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Redirecting Management Research Toward Extreme Events and Power Laws

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Beyond Gaussian Averages: Redirecting Management Research Toward Extreme Events and Power Laws

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ABSTRACT

Practicing managers live in a world of 'extremes' but management research is based on Gaussian statistics that rule out those extremes. On occasion, deviation amplifying mutual causal processes among interdependent 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 draw a 'line in the sand' between Gaussian (based on independent data points, finite variance and emphasizing averages) and Paretian statistics (based on interdependence, positive feedback, infinite variance, and emphasizing extremes). Quantitative journal publication depends almost entirely on Gaussian statistics. We draw on complexity and earthquake sciences to propose redirecting Management Studies. **Conclusion**: **No statistical findings should be accepted into Management Studies if they gain significance via some assumption-device by which extreme events and infinite variance are ignored.** The cost is inaccurate science and irrelevance to practitioners.

Keywords: Power laws; fractals; Gaussian; Pareto; Mandelbrot; distribution; robustness; interdependence; positive feedback; extremes; complexity; earthquakes; normal science

Virtually all of organizational research presumes Gaussian (normal) distributions, with finite means and variances, with appropriate statistics to match – for evidence, study any random sample of current research papers of your choosing. It follows that virtually of our research-based lessons to managers stem from Gaussian-based research. Suppose this premise is mostly wrong. What then?

The coast of England 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 the same. Scalability results from what Benoit Mandelbrot (1982) calls '*fractal geometry*'. A cauliflower is an obvious example. Cut off a 'branch'; cut a smaller branch from the first branch; then an even smaller one; and then even another, and so on. Now set them in line on a table. Each fractal[1] subcomponent is smaller than the former; each has the same shape and structure. They exhibit a '*power law effect*' because they shrink by a fixed ratio. Cauliflowers, and more generally power laws, call for '*scale-free theories*' because the same theory applies to each of the different levels.[2] Power law effects are Pareto distributed – they have '*fat tails*', nearly infinite variance, unstable means, and unstable confidence intervals. Oppositely, 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 and publication are easier.

Quantitative management researchers tend to presume Gaussian (normal) distributions with matching statistics – for evidence, study any random sample of their current research. *Suppose this premise is mostly wrong*. It follows that (1) publication decisions based on Gaussian statistics could be mistaken, and (2) advice to managers could be misguided. Should we change?

Power laws seem ubiquitous – they appear in leaves, coastlines, and music (Casti, 1994). Cities follow a power law when ranked by population (Auerbach, 1913). The structure of the Internet follows a power law (Albert *et al*., 1999), as does the size of firms (Stanley *et al*., 1996; Axtell, 2001). Bak (1996) finds them in the avalanches of his famous sand piles. Later on we list eighty kinds of power laws (with cites) ranging from atoms to galaxies, DNA to species, and networks to wars. Brock (2000) says scalability is the fundamental feature of the Santa Fe Institute's (SFI) approach to complexity science.

Several theories explain power laws (Newman, 2005; Andriani and McKelvey, 2006). Frequently they hinge on *interdependence* among data points and a possible ensuing positive feedback process. Herein lies the problem for 'normal' science: Most quantitative research involves the use of statistical methods presuming *independence* among data points and Gaussian 'normal' distributions. Greene's (2002) textbook, *Econometric Analysis*, is excellent compendium of 'robustness' techniques that all depend on assuming away interdependence and eradicating the effects of Paretian fat tails. The trouble is that the many findings of power law phenomena across many natural and social sciences indicate that interdependent phenomena are far more prevalent than 'normal' statistics assumes and the consequent extremes have far greater consequence than the 'averages' in between.

We argue that most, if not all, of the interdependence-based power law theories apply to management research. Thus, there is good reason to believe that power law effects are also ubiquitous in organizations and have far greater consequence than current users of statistics presume. To the extent this is true, researchers ignoring power law effects risk drawing false conclusions in their articles and promulgating useless advice to managers. This because what is important to most managers are the extremes they face, not the averages. Given this, we raise the question: *How to 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? By way of initiating such a change in management research, we suggest earthquake science as a more telling underlying discipline, along with continuing lessons from complexity science and econophysics (McKelvey, 2004; Mantegna and Stanley, 2000; Newman, 2005).

We begin by with an introduction to power law phenomena in both natural and social sciences, discussing nine of them in more detail. In Section 2 we focus on the predominance of interdependence over independence in phenomena studied by management researchers. We question the basic assumptions of statistics-based methods and the robustness techniques used to dismiss interdependence effects. We draw implications for management research in Section 3. Our conclusion crystallizes the several arguments aimed at redirecting quantitative research methods applied to management practice and organizational functioning.

1 POWER LAW PHENOMENA

[1] Simply put, fractals appear similar at any scale of observation. In mathematical terms, fractal objects exhibit fractional dimensionality, that is, they are neither lines, nor surfaces or volumes. Their dimension falls in between the classical dimensions of Euclidean geometry (Schroeder, 1991).

[2] Our discussion of the organizational and managerial implications of scale-free theory is postponed because of obvious space limitations.

In recounting the SFI 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.

Many complex systems – resulting from emergent dynamics – tend to be '*self-similar*' across levels. That is, the same process drives order-creation behaviours across multiple levels of an emergent system (Kaye, 1993; Casti, 1994; West *et al*., 1997). These processes are called '*scaling laws*' because they represent empirically discovered system attributes applying similarly across many orders of magnitude (Zipf, 1949). *Scalability* occurs when the relative change in a variable is independent of the scale used to measure it. Brock (2000, 30) 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.

Included in fractal geometry are power laws, which are frequently '…indicative of correlated, cooperative phenomena between groups of interacting agents…' (Cook *et al*., 2004). Power laws often take the form of rank/size expressions such as $F \sim N^{-\beta}$, 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. Theories explaining power laws are also scale-free. This is to say, the same explanation (theory) applies at all levels of analysis. Natural scientists tend to use the term 'scale-free' – as in measure-independent – as opposed to 'level-free'. We will stay with their term.

Power law phenomena exhibit Paretian rather than Gaussian distributions – see Figure 1. The difference lies in assumptions about the correlations among events. In a Gaussian distribution the data points are assumed to be *independent-additive* (hereinafter simply 'independent'). Independent events generate normal distributions, which sit at the heart of modern statistics. When causal elements are *independent-multiplicative* they produce a lognormal distribution, which turns into a Pareto distribution as the causal complexity increases (West and Deering, 1995). When events are *interdependent,* normality in distributions is *not* the norm. Instead Paretian distributions dominate because positive feedback processes leading to extreme events occur more frequently than 'normal', bell-shaped Gaussian-based statistics lead us to expect. Further, as tension imposed on the data points increases to the limit, they can shift from independent to interdependent (more on this later).

For sure, not all data points interact to produce power law effects. Especially in natural science, data points are frequently independent. In social phenomena, however, power laws seem more likely because interdependence is more prevalent. It is also true that power laws may result from causes other than interdependence-caused fractals (Andriani and McKelvey, 2006). Interdependence, nevertheless, is a common cause of power law effects and Pareto distributions. Given their scale-free nature, fractals always call for scale-free theory. In what follows, however, we zero in on the implications of power law effects and fat tails against the use of Gaussian statistics. We develop organizational scale-free theory elsewhere (Andriani & McKelvey, 2006).

Physical, biological, social, organizational, and electronic systems show an impressive variety of fractal phenomena (Kaye, 1993). We list many in Table 1 (many categories include several studies, though we mostly cite just one). Below, we illustrate some lines of fractal research further. Many leading scholars believe that power laws are the best analytical framework to describe the origin and shape of many natural objects (Mantegna and Stanley, 2000). Given the ubiquity of these findings, and the nature of the underlying scale-free theory, we think they are equally ubiquitous phenomena in organizations, but unknown and unappreciated as to their causes and effects. In sum, power laws usually indicate the presence of three underlying features: (1) fractal structure; (2) scale-free causes (and scale-free theories); and (3) Pareto distributions.

>>>Insert Figure 1 and Table 1 about here<<<

1.1 Fractal Geometry

Fractal geometry was developed by Mandelbrot (1975) to make sense of the rough, irregular shapes of most natural objects, from cauliflowers to coastlines, trees, and galaxies. As Mandelbrot (1975: 1) writes: '*Clouds are not spheres, mountains are not cones, coastlines are not circles, and bark is not smooth, nor does lightning travel in a straight line*'. The coasts of England and Norway exemplify scalability: the length of the coast profile depends with inverse proportionality on the length of the ruler – i.e., the smaller the ruler, the longer the coast. A fractal (Mandelbrot and Hudson, 2004, 118) is: 'a pattern or shape whose parts echo the whole'. Fractals are self-similar objects. Like the cauliflower, so the Eiffel Tower: the four largest sections are made up of large trusses, which are composed of smaller trusses, etc. (Mandelbrot, 1982, 131–132).[3]

[3] Mandelbrot argues that Eiffel's Tower 'incorporates the idea of a fractal curve full of branch points.' Just last year Weidman and Pinelis (2004) proved that the four corner columns of the Tower are shaped as two log normal distributions – one for the base and one for the upper tower. They appear as Paretian distributions on end (more on these later). These formulas result from Eiffel's discovery that by using Paretian shaped columns all the trusses could be designed as tension truss members, thereby vastly reducing the overall weight of the Tower – a truly remarkable achievement that is still a marvel to observe!

