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Beyond Gaussian averages: redirecting international business and management research toward extreme events and power laws

Pierpaolo Andriani[1] and
Bill McKelvey[2]

[1]*Durham Business School, Durham, UK;*
[2]*The UCLA Anderson School of Management, Los Angeles, CA, USA*

Correspondence:
Bill McKelvey, The UCLA Anderson School of Management, 110 Westwood Plaza, Los Angeles, CA 90095-1481, USA.
Tel: +1 310 825 7796;
Fax: +1 310 206-2002;
E-mail: mckelvey@anderson.ucla.edu

Abstract
Practicing managers live in a world of 'extremes', but international business and management research is based on Gaussian statistics that rule out such extremes. On occasion, positive feedback processes among interactive data points cause extreme events characterized by power laws. They seem ubiquitous; we list 80 kinds of them – half each among natural and social phenomena. We use imposed tension and Per Bak's 'self-organized criticality' to argue that Pareto-based science and statistics (based on interdependence, positive feedback, scalability, (nearly) infinite variance, and emphasizing extremes) should parallel the traditional dominance of Gaussian statistics (based on independent data points, finite variance and emphasizing averages). We question quantitative journal publications depending on Gaussian statistics. The cost is inaccurate science and irrelevance to practitioners. In conclusion, no statistical findings should be accepted into business studies if they gain significance via some assumption device by which extreme events and (nearly) infinite variance are ignored. Accordingly, we suggest redirecting international business studies, and management research in general.
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Introduction

> The most diverse attempts continue to be made to discredit in advance all evidence based on the use of doubly logarithmic graphs. But we think this method would have remained uncontroversial, were it not for the nature of the conclusion to which it leads. Unfortunately, a straight, doubly logarithmic graph indicates a distribution that flies in the face of the Gaussian dogma, which long ruled uncontested. The failure of applied statisticians and social scientists to heed Zipf helps account for the striking backwardness of their fields (Mandelbrot, 1983: 404).

Most quantitative business studies researchers presume Gaussian (normal) distributions with finite means and variances and use appropriate statistics to match: for evidence, study any random sample of current research papers of your choosing. It follows that virtually all of our quantitative research-based lessons to managers stem from Gaussian-based research. On the other hand, best-selling

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books such as *In Search of Excellence*, *Salim Group, Control Your Destiny…*, *The Challenger Disaster, Hidden Value, Good to Great*, *What Went Wrong at Enron*, *Strategy is Destiny*: *'Tangento' en Parmalat?* and *Boeing vs Airbus*,[1] are case studies of rare and/or extreme events – organizations that are extremely good or associated with disasters. The cases we use in our classrooms are almost always cases about very good or bad firms; they are seldom, if ever, about 'average' firms.

Could it be that findings from journal articles legitimated by statistical significance based on Gaussian assumptions and statistics are mistaken, and the derived advice to managers is at odds with reality? We believe the time has come to work toward a different, but equally legitimate, research and teaching approach. We draw our solution from complexity science (West and Deering, 1995) and econophysics (Mantegna and Stanley, 2000; Newman, 2005); our solution builds from full acceptance of Pareto distributions and then scalability, fractal structures, power laws, and scale-free theory.

The coast of Norway appears jagged, no matter what kind of measure is used: miles, kilometers, meters, or centimeters. This is called '*scalability*': no matter what the scale of measurement, the phenomena appear about the same. Scalability results from what Mandelbrot (1983) calls *fractal geometry*.[2] A cauliflower is an obvious example. Cut off a floret; cut a smaller floret from the first floret; then an even smaller one; and then one another yet, and so on. Each fractal subcomponent is smaller than the former; but each has the same shape, structure, function, cause, and causal explanation. If the florets are plotted by size and frequency they are *Pareto distributed*.

If plotted on double-log paper, Pareto distributions show the distinctive *power law* signature – a negatively sloping straight line. Power laws seem ubiquitous – they pertain to leaves, coastlines, and music (Casti, 1994). They apply to earthquakes, web hits, phone calls, wealth, and word frequency; cities; and firms (see Table 1). Power law phenomena call for *scale-free theories* because the same cause and explanation apply to each of the different levels.[3] They exhibit the *power law signature* because they shrink by a fixed ratio.

Does it matter? Pareto distributions have long ('*fat*') tails, nearly infinite variance, and consequently unstable means and confidence intervals. By contrast, Gaussian distributions have vanishing tails, thereby allowing focus to dwell solely on limited variance and stable means. As a result, confidence intervals for statistical significance are clearly defined, stable, and narrowed, with the result that attaining statistical significance, publication, and then career advancement, is easier. Power laws indicate 'correlated, cooperative phenomena between groups of interacting agents'[4] (Cook *et al.*, 2004). They often take the form of rank/size expressions such as $F \approx N^{-\beta}$, where F is frequency, N is rank (the variable), and β, the exponent, is constant. In exponential functions the exponent is the variable and N is constant.

Gauss *vs* Pareto is not a simple either-or divide. Rather, it can depend on circumstances that increase the likelihood of interdependent interactions. We argue that two general conditions are most apt to cause the shift from independent-additive to interaction with possibility of positive feedback – that is, power law conditions: (1) increased tensions of various kinds, and/or (2) lower cost and greater ease of making connections. We base our logic on Bak's (1996) concept of *self-organized criticality* (SOC). We also hold that because of SOC effects most, if not all, of the interdependence-based power law theories apply to management research and international business studies. Power law effects are thus widespread in organizations, and have far greater consequence than current users of statistics presume.

We suggest that the international business (IB) arena is especially vulnerable to SOC effects. Globalization imposes cultural-diversity-based tensions on managers and organizations. Other criticality tensions on Europe and the US stem from the low-cost producer status of India and China. Technology-sourced tensions affect IB even more than they do Europe and the US simply because they are newly imposed. The recent enlargement of the EU is another source of imposed tension on firms. All this in the context of new email, Internet, and mobile phone technologies making global connections easier and cheaper. Tension is also increasing in the IB world owing to environmental changes that require new international institutional and ethical approaches: water scarcity and related cross-border disputes, cross-border immigrant labor, pollution spreading from country to country, and climate change are generating new forms of interdependency among MNEs and with institutions, societies and social groups. Corporate social responsibility is about these new interdependencies. Increased connectivity in IB calls for network approaches that sit at the heart of Paretian statistics.

Table 1 Some examples of natural and social power law phenomena

Natural science	*References*	*Social science*	*References*
Physics		*General social*	
Brownian motion	West and Deering (1995); Gardner (1978)	Music	Casti (1994)
Fractures of materials	Sornette (2002)	Language word usage; Deaths of languages	Zipf (1949); Abrams and Strogatz (2000)
Sandpile avalanches	Bak (1996)	Structure of WWW	Albert *et al.* (1999)
Laser technology evolution	Baum and Silverman (2001)	Structure of Internet hardware	Faloutsos *et al.* (1999)
Brush-fire damage	Bak (1996)	Number of hits received from website per day	Adamic and Huberman (2000)
Amount of yearly precipitation	Nekola and Brown (2007)	News website visitation decay patterns	Dezsö *et al.* (2006)
Water levels in the Nile	Casti (1994)	Number of telephone calls and emails	Aiello *et al.* (2000); Ebel *et al.* (2002)
Hurricanes and floods	Bak (1996)	Social networks	Watts (2003)
Number of minerals per country	MINDAT	Sexual networks	Liljeros *et al.* (2001)
Earthquakes	Gutenberg and Richter (1944)	Actor networks	Barabási and Bonabeau (2003)
Power system blackouts	Carreras *et al.* (2004)	Co-authorships	Newman (2001)
Coastlines	Casti (1994)	Publications and citations	Lotka (1926); de Solla Price (1965)
Magma rising through earth's crust	Weinberg and Podladchikov (1994)	Delinquency rates	Cook *et al.* (2004)
Size of asteroid hits	Hughes and Nathan (1994); Marsili and Zhang (1996)	Aggressive behavior among boys during recess	Warren *et al.* (2005)
Sun spots	Hughes *et al.* (2003)	Global terrorism events	Dumé (2005)
Galactic structure	Baryshev and Teerikorpi (2002)	Distribution of family names	Zanette and Manrubia (2001)
		Size of villages	Carneiro (1987)
Biology		Traffic jams	Nagel and Paczuski (1995)
Frequency of DNA base chemicals	Selvam (2002)	Number of inventions in cities	Bettencourt *et al.* (2005)
Genomic properties (DNA words)	Luscombe *et al.* (2002)	Cities	Estoup (1916); Zipf (1949)
Genetic circuitry	Barabási (2002)	Casualties in war	Cederman (2003)
Protein–protein interaction networks	Song *et al.* (2005); Wuchty and Almaas (2005)	*Firms*	
Metabolism of cells	West *et al.* (1997)	Cotton prices	Mandelbrot (1983)
Cellular substructures	Wax *et al.* (2002)	Consumer product sales; long tails	Moss (2002); Anderson (2006)
Magnitude estimation of sensorial stimuli	Roberts (1979)	Copies of books sold	Hackett (1967)
Circulation in plants and animals	West *et al.* (1997)	Blockbuster drugs sold; movie profits	Buchanan (2004); De Vany (2004)
Phytoplankton	Jenkinson (2004)	Distribution of Wealth	Pareto (1897); Levy and Solomon (1997); Hegyi *et al.* (2007)
Willis's law: number versus size of plant genera	Willis (1922)	Price movements on exchanges	Mandelbrot and Hudson (2004)
Brain functioning	Stassinopoulos and Bak (1995)	Economic fluctuations	Scheinkman and Woodford (1994)
Tumor growth	Brú *et al.* (2003)	Growth rate of countries' GDP	Lee *et al.* (1998)
Bronchial structure	Goldberger *et al.* (1990)	Entrepreneurship/innovation	Poole *et al.* (2000)
Fetal lamb breathing	Szeto *et al.* (1992)	Intra-firm decision events	Diatlov (2005)
Heart beat rates	Nahshoni *et al.* (1998)	Job vacancies	Gunz *et al.* (2001)
Death from heart attack	Bigger *et al.* (1996)	Income	Clementi and Gallegati (2005)
Predicting premature births	Sornette (2002)	Growth rates and internal structure of firms	Stanley *et al.* (1996)
Functional networks in brain	Shin and Kim (2004)	Firm size	Axtell (2001)
Punctuated equilibrium	Bak and Sneppen (1993)	Supply chains; bankruptcies	Scheinkman and Woodford (1994); Delli Gatti *et al.* (2004)
Body size of species	Haskell *et al.* (2002)	Director interlock structure	Battiston and Catanzaro (2003)
Epidemics	Liljeros *et al.* (2001)	Alliance networks among biotech firms	Barabási and Bonabeau (2003): 207, building on Powell *et al.* (2005)
Frequency of species	Willis and Yule (1922)	Italian industrial districts	Andriani (2003a)
Size distributions in ecosystems; predators	Camacho and Solé (1999)	Transition economies	Podobnik *et al.* (2006)
Mass extinctions	Bak (1996)		

To the extent that interdependence applies, researchers ignoring power law effects risk drawing false conclusions in their articles and promulgating inaccurate advice to managers. This because managers increasingly work in surroundings prone to Paretian extremes, not Gaussian averages. Given this, we raise the question: *How can we redirect management research toward the study of extremes in ways that still fall within the bounds of an effective science* – one that still offers credible bases for asserting truth claims?

