut will remain strictly local. Now place the net under tension by stretching it taut. If the net is taut enough, then a single cut could initiate a tear that would instantaneously spread from one end of the net to the other. A similar dynamic underlies the power blackouts that occasionally afflict the New England power grid when the utilities, by temporarily shutting down one overloaded station, trigger a cascade of further shutdowns throughout the North East US. Given tension plus connectivity, then, what starts off as a TIE can rapidly propagate throughout any network, growing in severity as it does so, with an extreme outcome the result. An adaptive strategy in the Complexity Regime of the Ashby Space thus needs a data-processing epistemology appropriate to the ontology underpinning the scale-free regularities that it is called upon to deal with.

Anticipating scalability – the TIEs that bind

The focus on negative feedback and equilibrium that has characterized the 'object' view of organization and much economic thinking delivers predictability, control and the maintenance of organizational identity – i.e. survival – at a low cost. After all, equilibrium spells stability and stability, in turn, maintains identity and facilitates prediction and control. Positive feedback, by contrast favours emergent self-organizing outcomes that might be anticipated *but cannot be* predicted. New order suddenly appears, often at the expense of the old order – a complexity interpretation of Schumpeter's (1934) creative destruction – but no one can tell where or when it will happen. The adaptive challenge is to anticipate it and to recognize and reinforce or negate it – i.e. to manage it – when it appears. *This, however, turns out to be less a question of how to anticipate the downstream processes of emergent self-organization than of how to anticipate the upstream scalability dynamics that drive these*. Recall that two key elements giving rise to self-organization are adaptive tension and connectivity. Positive feedback between elements connected under tension is one source of scalability that may push some TIEs to scale up – possibly to deliver extreme outcomes – but there are others. In Table 16.1 we list six that Andriani and McKelvey (2009) suggest readily apply to organizations. For example:

- *Hierarchical modularity*: Drug and toy companies having products produced in the Chinese hinterland have discovered that too much local (modular) autonomy due to culture, language, distance, time zones, cheating on product standards, trying to cut production costs, coupled with the long-distance-based costs of exerting more hierarchical monitoring (i.e. increasing connection costs) led to poisonous products. They paid a high price for modularity bordering on anarchy. Walmart has abandoned some large merger attempts in foreign countries because the connection costs of trying to get firms in foreign culture to behave like US Walmart stores were too expensive, even unworkable. Hence Simon's (1962) call for *near decomposability*, but not anarchy and Gell-Mann's (1994) *effective complexity* – just the right number of connections.
- *Combination theory*: It is like the 'perfect storm': A container ship is loaded top-heavy; a severe storm hits; the engine stalls for some unknown reason; the ship can't be steered 'into the storm'; consequently it capsizes. If any deviation occurs by itself, nothing happens. But all three together produce the extreme event.
- *Least effort*: For Zipf and his analyses of language, it was all about efficiency – I don't want to use words you don't know; you don't want to learn words I am not going to use. Over the past decades even unabridged dictionaries have shrunk in number of words – go to your library and check it out! Dahui et al. (2005) show that Zipf's Law of least effort applies only to changing language; Ishikawa (2006) and Podobnik et al. (2006) show that it only applies to industries and economies in transition as opposed to static ones. But further analysis of Zanini's (2008) industries (Drayton, 2010) shows that the power-law line of *market capitalization* is straightest in the most mature industries, insurance and machinery; see Figure 16.8. This appears opposite to what Dahui et al., Ishikawa, and Podobnik et al., find. It suggests that in free-market-based economies, market capitalization (i.e. stock-market prices) trends towards maximum 'least-effort' efficiency as traders buy and sell on information based on 'fundamentals' (i.e. valid information about the true value of the well understood mature firms); this, then, leads to the improved power-law signatures.
- *Preferential attachment*: With the 'hub and spoke' airport design, the more flights arriving at an airport, the higher the incentive for other flights to depart from there; the more flights departing from there, the more incentive for more flights to land there – the air transport equivalent of 'the rich get richer'.
- *Spontaneous order creation*: In Wikipedia, for example, one person writes a controversial entry. Others join in to expand, correct, add references, etc. Controversy, instability, and constant revising of what some other person writes emerge. The Wiki 'hierarchy', which has also emerged over the years, begins to exert a stronger 'review' role, hoping for abduction to the best explanation and stability as well.
- *Self-organized criticality*: Unlike the firms frozen in states of efficiency producing obsolete products—described in Danny Miller's *Icarus Paradox* book—effective firms have to keep changing their product lines to keep up with changing technologies and customer tastes. Perhaps we see this most obviously in hamburger stands around the world; they are pretty good at adapting to changing local tastes and to what competing hamburger chains are offering.