Fractals are not idle mathematical curiosities. Fractals and power laws are found from atomic nanostructures (~10^{-10} meters) to galactic megaparsecs (~10^{22} m) – across a range of 32 orders of magnitudes (Baryshev and Teerikorpi, 2002). In biology, West and Brown (2004) 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. Power law systems do not exhibit a characteristic scale and consequently enjoy some peculiar statistical properties. Systems that scale linearly are part of a family of distributions named after the French mathematician Cauchy:

> As a result of this linear scaling, the distribution of the average of N identically distributed Cauchy variables is the same as the original distribution. Thus, averaging Cauchy variables does not improve the estimate…. This is in stark contrast to all probability distributions with a finite variance, σ^2, for which averaging over N variables reduces the uncertainties by a factor $1/\sqrt{N}$. This nonstandard behavior of the Cauchy distribution is a consequence of its weakly decaying 'tails' that produce too many 'outliers' to lead to stable averages (Schroeder, 1991, 159).

This observation appears over and over in the following examples – the point is crucial.[4]

1.2 Spatio-structural Properties of Systems

This category groups spatio-structural properties of networks, assuming nodes or links as units of analysis. We discuss two: (1) rank-size rules focusing on nodes, which can be cities (size of population), words (frequency in languages), profits of firms (production of wealth), etc.; and (2) connectivity patterns that derive generic features of networks from the connectivity topology.

Language and Cities. Zipf (1949) found that a power law applies to word frequencies (Estoup, 1916, had earlier found a similar relationship). Casti (1994, Ch. 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. Zipf's Law, a rank/frequency power law, is a classic example of a scale-free effect. 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) – see Figure 2. 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)

>>>Insert Figure 2 about here<<<

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.

In their initial *small world* model, Watts and Strogatz also assume that links are Gaussian distributed. Studying the World Wide Web, however, Barabási and colleagues (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 the absence of a stable 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, metabolism of cells, Internet, and networks of sexual contacts (Liljeros, 2001)).

Industrial Agglomerations. Here we report the work that one of us has done on power laws and industrial agglomerations in Italy (Andriani, 2003a,b). Axtell (2001) shows that the distribution of firm size follows a power law. Our work extends Axtell's analysis to a sub-regional context.

The agglomerations we consider are the so-called travel-to-work areas (TWAs) in Italy. 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-TWAs commuting (ISTAT, 1997). In Italy, TWAs are organized into a taxonomy (Sforzi, 1990; Cannari and Signorini, 2000) that divides the agglomerations into two groups: cluster-based (type D) and non-cluster-based (type A) agglomerations[5]. To test whether Italian industrial agglomerations follow a

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[4] Vilfredo Pareto discovered the 'wealth' power law – Pareto's Law – and 'Pareto distribution' in 1897. Though other related distributions exist – Cauchy, Lévy – we stay with Pareto since he was the first.

[5] The basic idea is that the higher the percentage of home-to-work commuting taking place within the boundaries of an area, the higher the chance of capturing within the area some territorially-specific social and industrial aspects. TWAs represent an algorithmic way to define the micro-units of analysis of economic geography and economic sociology. In Italy the 1992 Census identified 784 units. 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 (Becattini, 1990; Storper, 1997). This is based on a multi-criteria scale (ISTAT) that includes the

power law, we use linear regression. The results for both types of agglomerations (D and A) are statistically significant (type D: $r = 0.997$, $p < 0.0001$, slope $\beta = -0.995$; type A: $r = 0.995$, $p < 0.0001$, slope $\beta = -0.997$); they 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 at a generic time *t* is power law distributed indicates that the growth mechanisms (that give rise to that distribution) follow a power law (see also Stanley *et al*., 1996). Interestingly, the division between cluster and non-cluster type doesn't seem to affect the power law distribution in terms of regression coefficient and/or slope. This is surprising as it indicates that the growth mechanisms are independent from 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.

>>>Insert Figure 3 about here<<<

1.3 Dynamic Properties

Our second category covers theories describing the dynamics of how and when new entities emerge. In this case, a power law characterizes the nature of the behavioral properties of a system subjected to a perturbation of some kind. Whereas the former category focuses on the type of distribution of the network-forming elements (nodes and links), this one analyses a network's emergent collective behavior. Classical examples are phase transition models in physics (Haken, 1977) and Bak's (1996) *self-organized criticality* (SOC). In both cases, the emergence of a power law is due to emerging connectivity. However, in SOC the system evolves spontaneously towards the critical threshold, whereas in phase transition models the order parameters must be activated by an external agent (i.e., energy source) to achieve criticality.

Coevolution. In economics, the idea of positive returns dates back to Young (1928). Arrow (1962) introduces mutual causal learning effects (see also Holland, 1986). Maruyama's (1963) classic paper on deviation amplifying mutual causal processes introduces the idea that some interactions are not negative feedback processes but foster the opposite – positive feedback. Interaction among agents[6] and mutual causality lie at the heart of SFI's theories of emergent self-organization (Arthur, 1983, 1988; Holland, 1988). As time progresses, each agent makes connections and then may coevolve with other agents, perhaps a little with all of them at first but then positive feedback sets in with some negative feedback with others and some mutual causal relationships expand and others contract. The result may be the formation of networks and perhaps groups of agents, that is, new order. Assuming that the set of agents is large enough and enough time passes, a power law arrangement of connected agents and perhaps newly formed groups (agents) results. Axelrod and Bennet's (1993) study of alliance formation is one example of emergent structure from coevolution. Another is Carley and Hill's (2001) study where (1) the formation of subgroups occurs, followed by (2) the emergence of culture that supervenes to alter agents' coevolutionary search for improved performance.

Economics, Finance, and Movies. Pareto (1987) first noticed power laws and fat tails in economics. Zipf (1949) and Mandelbrot (1963) rediscovered them in the 20th century, spurring a small wave of interest in finance (Fama, 1965; Montroll and Shlesinger, 1984). However, the rise of the 'standard' model of efficient markets,[7] sent power law models into obscurity. This lasted until the 1990s, when the occurrence of catastrophic events, such as the 1987 and 1998 financial crashes, that were difficult to explain with the 'standard' models (Bouchaud *et al*., 1998), re-kindled the fractal model. The case against the 'standard' model is set by Mandelbrot (Mandelbrot and Hudson, 2004, 13) with a simple observation:

> …By the conventional wisdom, August 1998 simply should never have happened…. The standard theories…would 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 percent 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: The price of virtually any stock or commodity exhibits punctuated equilibrium behavior, in which chaotic and turbulent periods alternate with stable ones (Mandelbrot, 1963; Fama, 1965; Bouchaud *et al*., 1998; Moss, 2002). Wassily Leontief, Nobel Laureate in economics, recognized the struggle of orthodoxy with reality:

> In no field of empirical inquiry has so massive and sophisticated a statistical machinery been used with such indifferent results. (quoted in Mandelbrot and Hudson, 2004, 275)

Another example of power laws in economics appears in the book *Hollywood Economics* (De Vany, 2004). He

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relative weight of (a) manufacturing activities, (b) employment in SMEs and (c) incidence of specialization in manufacturing sectors.

[6] '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.

[7] Signified by Portfolio Theory (Markowitz, 1959), the Capital Asset Pricing Model (Sharpe, 1964), and the Black-Scholes (1973) Option Pricing Theory.

shows that movie profits are Pareto distributed, i.e., form a power law. 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. Budgets are uncorrelated with earnings and the 'star system' allows no indication about final success. The only recognizable pattern is Paretian distributions of profits.

Self-Organized Criticality. This group of models 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 induces a systemic reaction that can span any order of magnitude, with a frequency distribution expressed by a power law. This is counter-intuitive. We generally assume a linear relationship between perturbation size and a system's reaction, i.e., small causes yield small effects. This is true before SOC is attained. Thus, before criticality, each falling grain has a constant probability of displacing an adjacent grain. The probability of an avalanche therefore scales exponentially with the number of sand grains. This makes large avalanches highly unlikely. However, at criticality a power law distribution results from the global connectivity of the sandpile. As Bak (1996, 60) writes: 'In the critical state, the sandpile is the functional unit, not the grain of sand'. SOC dynamics arise when an emergent system of links connects local pockets into a coevolving whole such that small and local fluctuations may be amplified to achieve systemic effects. More generally, as the tension in the system increase 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.[8] Mathematically this means that sandpile behavior obeys a power law of the type: $F \sim S^{-\alpha}$, where F represents avalanche frequency with size S.

SOC occurs frequently (Buchanan, 2000). From the dynamics of earthquakes (Gutenberg and Richter, 1944) and the succession of booms and busts in economic cycles (Krugman, 1996), to the dynamics of supply chains (Scheinkman and Woodford, 1994), a common pattern appears across disparate fields. A few implications follow. First, the fact that a self-critical system spontaneously tunes itself towards a self-critical state (Bak and Chen, 1991; 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) – makes reductionism inappropriate for the study of SOC. Second, the conventional explanation regarding mass extinctions (e.g., dinosaurs at the end of Cretaceous Period) is imputed to exogenous events (asteroid or eruptions). Instead, according to SOC, internal causes may have been progressively amplified until a catastrophic chain reaction took place (Raup, 1999, 217–218; Gould, 1990).