We begin with an introduction to power law phenomena. We discuss some social and organizational power laws in more detail. We then focus on SOC and tension effects in IB. Following this, we question the basic assumptions of statistics-based methods and the robustness techniques used to dismiss interdependence effects. We then draw implications for management research. Our conclusion crystallizes the several arguments aimed at redirecting quantitative research methods applied to IB research and management practice.

Power law phenomena

In recounting the Santa Fe Institute's Vision, Brock (2000: 29) says:

> The study of complexity … is the study of how a very complicated set of equations can generate some very simple patterns for certain parameter values. Complexity considers whether these patterns have a property of universality about them. Here we will call these patterns scaling laws.

He observes that the study of complexity 'tries to understand the forces that underlie the patterns or scaling laws that develop' as newly ordered systems emerge (Brock, 2000: 30).

There are two kinds of scalability: (1) the coast of Norway looks pretty much the same no matter which measure is used, meters or miles; (2) a causal dynamic is scalable because it operates in the same way at multiple levels. The first is *result* scalability; the second is *cause* scalability. A fractal structure exhibits both aspects. The underlying cause is the same from the whole down to the smallest part; the 'look' of it is pretty much the same at all levels as well.

Power law phenomena exhibit Paretian rather than Gaussian distributions: see Figure 1. The difference lies in assumptions about interconnectivity. In a Gaussian distribution the data points are assumed to be *independent-additive* (hereinafter simply 'i.i.d.' – independent, indentically distributed). Independent events generate normal distributions, which sit at the heart of modern statistics. When causal elements are *independent-multiplicative* they produce a log-normal distribution, which turns into a Pareto distribution as the causal complexity increases (West and Deering, 1995). When events are *interactive*, normality in distributions is *not* the norm. Instead Pareto distributions dominate because positive feedback processes (or other scale-free dynamics: Andriani and McKelvey, 2007) leading to extreme events occur more frequently than 'normal' bell-shaped Gaussian-based statistics lead us to expect.

Physical, biological, social, organizational, and electronic systems show an impressive variety of power law phenomena (Kaye, 1993). We list 80 kinds of power laws ranging from atoms to galaxies, DNA to species, and networks to wars in Table 1.[5] Many leading scholars believe that fractals are the best analytical framework to describe the origin and shape of many natural objects (Bak, 1996; West and Deering, 1995; Newman, 2005). Given the ubiquity of these findings, and the nature of the underlying scale-free theory, we think they are equally ubiquitous in organizations, but unknown and unappreciated as to their causes and effects.

Fractal geometry

Fractals are not idle mathematical curiosities. Fractals and power laws are found from atomic nanostructures ($\sim 10^{-10}$ m) to galactic megaparsecs ($\sim 10^{22}$ m) – across a range of 32 orders of magnitudes (Baryshev and Teerikorpi, 2002). In biology, West *et al*. (1997) demonstrate a power law relationship between the mass and metabolism of virtually any organism and its components – based on fractal geometry of distribution of resources – across 27 orders of magnitude (of mass). Self-similarity is key to a fundamental property of fractals and power laws; linear scalability is now recognized as an inherent characteristic of living systems (Gell-Mann, 2002). We demonstrate this in more detail in the following examples; we show linear scalability and power laws occurring at multiple social and organizational levels of analysis.

Power laws at different category levels of social analysis

Linear scalability and power law effects appear within and at different category levels of analysis, from language down to networks. We start with language – the broadest complex adaptive system – and then progress down to cities, markets, villages, and networks. A particular scale-free cause operates across levels within each category level, but they differ from one category level to the next.

Language

Estoup (1916) and Zipf (1949) found that a power law applies to word frequencies. Casti (1994: Chapter 6) shows that, whereas a monkey at a typewriter generates different words of equal length at equal probability, word usage in English follows a perfect power law: if word usage frequencies and rank order are plotted on double-log scales, the words *the*, *of*, *and*, *to*, *I*, *or*, *say*, *really*, *quality* diminish at a perfect -1 slope.[6] Zipf's law, a rank/frequency power law, is a classic example of a scale-free effect.

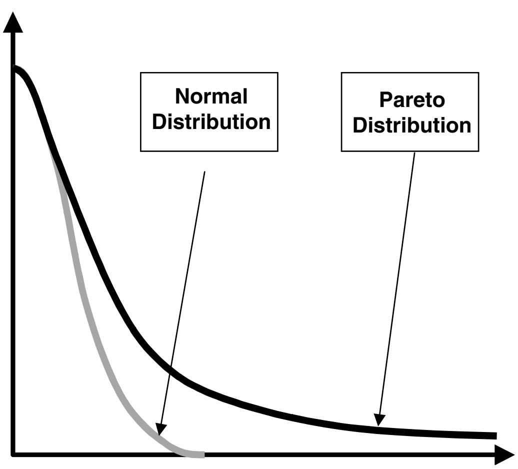

Figure 1 Gaussian *vs* Pareto distributions.

Cities

Auerbach (1913) discovered that the rank/size plot of American metropolitan cities obeys a power law (on a double logarithm graph, size and rank of cities fit a straight line with slope of -1). Krugman (1996) replicated it in the 1990s. His findings were so remarkable that he concluded: 'We are unused to seeing regularities this exact in economics – it is so exact that I find it spooky' (p 40). They are shown to apply to cities from 1790 to 1993 when ranked by population (Auerbach, 1913; Zipf, 1949; Krugman, 1996). Krugman suggests the city power-law signature signifies self-organized economies. Using 2005 data, we show the baseline power law signature of several apparently fully self-organizing economies – US, Japan, China, India, and Turkey – in Figure 2. We do this to give a quick 'power law look' of other seemingly well-performing economies besides the US.

Markets

The case against the 'standard' model in finance is set by Mandelbrot (Mandelbrot and Hudson, 2004: 13)

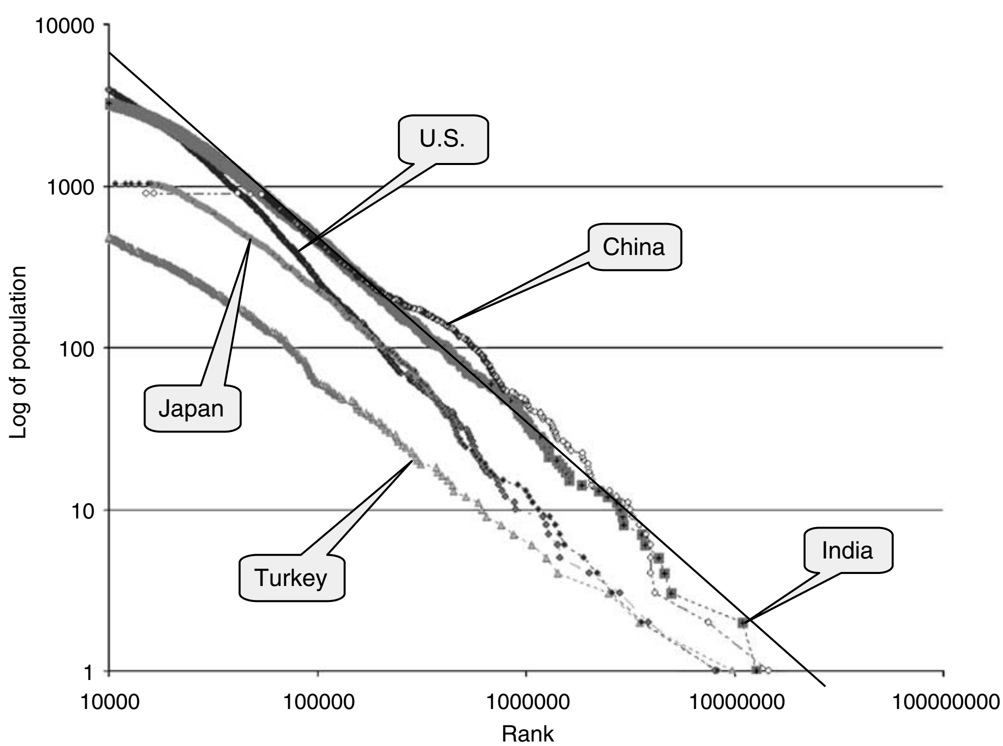

Figure 2 Log–log depiction of city rank in economies showing self-organization-based power laws based on city rank/size distributions (2005 data). Data from http://population.mongabay.com/ (accessed 31 March 2007)

with a simple observation:

> By the conventional wisdom, August 1998 simply should never have happened. … The standard theories … estimate the odds of that final, August 31, collapse, at one in 20 million – an event that, if you traded daily for nearly 100,000 years, you would not expect to see even once. The odds of getting three such declines in the same month were even more minute: about one in 500 billion (p 4). … [An] index swing of more than 7% should come once every 300,000 years; in fact, the twentieth century saw forty-eight such days.

The reason for the discrepancy between reality and theory lies in the crucial assumption by finance orthodoxy: variations in price are statistically independent, and normally distributed. These assumptions allow the use of calculus, modern probability and statistical theory, and give rise to a vast edifice of sophisticated mathematics. However, they conflict with reality.

Movies

Another example of power laws in economics appears in the book *Hollywood Economics* (De Vany, 2004). He shows that movie profits are Pareto-distributed. He demonstrates that the fat tails of the Pareto distribution dominate the movie industry: extreme events occur that should be negligible in a Gaussian world. The industry survives thanks to blockbuster movies that 'have legs' and compensate for the dismal failures of most movies – which have little effect on a studio's financial performance. In fact, movies don't seem to show any significant correlation between any of the variables used to predict final profits. The only recognizable pattern is the truncated Pareto distribution of profits.

Structural complexity of villages

Galileo's *square-cube law* is the oldest recognized cause of scale-free dynamics and power law outcomes. In a study of 46 single-community societies, Carneiro (1987) shows that many villages never exceed a relatively small size because their organizing ability does not keep up with the volume of their population. The square-cube law limits their size unless they develop what he terms *structural complexity*, which allows their organizing ability (the square) to keep up with population (the cube). As their population grows, villages face a stark choice: split or evolve. By splitting they get their population volume back down into a proper relationship with their organizing ability. By evolving they develop additional *complexity traits* (Carneiro's term) that give them the organizing capability to cope with larger population. We apply the square-cube law to organizations later on.