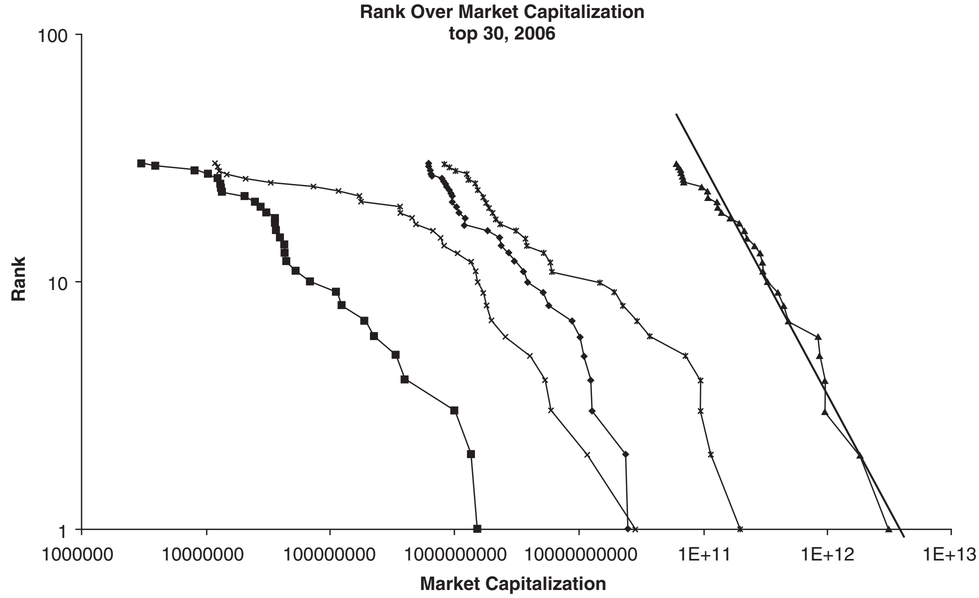

Figure 16.8 Zanini's industry market capitalizations in power-law form
Left to right, plots are of software, chemicals, machinery biotech R&D, and insurance.

Given the complex interactions involved, one cannot predict scalable outcomes. Nevertheless, an understanding of adaptive tension and connectivity allows one to rationally anticipate and adapt to the dynamics of scalability. Spotting meaningful TIEs then becomes easier since one knows what to look for. The greater the familiarity of scholars and practitioners with scalability dynamics, the earlier they are likely to spot and respond adaptively to meaningful TIEs. This will allow them to competently engage with the

Table 16.1 A sample of scale-free theories of nature*

1 *Hierarchical modularity*: As number of employees, *n*, in a firm increases, connectivity could increase by up to *n*(*n*–1)/2, producing an imbalance between the gains from more employees vs. the cost of maintaining connectivity; consequently organizations form modular designs so as to reduce the cost of connectivity; Simon argued that adaptive advantage goes to 'nearly decomposable' subsystems (Simon, 1962).

2 *Combination theory*: The interactive combination of multiple exponential or lognormal (or other skew) distributions or increased complexity of components (subtasks, processes) results in a power law distribution (West and Deering, 1995; Newman, 2005).