Biological Growth Units. Take a simple biological entity attempting to survive and grow in its habitat. Bykoski (2003) calls such a bioeconomic agent a 'growth unit', which is '…an integral robust entity'.[9] At the simplest 1-cell level, a unit gains some advantage in coping with its habitat – accomplishing all of Kauffman's tasks[10] – if it grows. Growth is for some reason and in the bio- and econospheres the reason is usually coping with a demanding environment – resources, constraints, competitors. A bio-unit can do this by growing in size, i.e., doubling, and then doubling again, and so on. Furthermore, from Ashby's (1956) *Law of Requisite Variety* we know that entities that increase internal variety to match external variety have improved adaptive capability. But, only multi-cell units can build up variety. These reasons are why many biota eventually grew from the initial 1-cell organisms to dinosaurs and mammals.

While divisions increase by the square, however, their pair-wise connections, c, increase by the formula: $n(n–1)/2$, where n = # of units; thus if n = 2, 4, 8, 16, 32, 64 then c = 1, 6, 28, 120, 496, 4032. A unit has to accomplish two things: (1) Some of its energy must go toward coping with its environment – it has to move, find food, process what it ingests, accomplish Kauffman's tasks, etc.; and (2) Some of its energy goes into maintaining and using the pair-wise communications with other units. Because of the $n|c$ ratio, at some point the amount of energy going into communication significantly detracts from the unit's ability to cope successfully with its environment. At this point the unit divides into two units (often) specializing in different tasks, bringing the over-communication problem back under control. The underlying cause of the power law is the basic $n|c$ relationship and the need to keep dividing to better cope with the environment but keep communication costs under control. Carneiro (1987) focuses on the surface/volume ratio – a 2/3 power law called the Square-Cube Law – to explain why villages never exceed a relatively small size.

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[8] 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: http://en.wikipedia.org/wiki/Bose-Einstein_condensate

[9] Bykoski's *units* are, of course, *agents*. But, here we will use the term *unit* when we refer to an *agent* with growth capabilities – since many agents do not grow. Units can grow by *doubling* or by *attracting* a new unit into the system and then connecting with the new unit. Cells grow by splitting; species grow when members attract mates that produce offspring.

[10] Kauffman (2000), a biologist, argues that a bioeconomic agent survives by 'earning a living' (e.g., a bacterium swimming in the blood to find food or a firm trying generate income). From this basis he says, 'work is the constrained release of energy' (p. 100). He then points out that to survive and grow, agents have to complete a number of tasks to actually self-organize – tasks '…involving work, constraint, constraint construction, propagating work, measurements, coupling, energy, records, matter, processes, events, information, and organization.' (p. 104)

Determinism. First, we have *macro*-deterministic theory in which the joint probability of equally probable higher-level external constraints occurring at the same time sets up a power law.[11] In Table 2 we show several ecological constraints regulating a species, each having some functional form. For each, there is some rate at which it could deviate to significantly undermine advantageous species adaptation, say once in several hundred years, because of underlying geological and climatic changes. This would set in motion a rank/size power law of species extinctions. Gould (1990), Raup (1993), and Bak (1996) offer additional discussions of randomly occurring ecological causes of mass extinctions (or explosions).[12]

>>>Insert Table 2 about here<<<

Second, we could have a *micro*-deterministic theory built from reductionist causes – also shown in Table 2. For a particular species, each of these has some advantageous configuration. There is some probability that each may not be advantageous, leading to adaptive insufficiency in a changing world. This sets up a power law effect (Raup, 1986; Bak, 1996).

Intra-Organizational Power Laws. Stanley *et al*. (1996) report out a study on the statistical properties of all publicly traded manufacturing firms listed in Compustat (US) for the period 1975–1991. They start with Gibrat's model of company growth, which assumes that growth in sales is independent of firm size and uncorrelated in time (i.e., lognormal). They find that, in reality, variance in growth rate is Paretian not Gaussian, and follows a power law with exponent β:

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

where: $\sigma(s_0)$ is standard deviation of growth per year based on initial sales value, s_0; growth rate = $r = S_1/S_0$ = change in yearly sales; $s_0 \equiv \ln S_0$; a is a constant (~6.66); β = the slope of factors affecting growth – ranging from ½ to 0.

The equation holds over seven orders of magnitude of firm size. The power law holds when growth is measured as cost of goods sold (β ~.16), assets (β ~.17), property, plant and equipment (β ~.18), and number of employees (β ~.16).

Given their findings, 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, causing a Markov chain along the hierarchical levels – each subsequent action-step at time t is a replica of action at step t–1. 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, i.e., *all* parts of the firm operate independently, then β = ½. Usually the employees follow orders with some probability. Thus, for a β = ~.15 or so (given the findings by Stanley *et al*.), we expect a power law effect to obtain. Note that β ~.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 β ~.15 – and a power law event – as depicted in Figure 4.

>>>Insert Figure 4 about here<<<

Diatlov (2005) also applies power law dynamics to intra-organizational decision events. He sees an equivalent 'power law of power'. 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's process and quotes Lindblom (1968: 25–27) as saying: 'Policy making is typically a never-ending process of successive steps in which continual nibbling is a substitute for a good bite'. Also building from Lindblom's (1959) '*science of muddling through*', Cohen, March, and Olsen (1972) develop their '*organized anarchy*' approach – the 'garbage-can model'. Organized anarchy reflects both top-down and bottom-up creation of β ~.15. These leading scholars, after intensive studies of emergent strategy, *all* describe the base-line conditions for β ~.15. Diatlov's point is the idea that *both* Fordist and self-organizing forms produce power law effects *inside* organizations (see also Bak, 1996).

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[11] In general a multiplicative process can generate either a distribution called *lognormal* or a power law (West and Deering, 1995). In the former, the logarithm of the variable generates a bell-shaped symmetric distribution. It is often a matter of judgment to decide whether experimental data fit a Pareto or a lognormal distribution (West and Deering, 1995). The difference between the two resides in the amplificative character of the power law. As West and Deering (p. 126; 156, 157) point out: 'The scale-free character of the underlying process is shown to provide an amplification process that induces the transition from lognormal to inverse power law…. As lognormal systems become ever more complex, their distributions become broader, and they take on more of the qualities associated with 1/*f*-behavior…. This means that increasingly complex lognormal phenomena take on more of the fractal, or scale-invariant, characteristics of systems governed by inverse power laws.'

[12] For a recent review of the arguments about an asteroid hit vs. the joint probability of other changes in ecological elements such as climate, sea level, oxygen level, etc., see Wright (2005).

Diatlov's research (2005) 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 power law configuration of *internal* organizational decision events.

So far, our separation of power law phenomena into spatio-structural and dynamic phenomena begs the question whether the different phenomena described by power laws share a common property. Mandelbrot (1963); quoted in 2004, 170) writes:

> *…The cotton story shows the strange liaison among different branches of the economy, and between economics and nature. That cotton prices should vary the way income does; that income variations should look like Swedish fire-insurance claims; that these, in turn, are in the same mathematical family as formulae describing the way we speak, or how earthquakes happen—this is, truly, the great mystery of all.*

Simon (195, 425) pointed to a common probability mechanism:

> [The power law's] *appearance is so frequent, and the phenomena in which it appears so diverse, that one is led to the conjecture that if these phenomena have any property in common, it can only be a similarity in the structure of the underlying probability mechanism.*

Others also argue that the appearance of power laws points to common underlying dynamic and coevolutionary mechanisms (Bak, 1996; Lee *et al*., 1998; Shin and Kim, 2004; West and Brown, 2004). Stanley, a founder of econophysics, writes:

> *If the same empirical laws hold for the growth dynamics of both countries and firms, then a common mechanism might describe both processes. (*Stanley *et al*., 1996, 3277)

We believe the underlying mechanism has become apparent. Across all nine kinds of power law phenomena we see that the causal dynamic is *interdependence among agents* (data points) that – with some probability – leads to power law effects. Their positive-feedback-based volatility spikes and consequences may be most obvious among markets, earthquakes, and hurricanes, but evidence indicates they appear everywhere, even among social phenomena, even including organizations. For some natural scientists, power laws have reached the mathematical regularity of pervasive natural laws such as gravity or entropy production (Bak, 1997; Halloy, 1998).

2 CONNECTIONISM VS. INDEPENDENCE IN ORGANIZATIONS

2.1 Mohr's Variance vs. Process Theories

As noted earlier, Mandelbrot started arguing for the importance of fractal geometry and power law thinking in economics and finance in the 1960s. Perhaps the first person to go down this path in organization theory is Laurence Mohr, who argues for differentiating between '*variance*' and '*process*' theory. As it turns out, his argument also rests on the fundamental distinction between independence and interdependence. Mohr (1982) begins his book by reviewing some 984 findings about what leads to innovation. The results are consistently one/third negative with nothing unequivocally positive – i.e., no clear causal determinant. He concludes by asking, what is the point of doing yet another study, given these circumstances? He then describes all the foregoing studies as examples of 'variance theory' and proposes 'process theory' instead. He defines them as follows (our emphasis):

- '*<u>Variance theory</u>*, roughly, is the common sort of hypothesis or model, such as a regression model, whose orientation is toward explaining the variance in some dependent variable'.
- '*<u>Process theory</u>* presents a series of occurrences in a sequence over time so as to explain how some phenomenon comes about. Diffusion models are often good examples of the latter'.