Social networks

The legendary Hungarian mathematician Paul Erdos, in introducing random network theory, assumed links are randomly distributed across nodes and form a bell-shaped distribution, wherein most nodes have a typical number of links, with the frequency of remaining nodes rapidly decreasing on either side of the maximum. Watts and Strogatz (1998) show, instead, that real networks follow the *small world* phenomenon whereby society is visualized as consisting of weakly connected clusters, each having highly interconnected members within. This structure allows cohesiveness (high clustering coefficient) and speed/spread of information (low path length) across the whole network. Studying the World Wide Web, Barabási *et al*. (2000) find that the structure of the Web shows a power law distribution, where most nodes have only a few links, and a tiny minority – the hubs – are disproportionately very highly connected. The system is scale-free: no node can be taken to represent the scale of the system. Defined as a *scale-free network*, the distribution shows (nearly) infinite variance and an unstable mean. It turns out that most real life *small world* networks are scale-free (Ball, 2004) and fractal (Song *et al*., 2005). Scale-free networks appear in fields as disparate as epidemiology, the metabolism of cells, the Internet, and networks of sexual contacts (Liljeros *et al*., 2001).

Power laws at different levels of organizational analysis

Organizational power law findings have been increasing as of late. In this section we show that they apply both within and at different category levels of analysis. Though we cover only four levels in more detail here, we show 24 kinds of business-organization-related power law effect in Table 1. As before, we point to the various underlying scale-free causes creating scalability within each level.

Industrial agglomerations

Simon's (1955) and Axtell's (2001) findings that firms' size distribution follows a power law distribution is not related to geography. We ask whether the power law distribution of firms' size holds when geographic agglomerations are analyzed – in other words, whether the fact that firms share the same territory and consequently have a higher probability of interacting with each other plays a role in the firms' size distribution. Here we report the work that one of us has done on power laws and industrial agglomerations in Italy (Andriani, 2003a, b).

The agglomerations we consider are the so-called *travel-to-work areas* (TWAs)[7] in Italy. To test whether Italian industrial agglomerations follow a power law, we use linear regression. The data show that interconnected agglomerations of firms very strongly fit the rank/size power law distribution with slope of -1 (see Figure 3). The fact that the distribution of firms' size is power law distributed indicates that the underlying growth mechanisms follow a power law (see also Stanley *et al*., 1996). Interestingly, we don't see any significant distinction between agglomeration based on industrial clusters and generic agglomerations. This is surprising, as it indicates that the growth mechanisms are independent of the internal logic of organizing. We speculate that the power law distribution in firms' size points towards a universal growth mechanism, based on a fractal distribution of economic resources.

Firms

Stanley *et al*. (1996) report a study of the statistical properties of all publicly traded manufacturing firms listed in Compustat (US) for the period 1975–1991. They find that variance in growth rate is Paretian, not Gaussian, and follows a power law with exponent β:

$$\sigma(s_0) = aS_0^{-\beta} \tag{1}$$

where σ (s_0) is standard deviation of growth/year based on 1 January sales value, S_0; growth rate$=\ln(S_1/S_0)$=change in sales year to year; $s_0 \equiv \ln S_0$; a is a constant; and β is the slope of factors affecting growth (β ranges from $\frac{1}{2}$ to 0).

This equation holds over seven magnitudes of firm size, whether growth is measured as cost of goods sold ($\beta \sim 0.16$), assets ($\beta \sim 0.17$), property, plant and equipment ($\beta \sim 0.18$), or number of employees ($\beta \sim 0.16$).

Stanley *et al.* conclude that processes governing growth rates are scale-free. They give an example of a hierarchical 'Fordist' type organization where the CEO can order an increase in production. If it is carried out exactly from top to bottom of the firm, then the organization is strongly interdependent (β=0 for total top-down control). But lower-level managers and employees rarely follow orders exactly. If they *all* ignore the CEO's order – that is, *all* parts of the firm operate independently – then $\beta=\frac{1}{2}$. Usually the employees follow orders with some probability. Thus, for $\beta = \sim 0.15$ or so (given the findings by Stanley *et al.*), we expect a power law effect to obtain. Note that $\beta \sim 0.15$ could be due to a CEO's order implemented with some probability, or it could be due to an emergent self-organizing process by the employees. Bottom line: either top-down control or bottom-up self-organization can produce $\beta \sim 0.15$ – and a power law event – as depicted in Figure 4.

Internal structure

Nobel Laureate Herbert Simon (1962) argued the case for 'nearly decomposable' subunits – the basis of what is now called 'modular design' (Baldwin and Clark, 2000). The idea of growing by subdividing organizations into modular parts responds to a well-known cause of scalable dynamics: the *square-cube law*. It explains the design of the cauliflower: as its volume grows to assure it a survivable mass in its niche, the cauliflower subdivides into ever small parts to assure that the ratio of its energy-gathering surface stays in required proportion to its volume. Mason Haire (1959) first applied the square-cube law successfully to four firms. Levy and Donhowe (1962) confirmed his findings in 62 firms in eight industries. Stephan (1983) applied the square-cube

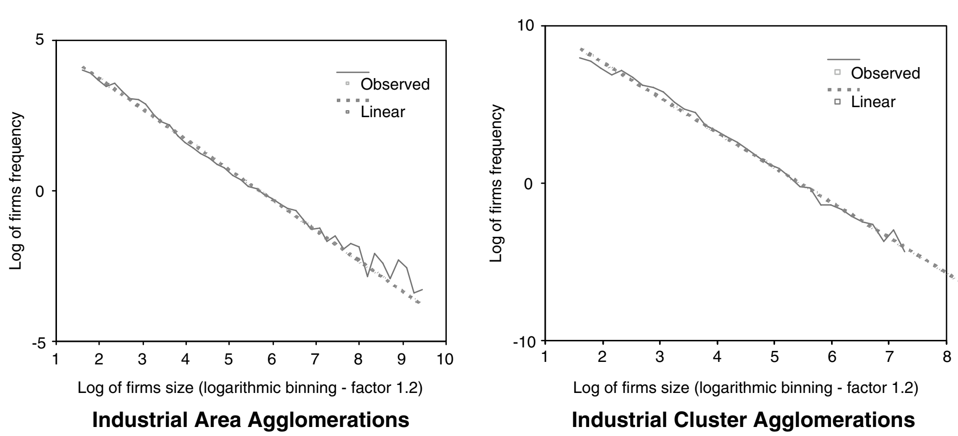

Figure 3 Comparison of cluster power law with the $-\beta$ slope power law (cumulative distribution).

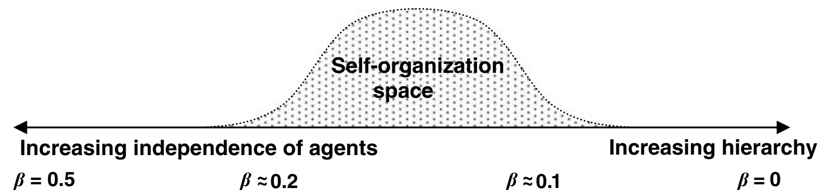

Figure 4 Self-organization between agent autonomy and hierarchical systems.

law to firms in terms of effectiveness. Employees dealing with people outside the firm are *surface* employees – they bring in the resources from the environment. *Volume* employees are those inside who produce and coordinate: they are resource users. As firms grow, then, they have to maintain the square-cube ratio by adding more surface units, or by making them more efficient. This creates the square-cube power law effect.

Internal decision events

Diatlov (2005) applies power law dynamics to intra-organizational decision events. For years Mintzberg has been pushing the idea of strategies as weeds (Mintzberg and McHugh, 1985). Diatlov quotes Mintzberg *et al.* as follows:

> Strategies could be traced back to a variety of little actions and decisions made by all sorts of different people sometimes accidentally or serendipitously, with no thought of their strategic consequences. Taken together over time, these small changes often produce major shifts in direction. (Mintzberg *et al.*, 1998: 178)

Diatlov also observes that Braybrooke and Lindblom's (1963) *disjointed incrementalism* fits Mintzberg *et al.*'s view. Also building from Lindblom's (1959) *science of muddling through*, Cohen *et al.* (1972) develop their *organized anarchy* approach – the 'garbage-can model'. Weeds, muddling, and organized anarchy reflect both top-down and bottom-up order-creation fitting Stanley *et al.*'s $\beta \sim 0.15$.

Diatlov's research (2005) provides data in support of the foregoing power law argument. He tracks the implementation of 'information technology' inside financial institutions, ranging from local, lower-level, short-term, frequently changed decision events to longer-term, upper-level, and more pervasive managerial decisions covering longer time horizons. He is the first researcher we know of who shows a rough power law configuration of *internal* organizational decision events.

Power laws signify the underlying mechanism – scale-free causes (Andriani and McKelvey, 2007). This mirrors the biological, social, and organization power law findings in Table 1. While extreme events and consequences may be most obvious among markets, earthquakes, and hurricanes, evidence that indicates analogous extreme events appears among social and organizational phenomena.

Self-organized criticality and tension effects

Per Bak's *self-organized criticality* (SOC) is a scale-free theory that applies to the *frequency/magnitude of change events*, as opposed to 'things' such as words, cities, or firms. It readily applies to business changes, as demonstrated by Stanley *et al.* (1996). In the next section we then apply SOC theory to explain the tension-based criticality state that, once reached, produces Pareto rather than Gaussian distributions. We mention key IB tensions in the subsequent section.

Bak's 'self-organized criticality' power law

Self-organized criticality (SOC) is symbolized by Bak's (1996) sandpile experiments. A sandpile subjected to an infinitesimal external perturbation (sequentially adding single grains of sand) evolves toward a critical state, characterized by a critical slope, whereby any additional grain may induce a systemic reaction that can span any order of magnitude, with a power law frequency distribution. The tension imposed by gravity is at the core of criticality, along with irregularly shaped grains. Starting from a flat surface, as grains of sand accumulate they are i.i.d. Being irregular, they cling together enough to form a pile. When the edge of the pile reaches a particular angle (criticality), the gravitational *tension* against piling higher dominates the '*clinging*' effect. This happens via small to large avalanches of sand. The distribution of many smaller to one large change shows a power law.

This is counter-intuitive. We generally assume a linear relationship between perturbation size and a system's reaction: that is, small causes yield small effects. This is true before criticality is attained. SOC dynamics arise when an emergent system of links connects local pockets into a co-evolving whole such that small and local fluctuations may be amplified into extreme effects. As the tension in the system increases to the SOC limit (usually as a result of externally imposed tension; in Bak's SOC this is a function of the accumulating sand grains), independent data points become interdependent.

SOC occurs frequently (Bak, 1996; Buchanan, 2000). It generates all of the tension-based, change-related, event-type power law phenomena in Table 1: earthquakes, booms and busts in economic cycles, war casualties, market transactions, movie and consumer sales, traffic jams, supply chain dynamics, and so on. The SOC dynamic appears across disparate fields. Two implications follow:

(1) Systems spontaneously tune themselves towards self-critical states (Kauffman, 1995): that is, 'the system organizes itself towards the critical point where single events have the widest possible range of effects' (Cilliers, 1998: 97). This makes Gaussian statistics inappropriate for the study of SOC.
(2) The conventional explanation regarding macro events is imputed to comparatively large exogenous causes. Instead, according to SOC, endogenous fluctuations (causes) may be progressively amplified until a catastrophic chain reaction takes place. For instance, in Scheinkman and Woodford's (1994) model, economic shocks in idealized economies can be initiated by tiny endogenous fluctuations.