3 *Least effort*: Word frequency is a function of ease of usage by both speaker and listener; this gives rise to Zipf's (power) Law; the efficiency of least effort is now found to apply to changing language as well as firms and economies in transition (Zipf, 1949; Dahui et al., 2005; Ishikawa, 2006; Podobnik et al., 2006).

4 *Preferential attachment*: Given newly arriving agents into a system, larger nodes with an enhanced propensity to attract agents will become disproportionately even larger (Barabási, 2002).

5 *Spontaneous order creation*: Heterogeneous agents seeking out other agents to copy/learn from so as to improve fitness generate networks; given positive feedback, some networks become groups, some groups become larger groups and hierarchies (Holland, 1995; Kauffman, 1993).

6 *Self-organized criticality*: Under constant tension of some kind (gravity, ecological balance), some systems reach a critical state where they maintain stasis by preservative behaviours – such as Bak's small to large sandpile avalanches – which vary in size of effect according to a power law (Bak, 1996).

*We list six out of fifteen scale-free theories discussed by Andriani and McKelvey (2009).

Complexity Regime in the Ashby Space instead of escaping prematurely either into the Chaotic or the Ordered Regime.

DISCUSSION

Wiener's 1948 book on cybernetics was about control in animals and machines. Bertalanffy's 1968 book on general systems theory also framed systems in terms of top-down control processes: as in thermostats, negative feedback loops keep systems targeted on the objectives of their designers. Extending these authors' insights to cover human organizations, Thompson (1967) saw top management bureaucracies as top-down control devices that created machine-like working conditions for lower-level employees. Yet in the same period some organizational theorists (Burns and Stalker, 1961) discovered a bottom-up process of autonomous, organic changes emerging from below in organizations that allows them to respond flexibly and adaptively to changing environmental conditions (Lawrence and Lorsch, 1967). In sum, in the 1960s we see organization theory adopting the basic tenets of Ashby's *Law*, holding that efficacious adaptation occurs only when internal variety/complexity matches external variety/complexity. The Ashby Space invites organizational practitioners and scholars to now go one step further and to incorporate the insights of complexity theory with those of Ashby. It offers them a set of regimes – the chaotic, the complex and the ordered – that can help them to adapt intelligently and economically to the ever wider set of contingencies that confront them in a complex and globalizing world, one in which TIEs can rapidly scale up to produce extreme outcomes. But what are the limits of adaptation? Is there, for example, any limit to the expansion by human beings of their data-processing and schema-building resources – i.e. to the vertical expansion of the budget area ***OAB*** of Figure 16.2? A brief look at the 2007 liquidity crisis illustrates the issues involved.

An example

By August 2007 some 8,000 US (smaller) banks (Guerrera, 2009) accepted minimalist risk/reward positions by staying away from subprime mortgages, teaser loans, and by insisting that mortgage borrowers show proof of income and good credit. Such caution kept them firmly ensconced in the Ordered Regime of the Ashby Space. Some 12 major banks and over 100 other smaller banks, however, had adopted a risk/reward profile that increased the level of adaptive tension confronting them and tipped them over into the Complexity Regime of the Space. Their financial engineering models, derivatives, credit default swaps, securitized loan packages, etc., gave rise to risky loans amounting to some $50 trillion worldwide (Cooper, 2008; Morris, 2008; Foster and Magdoff, 2009). While these loans had appeared solid before the bursting of the US and other housing bubbles (e.g. in the UK and Spain, among others) – they became increasingly toxic over the course of the year. Yet, while many of these high-risk banks went bankrupt, the few that remained – Goldman Sachs, Morgan Stanley, Citigroup, Bank of America, and Wells Fargo – were able to exploit the Federal Reserve bailouts by engaging in merger and acquisition activity to emerge far stronger and larger than they had been. Here we see both positive and negative scalability dynamics at work, triggered by some early TIEs – the invention of derivatives in 1973 and of mortgage-backed securities *c.* 1985 (McKelvey and Yalamova, 2011; Yalamova and McKelvey, 2011b).