In discussing process theory, Mohr emphasizes the term, '*interaction*', and introduces the term, '*complexity*', drawing from Brunner and Brewer (1971, 14):

> …*Complexity* refers to the interdependence of influences in the world itself, whereas *interaction* refers to the same sort of phenomenon as it is formalized in one's models of the world.

What is important is 'their role as amplifiers or contractors of the impact of other causes'. (p. 14)

> Process theory eschews efficient causality [Aristotle's energy-based force] as explanation and depends instead on *rearrangement* – that is, on the joining or separation of two or more specified elements rather than on a change in the magnitude of some element. (p. 45)

Mohr shifts from independence and variance analysis to *interdependence*, *connectionism*, *mutual causal*, and *coevolutionary* processes. In essence, he shifts from Gaussian to Paretian science.

2.2 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. (Nobel Laureate P. W. 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) proportionality between cause and effect, and (2) that 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 efficient causality to operate, equations to be solved, and predictive modeling. Economics, for instance, is almost theistic in its (scarcely verified) assumption that economic phenomena trend toward '*general equilibrium*' (Mirowski, 1989, 1994; 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 to 'equilibrium' time. For this to be true the many elements comprising a system must be assumed *independent*[13] data points. If we take 100 companies approximately of the same size belonging to the same sector and assume independence, and plot a variable, say profit, we expect most events to pack around the mean, exhibiting the classic bell curve. The bell shaped distribution is by far the most studied statistical distribution; it is assumed to correctly characterize much of our discoveries about the natural and social worlds. In real life, however, *the crux of the point is whether all events are independent*. 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 *interdependent*, not independent!

Gaussian and Paretian distributions differ radically. The Gaussian distribution is reliably characterized by its stable mean and finite variance (Greene, 2002). A Paretian distribution doesn't show a well-behaved mean and 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). There are two major implications:

1. 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. Absent 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).
2. Paretian tails decay more slowly than those of normal distributions. These fat tails affect systems' behaviors in significant ways. Extreme events, that in a Gaussian world could be safely ignored, are not only more common than expected but also of vastly larger magnitude and consequence. For instance, '[standard] *theory suggests the over that time* [1916–2003] *there should be fifty-eight days when the Dow moved more than 3.4 percent; in fact, there were 1001*. (Mandelbrot and Hudson, 2004, 13).

Statistics: Obscuring Rather than Clarifying? A power law world is dominated by extreme events ignored in a Gaussian-world. In fact, the fat tails of power law distributions make large extreme events orders-of-magnitude more likely. In a 'normal' world, where distributions show finite variance, extreme events are so different from the typical and so 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 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 of scale 7 and higher, etc. 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. If this is true, 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 power-law world. We need methods and statistics that include (if not actually celebrate) extremes rather than assume them away!

Power Law Statistics. A non-Gaussian world demands methods accounting for path-dependency, nonlinearities, emergent properties of systems, and the dynamics of multiple punctuated equilibria. The assumption of independence of events, which underlies the Gaussian world and the classical reductionist '*variance process*' approach (Mohr, 1982) and the linear approach that underlies large parts of classical and quantum sciences (West and Deering, 1995) could lead to the wrong analytical tools and conclusions when dealing with connectionist dynamics (Kauffman, 1993; Holland, 1995). 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 4th study, they note that '…observing outliers may be more informative than observing average or typical entities….' They then

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[13] The issue of independence depends on the linearity (or nonlinearity) of the dynamics that generate the data points (West and Deering, 1995). If a system is linear, then its overall dynamic results from (a) the linear addition of the dynamics of its single components and (b) the principle of proportionality between cause and effect. Systems that are moderately nonlinear can be treated as the combination of a linear system plus a perturbation term. In practical terms, this means that the nonlinearity can be assumed away. In both cases, the system's dynamic is additive, and respects the basic conditions for the application of the Gaussian statistics. In the presence of cooperative phenomena or of strong coupling between the system's parts, however, no perturbation theory can be used to linearize the system. The parts and the measures obtained are strongly interdependent. Under these conditions, the basic conditions for the application of Gaussian statistics are not respected. Furthermore, the more tension imposing on a system the more likely interdependence and SOC prevails.

mention the Anderson quote we started this section with.

Where extreme events dominate and variability is infinite, the most statistics can do is to indicate the shape of the distribution, that is, the general attractor[14] toward and around which the events will tend to self-organize (Gleick, 1987; De Vany, 2004). The universality of the power law attractor – really the underlying interdependence-and-positive-feedback effects – is confirmed by the fact that these effects exist at 27 magnitudes in the biological world, as shown across many sciences. In light of this vast generality, we detail the main features of a power law based statistical method in Table 3.

>>>Insert Table 3 about here<<<

2.3 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 normal distribution)[15]

Management researchers using statistics as their basis of making truth claims – usually translated as findings significant at $p < .05$ or .01 – mainly use statistical methods calling for Gaussian distributions. Gaussian science, so to speak, produces equations looking like this:

$$\text{Variance of a } \underline{\textit{dependent variable}} = \int \underline{\textit{variables}} + \underline{\textit{error term}} \tag{1}$$

In Paretian science the expression looks like this:

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

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 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*, (2002) is in its 5th edition and is the standard for many econometricians and other social science researchers. He begins his ~950 pages of analysis with linear multiple regression and its five endemic assumptions: (1) independence among data points; (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: White test, Goldfeld-Quandt test, Breusch-Pagan/Godfrey LM Test, weighted least squares, two-step estimation, maximum likelihood estimation, model-based tests (i.e., analysis of residuals, Wald test, likelihood ratio test, Lagrange multiplier test, multiplicative and groupwise heteroscedasticity models), the ARCH [autoregressive, conditionally heteroscedasticity (Engle, 1982)] model (three variants), with the generalized form, GARCH (Bollerslev, 1986), being most preferred – and now most widely used by finance scholars and practitioners alike. GARCH '…allows the variance to evolve over time' (p. 242). ARCH/GARCH assumes that model errors appear in clusters and that the '…forecast error depends on the size of the previous disturbance' (p. 238) – it treats variance as a '…moving average of squared returns' (Engle, 1982).

Econometrics always assumes that data points are additive independent. Conditions calling for GARCH occur, but adjustments are made in modeling without ever giving up on the independence assumption. A plot of the GARCH moving average shows that any *power law driven peak* – a volatility-extreme based on interdependence of some kind (Mandelbrot and Hudson, 2004) – is adjusted down to slightly above the average blip by the moving average process. This is clearly shown in Figure 5, where the heavy black line, representing variance according to GARCH in no way represents extreme events – the 1929 and 1987 spikes extend well beyond the top of the graph.[16]

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[14] We define **attractor** as the dynamical state toward the system evolves after some passage of time. The simplest kind os a basin or equilibrium point. The torus and 'strange attractors' are more obscure (see Gleick, 1987).

[15] Quoted in West and Deering, 1995, 83

[16] The 1929 spike extends 4' above the top of the graph; the 1987 spike extends 2' above! If you download Ghysels, Santa-Clara, and Valkanov's

Greene ignores the *Pareto*, *Zipf*, *Cauchy*, or *Lévy* distributions. Nor does he discuss *interdependent*, *interacting*, *connectionist*, *interconnecting*, *coevolutionary*, or *mutual causal* data points, events, or agents.[17] 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 *interdependent* agents that, with some probability, are set off in a cycle of positive feedback progression resulting in an extreme event. In fact, none of the robustness adjustments to failing linear multiple regression assumptions that Greene discusses deal with the real-world's *probable* – not just possible – losses of independence. None! Needless to say, even GARCH ignores the power law extremes that Mandelbrot has been observing in financial markets for 50 years (Mandelbrot and Hudson, 2004).

Ironically, GARCH actually falls into a statistical never-never land. It uses its moving average to try to include the effects of interdependence-caused extremes but it never lets go of its assumption of independent data points. It widens the confidence intervals for those trying to stay with independence assumptions fitting the 'in between extremes' phenomena but it doesn't account for the extreme variance effects of fat tails. Hence it fits neither Gaussian nor Paretian worlds.

>>>Insert Figures 5 and 6 about here<<<

To conclude, the various robustness tests Greene discusses, even including the best and most widely used one, GARCH, give no assurance whatsoever that modern-day researchers account for the effects of extreme events in their statistical analyses. Let's put this in California earthquake terms – where we average ~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 6- and 7-level quakes occurring within decades. In effect, it is as if Greene and virtually all modern regression modelers want Californians building and living in high-rise buildings to think that using a moving average (GARCH) of quake variance over the thousands of harmless (average) quakes will lead to building codes that protect against the 8- and 9-level 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 – i.e., the effects of fat-tailed Pareto distributions. Needless to say, GARCH also doesn't accommodate the power law extremes that Mandelbrot has been observing in financial markets over the past 50 years (Mandelbrot and Hudson, 2004). ***Robustness tests and 'solutions' do not, and cannot shift statistics from the Gaussian to Paretian worlds*.**

Normal science keeps searching for the Holy Grail of prediction even though leptokurtosis and volatility clustering suggest this is an act of faith rather than well-considered strategy. Though it is hard enough to predict earthquakes occurring within an unchanging power law scale, worse for social scientists, it is frequently the case that in social systems, after an extreme event, some of the underlying causal dynamics (rules) are changed. Thus, while even governments can't change subsurface geology and plate tectonics, politicians can and did introduce the Sarbanes-Oxley Act after the Enron debacle. The latter makes the problem more difficult, but does not undermine the basic issue management research faces, of needing redirection from Gaussian to Paretian science.

