



**Brewing the future:
stylized facts about innovation and their
confrontation with a percolation model**

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Working Paper 03.06

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April 2003

Brewing the future: Stylized facts about innovation and their confrontation with a percolation model

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Paper prepared for the EMAEE Conference, Augsburg, April 10-12, 2003

March 2003

Abstract

Innovations are known to arrive more highly clustered than if they were purely random and independent. Their distribution of importance (as measured in returns or citation rates) is highly skewed and appears to obey a power law or lognormal distribution. Technological change has been seen by many scholars as following ‘technological trajectories’ in some space of technological characteristics and being subject to ‘paradigm’ shifts from time to time. Innovations appear to arrive in clusters. Thus the innovation process is clearly more highly structured than a simple random process, but is still characterized by high unpredictability and risk. We first summarize some of these empirical observations, drawing on well-known as well as innovative statistical measures. We then briefly review a ‘percolation’ model of the innovation process (Silverberg 2002, Silverberg and Verspagen 2002) and analyze its statistical properties on simulated data with respect to these measures. The model is able to generate similar patterns of clustering in both ‘space’ and time, highly skewed distribution ranging between a pure-Pareto in the tails to a lognormal, and structured technological trajectories.

Keywords: innovation, percolation, search, technological change, R&D, clustering

JEL codes: C15, C63, D83, O31

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1. Introduction

The paradoxical characteristic of innovations is that their nature, significance and date of arrival are intrinsically unknowable in advance – if we knew them in detail, then the innovation would in effect have already happened. It is this property of intrinsic uncertainty that makes innovations so central and different from other factors in the theory of long-term economic evolution. On the assumption of total ignorance and independence, the natural approach would be to regard discrete innovations as generated by a simple stochastic point process such as the time-homogeneous Poisson. At the same time we know that technologies are not picked out of a hat at random times in random orders – to some extent there is a logical order in which they can be discovered, and they build on each other. Modern computers could not exist without a mastery of electronics (although Babbage tried and failed to make a purely mechanical one in the 19th century), electronics without a mastery of electricity, and electricity without the metallurgical skills necessary to make wires. Thus we shall argue in the following, based both on empirical evidence and a theoretical model, that the innovation process, while highly uncertain and stochastic, is still more structured in important respects than such a null hypothesis would suggest.

While the study of the statistical properties of the innovation process is scientifically interesting in its own right, it also has important implications for economic theory and innovation management. If innovations are drawn from a highly skewed and even infinite variance process (Pareto), then economic growth may be even more erratic than if they are of constant ‘size’ but generated by a Poisson process (see Sornette and Zajdenweber 1999 on the former case, Silverberg and Lehnert 1996 on the latter). And if they are drawn from an infinite variance and even infinite mean process, then R&D risk management and portfolio policy are confronted with such risk that the standard tools of capital asset management theory are inapplicable (Scherer and Harhoff 2000).

We tend to think of innovations as distinct, easily identifiable entities. However, closer inspection reveals that they are anything but: they can be resolved into smaller sub-steps, making the definition and dating of important innovations controversial and somewhat arbitrary (this has serious implications for patent litigation). Nevertheless, when the minimum number of essential subunits comes together, one does have the feeling that the innovation ‘pops out’ and becomes a recognizable ‘Gestalt.’ Thus a seemingly simple innovation such as the bicycle has been shown to be a concatenation of many sub-innovations spread out over time:

In 1818, K.V. Drais de Sauerborn presented his Draisine, a kind of walk-drive bicycle (Laufrad). In 1839 Mannilau demonstrated how wheels can be driven by pedals, and in 1861 at the latest pedals were built into the Draisine. In 1867 they were used on the front wheel by Michaux, and during the next few years the bicycle industry in France grew rapidly. A model of the bicycle approaching the one we are accustomed to today was constructed by Lawson in 1879, but a commercially successful ‘safety bike’ was not introduced by Starley until 1885. If we take 1818, 1839 or 1861 alternatively as years of invention, and 1867, 1879 or 1885 alternatively as years of basic innovation, we can obtain 9 different results for the time-span between invention and innovation. [Brockhoff (1972, p. 283), cited by Kleinknecht (1987, p. 61)]

Numerous other examples could undoubtedly be found in the history of technology to reinforce this point. What we normally perceive as a unitary entity, a radical innovation, in reality is usually composed of a number of smaller steps dispersed in time, often involving

borrowing from other fields or dependent on specific unrelated advances in order to make the final step possible. In the bicycle case we could add the availability of pneumatic tires and ball bearings (and thus precision machining, the precision grinding machine ...) as essential complementary innovations without which the bicycle boom of the 1890s would have been unthinkable. The bicycle is not one innovation but a succession of several smaller ones. In fact, our problem is not reducible à la Schumpeter to just radical vs. incremental innovations; rather innovations come in all sizes, suggesting a fractal structure to the process of innovation

This ambiguity regarding the timing and definition of innovations is not merely a matter of historical curiosity. It can also be profitably exploited in a representation of technology as consisting of a multitude of elemental small inventive steps that must come together, much like the pieces of a mosaic, to form a coherent whole and constitute an innovation. The purpose of this paper is to present a model of the dynamics of this process making as few assumptions about the nature of technology as possible except that it is in some sense complex and shrouded in uncertainty, and confront it with certain stylized but quantifiable empirical facts derived from innovation research.

The paper is organized as follows. In Section 2 we briefly present some stylized facts about technical change and innovation and some empirical data highlighting a number of distinctive statistical patterns associated with the innovative process. Section 3 outlines the framework of the model, which was first sketched in Silverberg (2002) and explored numerically in Silverberg and Verspagen (2002). Section 4 presents the results of extensive numerical simulations analyzed from the perspective of the clustering properties revealed in Section 2. In Section 5 we review the comparison of empirical and simulated data, relate our framework with related approaches such as evolutionary landscape models, and draw some conclusions.

2. Stylized Facts about Innovation and Technological Change

The historical development of technology is by now a much-studied subject, by historians of technology as well as social scientists such as economists. For the economist, the impact of technology on variables such as economic growth, industrial development and structural change is of prime interest. But economics has also suggested that economic factors, such as, for example, profit-driven search in technology space, or learning-by-doing in production processes drive technological development. From this point of view, several stylized facts about the innovation and technology development process (in relation to economic factors) have been put forward. Some of these are by now well founded in empirical, quantitative evidence, while others still remain somewhat speculative. The model we analyze in this paper provides a causal structure geared at explaining several of these stylized facts, in particular those that have been put forward by scholars in the evolutionary economics tradition.

The aim of this section is to outline these stylized facts that will be ‘explained’ by our model. We will briefly discuss their context in the literature on economics and technology, and present some illustrative data as well as suggested techniques for analysis of the data. The techniques will also be applied in later sections analyzing the (artificial) data generated by the model, so that we may compare the simulation outcomes to the patterns found in the empirical data. The stylized facts we will discuss are clustering of major innovations in time, clustering of innovations in ‘technology space’, and the empirical distributions of the size of innovations.