Tension-induced SOC

While tension equates to Bak's 'criticality' slope in a sandpile, it equates to R_{c1} in thermodynamics and complexity science. R_{c1} is the *first critical value* of the Reynolds measure of energy. At this point a phase transition toward new order occurs: turbulence in fluid flow; the rolling boil in a teapot. Bak's insight is that tension level initiates the self-organization of the system, which spontaneously evolves above R_{c1}: this is where change events become Pareto distributed. It follows that below R_{c1} many change events are i.i.d. and fit Gaussian thinking, whereas above R_{c1} they are typically Pareto distributed.

Given the foregoing, we can't just think of Gaussian and Paretian worlds as 'either–or'. In social systems, for sure, tension is the reason why data points shift from i.i.d. to Pareto distributions and power laws. In social systems tension may be induced by political activities: for example, the tension generated by decades of socialist rule in Eastern Europe suddenly crystallized in the pacifist self-organized manifestations that led to the fall of the Berlin Wall. The slow build-up of popular antiwar sentiment about the failure of the Vietnam and Iraq wars eventually induced emergent demonstrations and political changes. Alternatively, tension may be induced by managers: Jack Welch's phrase, 'Be #1 or 2 in your industry or your division will be sold',[8] served to induce tension at GE. Or it may be induced by competitive context: Schumpeter (1942) held that environmental shocks are the tension behind 'creative destruction' and entrepreneurship. Economists hold that the tension between supply and demand induces activity in economies. Tension results from human interactive learning, influence, and change (Holland, 1988).

While it is convenient for us to compare Gaussian and Paretian worlds, thereby implying that they both exist side by side in steady state, in point of fact the Paretian world often comes and goes depending on whether the driving tension is above or below R_{c1}. Consequently, once people in organizations take up the gauntlet and respond to tension, their responses – as acts of change – will be Pareto distributed, and the nature of the entities created will also be Pareto distributed. In short, both the change activities and the emergent structure and processes will show the power law signature.

Tension in international business

IB is especially subject to the tensions noted above: political tensions, income disparity, managerially imposed tensions, entrepreneurially driven tensions, supply/demand and other competitive economic tensions, and bottom-up tensions from self-organization based on human interactions. Buckley and Lessard (2005: Figure 4) list a set of more specific IB tensions due to: outsourcing or offshoring; emerging markets; emergent economic powers such as China and India; virtual firms; global branding and distribution; and the impact of multinational firms. Since differences around the globe are far greater than those within a single country, the probability of Pareto distributions around the globe are comparably greater. They may be set off by:

(1) tensions set in motion by dramatic political, economic, technology, and economic resources (as opposed to simple natural resources such as oil); and
(2) other tensions, such as differences between G8 and developing countries, conflicting national policies, availability of capital markets, regional

> differences in markets for goods and services, governmental protection policies (tariffs), different labour competencies and labour markets, and so on (Buckley and Ghauri, 2004).

Additional tension results from the nested structure of IB. Managers' decision-making has to simultaneously take into account multiple nested dimensions – local, national, international, macro-regional and global – while at the same time balancing legal, political, economic, regulatory, and ecological issues that all affect the evolution of IB phenomena. SOC-related phenomena emerge in the structure of organizations and markets. The firm itself 'becomes the hub of a network of interlocking joint ventures' (Buckley and Ghauri, 2004: 85). The connectivity of the markets causes the emergence of *global commodity chains*, which are

> sets of inter-organisational networks clustered round one commodity of product, linking households, enterprises and states to one another within the world economy. These networks are situationally specific, socially constructed and locally integrated, underscoring the social embeddedness of economic organisation. (Buckley and Ghauri, 2004: 90)

Buckley and Lessard (2005) note the growth of virtual firms. This sets in motion low- to no-cost virtual connections such as email, teleconferencing, phoning via Skype, and a host of Internet transactions. These make interdependence cheaper and more available. The more dramatic tensions mentioned immediately above plus the virtually free transaction costs of the Internet age combine to produce a far higher probability of fractals, Pareto distributions and power laws in IB than in domestic settings. In short, IB managers face Pareto much more than Gaussian distributions. IB research based on Gaussian statistics is thus based even more on false assumptions, is more inaccurate, and is more misleading to IB practitioners.

Connectionism *vs* independence in organizations

Pareto *vs* Gauss

> Scientists tend to place too much focus on averages … [whereas] much of the real world is controlled as much by the 'tails' of distributions as means or averages: by the exceptional, not the commonplace; by the catastrophe, not the steady drip. … We need to free ourselves from 'average' thinking. (Anderson, 1997: 566)

Extremes *vs* averages

Linear thinking is normal. Scientific and mathematical models are based on the concepts of equilibrium and linearity. Linearity means two things: (1) there is proportionality between cause and effect; and (2) the dynamic of a system can be reconstructed by summing up the effects of single causes acting on single components (Nicolis and Prigogine, 1989), which allows the operation of efficient causality, the solution of equations, and predictive modelling. Economics, for instance, is almost theistic in its (scarcely verified) assumption that economic phenomena trend toward *general equilibrium* (Mirowski, 1989; Ormerod, 1994). However, this assumption allows linear equations and analytical simplicity. Meyer *et al.* (2005) cite Abbott's (2001: 7) discussion about how the 'general linear model' from Newtonian mechanics came to 'subtly shape sociologists' thinking'.

By focusing on systems in equilibrium, researchers implicitly accept that the number of possible states a system may attain is limited (and computable), and that search time following the onset of instability is short compared with time at equilibrium. For this to be true, the many elements comprising a system must be assumed i.i.d. If we take 100 companies of approximately the same size belonging to the same sector, assume independence, and plot a variable – say profit – we expect most events to pack around the mean, exhibiting the classic bell curve. This distribution is by far the most studied statistical distribution; it is assumed to characterize correctly most of our discoveries about the natural and social worlds. The crux of the point, however, is *whether all events are i.i.d.* In real life, for example, these companies could: benchmark against each other; imitate those perceived as successful; exchange information; organize cartels; pursue mergers and acquisitions; compete for limited resources, etc. In a word, they are most likely *interactive*, not independent!

Gaussian and Pareto distributions differ radically. The Gaussian distribution is reliably characterized by its stable mean and finite variance (Greene, 2002). A Pareto distribution doesn't show a well-behaved mean or variance. A power law therefore has no 'average' that can be assumed to represent the typical features of the distribution, and no finite variance upon which to base confidence intervals (Moss, 2002). The dream of social science – of building robust frameworks that allow prediction – is shattered by the absence of statistical regularities in phenomena dominated by persistent interconnectivity. In the absence of a stable mean and finite variance, the probabilistic assessment of individual outcomes becomes much more difficult.

This point reflects the more pervasive and structural issue of *non*linearity and emergence in complex systems (Sornette, 2003).

Statistics: obscuring rather than clarifying?
A Paretian world is dominated by extreme events ignored in a Gaussian world. In fact, the long tails of Pareto distributions make large extreme events orders of magnitude more likely. In a 'normal' world, where distributions show finite variance, extreme events are so very rare that they don't significantly influence either the mean or the variance. Hence ignoring them is a safe strategy. However, insurance companies that use normal distributions to assess the likelihood of extreme events often get their fingers burned. Hurricane Katrina of August 2005, the Christmas 2004 tsunami in Asia, the four hurricanes hitting Florida in 2004, the tremendous devastation following floods in Central Europe in 2003, earthquakes exceeding 7 on the Richter scale – all these indicate that we are not in a 'normal' world. On the contrary, the action and highest cost is in the tails (Kirchgaessner and Kelleher, 2005). In the movie industry almost all the profit come from the blockbusters – that is, the extreme events – with the majority of the movies contributing next to nothing to profitability. In these circumstances, normal distribution statistics obscure rather than clarify. The practices of

(1) searching for the mean so as to conveniently summarize the nature of a phenomenon without attending to the full range of its nature,
(2) relying on variance to build confidence intervals and therefore assess the likelihood of single events, and – even more damaging –
(3) the habit of excluding outlying events

all become misleading or openly wrong in a Paretian world. We need methods and statistics that include extremes rather than assume them away!

Nowhere is a case more compellingly made for a transition from Gaussian to Paretian statistics than by Meyer *et al*. (2005). Even though they start with 'normal' organization science research methods, in each of the four studies conducted they find interdependency effects dominating and as a result have to throw out the conventional methods they start with. They conclude with a focus on 'hubs, connectors, and power laws', scale-free theory, and the interdependency and positive feedback effects found in network formations. In their discussion of their fourth study, they note that 'observing outliers may be more informative than observing average or typical entities.' They then mention the Anderson quote we started this section with.

Robustness tests bury the most important variance

> All the world believes it firmly, because the mathematicians imagine that it is a fact of observation and the observers that it is a theorem of mathematics (Henry Poincaré, 1913, about the Gaussian distribution).[9]

Management researchers using statistics as their basis of making truth claims – usually translated as findings significant at $P<0.05$ or 0.01 – use mainly statistical methods calling for Gaussian distributions. Gaussian science, so to speak, produces equations looking like this:

$$\text{Variance of a } \textit{dependent variable} = \int \textit{variables} + \textit{error term} \tag{2}$$

In Paretian science the expression looks like this:

$$\text{Variance of a } \textit{dependent variable} = \int \textit{variables} + \textit{extremes} + \textit{error term} \tag{3}$$

where 'extremes' includes power law events stemming from interacting, self-organizing, mutual causal agent behaviors rather than the 'independent' events underlying the variables' variance (Sornette, 2003). Normal science, which is really 'normal-distribution-based science', wants us to assume away the presence of the '*extremes*', turning instead to tests of robustness within the Gaussian framework of handling data to show this assumption is not damaging.

Greene's textbook *Econometric Analysis* (Greene, 2002, 5th edn) is the standard for many econometricians and other social scientists. Greene begins his $\sim$950 pages of analysis with linear multiple regression and its five endemic assumptions:

(1) i.i.d.;
(2) linear relationships among variables;
(3) exogenous independent variables;
(4) homoscedasticity and nonautocorrelation; and
(5) normal distribution.

Mostly, the book focuses on how to make econometric methods work when one or more of these assumptions are untrue of the data. Given *nonlinearity*, for example, Greene says, 'by using logarithms, exponentials, reciprocals, transcendental functions, polynomials, products, ratios, and so on, this 'linear' model can be tailored to any number of situations' (p 122). As for the *normal distribution* assumption, he says:

> large sample results suggest that although the usual t and F statistics are still usable … they are viewed as approximations whose quality improves as the sample size increases. … As n increases, the distribution … converges exactly to a normal distribution. (p 105)

Greene observes that

> heteroscedasticity poses potentially severe problems for inferences based on least squares [regression analysis]. … It is useful to be able to test for homoscedasticity and if necessary, modify our estimation procedures accordingly. (p 222)

He then takes some 25 pages to discuss typically used methods to minimize the effect of varying variances.