2.4 Confronting Extreme Variance Head On

What is the meaning of 'robustness' and how should we define an effective science of extremes?

Paretian Rank/Frequency Effects. Table 4 defines four statistical possibilities:

>>>Insert Table 4 about here<<<

Type 1 is the statistician's dream. Direct linear relation; variance is critical; mean is ignored. There is a perfect correlation, except for the anaerobic effect and a slight error in measuring calories. Type 2 is quite the opposite. The seat designer would prefer everyone to be 'average'. The variance is ignored. In Type 3 we are worried about the linear relation of height/weight to sports performance, which happens to be obscured by the large bulge of more average people in the middle. Here the mean is irrelevant and the variance is what counts, as long as the meaningful variance is not overwhelmed by measurement error. The large bulge in the middle increases statistical significance but also obscures the linear covariance relationship. Finally, in Type 4, most of the people are irrelevant but the one extreme is truly deadly. In Type 1, the average is uninteresting. In Type 2, the average is critical and variance is a nuisance. In Type 3, we have a huge cluster around the mean but it is the extremes that tell the tale. In Type 4, the only thing interesting is the one extreme – neither mean nor variance is useful.

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paper you can see their chart in color: http://www.personal.anderson.ucla.edu/rossen.valkanov/risk_return_paper.pdf

[17] Even more broadly, microeconomics does likewise. Forni and Lippi (1997) discuss 'heterogeneous agents' [a concept central to complexity science (Holland, 1988)] but never consider the idea that they might interact! As ludicrous as it may seem, most of math and statistics in Economics is based on the assumption that people neither communicate with, learn from, nor influence each other!

One point in making these distinctions is to observe that management researchers tend to conduct research with the ideal of Type 1 in mind. 'Robustness' is aimed at trying to improve methods (or reshape distributions) to the point that researchers can make Type 1-based truth claims, even though they have Type 3 or 4 findings. A second point is that our current 'journal-approved' quantitative research methods systematically miss the most important things in most managers' work lives – the extreme events – such as the Alfred Sloan (GM), Jack Welch (GE), Bill Gates (Microsoft), Andy Grove (Intel), Toyota and Honda, eBay, Google, Post-its and other dramatic successes as well as dramatic failures like LTCM, Enron, California energy crisis, Parmalat, NY blackout, Iraq intelligence failures, the Edsel, the 1987 Asian financial meltdown, and so on. For other managers, the positive and negative extremes affecting their lives don't make the headlines, but are nevertheless important to the individual concerned.

Implications of Unstable Means and Variance. As we noted at the outset of Section 2.3, most researchers are concerned with the relative proportion of causal and error variance (Equation 1). Misplaced faith in the robustness tests discussed by Greene (2002) deludes them into thinking they can ignore the effect of extremes – and associated infinite variance – on their analysis of covariance in their presumed Gaussian distribution. As we have noted, in Gaussian distributions some variance is essential, but variance in the tails is usually attributed to error or outlier effects; the latter are often deleted.

As the influence of extremes in a function increases, the influence of the Paretian distribution gains over the Gaussian distribution. The meanings that can be sensibly attached to means and variances change fundamentally. In Pareto distributions the tails are fat and more extreme events have more powerful effects – Hurricane Katrina, strong earthquakes, or the Enron bankruptcy. Because of the fat tails, variance is very large and unstable; because of possible extreme events the mean of the distribution is unreliable. Research findings, in reality, risk becoming irrelevant when means are unstable and variance is infinite. Researchers keep assuming Equation 1 prevails even though the widespread findings of power law effects suggest that Equation 2 often dominates. As Meyer *et al*. tell their story *they*, trying all the time to be sound quantitative researchers, keep using methods fitting Equation 1 when, in fact, in each of their four studies Equation 2 was the valid representation – eventually causing them to abandon Equation 1 methods.

3 REDIRECTING MANAGEMENT RESEARCH

On January 9th, 1857 a #9 magnitude quake occurred, stretching 220 miles along the San Andreas Fault in California. At one point one may observe that 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 #6.7 Northridge quake in 1994 – local to the LA area with visible earth movement of a few *inches* – was $44 billion, 51 people killed, 9000 injured, 22,000 left homeless. A #9 quake is more than 100 times larger!! The really big ones in financial markets occurred in 1929 and 1987 – some 60 years apart (Figure 5). But just since 1987 we have had other extreme events: the Asian crisis of 1997, the Russian meltdown of 1998, and the burst of the dotcom bubble and ensuing Parmalat and Enron *et al*. collapses in 2001–2003, with multibillions lost each time. These are the negative ones. We also have multibillion dollar positive events like Microsoft, GE, Intel, eBay, Google, etc., in the organizational/managerial world.

3.1 What Basis for Truth Claims, If Not 'Normal' Science Statistics?

Traditional Justification Logic and Normal Statistics. Instead of seeing extreme variance in management- and/or organization-based 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, almost everything humans experience moves at speeds orders of magnitude slower than the speed of light – hence theories and methods consistent with Newtonian mechanics remain valid. As objects in space get closer to the speed of light, theories and methods consistent with Relativity Theory become more binding. For earth-bound scientists and engineers, however, 'old' Newtonian Mechanics is of much more use than relatively 'new' Relativity Theory.

Our view is that for organizational research the '*new*' is more relevant that the '*old*'. For us, *old* is Gaussian-based science; *new* is Paretian-based science. We argue that the *new* prevails much more than the *old*. But we agree, the *old* is still present in some proportion. A more sensible approach for management research is to begin each study with the following test:

- Given Proof of Independence – Use Normal Statistics – the *Old*.
- Absent Proof of Independence Assume Interdependence – Use Power-Law Thinking – the *New*.

We think this test is broadly important in management research, and in other kinds of social research. Each of the nine broad categories of power law phenomena discussed earlier (Section 1) – and to some extent related underlying theory – includes the possibility of an extreme event stemming from interdependence among agents. More importantly, ALL of the various interdependency possibilities appear to apply in organizations. Not just one out of five some of the time, but ALL OF THEM! This doesn't mean extreme events occur all the time everywhere. But it does mean that some probability of the *benefit of positive* or *risk of negative* extremes is present all the time and everywhere – and at a much higher rate of occurrence: #9-level quakes occur in a region roughly once every 200 years; #9-equivalent financial disasters (Great Depression, 1997 Asian Crisis) occur at a rate of around two per century. Mandelbrot finds that large financial crises occur once every five years (see Figure 5).

Finally, there is a figure/ground reversal. Current methodology takes the Null Hypothesis as: *phenomena are independent until proven otherwise* (and current practice mostly attempts to assume away the problem). Rather, for a redirected organization science the NULL assumption should be one of *interdependence until proof of independence obtains*.

3.2 Lessons from Earthquake Science—A 'New' Underlying Discipline?

Why Earthquake Science? Management scholars draw on a wide variety of underlying disciplines ranging from natural science to social sciences such as economics, sociology, and anthropology. Among the latter, economics is most rigid in placing its faith in the 19th century equilibrium-based mathematical methods of classical physics (Mirowski, 1989, 1994; Ormerod, 1994; Colander, 2000), but we also see mathematical sociology (Abbott, 2001) and mathematical anthropology (Read, 1990).

While many disciplines – from microbiology to astrophysics – now report out power law phenomena (see Table 1), we zero in on earthquake science for four reasons: (1) quakes are unquestioned power law phenomena; (2) earthquake science is a fully legitimate natural science; (3) everyone knows about quakes and some have experienced them; and (4) most importantly and most relevant to the presumed practitioner orientation of management research, states like Japan and California have taken the lead in learning how to investigate, live with, and protect against extreme phenomena – as opposed to, for example, Wall Street's zeroing in on averages and ignoring the extremes.

Research Activities. To give you some idea of what the components are for an 'extreme-oriented' science, we draw from the U.S. Geological Survey, which is located in San Francisco, which sits on top of the San Andreas Fault. We don't give details on the geo-seismic origins of the headings (see their webpage). We just use them to suggest how an extreme-based management research might decompose into more specific research activities. These are defined in Table 5. As you can see, earthquake science readily provides a model for an 'extreme-based' management research.

>>>Insert Table 5 about here<<<

In their 'concluding thoughts' Meyer *et al*. (2005) point to two disciplines, history and complexity science, as part of the frontier. Their paper seconds our assertion that complexity science is a discipline aimed at studying the outcome effects of interdependency. While they don't mention earthquake science, their studies reflect it.