2.1. Temporal clustering of (major) innovations

The debate on temporal clustering of innovations was initiated by what appears, with hindsight, to be a rather casual remark in Schumpeter's seminal work *Business Cycles*: “[Innovations] are not evenly distributed in time, but (...) on the contrary they tend to cluster, to come about in bunches, simply because first some, and then most firms follow in the wake of successful innovation” (Schumpeter, 1939, p. 75). For Schumpeter, such ‘bunches’ of major (radical) innovations were the driving force of long waves of 50-60 years duration, such as the ones Kondratieff (1926/1935) claimed to have discovered in the historical data. Kuznets (1940), in a review of Schumpeter's two volumes, already pointed to the lack of causal explanation of Schumpeter's temporal clustering hypothesis. This became the subject of a lively debate in the 1970s and 1980s after Mensch (1975/1979) put forward actual empirical time series data together with a new causal explanation for the temporal clustering effect. The causal explanation offered by Mensch was that depression periods of the long wave, by the low profit rates they cause, would trigger search for new technological opportunities, while during boom times, entrepreneurial spirits would mainly take the form of exploiting the fresh profit opportunities of the newly introduced major innovations.

The empirical evidence presented by Mensch was challenged by Freeman, Clark and Soete (1982), as well as Solomou (1986), while Kleinknecht (1987, 1990) found support for the clustering hypothesis. All these tests were based on time series of basic (major) innovations, taken from historical works such as Jewkes, Sawers and Stillerman (1958). The constructed time series all took the form of the number of basic innovations that took place each year. Obviously, there are at least two arbitrary procedures involved in the construction of these data: the exact time (year) of innovation, and the assessment of what constitutes a major innovation, and what falls below this threshold. In an earlier paper, Silverberg and Verspagen (2003), we merged the existing time series for basic innovations into one series combining the observations by the different authors who have contributed to this field. This time series, along with some trend estimates that we will explain below, are depicted in Figure 1.

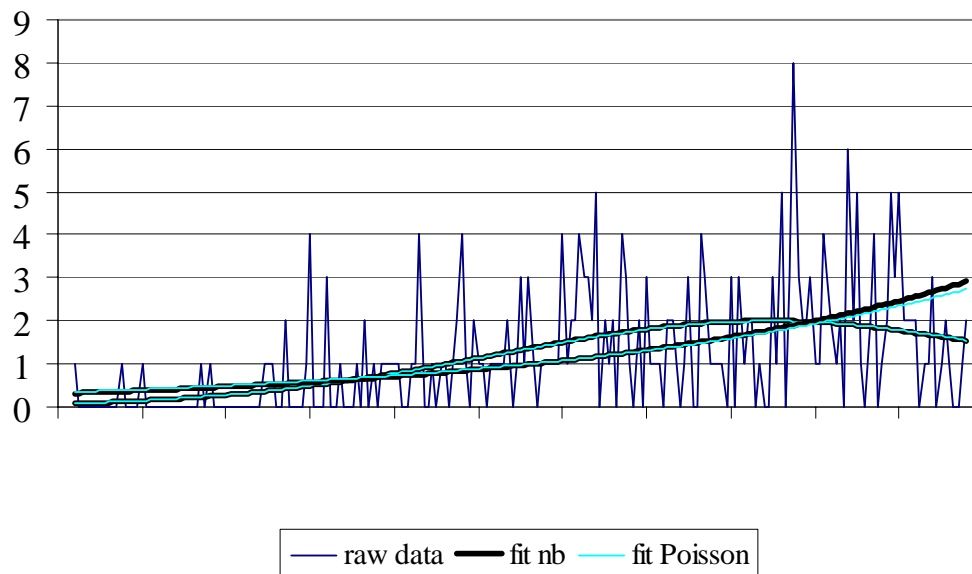


Figure 1. Poisson-regression analysis of radical innovation time series for first and third degree polynomial trends of the log of the arrival rate. While the point estimates of the Poisson and negative-binomial models are virtually identical, the latter is statistically preferred. The long-term trend is also apparent. Source: Silverberg and Verspagen (2003).

It is clear from Figure 1 that the number of major innovations observed every year is relatively small, with a substantial number of years with zero observed innovations. This suggests the use of probability distributions that are well suited to describe so-called count (or integer-valued) data, such as the Poisson distribution. As early as 1974, Sahal (1974) suggested using a statistical method based on the Poisson and negative binomial distributions to describe time series of incremental innovation. Visual inspection of the histograms of the data in Figure 1 and similar time series also suggests a Poisson-like process (Silverberg and Verspagen, 2003). According to the Poisson distribution, the probability P of y events (innovations) during a time interval T is given by:

$$P(y) = \frac{e^{-\lambda T} (\lambda T)^y}{y!},$$

where λ is the parameter measuring the (fixed) arrival rate of innovations. It is easily shown that the expected number of events per unit time is λ , which also happens to be the variance of the distribution. Note that time series generated from a time-homogeneous Poisson process will not display a completely uniform pattern of occurrences of the random event. In other words, to the naive eye some clustering will characterize even this simplest point process.

Empirical data often show a larger variance than mean for the dependent variable, a phenomenon termed ‘overdispersion.’ Hausman, Hall and Griliches (1984) for example observed overdispersion in their firm-level patent database. A model that can account for overdispersion may be obtained by adding an unobserved random effect to the mean of the Poisson distribution (Hausman, Hall and Griliches, 1984). This leads to a modified probability distribution of the type:

$$P(Y = y | u) = \frac{e^{-\lambda u} (\lambda u)^y}{y!},$$

where u is a random variable for which some distribution must be assumed (see Greene 1995, p. 939). The variable u may, for example, reflect random noise, or cross-sectional heterogeneity (when the model is estimated in the cross-sectional dimension). Assuming that u is gamma distributed, one obtains the following unconditional distribution (Cameron and Trivedi 1998, p. 71):

$$P(Y = y | x) = \frac{\Gamma(\alpha^{-1} + y)}{\Gamma(y + 1)\Gamma(\alpha^{-1})} r^y (1 - r)^{\alpha^{-1}}, \text{ where } r = \frac{\lambda}{\lambda + \alpha^{-1}}.$$

This distribution is known as the negative binomial distribution and has mean λ and variance $\lambda(1 + \alpha\lambda)$ for $\alpha > 0$. When α approaches 0, the model reduces to a standard Poisson model, and the variance becomes equal to λ again. A test of the Poisson against the negative binomial distribution can be implemented by the null hypothesis $\alpha = 0$.

The Poisson and negative binomial models were used by Silverberg and Verspagen (2003) to test various hypotheses about temporal clustering of basic innovations. The first one was that the arrival rate of innovations varies in time, either in a strictly periodic way, or following the movements of some macroeconomic variable such as the profit rate. No evidence was found in favor of this hypothesis. A second hypothesis tested for cumulative forces at work in the technology-generating process, leading to autocorrelation in the observed time series. This hypothesis was tested using an autoregressive model. Although some significant autoregressive terms were found, these did not take on parameter values that led to long persistence of random shocks to the arrival rate of innovations. Rather, the shocks in the arrival rate were observed to die out quite quickly, there again not finding any support for this form of temporal clustering.