Greene ignores the Pareto, Zipf, Cauchy, and Lévy distributions. Neither does he discuss *interdependent*, *interacting*, *connectionist*, *interconnecting*, *coevolutionary*, or *mutual causal* data points, events, or agents. Nor does he discuss when independence shifts to interdependence, or the reverse. These possibilities don't seem to appear in econometricians' assumptions about data. And yet, in our foregoing analysis, we see that most theories underlying every kind of power law discovery include a reference to interconnection of some form: power law phenomena overwhelmingly depend on *interactive* agents that, with some probability, are set off in a cycle of positive feedback progression (or other scale-free cause) resulting in an extreme event. In fact, none of the robustness adjustments to failing linear multiple regression assumptions that Greene discusses deals with the real-world's *probable* – not just possible – losses of independence. To conclude, the various robustness tests Greene discusses give no assurance that modern-day researchers account for the effects of extreme events in their statistical analyses.

Let's put this in California earthquake terms. In California we average $\sim$16,000 insignificant quakes every year and a 'really big one' (e.g., where the ground moves 30 feet north) once every 150–200 years, with scale 6 and 7 quakes occurring within decades. In effect, it is as if Greene and virtually all modern regression modellers want Californians building and living in high-rise buildings to think that using a moving average of quake variance over the thousands of harmless (average) quakes will lead to building codes that protect against the scale 7 and 8 quakes. Anyone living through a significant quake in California will tell you this is nonsense. No amount of so-called 'robustness improvements' to the standard linear multiple regression model allow it to model the effects of extreme quakes on buildings, bridges, lives, and damage costs – that is, the effects of fat-tailed Pareto distributions. *Robustness tests and 'solutions' do not, and cannot, shift statistics from the Paretian to Gaussian worlds without error.*

Some typical errors

In this section we give some examples of the subtle distortions that Gaussian thinking introduces in the way research is conducted in IB. The assumptions underlying Gaussian thinking – randomness, independence, and hence additivity – do not apply to most IB phenomena. Researchers, lacking alternative analytical options, are forced to reduce the complexity of IB phenomena to oversimplified representations amenable to currently popular analytical treatments. This leads to incorrect modeling, and to a neglect of coevolution, emergence, diversity, innovation and extreme events. We see researchers over and over again studying complex scalable dynamics but applying the ritualistic tools of reductionism.

(1) Researchers in IB (and beyond) take an uncritical approach to unknown or partly unknown variables. Gaussian thinking legitimizes researchers in assuming that these unknown variables can be treated as random, normally distributed and additive. For instance, Shaver (1998), discussing whether entry mode choice affects FDI survival writes: 'I *assume that* u_i is normally distributed with zero mean and unit variance. Moreover, u_i will be attributable, in part, to unobservable characteristics that affect entry mode choice' (p. 573). u_i represents a disturbance term that affects firm attributes and industry conditions. Buckley and Carter (2004: 374) write: '*We shall take it that* the v_{ij}'s are normally and independently distributed random variables $v_{ij}(x)$, dependent on the state of the world x and with means $\bar{v}_{ij}$ and standard deviations s_{ij} (our emphasis). These researchers subscribe to the deterministic noise-signal model (West, 2006): the system is treated as deterministic, whereas the noise derives from the system–environment interactions. Consequently, coevolutionary dynamics is relegated to a disturbance.

(2) Reality is conveniently linearized, but the implications are not discussed. Take for instance Buckley and Carter (2004: 376) on knowledge combination in MNEs. They write:
However, no single individual holds all of the firm's knowledge, so that strategic managers are not the only active deliberative agents. The participants each act on their own initiative in response to unfolding particular circumstances, insofar as they are the individuals with the best knowledge of these circumstances. Thus the firm does not comprise a single entrepreneur, but instead is a team of entrepreneurs, … a coalition of active agents.
Treating the firm as 'a team of entrepreneurs' allows them to reduce the complexity of a firm's knowledge to the sum of the contributions of each 'entrepreneur'. But it buries the potential coevolutionary positive feedback or other scalability dynamics in the i.i.d. assumption. The fact that knowledge at the firm level is usually an emergent property from a group of individuals rather than an i.i.d. agent is not discussed. Hence Gaussian thinking may obscure emergent nonlinear dynamics.
(3) Reliance on Gaussian thinking masks the intrinsic diversity of IB phenomena. Many Gaussian-based analyses represent an extremely simplified version of the field, as, for instance, when they simplify the field of entry mode into a third country to the simple dichotomy of greenfield *vs* acquisition (Harzing, 2002). For the sake of analytical treatment, important but scarcely quantifiable options, such as joint ventures and mixed mode, are neglected. The IB field has all to gain from adopting a 'long tail' view (Anderson, 2006). Anderson's research demonstrates that focusing on average events in markets leads to a minimum common denominator view of markets and competition. Once the focus shifts to the 'long tail' of a Pareto distribution of product sales, a large diversity of consumer preferences and consequent changes in business strategy come to light.
(4) There is uncritical acceptance that the task of IB strategy scholars consists in 'regressing a measure of performance on the strategy choice of a group of firms. The coefficient estimate of the strategy choice variable has then been used to identify superior strategies' (Shaver, 1998: 571).
 (a) Even if one accepts the research validity of this approach, it still means little to the practitioner. Translating from statistical to individual case validity means accepting that the world offers a finite number of options, that the occurrences of the options are repeatable, and that the options are independent. Researchers *assume* rather than demonstrate this. Given the aforementioned global tensions and lowered connectivity costs, this assumption is especially unlikely to be true in IB.
 (b) Researchers don't seem to be particularly concerned about the emergence of new strategies. New strategies emerge as outliers in the tail of the distribution, and acquire legitimacy by diffusing in progressively larger samples of the population. Gaussian thinking masks the emergence of new strategies. The practice of giving advice to managers on the basis of statistical relevance offers dubious usefulness. By focusing on the center of the distribution, Gaussian thinking hides the emergence of innovation out in the tail.
(5) Reliance on the Gaussian approach masks extreme events, such as the emergence of new strategies.

In this paper we offer a methodological antidote to 'Gaussianism'. Researchers will object that Paretian science is at best an interesting promise without practical mathematical tools and that we indicate the limitations of existing frameworks without offering realistic and practical alternatives. We respond that fractal calculus (although much more complex and considerably less developed than corresponding traditional calculus) is a valid platform to describe fractal phenomena (West *et al.*, 2003).

Redirecting management research

On 9 January 1857 a 7.9 magnitude quake occurred in California, stretching 220 miles along the San Andreas Fault. At one point, the part of California west of the fault moved *30 feet* north. Californians are still waiting for the next 'big one'. The cost of the scale 6.7 Northridge quake in 1994 – local to the LA area with visible earth movement of a few *inches* – was $44 billion, with 51 people killed, 9000 injured, and 22,000 left homeless. A scale 8 quake is roughly 30 times larger! The really big ones in financial markets occurred in 1929 and 1987 – some 60 years apart. But just since 1987 we have had other extreme events: the Asian crisis of 1997, the Russian meltdown of 1998, the burst of the dotcom bubble and ensuing Parmalat and Enron *et al.* collapses in 2001–2003, and the recent subprime-mortgageinduced volatility of 2007, with multibillions lost each time. These are the negative ones. We also have multibillion dollar positive events such as Microsoft, GE, Intel, eBay, Google, the growing economic dominance of China, offshoring in India, growth in private equity buyouts, and so on.

What basis for truth claims, if not 'normal' science statistics?

Traditional justification logic and normal statistics

Instead of seeing extreme variance in management-related regression functions as something to use robustness techniques to eradicate, we suggest that a more sensible approach is to draw on the way that physicists and engineers handle *Newtonian mechanics vs relativity theory. Their world changes depending on the speed at which phenomena are moving*. On earth, theories and methods consistent with Newtonian mechanics remain valid. As objects approach the speed of light, theories and methods consistent with relativity theory apply. For earth-bound scientists and engineers, however, the 'old' Newtonian mechanics applies best.

For global research the 'new' is more relevant than the 'old'. For us, *old* is Gaussian-based; *new* is Paretian-based science. *Our world changes depending on tension and low-cost-connection effects* that make the new more likely than the old. But, we agree, the old is still present under low-tension conditions. Even so, a more sensible approach for global studies is to begin each study with the following test:

(1) Given proof of independence; use normal statistics: the *old*.
(2) in the absence of proof of independence, assume interdependence, use Pareto and power-law thinking: the *new*.

We believe this test is vitally important in IB research, and also in other kinds of social and management research. The ten examples of power law phenomena detailed earlier include the possibility of an extreme event stemming from interdependence among agents. Ranging from language down to organizational decision events, we find it hard to argue that these and similar power law dynamics do not pervade IB and most other management arenas. This doesn't mean extreme events occur all the time, everywhere. But it *does* mean that some probability of the tension-induced *benefit of positive* or *risk of negative* extremes is present all the time and everywhere.

Finally, there is a figure/ground reversal. Current methodology takes the null hypothesis as: *phenomena are i.i.d. until proven otherwise* (current practice mostly assumes away the problem). Given the pervasive international tensions we discussed earlier, the null assumption for international (and domestic) research should be one of *interdependence until proof of independence obtains*.

Discussion

Many management scholars have pointed to the growing disjunction between multiparadigmatic 'science' appearing in journals and practitioner-oriented writing (e.g., Lawler *et al*., 1985; Brief and Dukerich, 1991; Anderson *et al*., 2001; Rynes *et al*., 2001; McKelvey, 2003a, 2006; Bennis and O'Toole, 2005; Ghoshal, 2005; Van de Ven and Johnson, 2006). We suggest that the fundamental problem stems from favoring Gaussian over Pareto distributions. Virtually all of the statistics-based journal research rests on assumptions of independent events (i.i.d.) and Gaussian distributions. In obvious contrast, if one scans 'business media' books, such as Peters and Waterman (1982), O'Reilly and Pfeffer (2000), Collins (2001), and so on, one sees that most of the cases and stories are about extreme events – successes or failures; they are seldom about 'averages'. Add to this list cases used in classrooms and the books describing extreme events we mention at the outset. No wonder there is a disjunction: managers live in the world where *extremes* matter as much or more than i.i.d.; researchers use i.i.d.-based statistics to report findings about *averages*. Evidence suggests that most extremes are due to interdependency effects.

People lacking personal experience with extreme events may think averages are acceptable substitutes. People hit by Hurricane Katrina or the Indian Ocean tsunami, or who live through earthquakes in Turkey or Japan, floods along the Danube or Ganges, or survive an avalanche in the Alps think differently. Natural extremes seem mostly negative. Business extremes are both positive and negative. Early employees at Microsoft have one view of an extreme; those who were at Enron see theirs rather differently. Scholars need to step beyond the idea that *studying averages* is the only 'good' science, is the only method relevant to good management research, and is what offers something useful to managers. Sometimes yes, but we think *mostly no* for management researchers. Needless to say, this is an empirical question. We argue that tension forces setting up the conditions of Per Bak's (1996) *self-*

organized criticality shift firms from i.i.d. to multiplicative to interactive causal dynamics.