- They argue the importance of studying the 'history' of extreme nonlinear events – **#1** in Table 5;
- Their 1st study focuses on '*jolts*' (p. 6) – the target of earthquake science;
- They focus on multiple levels of analyses fits **#3** – deep structure analysis (plate tectonics in geology);
- They emphasize real-time analysis ('get into the field right away', p. 6) – **#5** in Table 5, and especially in their ongoing study of network formations;
- In study 3 they abandon the general linear model in favor of 'vector autoregressive technique' – a special method new to organization science and applicable to 'interdependent systems of variables' (p. 13) – **#4** in Table 5;
- Their use of the Anderson quote (p. 18) mentioning 'tails' suggests their recognition of interdependencies and fat-tailed Pareto distributions – characteristic of earthquake dynamics;
- They say, 'narrow your scope of observation…select promising exemplars' (p. 6) – this is like earthquake scientists studying samples of quakes of the same size (i.e., all #9s) or kinds (i.e., subduction or strike-slip);
- Throughout their paper they emphasize focus on interdependencies, ending up mentioning power laws and scale-free theory (p. 17). All four of their studies sow the seeds of possible power law effects, and implicitly call for joint-probability-based deterministic kinds of studies, as we see in earthquake science.

By now many studies have drawn from complexity science. Meyer *et al*. do this as well, but they especially, though implicitly, underline our call for adding earthquake science as an underlying discipline.

4 DISCUSSION

We won't go through the entire list, but many management scholars have pointed to the growing disjunction between multiparadigmatic 'science' appearing in journals and practitioner-oriented writing (Beyer and Trice, 1982; Lawler *et al*., 1985; Brief and Dukerich, 1991; Pfeffer, 1993; Anderson *et al*., 2001; Beer, 2001; Rynes *et al*., 2001; Weick, 2001; McKelvey, 2003a; Bennis and O'Toole, 2005; Ghoshal, 2005; Van de Ven and Johnson, 2006; McKelvey, 2006). We suggest that the fundamental problem stems from favoring Gaussian over Paretian distributions. Virtually all of the statistics-based journal research rests on assumptions of independent events and Gaussian distributions. In obvious contrast, if one scans 'business media' books, such as *Organization and Environment* (Lawrence and Lorsch, 1967), *In Search of Excellence* (Peters and Waterman, 1982), *Built to Last* (Collins and Porras, 1994), *Rejuvenating the Mature Business* (Baden Fuller and Stopford, 1994), *Images of Organization* (Morgan, 1986), *Hidden Value* (O'Reilly and Pfeffer, 2000), *Good to Great* (Collins, 2001), *Knowledge Emergence* (Nonaka and Nishiguchi, 2001), and on and on, one sees that most of the cases and stories are about extreme events – successes or failures – but seldom about 'averages'. Add to this list many of the cases you use in the classroom. No wonder there is a disjunction – managers live in the world of *extremes*; researchers use statistics to report findings about *averages*. There is reason to believe that most of these extremes are due to interdependency and positive feedback.

It is easy for people with no personal experience with an extreme event to think studies of averages are acceptable substitutes. People who just experienced Hurricane Katrina, the South East Asian tsunami or who live through earthquakes in California or Japan, floods along the Danube, or survive an avalanche in the Alps think differently. Natural extremes seem mostly negative. Organizational 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. The first thing we scholars have to do is get over the idea that studying averages is the only 'good' science, is the only thing relevant to good management research, and offers something useful to managers. Sometimes yes, but we think mostly no for management researchers. Needless to say, this is an empirical question – When and under what conditions do organizational data points shift from independent to multiplicative to interdependent causal dynamics?

To bolster our argument, that organization science needs to attend to the consequences of *interdependent* as well as *independent* events, we start by listing eighty kinds of power law phenomena (in Table 1). In Nature, they range from atomic and microbiological to galactic fractals; half are social; some pertain to organizations. Nine of these – from physics, biology, social science, and management research – we describe in more detail. Power law research is an aspect of natural and even social science that has barely seeped into management research – though we do note that Mohr (1982) was the first to make the distinction between both kinds of management-related research (though he did not quite make the leap to fractals and power laws). We pay special attention to the standard practice of conducting *robustness* tests (Greene, 2002) so as to conveniently sweep Paretian phenomena under the rug, so to speak, and continue with Gaussian analyses and statistics – all to keep referees and journal editors happy and get published.

Our review of power law phenomena significantly challenges the prevailing assumption about the independence of data points. Once independence 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 interdependent events to progress – because of positive feedback – 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 independence assumption – the result will be Gaussian science and with it a denial of extreme events, a denial of infinite variance, a denial of unstable means – adding up to denial of Paretian 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 fosters 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 the seven sub-fields of earthquake science, we draw seven parallel application areas, each of which offers a different perspective and approach for studying extreme events, including prediction and protection. Each application area calls for a different kind of management research. A number of these already appear in the Meyer *et al*. (2005) article. Other examples are Perrow (1984) and Marcus and Nichols (1999) – nuclear reactors, and Haunschild and Sullivan (2002) – airline accidents, though these studies do not get into power law effects.

One of the lessons from earthquake science is that instead of lumping *all* earthquakes together, they study separate samples of '#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 #9s – i.e., Xerox, the IBM PC, INTEL, ENRON and Parmalat, crony capitalism, etc. With narrowed samples of similar extremes, Gaussian statistics and 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 phenomena.

There are numerous conditions where natural data points *do* remain independent – atoms and most molecules don't study, relate to, look at, or learn from, other atoms or molecules. In some cases, however, the imposition of energy past some critical point – e.g., Bénard's (1901) 1^{st} critical value and resulting phase transition or the Bose-Einstein condensate effect – turns even independent natural science data points into interdependent ones. In natural science, perhaps, scientists should still start with the NULL condition of *independent* data points. 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 *<u>inter</u>dependence*. **<u>Researchers should start with this assumption</u>.** 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 business, organizational, or management received view if they gain significance via some***

assumption-device by which extreme events and (nearly) infinite variance are ignored.

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Figure 1: Gaussian vs. Pareto Distributions

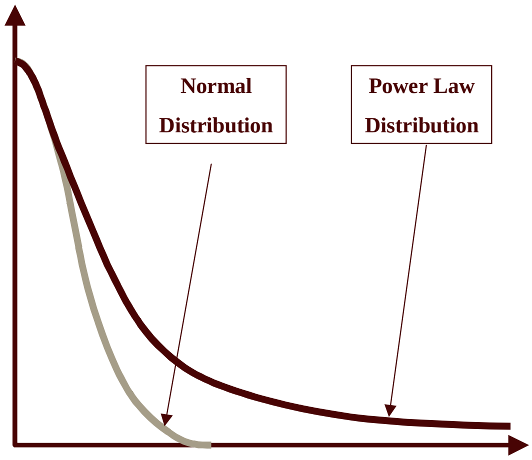
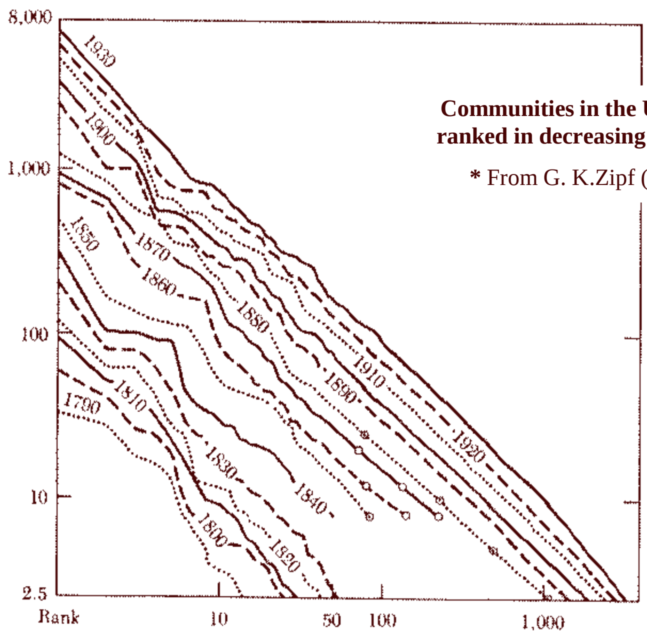


Figure 2: Log Log Depiction of City Rank by Size as –1 Slope*

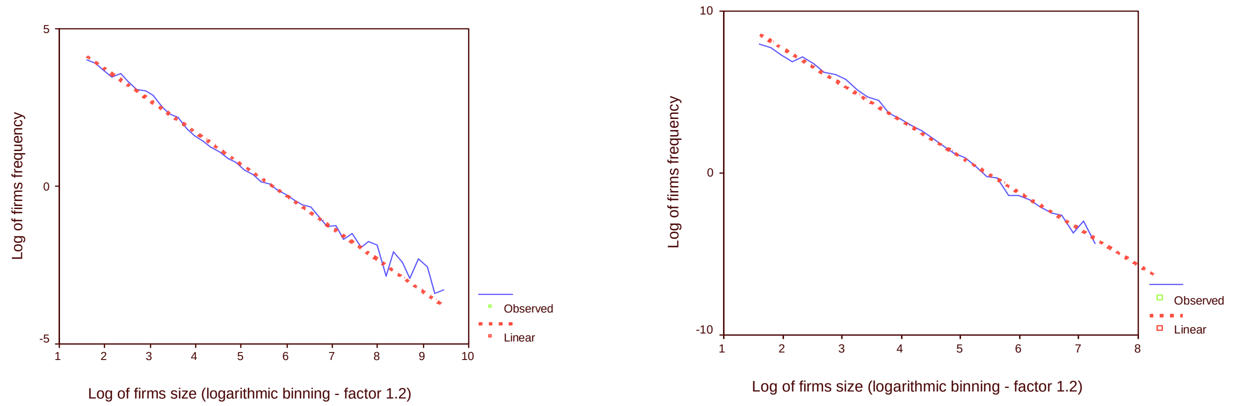
Size
(in thousands)



Communities in the U.S. of 2500 or more inhabitants, ranked in decreasing order of population size.