In fact, the only form of clustering for which strong evidence was found was overdispersion: the parameter α in the negative binomial model was always significant, implying that the variance of the processes observed in the data is high as compared to the standard Poisson

model. In other words, compared to the Poisson benchmark, there are periods of relatively high and low activity in the time series for basic innovations. Obviously, this is a statistical measure of temporal clustering, or concentration, which remains unexplained in economic or technological terms. In fact, as the above summary of results points out, any economic or technological explanation that relies on strict periodicity in the arrival rate of innovations, or a close relation to aggregate macroeconomic variables, seems to be without support in the data. Concluding, we may set as a task for our model below to explain temporal clustering (overdispersion) in the time series for major innovations, without resorting to a behavioral mechanism based on the assumption that the intensity or direction of technological search changes systematically with (macro)economic variables.

2.2. Clustering of innovations in technology space

In the economic literature analyzing the development of technological change there are numerous suggestions that the innovative process follows relatively ordered pathways, as can be measured ex post in technology characteristics space. Examples of propositions in this direction are Nelson and Winter's (1977) *natural trajectories*, Sahal's (1981) *technological guideposts*, and Dosi's (1982) *technological paradigms*. Empirically oriented contributions that illustrate the point are, e.g., Foray and Grübler (1990), Saviotti (1996) and Frenken and Leydesdorf (2000).

These concepts are often used in explaining the specific direction in which a technology develops after an initial radical breakthrough takes place. The factors that may influence such a trajectory are incremental improvements that take place during the diffusion process of the basic design, and external circumstances such as characteristics of demand, factor prices, patterns of industrial conflict, etc. Dosi describes the result of this as a "model and pattern of solution of selected technological problems, based on selected principles from the natural sciences and on selected material technologies". From all the possible directions technological development may take, only a small portion are realized.

Along the development of the trajectory, incremental innovation and diffusion go hand in hand. Diffusion of the basic design is stimulated by the incremental improvements, which increase the value of the technology and thus make it more attractive for users. At the same time, diffusion increases the scale at which the technology is used, and hence makes it more attractive to develop improvements. Incremental innovation is also used as a means of competition between the suppliers of the technology.

The direction of the trajectory is governed by the specific circumstances in which the technology develops. For example, von Tunzelmann (1978) shows how the trajectory of innovation in steam engines in Cornwall in the 19th century was strongly influenced by the dearth of coal. These engines were employed to pump water from flooded copper and tin mines in a region far from coalmines. Thus, the coal needed to fuel the engines had to be brought into the Cornish area, and this made it relatively expensive to operate an engine. Hence, the main aim for engineers in the business of designing engines for Cornish miners was to get as much work done as possible per bushel of coal, and this goal dominated their design efforts. This led to a trajectory of increasing steam pressure and engine cylinder size. Under different circumstances, different trajectories in steam technology were pursued, leading to substantially different designs (see, e.g., Frenken and Nuvolari, 2002).

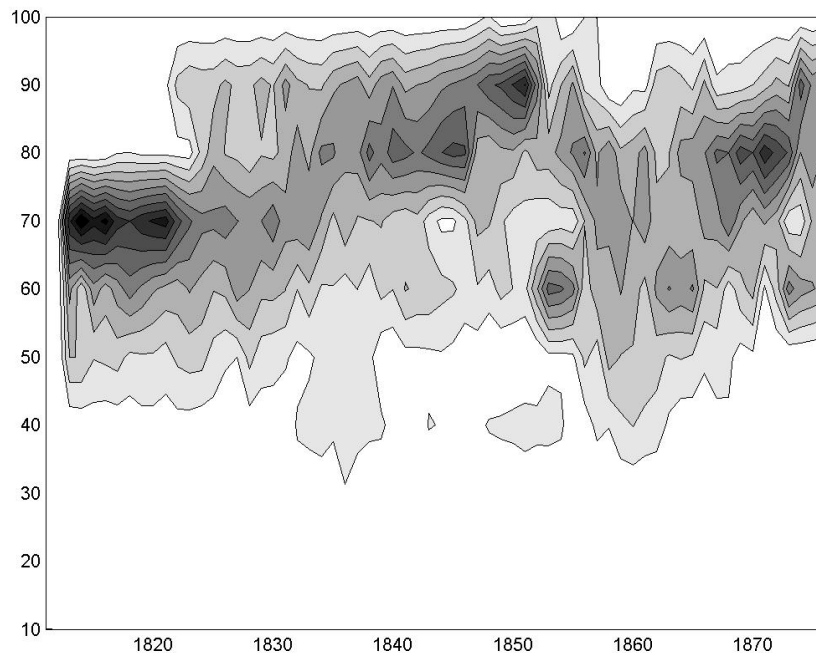


Figure 2: Distribution of the Cornish mining engines, cylinder size in inches on the vertical axis, time on the horizontal axis, darker shades indicate a higher percentage of total HP delivered by the total population (source and details about calculations and sample: Nuvolari and Verspagen, 2002)

The Cornish case is illustrated in Figure 2. Until the early 1820s, engines are concentrated in the size bracket around 70". After this, the size gradually increases to around 90". This can be shown to go hand-in-hand with a marked increase in performance. After 1850, the trajectory breaks up, and seems to split into two separate trajectories: one at a cylinder size around 60", and one around 80". Thus, besides the development of a single trajectory, the case also shows how trajectories may bifurcate.

The notions of trajectories, paradigms or guideposts again suggest clustering of innovation. The clustering effect is now set in technology space, rather than in time, as in the case of the previous subsection. Another difference is that clustering in technology space is largely a matter of incremental innovation, rather than the radical breakthroughs in Schumpeter's theory. As an explanation for the clustering in technology space, the literature mainly seems to offer the localized nature of technological search, together with specific designer's aims dictated by external circumstances. We will set it as a task for future research to investigate how the localness of search influences clustering of incremental innovations.

2.3. The size distribution of innovations

The above-mentioned studies approach radical and incremental innovations as being akin to distinct species (which in the model we will present later in this paper they to some extent are). However, we can also look at them as being different ends of a continuous spectrum of innovation 'sizes.' Recent literature such as Scherer (1998), Harhoff, Narin, Scherer and Vopel (1999), and Scherer, Harhoff and Kukies (2000), suggests that the distribution of innovation sizes, as captured by some measure or proxy of economic returns to R&D investment, is highly skewed, with most innovations having low or negative returns but with a sparse tail extending into the region of extremely high rates of return. The same tendency can be ob-

served using the data compiled by Trajtenberg (1990) for the ‘value’ of patents proxied by the number of patent citations. These data suggest that the distribution of innovations may follow a power law.