To bolster our argument that international business research needs to attend to the consequences of interactive as well as i.i.d. events, we start by listing over 80 kinds of power law phenomenon (in Table 1). In Nature, they range from atomic and microbiological to galactic fractals; over 40 are social and/or organizational. We describe 10 social and organizational power laws in more detail. Power law research is an aspect of natural and even social science that has barely seeped into international business or management research – though we mention Mason Haire's application of the square-cube law to organizations in 1959. We are especially critical of the standard practice of using *robustness* methods (Greene, 2002) to conveniently sweep Paretian phenomena under the rug, so to speak, and continue with Gaussian analyses and statistics.

Our review of power law phenomena significantly challenges the prevailing assumption about the independence of data points. Once i.i.d. collapses, and interdependence or interaction occurs, then the seeds of power law formations are planted. It is just a matter of time, just a matter of probability, for interactive events to progress into an extreme event. As long as researchers look at the *real* world through the 'normal' statistics lens – which means they have to make the i.i.d. assumption – the result will be Gaussian science and with it a denial of extreme events, a denial of (nearly) infinite variance, a denial of unstable means – adding up to denial of Pareto distributions. All of these denials act to narrow confidence intervals and allow researchers falsely to claim statistical significance and then assert their truth claims. This has produced many irrelevant and erroneous results, but bolsters discipline legitimacy.

We propose the obvious solution of adding, and then stressing more heavily, disciplines where emergent extreme phenomena, rather than averages, are dominant features. We mention two of these, *complexity* and *earthquake science*. Lessons from complexity science are conjoined with econophysics and power laws, and thus embedded throughout our paper. From earthquake science, we draw parallel application areas, each of which offers a different perspective and approach for studying extreme events, including prediction and protection (we detail this in Andriani and McKelvey, 2005). Each application area calls for a different kind of management and IB research. A number of these already appear in the Meyer *et al.* (2005) article (also detailed in Andriani and McKelvey, 2005). Other examples are Perrow (1984) and Marcus and Nichols (1999) – nuclear reactors – and Haunschild and Sullivan (2002) – airline accidents – though these studies do not quite get to power law effects.

One of the lessons from earthquake science is that instead of lumping *all* earthquakes together, they study separate samples of scale 7s, 8s or 9s. In point of fact, we have a large collection of case studies that are studies of extremes – those mentioned in the business media books above and also in many of the MBA teaching cases. We even have multiple studies of single extremes – parallel to a sample of scale 8s – e.g., Enron, GE, IBM, Intel, Li Fang, Parmalat, Salim Group, Xerox. With narrowed samples of similar extremes, small-sample nonparametric methods are highly appropriate. Starbuck (no date) presents 59 slides suggesting other ways of 'Learning from Extreme Cases', as he puts it.

We note that 50% of the power law findings we list are from highly respected natural sciences. In no way do we want to suggest that effective science epistemology be replaced by one-off case studies or the anti-science leanings of postmodernists (Holton, 1993; Koertge, 1998; McKelvey, 2003b). Earthquake science is a fully legitimate 'hard' science. We can learn from it how to conduct an effective science about extreme IB, management, or organizational phenomena.

Numerous conditions hold where natural data points *do* remain i.i.d.: for example, atoms and most molecules don't study, relate to, look at, or learn from, other atoms or molecules. Sometimes, however, the imposition of energy past some critical point – we discuss changes occurring at the first critical value of an imposed force – turns even independent natural science data points into interactive ones.[10] In natural science, perhaps, scientists should still start with the null condition of i.i.d. But in social science, where people *do* look at each other, *do* talk to each other, *do* learn from each other, *do* influence each other, etc., it seems to us that the null condition is one of *interdependence*. *Researchers should start with this assumption*. They should start with the idea in mind that extreme events are a natural part of the social world.

> No statistical findings, therefore, should be accepted into the IB, organizational, or management received view if they gain significance via some assumption device by which extreme events and (nearly) infinite variance are ignored.

IB is exposed more than any other management domain to the multiple tensions of changes in geographical, political, sociological, cultural and business environments. These tensions increase connectivities across many different and once separated areas of business practice. Such interdependencies call for research methods substantially different from traditions rooted in linear science, conventional epistemologies and Gaussian statistics. We agree with Buckley and Lessard (2005) when they argue that there is a 'missing middle' of IB theory, and that the void should filled by 'a community of scholars that cuts across disciplines and levels with a shared core'. To be IB-relevant, however, these scholars need new approaches that fully embrace the diversity, complexity and scalability of the connectivity-dominated phenomena that constitute contemporary IB. Methods have to be rooted in dynamic network theory (Newman *et al.*, 2006) and have to make better sense of extreme events induced by increased environmental tension. In sum, we think that IB is a natural candidate for Pareto-type thinking, and that there is no other field in management studies that could profit from it more than IB.

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Notes

[1]In order: Peters and Waterman (1982); Robison (1986); Tichy and Sherman (1994); Bredeson (1999); O'Reilly and Pfeffer (2000); Collins (2001); Fusaro and Miller (2002); Burgelman (2002); Horcajo (2005); Newhouse (2007).

[2]A fractal is 'a rough or fragmented geometric shape that can be subdivided in parts, each of which is (at least approximately) a reduced copy of the whole' (Mandelbrot and Hudson, 2004: 121). Similarity across scale is called 'self-similarity'.

[3]Our discussion of the organizational and managerial implications of scale-free theory appears elsewhere because of obvious space limitations; see Andriani and McKelvey (2007).

[4]'Agent' refers to semi-autonomous entities (i.e., 'parts' of systems), such as atoms, molecules, biomolecules, organelles, organs, organisms, species, processes, people, groups, firms, industries, etc.

[5]This is the most comprehensive list of power law phenomena across all sciences to date.

[6]While it appears so in the few words we show, word usage is not a function of word length overall.

[7]TWAs are relatively self-contained economic and social units, calculated by dividing a national territory into units that maximize internal home-to-work commuting and minimize inter-TWA commuting (ISTAT, 1997). TWAs represent an algorithmic way to define the micro-units of analysis of economic geography and economic sociology. In Italy TWAs are organized into a taxonomy (Sforzi, 1990; Cannari and Signorini, 2000) that divides the agglomerations into two groups: industrial-cluster-based (type D) and non-cluster-based (type A) agglomerations. The classification ranks industrial agglomerations according to the probability of including within their boundary an industrial cluster. The theoretical ground for this work is rooted in the Neo-Marshallian theory of industrial clusters (Storper, 1997). Type D: r=0.997, P<0.0001, slope β= −0.995. Type A: r=0.995, P<0.0001, slope β=−0.997.

[8]Actually, 'we would fix, sell, or close' (Tichy and Sherman, 1994: 108).

[9]Quoted in West and Deering (1995: 83).

[10]A classic form of this, known as the 'Bose–Einstein condensate,' explains the onset of superconductivity: at the tension limit – in this case because of extreme cold – particles shift from independence to interactivity, thereby allowing superconductivity. For more, see: [www document] http://en.wikipedia.org/wiki/Bose-Einstein_condensate (accessed 30 March 2007).

References

Abbott, A. (2001) *Time Matters*, University of Chicago Press: Chicago, IL.

Abrams, D.M. and Strogatz, S.H. (2003) 'Modelling the dynamics of language death', *Nature* **424**(6951): 900.

Adamic, L.A. and Huberman, B.A. (2000) 'The nature of markets in the World Wide Web', *Quarterly Journal of Electronic Commerce* **1**(1): 5–12.

Aiello, W., Chung, F. and Lu, L. (2000) 'A random graph model for massive graphs', *Proceedings of the 32nd Annual ACM Symposium on Theory of Computing*, ACM Press: Portland, OR, pp: 171–180.

Albert, R., Jeong, H. and Barabási, A.-L. (1999) 'Diameter of the World Wide Web', *Nature* **401**(6749): 130–131.

Anderson, C. (2006) *The Long Tail*, Random House Business Books: London.

Anderson, N., Herriot, P. and Hodgkinson, G.P. (2001) 'The practitioner–researcher divide in industrial work and organizational (IWO) psychology', *Journal of Occupational and Organizational Psychology* **74**(4): 391–411.

Anderson, P.W. (1997) 'Some Thoughts About Distribution in Economics', in W.B. Arthur, S.N. Durlauf and D.A. Lane (eds.), *The Economy as an Evolving Complex System II*, Addison-Wesley: Reading, MA, pp: 565–567.

Andriani, P. (2003a) 'The emergence of self-organisation in social systems: the case of the geographic industrial clusters', Unpublished PhD dissertation, Durham Business School, University of Durham, Durham, UK.

Andriani, P. (2003b) 'Using Complexity Theory to Define Industrial Clusters', in E. Mitleton-Kelly (ed.), *Complex Systems and Evolutionary Perspectives of Organisations*, Elsevier: Oxford, pp: 127–146.