As indicated by Figure 16.6, the Complexity Regime of the Ashby Space is sandwiched between order and chaos. The tipping point between the Ordered and Complex Regimes is often crossed by risk-induced tension – i.e. fear, greed, ambition, risk-taking, etc. – that leads to a phase transition. On the one hand, the 8,000 conservative small banks minimized their risks and remained in the Ordered Regime below the 1st critical value. They applied most of the conventional tools of risk management to achieve reductionist regularities. Given low levels of adaptive tension, they could pursue replicable and reliable routines and achieve levels of predictability that kept their response budgets under control.

On the other hand, in response to strong demands for wealth-creation and for large bonuses by both owners and senior employees, large banks pursued high-risk strategies that significantly increased the levels of adaptive tension they were exposed to. For them, fear, greed, ambition, and risk-taking increased tension to the point that a phase transition occurred. They thus found themselves in the Complexity Regime but getting ever closer to the 2nd critical value at the edge of chaos – i.e. the Chaotic Regime – as a positive feedback cycle (i.e. greed → risk-taking → more greed → more risk-taking → and so on, etc.) got amplified (Minsky, 1976, 1982; McKelvey and Yalamova, 2011).

Recent evidence from econophysics shows that stock-market traders cross a tipping point – indicated by what is termed the *Hurst exponent* – between efficient-market behaviour (Fama, 1970) and the herding behaviour (Brunnermeier, 2001; Hirshleifer and Teoh, 2003) that causes the power-law distribution of stock-market price volatilities (Alvarez-Ramirez et al., 2008; Yalamova and McKelvey, 2011a, 2011b). Herding behaviour results in the positive feedback and other scale-free dynamics, that, as Minsky (1982, 1986) and Yalamova and McKelvey (2011a, 2011b) argue, set off bubble build-ups. As greed and risk-taking push market tensions to the edge of chaos, they subsequently produce a market crash.

In the Complexity region of the Ashby Space we can expect to see increased levels of tension-induced connectivity and herding as traders and banks copy what appear to be the best trading rules/strategies at the time, given the absence of accurate information about fundamental values of firms. But eventually the variety of stimuli confronting traders and banks overpowers the seeming value of rule-based herding responses so that panicked reactions set in. We then see the collapse of herding-based, price-volatility-induced power laws as traders that are approaching the edge of chaos and the collapse of markets (Grech and Pamula, 2008) begin to jump ship. The headless chicken response now goes into full swing, and the adaptive resource budget gets squandered as the crash progresses. In the 2007 liquidity crisis, the failure of mortgage-backed loans quickly set up the conditions that gave rise to the ~$50 trillion's worth of toxic loans worldwide (Marshall, 2009).

In the Complexity Regime of the Ashby Space, power-law thinking trumps the Gaussian thinking and normal distributions on which most risk management models depend. Power law distributions show how TIEs can get amplified to generate extreme events. In this region, all that can be hoped for is anticipation, not prediction. Why, then, given the dangers, would managers and entrepreneurs ever want to operate in this space? Because, in this space, in contrast to the linear and hence calculable risk/returns associated with the Ordered Regime, TIEs can offer positive payoffs that may also be power law-distributed – i.e. being nonlinear the payoffs can be very large indeed. It is the relentless quest for extreme positive payoffs, forced on managers by corporate owners and talented employees that keeps pushing them to the Edge of Chaos (McKelvey, 2001, 2008). Scholars and practitioners who have some appreciation of the scalability dynamics in the Complex Regime of the Ashby Space stand a better chance of securing the payoffs available in this region while avoiding the dangers.

CONCLUSION

By integrating Ashby's perspective on the nature of efficacious adaptation with our growing understanding of the complexity phenomenon, the Ashby Space offers scholars and practitioners a conceptual framework for thinking through some of the more pressing problems that confront a globalizing world. What, for example, are the challenges of adapting to nonlinear changes in the climate?