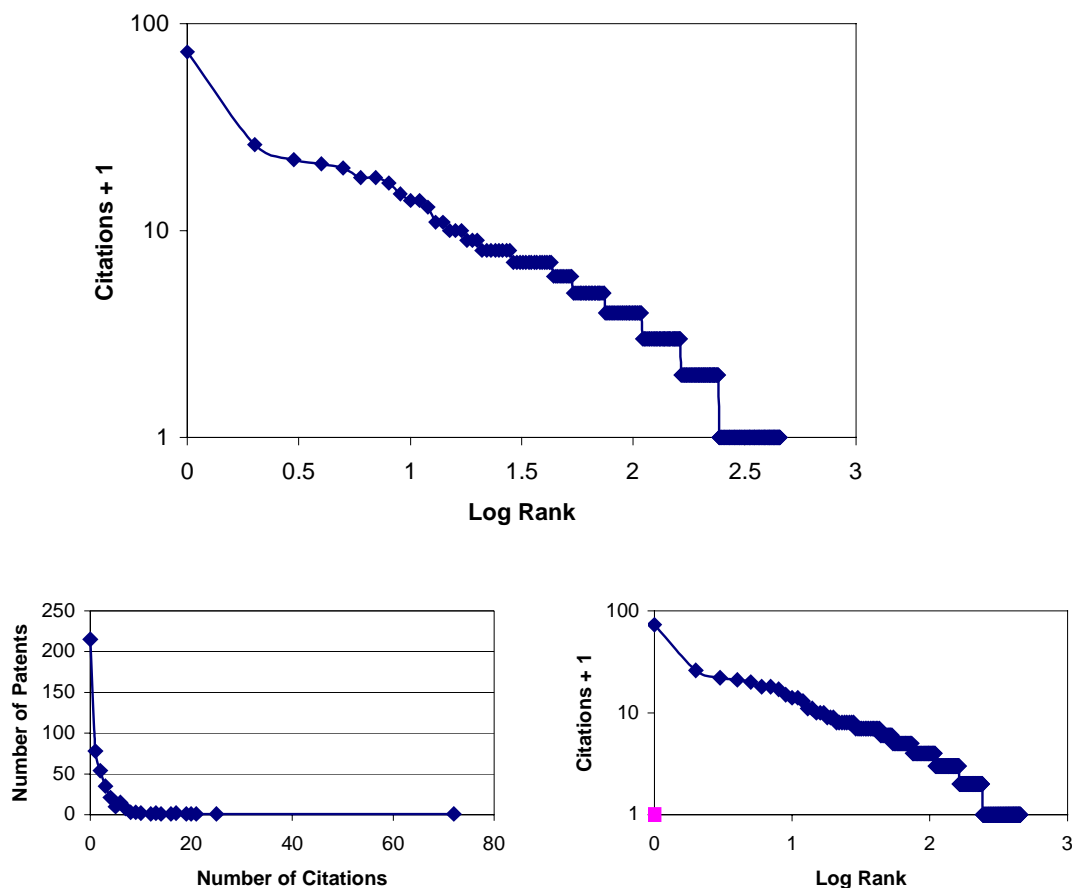


Figure 3. Raw (left) and rank-order (right, double-log scale) distributions of innovation ‘sizes’, counting self-citation, based on CT scanner patent citations. Data source: Trajtenberg (1990).

Figure 3 illustrates this for the data in Trajtenberg (1990), i.e., the distribution of US patents in CT scanners according to the number of times they are cited in subsequent patents. Plotted on a double-log scale, the data suggest a linear curve (power law). Similar plots are presented in the works cited above using data on economic returns.

A major issue investigated in this literature is whether the true underlying distribution of innovation value is Pareto (which would correspond to a truly linear curve in Figure 3), or more like the lognormal. This question may be posed for the complete distribution, or only for its tail describing the most valuable innovations (left part of Figure 3). In the latter case, the question becomes whether or not the distribution is heavy-tailed, i.e., whether or not the probability of very large innovations (expressed as the number of standard deviations above the mean) goes quickly to zero, or remains ‘real’ for interesting ranges. The issue of lognormality vs. Pareto, or heavy-tails vs. normal tails has important consequences for the moments of the distribution, and this may in turn have important theoretical consequences.

Scherer (1998) uses a wide range of data sources, such as US university patent portfolios, stock market returns on high-tech startups, income from pharmaceutical entities, and the value of German patents. Scherer, Harhoff and Kukies (2000) present more detailed estimates on the German patent sample in Scherer (1998). They mostly use ols-regression to estimate

the slope in the double-log cumulative distribution plots, and rely on the calculation of the moments of the distributions (such as the kurtosis). The conclusions do not clearly resolve the issue of lognormality vs. the Pareto distribution, at least not as far as the whole distribution is concerned. In some case, the observed nonlinearity is so strong that the lognormal distribution seems to be preferred, but in other cases, linearity is quite strong. In many cases, however, the Pareto distribution seems to be a good description for the tails of the distribution. This indeed suggests that the size distributions of innovation are heavy-tailed.

The nature of the innovation size statistics can be examined more rigorously by applying estimators from extreme-value analysis developed for the study of heavy-tailed distributions (cf. Crovella, Taqqu, and Bestavros 1998). Consider n observations of a random variable X_i , and denote by $X_{[i]}$ the order statistics $X_{[1]} \geq X_{[2]} \geq \dots \geq X_{[n]}$. Then the Hill estimator is defined as follows:

$$H(k, n) = \frac{1}{k} \sum_{i=1}^k (\ln X_{[i]} - \ln X_{[k+1]}).$$

Plotting this estimator against k for small values of k (compared to n) will indicate if it converges to some value, which will then be an estimate for the downward slope of the double-log rank-order plots of Figure 3, or the inverse of the exponent α of the estimated Pareto-Levy distribution:

$$N = \kappa V^{-\alpha},$$

where V is the value of an innovation, N is the number of innovations with value V or larger and κ and α are positive parameters.

The value of α governs the behavior of the Pareto-Levy distribution (cf. Focardi 2001). The relevant ranges for α are $\alpha > 2$, $1 < \alpha < 2$ and $\alpha < 1$. For $\alpha > 2$ (tail probabilities decline relatively quickly), the Pareto-Levy has a finite mean and variance, and the law of large numbers applies (a large number of independent and identically distributed variables tends to a Gaussian distribution). For the intermediate range $1 < \alpha < 2$, the distribution has infinite variance: increasing the number of draws from the distribution increases the variance in the set of drawn values. Below the threshold of 1, the variance and the mean are infinite. Thus, below the value $\alpha=2$, rare extreme observations (heavy tails) have an important impact on aggregate statistics.

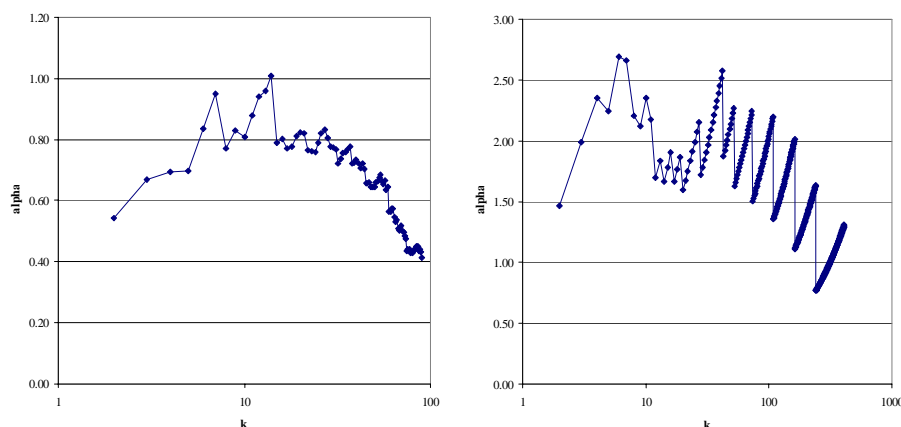


Figure 4. Hill estimator applied to Harvard University patent portfolio data used in Scherer (1998) (left), and to Trajtenberg's (1990) patent citation data (right).