* From G. K.Zipf (1949).

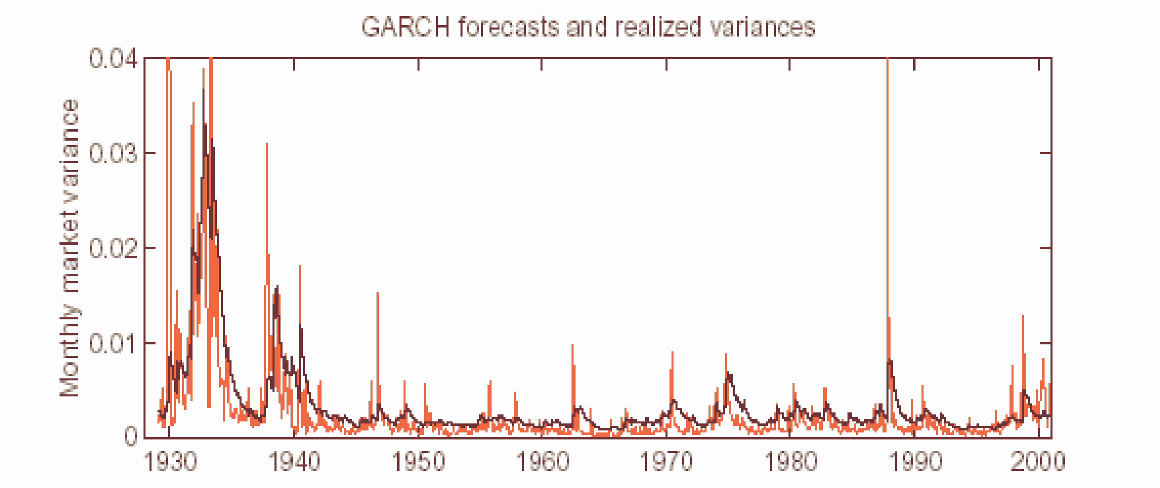
Figure 3: Comparison of Cluster Power Law to the –β Slope Power Law (cumulative distribution)



Industrial Area Agglomerations **Industrial Cluster Agglomerations**

Figure 4: Self-Organization between Agent Autonomy and Hierarchical Systems

Figure 5: Stock Market Volatility and GARCH



GARCH volatility (heavy–black) and realized volatility (lighter–red)
By permission from Ghysels, Santa-Clara, and Valkanov (2005).

Table 1: Some Examples of Natural and Social Power Law Phenomena

Natural Science		Social Science	
1.	Cities	1.	Language word usage
2.	Traffic jams	2.	Social networks
3.	Coastlines	3.	Structure of WWW
4.	Brush-fire damage	4.	Structure of the Internet hardware
5.	Water levels in the Nile	5.	Number of hits received from website per day
6.	Hurricanes & floods	6.	Blockbuster drugs
7.	Earthquakes	7.	Sexual networks
8.	Asteroid sizeshits	8.	“Fordist” power
9.	Sun spots	9.	Distribution of Wealth
10.	Galactic structure	10.	Publications and citations
11.	Sandpile avalanches	11.	Co-authorships
12.	Brownian motion	12.	Actor networks
13.	Music	13.	Job vacancies
14.	Epidemics	14.	Salaries
15.	Genetic circuitry	15.	Firm size
16.	Metabolism of cells	16.	Supply chains
17.	Functional networks in brain	17.	Growth rates & internal structure of firms
18.	Tumor growth	18.	Casualties in war
19.	Biodiversity	19.	Growth rate of countries GDP
20.	Circulation in plants and animals	20.	Price movements on exchanges
21.	Size distributions in ecosystems; predators	21.	Delinquency rates
22.	Fractals	22.	Movie profits
23.	Punctuated equilibrium	23.	Consumer products
24.	Mass extinctions	24.	Size of villages
25.	Brain functioning	25.	Cotton prices
26.	Predicting premature births	26.	Economic fluctuations
27.	Laser technology evolution	27.	Alliance networks among biotech firms
28.	Fractures of materials	28.	Entrepreneurship/innovation
29.	Magnitude estimation of sensorial stimuli	29.	Distribution of family names
30.	Willis’ Law: number vs. size of plant genera	30.	Copies of books sold
31.	Fetal lamb breathing	31.	Number of telephone calls and emails
32.	Bronchial structure	32.	Italian industrial districts
33.	Frequency of DNA base chemicals	33.	Deaths of languages
34.	Protein–protein interaction networks	34.	Director interlock structure
35.	Genomic properties (DNA words)	35.	Aggressive behavior among boys during recess
36.	Heart beat rates	36.	Number of inventions in cities
37.	Cellular substructures	37.	Macroeconomic effects of zero-rational agents
38.	Phytoplankton	38.	Global terrorism events
39.	Death from heart attack	39.	News website visitation decay patterns
40.	Magma rising through earth’s crust	40.	Intra-firm decision events

Natural: 1-(Estoup, 1916; Zipf, 1949); 2-(Nagel & Paczuski, 1995); 3-(Casti, 1994); 4-(Bak, 1996); 5-(Casti, 1994); 6-(Bak, 1996); 7-(Gutenberg & Richter, 1944); 8-(Hughes & Nathan, 1994; Marsili & Zhang, 1996); 9-(Hughes et al., 2003); 10-(Baryshev & Teerikorpi, 2002); 11-(Bak, 1996); 12-(West & Deering, 1995)Gardner, 1978); 13-(Gardner, 1978; Casti, 1994); 14-(Liljeros et al., 2001); 15-(Barabási, 2002); 16-(West et al., 1997); 17-(Shin & Kim, 2004); 18-(Brú et al., 2003); 19-(Haskell et al. 2002); 20-(West et al., 1997); 21-(Camacho & Solé, no date); 23-(Bak & Sneppen, 1993); 24-(Bak, 1996); 25-(Stassinopoulos & Bak, 1995); 26-(Sornette, 2002); 27-(Baum & Silverman, 2001); 28-(Sornette, 2002); 29-(Roberts, 1979); 30-(Willis, 1922); 31-(Szeto et al., 1992); 32-(Goldberger et al., 1990); 33-(Selvam, 2002); 34-(Song et al., 2005; Wuchty & Almaas, in press, no date2005a,b); 35-(Luscombe et al., 2002); 36-(Nahshoni et al., 1998); 37-(Wax et al., 2002); 38- Jenkinson, 2004); 39-(Bigger et al., 1996); 40-(Weinberg & Podladchikov, 1994).

Social: 1-(Zipf, 1949); 2-(Watts, 2003); 3-(Albert et al., 1999); 4-(Faloutsos et al., 1999); 4-(Buchanan, 2004); 5-(Adamic & Huberman, 2000); 6-(Buchanan, 2004); 7-(Liljeros et al., 2001); 8-(Diatlov, 2005); 9-(Pareto, 1897; Levy & Solomon, 1997); 10-(Lotka, 1926; deSolla Price, 1965); 11-(Newman, 2001); 12-(Barabási & Bonabeau, 2003); 13-(Gunz et al., 2001); 14-(Buchanan, 20002); 15-(Axtell, 2001); 16-(Scheinkman & Woodford, 1994); 17-(Stanley et al., 1996); 18-(Cederman, 2003); 19-(Lee et al., 1998); 20-(Mandelbrot & Hudson, 2004); 21-(Cook et al., 2004); 22-(De Vany, 2004); 23-(Moss, 2002); 24-(Carneiro, 1987); 25-(Mandelbrot, 1963); 26-(Scheinkman & Woodford, 1994); 27-(Barabási & Bonabeau, 2003, p. 207, building on Powell et al.); 28-(Poole et al., 2000); 29-(Zanette & Manrubia, 2001); 30-(Hackett, 1967); 31-(Aiello et al., 2000; Ebel et al., 2002); 32-(Andriani, 2003a); 33-(Abrams & Strogatz, 2003); 34-(Battiston & Catanzaro, 2003); 35-(Warren et al., 2005); 36-(Bettencourt et al., 2005); 37-(Ormerod et al., 2005); 38-(Dumé, 2005); 39-(Dezső et al., 2005); 40-(Diatlov, 2005).