Or of adapting to the emergence of asymmetric threats? What are the scalable opportunities that we can associate with the spread of the Internet or of mobile telephony? The above challenges will not be successfully addressed in the ordered regime of the Ashby Space. We must learn to wander out into the Complex Regime and explore what it has to offer us without necessarily falling into the Chaotic one. To succeed we need a more nuanced yet theoretically robust view of how organized systems partition their environment in their attempts to adapt to it within the resource envelope available to them. Current treatments of the human organization/environment interface are often too descriptive and too under-theorized to yield the insights needed. Much of the necessary thinking is today coming out of theoretical biology where the use of the terms 'organization' and 'environment' extends well beyond their application in management and the social sciences. The Ashby Space offers a conceptual bridge between these different disciplines. Future research – theoretical and empirical – should exploit the potential synergies on offer.

NOTES

1 Entropy measures a system's degree of disorganization, taking it to be the amount of uncertainty still remaining in the system once its observable, uncertainty-reducing regularities are accounted for.

2 Terms shown in SMALL CAPITALS are further defined in Table 16.1, with examples later in the chapter.

3 The term, *butterfly effects* dates back to the title of E.N. Lorenz's paper of (1972): 'Predictability: Does the flap of a butterfly's wings in Brazil set off a tornado in Texas?' Paper presented at the 1972 meeting of the American Association for the Advancement of Science. Washington, DC.

4 Fractals are defined as shapes that can be subdivided into parts, each of which is (at least approximately) a reduced-size copy of the whole (Mandelbrot, 1982). The same mathematical equation – or adaptive causal dynamic in biology or for firms – creates similar causal dynamics at each level of a fractal structure. See Andriani and McKelvey (this volume) for further discussion of fractals and scalability.

5 In what follows we do not distinguish between the variety that exists within a given stimulus or response vs. that which occurs across stimuli and responses. The distinction is one that the organism itself must make through acts of interpretation. See below.

6 A phylogenetic application of this argument would allow us to map the vertical and horizontal dimensions of the Ashby Space respectively onto Salthe's (1985) and Eldredge's (1985) ecological and genealogical hierarchies, yielding an evolutionary perspective on adaptation. See Brooks and Wiley (1988).

7 Although the horizontal axis could also be so partitioned, for ease of exposition we refrain from doing so.

8 Here, we are using the term 'chaotic' in its everyday sense. This is broader than its mathematical sense à la chaos theory (Guastello, 1995) since it mixes deterministic and stochastic processes.

REFERENCES

Aldrich, H.E. (1979) *Organizations and Environments*. Englewood Cliffs, NJ: Prentice-Hall.

Alvarez-Ramirez, J., Alvarez, J., Rodriguez, E., and Fernandez-Anaya, G. (2008) Time-varying Hurst Exponent for US Stock Markets. *Physica A*, 387: 6159–6169.

Anderson, P.W. (1972) More is different. *Science*, 177: 393–396.

Andriani, P. and McKelvey, B. (2009) From Gaussian to Paretian thinking: Causes and implications of power laws in organizations. *Organization Science*, 20(6).

Arthur, W.B. (1994) *Increasing Returns and Path Dependence in the Economy*. Ann Arbor, MI: University of Michigan Press.

Ashby, R.W. (1956) *An Introduction to Cybernetics*. London: Methuen.

Ashby, W.R. (1962) Principles of the self-organizing system. In: H. von Foerster and G.W. Zopf (eds) *Principles of Self-Organization*. New York: Pergamon, pp. 255–278.

Bak, P. (1996) *How Nature Works*. New York: Copernicus.

Ball, P. (2004) *Critical Mass*. London: Arrow Books.

Barabási, A.-L. (2002) *Linked*. Cambridge, MA: Perseus.

Bénard, H. (1901) Les tourbillons cellulaires dans une nappe liquide transportant de la chaleur par convection en régime permanent. *Annales de Chimie et de Physique*, 23: 62–144.