In Figure 4, we plot the value of the Hill estimator of a for the Trajtenberg data and Scherer's Harvard patent portfolio data.¹ We plot a fairly large range of k (as compared to the number of observations in the data, and inspect if there is a range with stable values of a , which can be taken as indication of a power-law distribution for the part of the distribution up to k . The saw-tooth behavior to the right in the Trajtenberg data is due to the integer-valued nature of the citation data.

For the Harvard data, there is indeed a convergence to a value $\alpha \approx 0.8$ (which is in the infinite variance and mean range) for small values of k , indicating heavy tails. For the Trajtenberg data, this is less obvious, although there seems to be some convergence just after $k=10$, to a value $\alpha \approx 1.75$ (which is in the infinite variance, finite mean range). Thus, both datasets seem to point to the existence of heavy tails in the distributions of innovation sizes.

Heavy tails in innovation distribution sizes have important theoretical consequences. Mainstream economic models have traditionally assumed either that uncertainty is absent (e.g., a deterministic relation between productivity increases and R&D), or that the stochastic behavior of innovations is limited to simple probability distributions in which uncertainty about a single innovation disappears if we aggregate over many draws from the distribution (Mandelbrot 1996, ch. 5 calls this *mild* randomness). Evolutionary scholars (e.g., Nelson and Winter 1977) have argued that this is not a very useful description of innovation reality. They argue that the Knightian concept of 'strong uncertainty' may be much more useful. In this case, a probability distribution of innovation sizes is not a useful concept, because the alternatives for which probabilities have to be defined may not even be known. Naturally, the rejection of the notion of a probability distribution makes it hard to model the innovation process quantitatively.

We suggest that the use of heavy-tailed distribution for innovation sizes is a useful alternative that comes a long way towards the 'evolutionary' concept of strong uncertainty. Such a distribution posits the occasional occurrence of very radical changes (such as the ones implicated in Schumpeter's theory of long waves), even though incremental innovations dominate empirical reality in terms of their overwhelming number of occurrences. The impact of radical innovations in the aggregate remains substantial, however, and thus entrepreneurs will somehow have to take them into account in their model of technological reality. At the same time, they do not have an easy way (such as a stable mean and variance of an observed distribution) of extrapolating from past technological experience, i.e., uncertainty remains. In Mandelbrot's terms, a world with heavy tails is characterized by *wild* randomness, and this may be a description of the empirical reality more acceptable to the evolutionary theorist than the mainstream world of *mild* randomness.

3. Technology Space as a Percolated Lattice and R&D as Stochastic Interface Growth

Our probabilistic model of innovation will hinge on two essential properties. First, that technologies can be embedded in a discrete topological space with a neighborhood structure reflecting their technological interrelatedness, and second, that over time technologies can only come 'online' by becoming contiguous to clusters of previously operational technologies, even if R&D search may take place in a more disjointed manner. For simplicity, consider a lattice, unbounded in the vertical dimension, anchored on a baseline (or space), with periodic boundary conditions. The horizontal space represents the universe of technological niches, with neighboring sites being closely related. While the technology space is represented here and in the following as one-dimensional (with periodic boundary conditions, i.e., a circle), it

¹ The Harvard patent data were kindly made available to us by F.M. Scherer.

can easily be generalized to higher dimensions or different topologies. The vertical axis measures an indicator of performance intrinsic to that technology and could also be conceived as multidimensional. For simplicity we will restrict ourselves to a two-dimensional lattice in the following.

A lattice site \mathbf{a}_{ij} can be in one of four states: 0 or technologically excluded by nature, 1 or possible but not yet discovered, 2 discovered but not yet viable, and 3, discovered and viable. A site moves from state 2 to 3, from discovered to viable, when there exists a contiguous path of discovered or viable sites connecting it to the baseline. The neighborhood relation we shall use is the von Neumann one of the four sites top, bottom, right and left $\{\mathbf{a}_{i\pm 1,j}, \mathbf{a}_{i,j\pm 1}\}$, with periodic boundary conditions horizontally. The intuition here is that a discovered technology only becomes viable or operational when it can draw on an unbroken chain of supporting technologies already in use. Until such a chain is completed, the technology is still considered to be under development – it is still an invention, not an innovation. Impossible states 0 remain so forever. State 1 can progress to state 2 if it is uncovered by the R&D search process, and state 2 can possibly but not necessarily progress to state 3 if a connecting chain exists and all its links are discovered.

The lattice dynamics result from the interplay of natural law with the history of human-driven technological search. Two extreme views stake out the range of approaches now current in technology studies, while a third represents a kind of philosophical compromise between the two:

1. The *social construction of technology (SCOT)* perspective says that any site we try is valid technological knowledge that can potentially be incorporated into a viable technology. Thus in this case, a tried site will immediately become occupied and placed in state 2. The paths that result from innovative search will be pure accidents of history.
2. The alternative *technological determinism (TD)* perspective says that a tested site only represents true technological knowledge if it accords with the a priori underlying laws of nature. Thus when we ‘invent’ a site, we must first test whether it is technologically possible (in state 1). If it is, we raise it to state 2, if not, we leave it in state 0. This is a bit like playing the game minesweeper. The paths that result will be a selection from the technologically possible ones.
3. A compromise view, which we shall call the *nothing is impossible at a price (NIP)* perspective, holds that any site can become viable if we are willing to invest sufficiently to develop it. The development costs can be a random variable between 0 and ∞ . The best-practice frontier (defined below) will advance at the points of least resistance and often be delayed until sufficient resources can be brought to bear against obstacles. The dynamics may resemble the self-organized criticality observed in the Sneppen (1992) model of ‘pinning’ interface growth.

If we are willing to allow for natural law, we must first initialize the lattice at time 0 by assigning each site the state 0 or 1. To reflect our a priori ignorance of the laws of nature we regard this as a random process creating a percolation on the lattice with some probability q .² The essential property of percolation is the behavior of connected sets as a function of the

² In this case we speak of site percolation, as opposed to working with the lines connecting nodes, known as *bond* percolation (see Grimmett 1989, Stauffer and Aharony 1994). For the purposes of this paper there is no obvious preference for one or the other (and bond percolation can always be reformulated as a site model). An early application of percolation theory to technological change can be found in Cohendet and Zuscovitch (1982). David and Foray (1994) applied a hybrid site and bond percolation model to the standardization and diffusion problem in electronic data interchange networks. Some recent applications of percolation theory to social science

(uniform and independent) probability of occupation of sites. On an infinite lattice (including the half plane) there exists a threshold probability p_c below which there is no infinite connected set and above which with probability one there is one (and only one) infinite connected set. The probability that any site will belong to the infinite connected set is zero below p_c and increases continuously and monotonically above p_c .³ For bounded lattices, the interesting question is the probability of finding a connected path spanning the lattice from the bottom edge to the top one. This will increase rapidly and nonlinearly in the neighborhood of p_c . A metaphor that may help to sharpen intuition is to regard rain falling on a yard as a percolation problem. After only a bit of rain the yard consists of islands of wetness surrounded by dry pavement. After more rain has fallen the yard suddenly flips to being islands of dryness surrounded by wetness. Regarding technology space as a percolation is of course only one way to generate a ‘complex’ problem setting. Other possibilities are the use of NK-landscapes (see e.g. Frenken 2001) or directed networks (Vega-Redondo 1994, although networks can also be used as the substrate for percolated structures).