Andriani, P. and McKelvey, B. (2005) 'Beyond Gaussian averages: redirecting management research toward extreme events and power laws', Academy of Management Annual Conference, Honolulu, HA, http://www.dur.ac.uk/resources/dbs/faculty/working-papers/BeyondGaussianAverages19Jun06.pdf (accessed 27 September 2007).
Andriani, P. and McKelvey, B. (2007) 'Extremes, power laws, and scale-free dynamics in organizations: theory and research implications', Academy of Management Annual Conference, Philadelphia, PA, August.
Auerbach, F. (1913) 'Das Gesetz der Bevolkerungskoncentration', *Petermanns Geographische Mitteilungen* **59**(1): 74–76.
Axtell, R.L. (2001) 'Zipf distribution of US firm sizes', *Science* **293**(5536): 1818–1820.
Bak, P. (1996) *How Nature Works: The Science of Self-Organized Criticality*, Copernicus: New York.
Bak, P. and Sneppen, K. (1993) 'Punctuated equilibrium and criticality in a simple model of evolution', *Physical Review Letters* **71**(24): 4083–4086.
Baldwin, C.Y. and Clark, K.B. (2000) *Design Rules: The Power of Modularity*, MIT Press: Cambridge, MA.
Ball, P. (2004) *Critical Mass: How One Thing Leads to Another*, Farrar, Straus & Giroux: New York.
Barabási, A.-L. (2002) *Linked: The New Science of Networks*, Perseus: Cambridge, MA.
Barabási, A.-L. and Bonabeau, E. (2003) 'Scale-free networks', *Scientific American* **288**(May): 60–69.
Barabási, A.-L., Albert, L., Jeong, H. and Bianconi, G. (2000) 'Response to: 'Power-law distribution of the World-Wide Web' (by L.A. Adamic and B.A. Huberman)', *Science* **287**(5461): 2115a.
Baryshev, Y. and Teerikorpi, P. (2002) *Discovery of Cosmic Fractals*, World Scientific: River Edge, NJ.
Battiston, S. and Catanzaro, M. (2003) 'Statistical properties of corporate board and director networks', Working paper, Laboratoire de Physique Statistique ENS, Paris.
Baum, J.A.C. and Silverman, B.S. (2001) 'Complexity, Attractors and Path Dependence and Creation in Technological Evolution', in R. Garud and P. Karnoe (eds.), *Path Dependence and Creation*, Lawrence Erlbaum: Mahwah, NJ, pp: 169–209.
Bennis, W.G. and O'Toole, J. (2005) 'How business schools lost their way', *Harvard Business Review* **83**(5): 96–104.
Bettencourt, L.M.A., Lobo, J. and Strumsky, D. (2005) 'Invention in the city: increasing returns to scale in metropolitan patenting', Working paper, Harvard Business School, Boston, MA.
Bigger Jr, J.T., Steinman, R.C., Rolnitzky, L.M., Fleiss, J.L., Albrecht, P. and Cohen, R.J. (1996) 'Power law behavior of RR-interval variability in healthy middle-aged persons, patients with recent acute myocardial infarction, and patients with heart transplants', *Circulation* **93**(12): 2142–2151.
Braybrooke, D. and Lindblom, C.E. (1963) *A Strategy of Decision*, Free Press: New York.
Bredeson, C. (1999) *The Challenger Disaster*, Enslow: Berkeley Heights, NJ.
Brief, A.P. and Dukerich, M. (1991) 'Theory in Organizational Behavior: Can it be Useful?', in B.M. Staw (ed.) *Research in Organizational Behavior*, Vol. 13, JAI Press, Inc.: Greenwich, CT, pp: 327–352.
Brock, W.A. (2000) 'Some Santa Fe scenery', in D. Colander (ed.) *The Complexity Vision and the Teaching of Economics*, Edward Elgar: Cheltenham, pp: 29–49.
Brú, A., Albertos, S., Luis Subiza, J., García-Asenjo, J.L. and Brú, I. (2003) 'The universal dynamics of tumor growth', *Biophysical Journal* **85**(5): 2948–2961.
Buchanan, M. (2000) *Ubiquity: The Science of History … or Why the World Is Simpler Than We Think*, Weidenfeld & Nicolson: London.
Buchanan, M. (2004) 'Power laws and the new science of complexity management', *Strategy+Business* **34**(Spring): 70–79.
Buckley, P.J. and Carter, M.J. (2004) 'A formal analysis of knowledge combination in multinational enterprises', *Journal of International Business Studies* **35**(5): 371–384.
Buckley, P.J. and Ghauri, P.N. (2004) 'Globalisation, economic geography and the strategy of multinational enterprises', *Journal of International Business Studies* **35**(2): 81–98.
Buckley, P.J. and Lessard, D.R. (2005) 'Regaining the edge for international business research', *Journal of International Business Studies* **36**(6): 595–599.
Burgelman, R.A. (2002) *Strategy is Destiny*, Free Press: New York.
Camacho, J. and Solé, R.V. (1999) 'Scaling and Zipf's Law in ecological size spectra', Working paper, Santa Fe Institute: Santa Fe, NM.
Cannari, L. and Signorini, L.F. (2000) 'Nuovi Strumenti per la Classificazione dei Sistemi Locali', in L.F. Signorini (ed.), *Modelli di Sviluppo Locale*, Meridiana: Roma, pp: 123–151.
Carneiro, R.L. (1987) 'The evolution of complexity in human societies and its mathematical expression', *International Journal of Comparative Sociology* **28**(2–3): 111–128.
Carreras, B.A., Newman, D.E., Dobson, I. and Poole, A.B. (2004) 'Evidence for self-organized criticality in a time series of electric power system blackouts', *IEEE Transactions on Circuits and Systems I* **51**(9): 1733–1740.
Casti, J.L. (1994) *Complexification*, Abacus: London.
Cederman, L.E. (2003) 'Modeling the size of wars: from billiard balls to sandpiles', *American Political Science Review* **97**(1): 135–150.
Cilliers, P. (1998) *Complexity and Postmodernism*, Routledge: London.
Clementi, F. and Gallegati, M. (2005) 'Pareto's Law of Income Distribution: Evidence for Germany, the United Kingdom, and the United States', in A. Chatterjee, S. Yarlagadda and B.K. Chakrabarti (eds.) *Econophysics of Wealth Distributions*, Springer: Milan, Italy, pp: 3–14.
Cohen, M.D., March, J.G. and Olsen, J.P. (1972) 'A garbage can model of organizational choice', *Administrative Science Quarterly* **17**(1): 1–25.
Collins, J. (2001) *Good to Great*, HarperBusiness: New York.
Cook, W., Ormerod, P. and Cooper, E. (2004) 'Scaling behaviour in the number of criminal acts committed by individuals', *Journal of Statistical Mechanics: Theory and Experiment* [www document] http://www.iop.org/EJ/article/1742-5468/2004/07/P07003/jstat4_07_p07003.html (accessed 31 March 2007).
Delli Gatti, D., Di Guilmi, C., Gaffeo, E. and Gallegati, M. (2004) 'Bankruptcy as an exit mechanism for systems with a variable number of components', *Physica A* **334**(1–3): 8–13.
De Vany, A. (2004) *Hollywood Economics*, Routledge: New York.
de Solla Price, D.J. (1965) 'Networks of scientific papers', *Science* **149**(3683): 510–515.
Dezsö, Z., Almaas, E., Lukács, A., Rácz, B., Szakadát, I. and Barabási, A.-L. (2006) 'The dynamics of information access on the Web', *Physical Review E* **73**(6): 066132 (6 pages).
Diatlov, V. (2005) 'Information technology in practice of organising', Unpublished PhD dissertation, School of Management, University of Southampton, Southampton, UK.
Dumé, B. (2005) 'Global terrorism follows a power law', *Physicsweb* (February): 1–2, [www document] http://physicsweb.org/articles/news/9/2/6/1. (accessed 31 March 2007).
Ebel, H., Mielsch, L.-I. and Bornholdt, S. (2002) 'Scale-free topology of e-mail networks', *Physical Review E* **66**(3): 035103 (4 pages).
Estoup, J.B. (1916) *Gammes Stenographiques*, Institut Stenographique de France: Paris.
Faloutsos, M., Faloutsos, P. and Faloutsos, C. (1999) 'On power-law relationships of the Internet topology', *ACM SIGCOMM Computer Communication Review* **29**(4): 251–262.
Fusaro, P.C. and Ross, M.M. (2002) *What Went Wrong at Enron*, Wiley: New York.
Gardner, M. (1978) 'White and brown music, fractal curves and 1/*f* fluctuations', *Scientific American* **238**(4): 16–32.
Gell-Mann, M. (2002) 'What is Complexity?', in A.Q. Curzio and M. Fortis (eds.), *Complexity and Industrial Clusters*, Physica-Verlag: Heidelberg, pp: 13–24.

Ghoshal, S. (2005) 'Bad management theories are destroying good management practices', *Academy of Management Learning and Education* **4**(1): 75–91.
Goldberger, A.L., Rigney, D.R. and West, B.J. (1990) 'Chaos and fractals in human physiology', *Scientific American* **262**(2): 42–49.
Greene, W.H. (2002) *Econometric Analysis*, 5th edn, Prentice-Hall: Englewood Cliffs, NJ.
Gunz, H., Lichtenstein, B.B. and Long, R. (2001) 'Self-organization in career systems: a view from complexity science', *Management* **5**(1): 63–88.
Gutenberg, B. and Richter, R.F. (1944) 'Frequency of earthquakes in California', *Bulletin of the Seismological Society of America* **34**(4): 185–188.
Hackett, A.P. (1967) *70 Years of Best Sellers, 1895–1965*, Bowker: New York.
Haire, M. (1959) 'Biological Models and Empirical Histories of the Growth of Organizations', in M. Haire (ed.), *Modern Organization Theory*, Wiley: New York, pp: 272–306.
Harzing, A.W. (2002) 'Acquisitions *vs* greenfield investments: international strategy and management of entry modes', *Strategic Management Journal* **23**(3): 211–227.
Haskell, J.P., Ritchie, M.E. and Olff, H. (2002) 'Fractal geometry predicts varying body size scaling relationships for mammal and bird home ranges', *Nature* **418**(6897): 527–530.
Haunschild, P.R. and Sullivan, B.N. (2002) 'Learning from complexity: effects of prior accidents and incidents on airlines' learning', *Administrative Science Quarterly* **47**(4): 609–643.
Hegyi, G., Néda, Z. and Santos, M.A. (2007) 'Wealth distribution and Pareto's law in the Hungarian medieval society', [www document] http://arxiv.org/abs/physics/0509045 (accessed 27 September 2007).
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*, Addison-Wesley: Reading, MA, pp: 117–124.
Holton, G. (1993) *Science and Anti-Science*, Harvard University Press: Cambridge, MA.
Horcajo, X. (2005) *'Tangento' en Parmalat? La Investigación del caso Parmalat*, HTML document available from Amazon.com.
Hughes, D., Paczuski, M., Dendy, R.O., Helander, P. and McClements, K.G. (2003) 'Solar flares as cascades of reconnecting magnetic loops', *Physical Review Letters* **90**(13): 131101.
Hughes, D.W. and Nathan, H.W. (1994) 'The distribution of asteroid sizes and its significance', *Planetary and Space Science* **42**(4): 291–295.
ISTAT INdS (1997) *I Sistemi Locali del Lavoro*, Vol. **10**, *Argomenti*, ISTAT: Roma.
Jenkinson, I.R. (2004) 'Book review of *Handbook of Scaling Methods in Aquatic Ecology* (L. Seuront and P.G. Strutton, eds.)', *Journal of Plankton Research* **26**(5): 585–587.
Kauffman, S.A. (1995) *At Home in the Universe*, Oxford University Press: Oxford, UK.
Kaye, B. (1993) *Chaos and Complexity*, VCH: New York.
Kirchgaessner, S. and Kelleher, E. (2005) 'UK bombs drive insurance debate', *Financial Times Europe* Monday, July 11, p: 5.
Koertge, N. (1998) *A House Built on Sand: Exposing Postmodernist Myths about Science*, Oxford University Press: New York.
Krugman, P. (1996) *The Self-Organizing Economy*, Blackwell: Malden, MA.
Lawler, E.E., Mohrman Jr, A.M., Mohrman, S.A., Ledford Jr, G.E. and Cummings, T.G. (1985) *Doing Research that is Useful for Theory and Practice*, Lexington Books: New York.
Lee, Y., Amaral, L.A.N., Canning, D., Meyer, M. and Stanley, H.E. (1998) 'Universal features in the growth dynamics of complex organizations', *Physical Review Letters* **81**(15): 3275–3278.
Levy, S. and Donhowe, G. (1962) 'Exploration of a biological model of industrial organization', *Journal of Business* **35**(4): 335–342.
Levy, M. and Solomon, S. (1997) 'New evidence for the power-law distribution of wealth', *Physica A* **242**(1–2): 90–94.
Liljeros, F., Edling, C.R., Amaral, L.A.N., Stanley, H.E. and Aberg, Y. (2001) 'The web of human sexual contacts', *Nature* **411**(6840): 907–908.
Lindblom, C.E. (1959) 'The science of 'muddling through'', *Public Administration Review* **19**(2): 79–88.
Lotka, A.J. (1926) 'The frequency distribution of scientific productivity', *Journal of the Washington Academy of Sciences* **16**(12): 317–323.
Luscombe, N.M., Qian, J., Zhang, Z., Johnson, T. and Gerstein, M. (2002) 'The dominance of the population by a selected few: power-law behaviour applies to a wide variety of genomic properties', *Genome Biology* **3**(8): research004.1–research004.7.
Mandelbrot, B.B. (1983) *The Fractal Geometry of Nature*, Freeman: New York.
Mandelbrot, B.B. and Hudson, R.L. (2004) *The (Mis)Behavior of Markets*, Profile: London.
Mantegna, R.N. and Stanley, H.E. (2000) *An Introduction to Econophysics*, Cambridge University Press: Cambridge, UK.
Marcus, A.A. and Nichols, M.L. (1999) 'On the edge: heeding the warnings of unusual events', *Organization Science* **10**(4): 482–499.
Marsili, M. and Zhang, Y.-C. (1996) 'Probabilistic fragmentation and effective power law', *Physical Review Letters* **77**(17): 3577–3580.
McKelvey, B. (2003a) 'From Fields to Science', in R. Westwood and S. Clegg (eds.), *Debating Organization*, Blackwell: Oxford, UK, pp: 47–73.
McKelvey, B. (2003b) 'Postmodernism *vs* Truth in Management Theory', in E. Locke (ed.) *Research in the Sociology of Organizations*, Vol. 21 Elsevier Science: Amsterdam, NL, pp: 113–168.
McKelvey, B. (2006) 'Comment on Van De Ven and Johnson's ''Engaged scholarship'': Nice try, but…', *Academy of Management Review* **31**(4): 822–829.
Meyer, A.D., Gaba, V. and Colwell, K.A. (2005) 'Organizing far from equilibrium: non-linear change in organizational fields', *Organization Science* **16**(5): 456–473.
Mintzberg, H. and McHugh, A. (1985) 'Strategy formation in an adhocracy', *Administrative Science Quarterly* **30**(2): 160–197.
Mintzberg, H., Ahlstrand, B. and Lampel, J. (1998) *Strategy Safari*, Pearson Education: London.
Mirowski, P. (1989) *More Heat Than Light*, Cambridge University Press: Cambridge, UK.
Moss, S. (2002) 'Policy analysis from first principles', *Proceedings of the National Academy of Sciences* **99**(Suppl. 3): 7267–7274.
Nagel, K. and Paczuski, M. (1995) 'Emergent traffic jams', *Physical Review E* **51**(4): 2909–2918.
Nahshoni, E., Adler, E., Laniado, S. and Keren, G. (1998) 'Fractal organization of the pointwise correlation dimension of the heart rate', *Med Hypotheses* **51**(5): 367–376.
Nekola, J.C. and Brown, J.H. (2007) 'The wealth of species: ecological communities, complex systems and the legacy of Frank Preston', *Ecology Letters* **10**(3): 188–196.
Newhouse, J. (2007) *Boeing vs Airbus*, Knofp: New York.
Newman, M.E.J. (2001) 'The structure of scientific collaboration networks', *Proceedings of the National Academy of Sciences* **98**(2): 404–409.
Newman, M.E.J. (2005) 'Power laws, Pareto distributions and Zipf's law', *Contemporary Physics* **46**(5): 323–351.
Newman, M., Barabási, A.-L. and Watts, D.J. (eds.) (2006) *The Structure and Dynamics of Networks*, Princeton University Press: Princeton, NJ.
Nicolis, G. and Prigogine, I. (1989) *Exploring Complexity*, Freeman: New York.
O'Reilly, C.A. and Pfeffer, J. (2000) *Hidden Value*, Harvard Business School Press: Boston, MA.
Ormerod, P. (1994) *The Death of Economics*, Wiley: New York.
Pareto, V. (1897) *Cours d'Economie Politique*, Rouge: Paris.
Perrow, C. (1984) *Normal Accidents*, Basic Books: New York.