Bertalanffy, L. von (1968) *General System Theory*. New York: Braziller.

Bhaskar, R. (1975) *A Realist Theory of Science*. London: Leeds Books. [2nd edn published by Verso (London), 1997].

Boyd, R. and Richerson, P.J. (1985) *Culture and the Evolutionary Process*. Chicago: The University of Chicago Press.

Brock, W.A. (2000) Some Santa Fe scenery. In: D. Colander (ed.) *The Complexity Vision and the Teaching of Economics*. Cheltenham, UK: Edward Elgar, pp. 29–49.

Brooks, D.R. and Wiley, E.O. (1988) *Evolution as Entropy*. Chicago: University of Chicago Press.

Brunnermeier, M.K. (2001) *Asset Pricing under Asymmetric Information: Bubbles, Crashes, Technical Analysis, and Herding*. Oxford, UK: Oxford University Press.

Buckley, W. (ed.) (1968) *Modern Systems Research for the Behavioral Scientist*. Chicago: Aldine.

Burns, T. and Stalker, G.M. (1961) *The Management of Innovation*, London: Tavistock.

Chaitin, G.J. (1974) Information-theoretic computational complexity. *IEEE Transactions on Information Theory*, 20: 10–15.

Churchman, C.W. and Ackoff, R.L. (1950) Purposive behavior and cybernetics. *Social Forces*, 29: 32–39.

Clark, A. (1997) *Being There*. Cambridge, MA: MIT Press.

Coase, R. (1937) The nature of the firm. *Economica*, 4: 386–405.

Cooper, G. (2008) *The Origin of Financial Crises*. New York: Vintage Books.

Corning, P. (2003) *Nature's Magic*. Cambridge, MA: Cambridge University Press.

Dahui, W., Menghui, L., and Zengru, D. (2005) True reason for Zipf's law in language. *Physica A*, 358: 545–550.

Dennett, D.C. (1987) *The Intentional Stance*. Cambridge, Mass: The MIT Press.

Drayton, C. (2010) Translating Zanini's power curves into power laws. Research project at the UCLA Anderson School of Management, Los Angeles, CA.

Eldredge, N. (1985) *Unfinished Synthesis: Biological Hierarchies and Modern Evolutionary Thought*. New York: Oxford University Press.

Etzioni, A. (1961) *A Comparative Analysis of Complex Organizations*. New York: Free Press.

Fama, E.F. (1970) Efficient capital markets: a review of theory and empirical work. *Journal of Finance*, 21: 383–417.

Fayol, H. (1916) Administration industrielle et générale. *Bulletin de la Société de l'Industrie Minérale*, No. 10.

Foster, J.B. and Magdoff, F. (2009) *The Great Financial Crisis*. New York: Monthly Review Press.

Gell-Mann, M. (1988) The concept of the Institute. In: D. Pines (ed.) *Emerging Synthesis in Science*. Reading, MA: Addison-Wesley, pp. 1–15.

Gell-Mann, M. (1994) *The Quark and the Jaguar*. New York: Freeman.

Gell-Mann, M. (2002) What is complexity? In: A.Q. Curzio and M. Fortis (eds) *Complexity and Industrial Clusters*. Heidelberg, Germany: Physica-Verlag, pp. 13–24.

Grech, D. and Pamula, G. (2008) The local Hurst exponent of the financial time series in the vicinity of crashes on the Polish stock exchange market. *Physica A*, 387: 4299–4308.

Gregory, R.L. (1981) *Mind in Science*. Middlesex, UK: Penguin Books.

Grünwald, P., Myung, I., and Pitt, M. (2005) *Advances in Minimum Description Length*. Cambridge, MA: MIT Press.

Guastello, S.J. (1995) *Chaos, Catastrophe, and Human Affairs*. Mahwah, NJ: Lawrence Erlbaum.

Guerrera, F. (2009) Old bank axioms gain new currency. *Financial Times* (Tuesday, July 7), p. 12.