If $q < p_c$, then there will only be finite connected sets (clusters) and technological change will eventually come to an end. If, however, nature is so bountiful that $q > p_c$, then there will be a unique infinite cluster and thus potentially unbounded paths of innovation (see Fig. 5). And the larger q , the denser the network of potentially viable technologies will be. The social construction of technology case results from technological determinism in the limit $q \rightarrow 1$. The ‘nothing is impossible for a price’ (NIP) case results from generating a random variable $q_{i,j} \in [0, \infty]$ at each site from some distribution. The site is declared discovered when the cumulative R&D devoted to developing it (possibly discounted) exceeds $q_{i,j}$. We hope to explore the NIP case in a future paper.

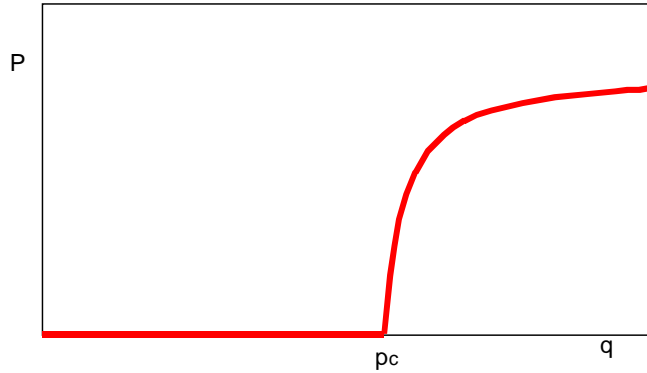


Figure 5. The probability that any site will be on the infinite cluster P as a function of the percolation probability q .

We now come to the R&D search half of the dynamics. At any point in time t a best-practice frontier can be defined consisting of the highest sites in state 3 for each baseline column (of which there are N_c):

$$BPF(t) = \{(i, j(i)), i = 1, N_c\}, \text{ where } j(i) = (\max j \mid a_{i,j} = 3).$$

(If there is no viable site in column i^* we set $j(i^*) = -1$.) The $BPF(t)$ is needed as the anchor for the R&D search process, which is characterized by a search radius m . Around each point $(i,$

problems include Solomon et al. (1999), Goldenberg et al. (2000), Gupta and Stauffer (2000) and Huang (2000a).

³ For bond percolation on the unbounded plane it can be proven that p_c is exactly $1/2$. For site percolation it has been numerically established to be around 0.593.

$j) \in BPF(t)$ with $j > -1$, i.e., around each occupied point on the frontier, we draw a (diamond-shaped) neighborhood of radius m containing all points at a distance of m or less (according to the ‘Manhattan’ metric induced by the neighborhood relation). We suppose R&D search to proceed within these local neighborhoods anchored around current best practice, and thus includes technology sites not only directly above the current best practice sites, but sites laterally related to it and even sites lying behind it. Search itself is viewed as uncertain and characterized by a uniform probability p_s of testing any one of the $2m(m+1)$ neighboring points (not counting the anchor point). If the total R&D ‘effort’ at the disposal of any point on the BPF is E , then

$$p_s = E / 2m(m+1).$$

If a site is tested and in state 0, i.e., it is intrinsically impossible under the TD assumptions, then it remains in this state. If it is in state 1 it is marked as ‘discovered’ and advanced to state 2. Sites already in state 2 or 3 remain unchanged. A site may be tested several times in a period if it is in the m -neighborhood of several sites on the BPF. At the end of each R&D cycle we test each site in state 3 (both newly discovered ones and those inherited from previous periods) to see if they can be connected to the baseline by a contiguous path of sites in state 2 or 3. If so, its state is advanced to 3 and the technology become a viable innovation. The fact that search continues to take place below the BPF means that the path connecting sites on the frontier to the baseline may shorten over time as ‘shortcuts’ and missing links are discovered. We regard this as true *incremental* innovation but will not deal with this aspect here.

Consistent with our ‘blunderbuss’ vision of the search process, we allow innovation to take place in a neighborhood of radius m centered around each point on the frontier. The union of these regions creates a band of innovative percolation extending ahead and behind of the frontier. Within this region new sites will be tested at random with some probability p . A discovered site of course need not connect immediately with the operational network. It is this fact that permits innovations of variable length (as measured by the jump in y they entail) to occur spontaneously. Thus we obtain a natural explanation of innovation clustering (but of the random kind), as shown in Figure 6. This happens when a disjoint extended network of discovered but not yet operational sites is finally connected to the technological frontier, and/or when an ‘overhanging cliff’ advances laterally, pulling up the BPF at neighboring sites by increments that can be much larger than m , the search radius, and are in fact unbounded from above.

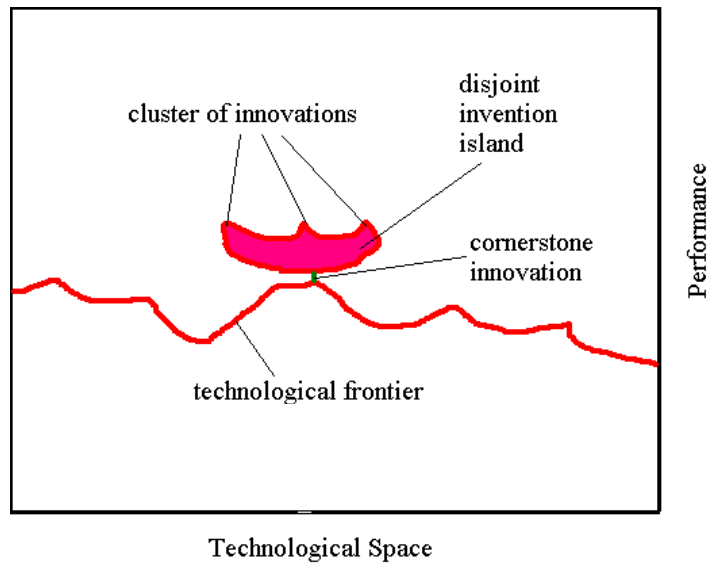


Figure 6. Clusters of innovations occur when disconnected islands of inventions are joined to the BPF by cornerstone innovations.

The computer implementation of the model is illustrated in Figure 7, which is a screen shot of the user interface in interactive mode. The rectangle on the upper right shows the state of the lattice at this point of time. Blue dots represent lattice sites with ‘impossible’ technologies (state 0), unmarked sites are possible technologies which have not yet been discovered (state 1), green ones discovered but not yet viable sites (state 2), and yellow sites are viable technologies, i.e., discovered and connected to the baseline (state 3). The red line represents the best-practice frontier (BPF) around which search is taking place in a band of radius 8. A typical pattern is shown of a mushroom cloud of yellow sites with overhanging cliffs, at the edges of which the BPF jumps in a discontinuous manner. The average rate of innovation per site in each period is shown by the red line in the lower-right rectangle, while the standard deviation of the BPF, a measure of the unevenness of technological advance, is given by the green line.