Peters, T.J. and Waterman, R.H. (1982) *In Search of Excellence*, Harper & Row: New York.
Podobnik, B., Fu, D., Jagric, T., Grosse, I. and Stanley, H.E. (2006) 'Fractionally integrated process for transition economics', *Physica A* **362**(2): 465–470.
Poincaré, H. (1913) *The Foundations of Science*, Science Press: New York.
Poole, M.S., Van de Ven, A.H., Dooley, K. and Holmes, M.E. (2000) *Organizational Change and Innovation Processes*, Oxford University Press: New York.
Powell, M.S., White, D.R., Koput, K.W. and Owen-Smith, J. (2005) 'Network dynamics and field evolution', *American Journal of Sociology* **110**(4): 1132–1205.
Roberts, F.S. (1979) *Measurement Theory, Encyclopedia of Math*, Vol. **7**, Addison-Wesley: Reading, MA.
Robison, R. (1986) *Indonesia: The Rise of Capital*, Allan & Unwin: Sydney, Australia.
Rynes, S.L., Bartunek, J.M. and Daft, R.L. (2001) 'Across the great divide: knowledge creation and transfer between practitioners and academics', *Academy of Management Journal* **44**(2): 340–355.
Scheinkman, J. and Woodford, M. (1994) 'Self-organized criticality and economic fluctuations', *American Economic Review* **84**(2): 417–421.
Schumpeter, J. (1942) *Capitalism, Socialism, and Democracy*, New York: Harper & Row.
Selvam, A.M. (2002) 'Quantum like chaos in the frequency distributions of the bases A, C, G, T, in Drosophila DNA', *Apeiron* **9**(4): 103–148.
Sforzi, F. (1990) 'The Quantitative Importance of Marshallian Industrial Districts in the Italian Economy', in F. Pyke, G. Becattini and W. Sengenberger (eds.), *Industrial Districts and Inter-Firm Co-Operation in Italy*, International Institute for Labour Studies: Geneva, Switzerland, pp: 75–107.
Shaver, J.M. (1998) 'Accounting for endogeneity when assessing strategy performance: does entry mode choice affect FDI survival?' *Management Science* **44**(4): 571–585.
Shin, C.W. and Kim, S. (2004) 'Self-organized criticality and scale-free properties in emergent functional neural networks', [www document] http://arxiv.org/abs/cond-mat/0408700v2. (accessed 31 March 2007).
Simon, H. (1955) 'On a class of skewed distribution functions', *Biometrika* **42**(3/4): 425–440.
Simon, H. (1962) 'The architecture of complexity', *Proceedings of the American Philosophical Society* **106**(6): 467–482.
Song, C., Havlin, S. and Makse, H.A. (2005) 'Self-similarity of complex networks', *Nature* **433**(7024): 392–395.
Sornette, D. (2002) 'Predictability of catastrophic events: material rupture, earthquakes, turbulence, financial crashes, and human birth', *Proceedings of the National Academy of Sciences* **99**(Suppl. 1): 2522–2529.
Sornette, D. (2003) *Why Stock Markets Crash*, Princeton University Press: Princeton, NJ.
Stanley, M.H.R., Amaral, L.A.N., Buldyrev, S.V., Havlin, S., Leschhorn, H., Maass, P., Salinger, M.A. and Stanley, H.E. (1996) 'Scaling behavior in the growth of companies', *Nature* **379**(6568): 804–806.
Starbuck, W.H. (2007) 'Learning from Extreme Cases', http://pages.stern.nyu.edu/~wstarbuc/extreweb/Extreweb_files/v3_document.htm (accessed 27 September 2007).
Stassinopoulos, D. and Bak, P. (1995) 'Democratic reinforcement: a principle for brain function', *Physical Review E* **51**(5): 5033–5039.
Stephan, G.E. (1983) 'A research note on deriving the square-cube law of formal organizations from the theory of time-minimization', *Social Forces* **61**(3): 847–854.
Storper, M. (1997) *The Regional World*, Guildford Press: New York.
Szeto, H.H., Cheng, P.Y., Decena, J.A., Cheng, Y.I., Wu, D.-L. and Dwyer, G. (1992) 'Fractal properties in fetal breathing dynamics', *American Journal of Physiology – Regulatory Integrative Comparative Physiology* **263**(1): R141–R147.
Tichy, N.M. and Sherman, S. (1994) *Control Your Destiny or Someone Else Will*, HarperCollins: New York.
Van de Ven, A.H. and Johnson, P.E. (2006) 'Knowledge for theory and practice', *Academy of Management. Review* **31**(4): 802–821.
Warren, K., Craciun, G. and Anderson-Butcher, D. (2005) 'Everybody else is: networks, power laws and peer contagion in the aggressive recess behavior of elementary school boys', *Nonlinear Dynamics, Psychology, and Life Sciences* **9**(2): 155–173.
Watts, D.J. (2003) *Six Degrees: The Science of a Connected Age*, Norton: New York.
Watts, D.J. and Strogatz, S.H. (1998) 'Collective dynamics of "small-world" networks', *Nature* **393**(6684): 440–442.
Wax, A., Yang, C., Backman, V., Badizadegan, K., Boone, C.W., Dasari, R.R. and Feld, M.S. (2002) 'Cellular organization and substructure measured using angle-resolved low-coherence interferometry', *Biophysical Journal* **82**(4): 2256–2264.
Weinberg, R.F. and Podladchikov, Y. (1994) 'Diapiric ascent of magmas through power law crust and mantle', *Journal of Geophysical Research* **99**(B5): 9543–9560.
West, B.J. (2006) *Where Medicine Went Wrong*, World Scientific: Singapore.
West, B.J. and Deering, B. (1995) *The Lure of Modern Science: Fractal Thinking*, World Scientific: Singapore.
West, G.B., Brown, J.H. and Enquist, B.J. (1997) 'A general model for the origin of allometric scaling laws in biology', *Science* **276**(4): 122–126.
West, B.J., Bologna, M. and Grigolini, P. (2003) *Physics of Fractal Operators*, Springer: Berlin.
Willis, J.C. (1922) *Age and Area: A Study in Geographical Distribution and Origin of Species*, Cambridge University Press: Cambridge, UK.
Willis, J.C. and Yule, G.U. (1922) 'Some statistics of evolution and geographical distribution in plants and animals, and their significance', *Nature* **109**: 177–179.
Wuchty, S. and Almaas, E. (2005) 'Peeling the yeast protein network', *Proteomics* **5**(2): 444–449.
Zanette, D.H. and Manrubia, S.C. (2001) 'Vertical transmission of culture and the distribution of family names', *Physica A* **295**(1–2): 1–8.
Zipf, G.K. (1949) *Human Behavior and the Principle of Least Effort*, Hafner: New York.

About the authors

Pierpaolo Andriani (PhD, Durham University) is Senior Lecturer in Innovation Management at Durham Business School, UK, and Visiting Professor at the University of Salento, Italy. His research interests are focused on the impact of complexity theory on organizational theory, industrial clusters and innovation.

Bill McKelvey (PhD, MIT, 1967; Professor, UCLA Anderson School.) His book *Organizational Systematics* (1982) remains a definitive treatment of organizational evolution. He co-founded UCLA's Center for Human Complex Systems & Computational Social Science. Co-edited *Variations in Organization Science* (1999) and special issues of *Emergence* (now *E:CO*) and *JIT*. Has 55 complexity-related papers.

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