Haken, H. (1977) *Synergetics, An Introduction*. Berlin: Springer-Verlag.

Hayek, F.A. (1967) *Studies in Philosophy, Politics and Economics.* Chicago, IL: University of Chicago Press.

Hirshleifer, D. and Teoh, S.H. (2003) Her behaviour and cascading in capital markets: A review and synthesis. *European Financial Management*, 9: 25–66.

Holland, J.H. (1975) *Adaptation in Natural and Artificial Systems*. Cambridge, MA: MIT Press.

Holland, J.H. (1988) The global economy as an adaptive system. In: P.W. Anderson, K.J. Arrow, and D. Pines (eds) *The Economy as an Evolving Complex System*. Reading, MA: Addison-Wesley, pp. 117–124.

Holland, J.H. (1995) *Hidden Order.* Cambridge, MA: Perseus Books.

Ishikawa, A. (2006) Pareto index induced from the scale of companies. *Physica A*, 363: 367–376.

Kast, F.E. and Rosenzweig, J.E. (1973) *Contingency Views of Organization and Management*. Chicago: Science Research Associates.

Kauffman, S.A. (1993) *The Origins of Order*. New York: Oxford University Press.

Koontz, H. and O'Donnell, C.J. (1964) *Principles of Management*. New York: McGraw-Hill.

Kuhn, T.S. (1962) *The Structure of Scientific Revolutions.* Chicago, IL: University of Chicago Press.

Lawrence, P.R and Lorsch, J.W. (1967) *Organization and Environment.* Cambridge, MA: Harvard Business School Press.

Lettvin, J.Y., Maturana, H.R., McCulloch, W.S., and Pitts, W.H. (1959) What the frog's eye tells the frog's brain. *Proceedings of the Institute of Radio Engineering*, 47: 1940–1951.

Lorenz, E.N. (1972) Predictability: Does the flap of a butterfly's wings in Brazil set off a tornado in Texas? Paper presented at the 1972 meeting of the American Association for the Advancement of Science. Washington, DC.

Mainzer, K. (1994) *Thinking in Complexity*. New York: Springer-Verlag. [5th edn published in 2007.]

Mandelbrot, B.B. (1982) *The Fractal Geometry of Nature*. New York: Freeman.

March, J.G. (1991) Exploration and exploitation in organizational learning. *Organization Science*, 2: 71–87.

March, J.G. and Simon, H.A. (1958) *Organizations*. New York: Wiley.

Marshall, A.G. (2009) Entering the greatest depression in history: More bubbles waiting to burst. *Global Research* (August 16): 1–11. http://www.globalresearch.ca/index.php?context=va&aid=14680

Maruyama, M. (1963) The second cybernetics. *American Scientist*, 51: 164–179.

Maturana, H.R. and Varela, F.H. (1980) *Autopoiesis and Cognition*. Dordrecht, The Netherlands: Reidel.

McGregor, D. (1960) *The Human Side of Enterprise*. New York: McGraw-Hill.

McKelvey, B. (2001) Energizing order-creating networks of distributed intelligence. *International Journal of Innovation Management*, 5: 181–212.

McKelvey, B. (2008) Emergent strategy via complexity leadership. In: M. Uhl-Bien and R. Marion (eds) *Complexity and Leadership: Part I.* Charlotte, NC: Information Age Publishing, pp. 225–268.

McKelvey, B. and Boisot, M. (2009) Redefining strategic foresight: 'Fast' and 'far' sight via complexity science. In: L.A. Costanzo and R.B. MacKay (eds) *Handbook of Research on Strategy and Foresight*. Cheltenham, UK: Elgar, pp. 15–47.

McKelvey, B. and Yalamova, R. (2011) The build-up to the 2007 liquidity crisis: An example of scalability dynamics in action. In: G. Sundström and E. Hollnagel (eds) *Governance and Control of Financial Systems: A Resilience Engineering Perspective*, Ch. 7.