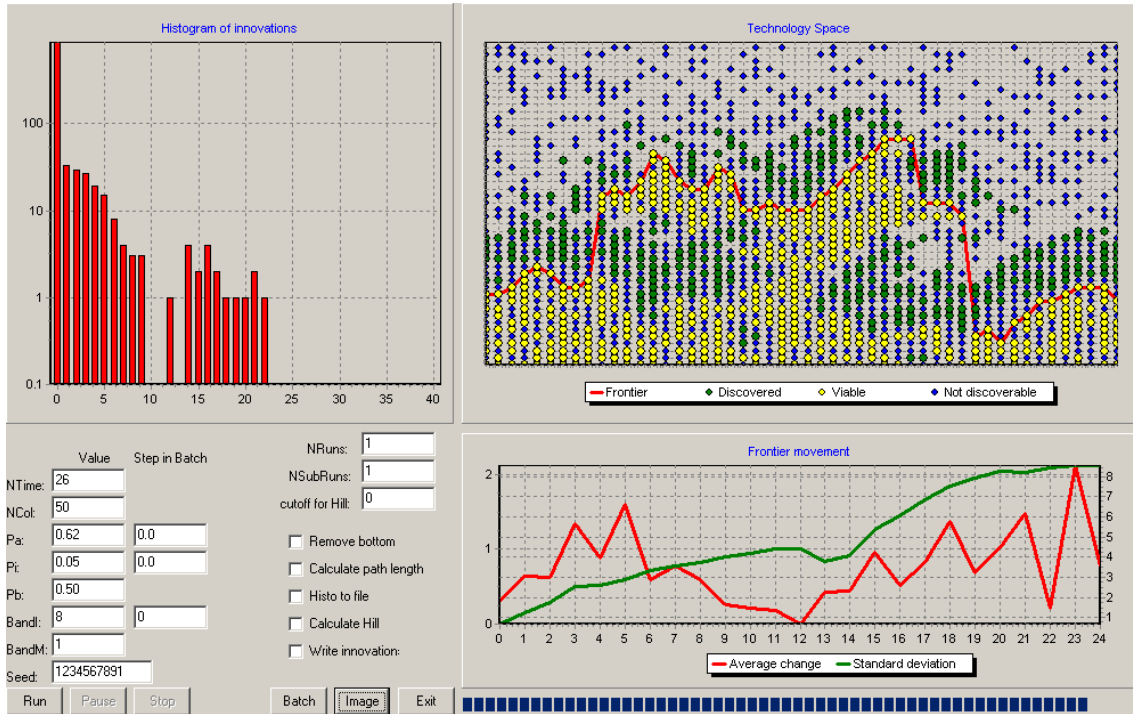


Figure 7. Screen shot of computer simulation at time 24. Snapshot of lattice on upper right, time series of average rate of innovation and standard deviation of BPF on lower right. A histogram of the number of innovations of various sizes can be discerned on the upper left.

4. Analysis of Numerical Simulations

We define an innovation as being any change in the height of a BPF site above the baseline, and its size as the number of vertical sites covered by the change in one time period. In Silverberg and Verspagen (2002) we explore the dynamics of R&D search as a function of the search radius m and the lattice percolation probability q . Not surprisingly, myopic search (m small) turns out to be a dangerous thing, with the system having a high probability of dead-locking even when an infinite cluster exists ($q > p_c$). The overall rate of technological change is shown to be an increasing function of both m and q .⁴

We will now examine in turn the temporal, spatio-temporal and size-clustering properties of numerically generated data.

4.1. Temporal clustering of radical innovations

In analogy to the empirical literature on the incidence of radical innovations discussed in Section 2.1, we will set a cut-off threshold ϑ to differentiate radical from minor innovations: innovation jumps $\geq \vartheta$ will be called radical, otherwise they are minor. We apply the same statistical technique used in Silverberg and Verspagen (2003) on historical data, namely Poisson regression, to decide whether a negative binomial model with positive overdispersion parameter α is significantly superior to a pure Poisson model of time series of simple aggregate counts per period (over all technology categories) of radical innovations. Recall that for the two historical time series we examined (our supersample and the Baker significant patent data) α is always significantly greater than zero and of order 0.24 – 0.27 for a model with

⁴ For a search radius of 2, however, there is actually a decline in this rate for certain ranges of q due to an unfavorable tradeoff between foresight and effort duplication.

simple exponential trend. We interpret this to mean that radical innovations do indeed cluster in the statistical sense, if not in the sense of a Schumpeterian theory of long waves (when they cluster is purely random and anything but quasi-periodic).

Figure 8 plots the Poisson arrival rate (mean number of innovations per unit period) and the estimated α for the negative binomial model (the arrival rate is invariant to the model estimated) for a range of values of the threshold ϑ and search radius m and a percolation probability of 0.6, i.e., just above the critical value. In all cases, the estimated α 's are highly significant (1% level). In general, the lower the level of aggregation of innovation (i.e., the higher the threshold ϑ), the higher the estimated α . Thus, radical innovations are more clustered than an aggregate of major and minor innovations together in our simulated data, and of course occur less frequently. Increasing the search radius also increases both of these values to some extent, particularly at low values of m (see Silverberg and Verspagen 2002 for a more extensive discussion of the effect of the search radius on innovation performance).

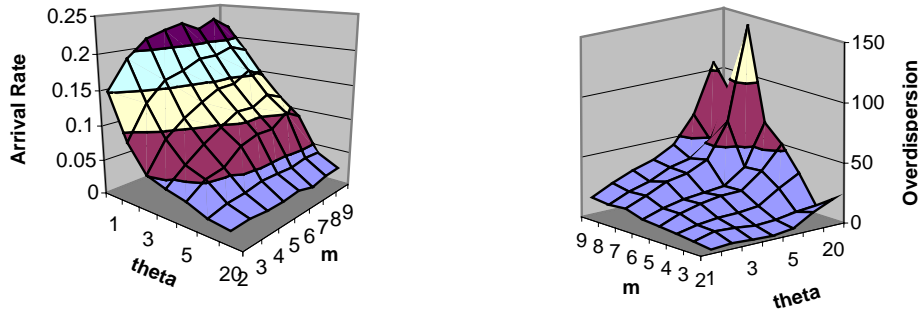


Figure 8. Poisson arrival rates (left) and overdispersion index α (right) for different values of threshold ϑ and search radius m .

Time series of innovation counts at different levels of ϑ display this clustering behavior clearly (Figure 9).

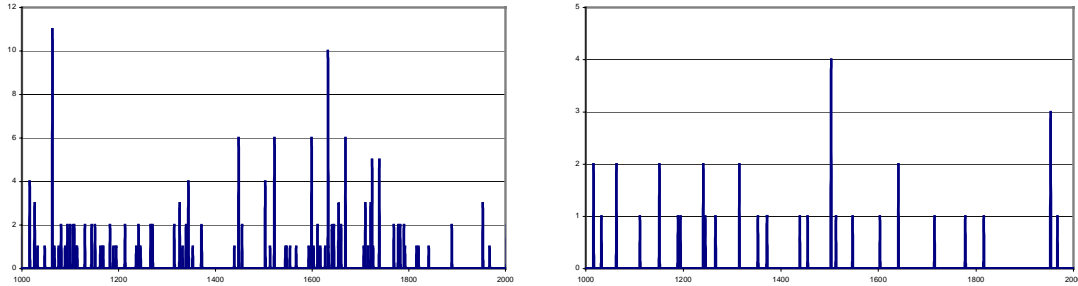


Figure 9. Innovation count time series for a threshold of 2 (left) and 10 (right) for a run with search radius 5. The temporal clustering is apparent.