Table 2: Macro and Micro Jointly Probably Causes of Extreme Events

Macro	Micro
Land configuration – flat, hilly, mountainous, island protection, etc., lack of glaciers, floods, etc.	Mutation rate
Water availability – rain, streams, rivers, lakes, etc.	Requisite variety
Sunlight – sheltered/unsheltered, forested/unforested, brush, caves, etc.	Fission
Oxygen – in air, in water, in other sources	Immune system
Food – main sources, substitutes	Coevolution
Shelter – holes, nests, caves, trees, bushes, etc.	
Predation, parasitism, disease, etc.	

Table 3: Key Elements of a Power Law-Based Statistics

1. Paretian distributions: In Paretian distributions, the mode (most frequent event) is smaller than the median (central point), which is smaller than the mean, which is stable. Contrary to the Gaussian, what appears as the 'mean' in a power law distribution is strongly and idiosyncratically influenced by extreme events,.

2. 'Infinite' variability: In Gaussian statistics, the larger the sample, the closer the convergence of the sample's mean and variance to the population's mean and variance. In Paretian distributions, the sample's mean doesn't converge to any value, the variance is very large (approaching infinity), and the 'independence assumption' is misapplied. This means that the use of mean, variance and confidence intervals for prediction is unreliable – confidence intervals change with the occurrence of each new extreme. This point leads to the '*Nobody knows anything*' principle (De Vany, 2004: 220): predicting single events under Gaussian assumptions is questionable. '*In this world nothing is 'typical' and every movie is unique*' (p. 258).

3. Extremes: The important part of Paretian statistics is in the tails. Extreme events are more frequent and disproportionate in size than in a Gaussian dominated world. In fact, opposite to Gaussian statistics, the larger the sample the more likely an even greater extreme will occur. See the body of literature known as the 'statistics of extremes' (Gumbel, 1958/2004; Coles 2001), initiated by engineers in the early 20th century for the purpose of designing flood-control dams. Their tables show this clearly. And, furthermore, in the Paretian world, the larger the sample the less likely one can assume independence or normality.

4. Scale-Free Fractal Structure: Like the jaggedness of the English coastline, power law phenomena show the same characteristics no matter what the measure. The dynamics and appearance of the phenomena appear the same at any scale. What this suggests is that similar (common) dynamical patterns are in action at different levels. Whether we take a whole series of events or sample a part of it, we find the same pattern of large discontinuous events irregularly appearing out of a background of finer perturbations. Given this, we need a fractal-based statistics.

5. Amplification: Fat tails result from the amplification of small events giving rise to positive feedback dynamics evolving to generate events of varying size. The major difference between a Gaussian and a Paretian distribution is that the former tends to *compress* the distribution of data points toward the mean (outliers are normally ignored and the assumption of independence restricts predictions to data within two or three standard deviations from the mean) whereas the latter (Paretian) captures the full extent of positive feedback effects.

6. Cascade dynamics: Power laws result from generalized self-organized criticality dynamics. As events unfold from the propagation of an initial 'tag' or instigating stimulus (Holland, 1995), given mutual causal, positive feedback processes, the logic of preferential attachment (*rich get richer)* generates a reinforcing trend, which extends the distribution's tails. For instance in the case of information-based cascades, success breeds success (see also note 7).

7. Universality: The dynamics of multiplicative and/or interdependent, connectionist phenomena lead to power law distributions forming the basis of a mathematical regularity having many of the earmarks of a universal 'Law' valid across much of time and space – as our Table 1 begins to suggest (see also Bak, 1997 and Halloy, 1998). The dynamics underlying this Law may, therefore, play the role of a universal 'force' toward which the dynamics of many kinds of emergent phenomena are attracted

Table 4: Four Different Configurations of Means and Variances

Type 1. We test the relation between number of steps climbed and burning calories. We study 1000 people. There is a little variance because of different anaerobic capabilities and measurement error, but we see a clear uniform distribution and a direct linear correlation. A Gaussian distribution gives us the mean level of energy burned at each step for the N = 1000 climbers – the covariance is critical and the mean ignored.

Type 2. We want to design airplane seats and so we measure the needed seat widths of a sample of 1000 people. We get a true Gaussian distribution; most people are right at the average and we design accordingly. Here the extremes don't matter – to the seat designers anyway.

Type 3. We want to know what kinds of people are most successful in professional football and basketball. We take measures of height and weight of 1000 people and find that most people are at the average; small people are ineffective at both sports; big people fare best. We get a Gaussian distribution, but clearly people at one end are better suited for the sport. In fact, we have a linear relation except that we have most of the sample in the middle, which tends to obfuscate the results.

Type 4. We do a study of who is involved in spreading the HIV virus and we find that, in a sample of 1000 people with HIV, one person has 3000 partners whereas most people have one or no partners (based on a power law finding about number of sexual partners from Sweden). This is a power law formation where people at one extreme do most of the damage – most people have no effect; the top few people can potentially infect thousands of partners. (Liljeros *et al*., 2001)

Table 5: Defining an 'Extreme-Based' Organization Science

1. ***Earthquake Geology—Historical Extreme Event Analysis*****.** This finds out when, where, and how often past extreme events occurred and, in addition, what size they were. This is basic historical, descriptive analysis. This also includes finding out where extreme events don't occur. For social science, it also includes both positive and negative events. It should also include reflexive analysis – people having experienced an extreme event can then alter some of the event-initiation or event-protection elements – whereas molecules can't.

2. ***Crustal Studies—Visible Organizational Deformation*****.** This involves studies of visible consequences of extreme event dynamics on organizational employees, suppliers, customers, shareholders, communities, and even governments – all of which were deeply affected, say, by the Enron debacle. This is more about more specific consequences than causes, history, or broader description. This area would include Bill Starbuck's (no date) slide show on extreme case analysis, for example.

3. ***Borehole Geophysics—Deep Structure Analysis*****.** This is the organizational equivalent of plate tectonics, that is, analysis of the very basic forces giving rise to the order-creation dynamics studied by complexity scientists. This could focus on the origins of dissipative structures and agent-rule-based positive feedback dynamics – see Lichtenstein and McKelvey (2004) for example.

4. ***Seismology—Special Methods Development*****.** At this time organization researchers don't use what normal science scholars would call '*robust methods*' on extreme events. We have case analyses – and by the way, most examples given in the business press and textbooks such as Morgan (1986) are extreme events – but nothing equivalent to seismology, which has essentially translated extreme event analysis into seismic wave analysis. We have Eisenhardt's (1989) article arguing for multiple case analysis, but it is not analogous to seismology and some would question its claimed robustness standard. But, obviously, conventional statistical analyses are inadequate, as we argue above. The cell phone and text-message based, structural equation, & neural net 'socio/computational approach' suggested by Boisot and McKelvey (2005) for pre-event counter-terrorism could be an example of such a new kind of approach.

5. ***Strong Motion Seismology—Real-time Extreme Event Analysis*****.** What happens to buildings and bridges *during* a quake is a key source of protecting against future damage by improving engineering and building codes. Instead of historical organizational analysis, this is more 'live' and on the spot reporting. For organizational extreme events that end up in court, we have the equivalent. Recent extremes – Enron, WorldCom, etc., have resulted in the Sarbanes-Oxley Act and the Enron case is slowly making its way through the court system. As this happens we will get more and more information about the actual course of events almost on a daily basis – very much like having instruments measuring shaking while it occurs. But not all extreme events end up in court. Very negative ones such as Enron do and very positive ones such as Microsoft (antitrust violation). But for most extreme events involving managers for good or bad, there is little record of the dynamics by which they unfold, except when someone writes up a detailed case analysis.

This is better than nothing, but again, we have the truth-claim and robustness problems. Earlier, however, we have noted that one could use samples of extreme cases.

6. ***Hazards and Safety Codes—Protecting Against Extreme Events in Advance.*** The difference between Wall Street and California is striking. California has building codes that, to the best of their ability, allow only building designs that will withstand the most extreme events. What *magnitude* quake is possible from the fault near a building and what design will withstand the shaking? Cost is not an issue. Buildings are designed to withstand extreme events, not average quakes. The most worrisome aspects of financial investment organizational life are the extremes, not the averages, but the code set by the governing body – the Bank for International Settlements in Basel – is based on a Gaussian approach to extremes. This is wrong on two counts (Mandelbrot & Hudson, 2004: 272): it ignores (1) the true extent of volatility in financial markets; and (2) the long-term dependency which causes catastrophic events to cluster. Why is there little protection against financial extremes? Well, extremes don't happen very often and protecting against unlikely events seems like a lot of wasted money. Yet, in the 20th century the U.S. lost far more billions in the many financial meltdowns than it did from major quakes. Employees, as the Enron employees found out, are especially vulnerable, though early Microsoft employees have done very well from their extreme event. The research question is what are the costs of negative extreme events, and not just the ones that make the headlines, but all the others? Sornette (2002) offers one answer.

7. ***Code Violations and Punishment—If Courts Don't Exist?*** Should managers pay some price? There is no blame for causing earthquakes. But after every quake, from the U.S. to Japan to Turkey we find that code violations occurred and people died. Can individuals in organizations be blamed if mutual causal volatility clusters occur? Can we even define an initiating event? McKelvey (2002) argues that positive feedback coevolution can be 'managed.' This is not yet a topic in any managerial training course. Can managers be held accountable for not starting or stopping mutual causal processes soon enough, or not steering them in the proper direction? Much research needs to be done before we have answers to questions like these.