Miller, D. (1990) *The Icarus Paradox*. New York: HarperBusiness.

Miller, J.G. (1978) *Living Systems*. New York: McGraw-Hill.

Minsky, H.P. (1982) *Can 'It' Happen Again?* Armonk, NY: M.E. Sharpe, Inc.

Minsky, H.P. (1986) *Stabilizing an Unstable Economy*. New Haven, CT: Yale University Press. [2nd edn published by McGraw-Hill, 2008.]

Morris, C.R. (2008) *The Two Trillion Dollar Meltdown* (revised and updated). New York: PublicAffairs.

Newman, M.E.J. (2005) Power laws, Pareto distributions and Zipf's law. *Contemporary Physics*, 46: 323–351.

Perrow, C. (1972) *Complex Organizations: A Critical Essay*. Glennview, Il: Scott, Foresman.

Plotkin, H. (1993) *Darwin Machines and the Nature of Knowledge.* Cambridge, MA: Harvard University Press.

Podobnik, B., Fu, D., Jagric, T., Grosse, I., and Stanley, H.E. (2006) Fractionally integrated process for transition economics. *Physica A*, 362: 465–470.

Prigogine, I. (1955) *An Introduction to Thermodynamics of Irreversible Processes*. Springfield, IL: Thomas.

Prigogine, I. and Stengers, I. (1984) *Order Out of Chaos*. New York: Bantam.

Salthe, S. (1985) *Evolving Hierarchical Systems: Their Structure and Representation.* New York: Columbia University Press.

Schrödinger, E. (1944) *What is Life?* Cambridge, UK: Cambridge University Press.

Schumpeter, J. (1934) *The Theory of Economic Development.* Boston, MA: Harvard University Press.

Simon, H.A. (1947) *Administrative Behavior*. New York: Macmillan.

Simon, H.A. (1962) The architecture of complexity. *Proceedings of the American Philosophical Society*, 106: 467–482.

Simon, H.A. (1986) Rationality in psychology and economics. *Journal of Business*, 59(4): S209–S224.

Sipser, M. (1997) *Introduction to the Theory of Computation*. Boston, MA: PWS Publishing Co.

Swenson, R. (1989) Emergent attractors and the law of maximum entropy production. *Systems Research*, 6:187–197.

Taylor, F.W. (1911) *The Principles of Scientific Management*. New York: Harper.

Thaler, R. (1992) *The Winner's Curse.* Princeton, NJ: Princeton University Press.

Thompson, J.D. (1967) *Organizations in Action.* New York: McGraw Hill.

Trist, E.L. and Bamforth, K.W. (1951) Some social and psychological consequences of the longwall method of coal getting. *Human Relations*, 4: 3–38.

Vermeij, G. (2004) *Nature: An Economic History*. Princeton, NJ: Princeton University Press.

Weber, B.H., Depew, D.J., and Smith, J.D. (eds) (1988) *Entropy, Information, and Evolution*. Cambridge, MA: MIT Press.

West, B.J. and Deering, B. (1995) *The Lure of Modern Science*. Singapore: World Scientific.

Wiener, N. (1948) *Cybernetics.* Cambridge, MA: MIT Press.

Williamson, O.E. (1975) *Markets and Hierarchies,* New York: Free Press.

Woodward, J. (1958) *Management and Technology*. London: HMSO.

Yalamova, R. and McKelvey, B. (2011a) Explaining what leads up to stock market crashes: A phase transition model and scalability dynamics. *Journal of Behavioral Finance*.

Yalamova, R. and McKelvey, B. (2011b) Using power laws and the Hurst coefficient to identify stock market trading bubbles. In: G. Sundström and E. Hollnagel (eds) *Governance and Control of Financial Systems: A Resilience Engineering Perspective*, Ch. 9

Zanini, M. (2008) Using 'power curves' to assess industry dynamics. *The McKinsey Quarterly,* November.

Zipf, G.K. (1949) *Human Behavior and the Principle of Least Effort*. New York: Hafner.