4.2. Clustering of simulated data in technology space

To examine clustering of innovations in technology space, we generate a space-time diagram of innovation activity by defining a variable $x_{i,j}$ which records the size of the innovation step at time j occurring in the column above technology baseline site i , selecting a lattice size of N_c for the number of technology columns and N_t for the number of time periods (for a total of $N = N_c N_t$ sites). We then see to what extent innovations cluster in particular areas of technology space at particular times by regarding this as a spatial clustering problem and applying Moran's I statistic (cf. Moran 1950, Terraseer 2003). Letting $z_{i,j} = x_{i,j} - E(x)$, this is defined as

$$I = \frac{N \sum_{i=1}^{N_c} \sum_{j=1}^{N_i} \sum_{i'=1}^{N_c} \sum_{j'=1}^{N_i, i' \neq i, j' \neq j} w_{i,i',j,j'} z_{i,j} z_{i',j'}}{S_0 \sum z_{i,j}^2},$$

where

$$S_0 = \sum_{i=1}^{N_c} \sum_{j=1}^{N_i} \sum_{i'=1}^{N_c} \sum_{j'=1}^{N_i} w_{i,i',j,j'}$$

and $w_{i,i',j,j'}$ is the connecting weight between sites (i,j) and (i',j') . Since we have been using nearest neighbor relationships in defining technological proximity until now, we select the weights as follows:

$$w_{i,i',j,j'} = \begin{cases} 1 & \text{if } |i-i'| + |j-j'| = 1 \\ 0 & \text{otherwise.} \end{cases}$$

Under the assumption that the values $x_{i,j}$ are drawn independently and at random from an unknown distribution, the expectation of I is

$$E(I) = \frac{-1}{(N-1)}.$$

The variance of I is a complicated expression we will not reproduce here. Applied to our artificial data, we always find results that are highly significant (at better than the 1% level). This is not surprising when we look at the patterns generated in a typical space-time plot (see Figure 10). The dots represent space-time sites at which positive innovation jumps have occurred, with the darkness of the dot reflecting the size of the innovation step (value of $x_{i,j}$). It is apparent that innovation takes place not only along broad fronts but also along well-defined corridors. There are clearly ‘hot’ areas of technological activity over extended periods of time and the picture is anything but white noise or ‘snow’ such as would be seen when a television screen is tuned between stations. In particular, there are islands of white resulting from islands of impossible technologies (in the TD perspective) in which no technological change occurs until an ‘end run’ has been performed to outflank them.

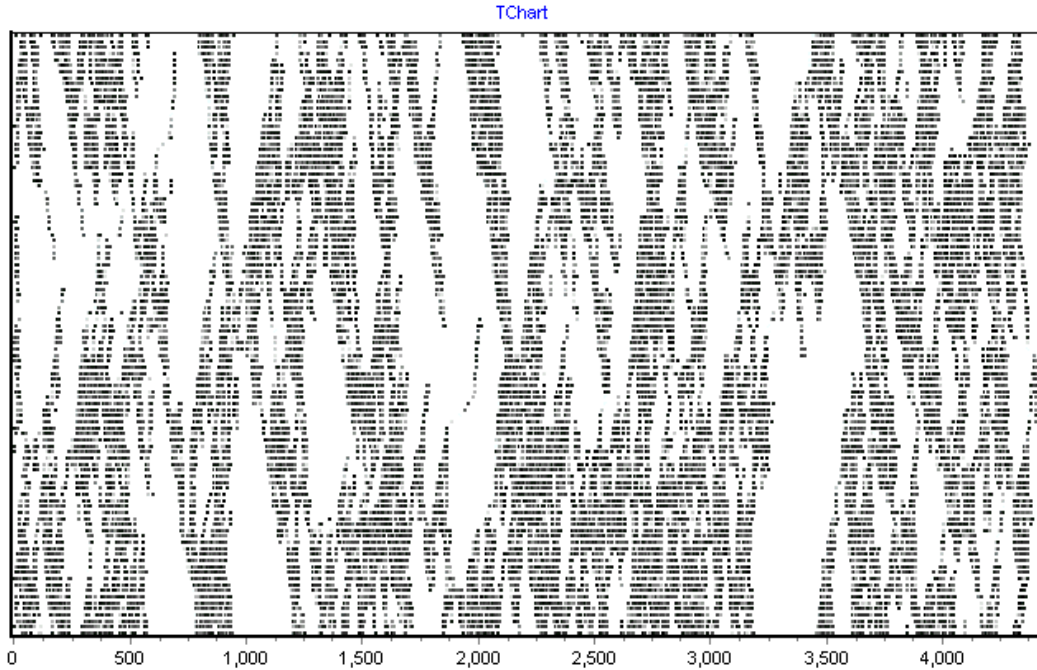


Figure 10. Space-time plot of innovation activity. The vertical axis represents the technological columns, the horizontal axis is time. Darker sites represents larger innovations.

4.3. Innovation size distributions

In Fig. 11 we present a raw innovation size distribution and the corresponding rank-order distribution of the same data. While it is clear that the distribution is highly skewed, the rank-order distribution does not quite conform to a power law. The plots in Fig. 12 show the rank-order distribution stepping through values of the search radius from one to ten. While linearity seems to hold over one or two decades on the right sides, the curves in general display clear convexity on the left (the fact that jumps greater than or equal to 100 are lumped together distorts the picture on occasion, however).

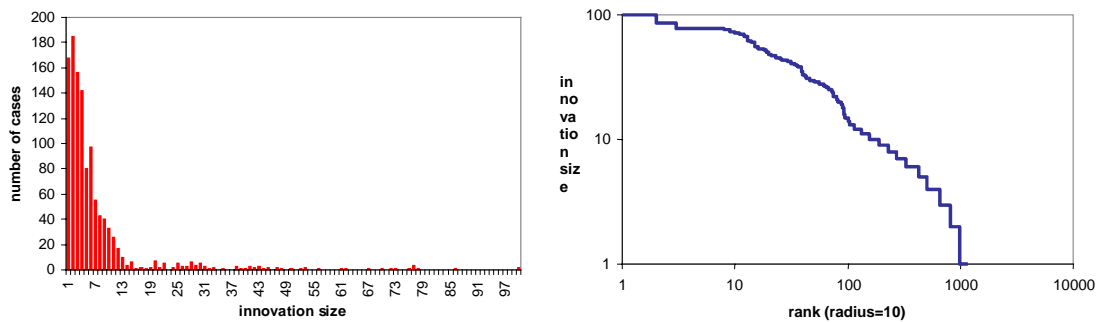


Figure 11. Raw size distribution (left) and rank-order distribution (right, double-log scale) of simulated data ($q=0.603$, $m=10$).

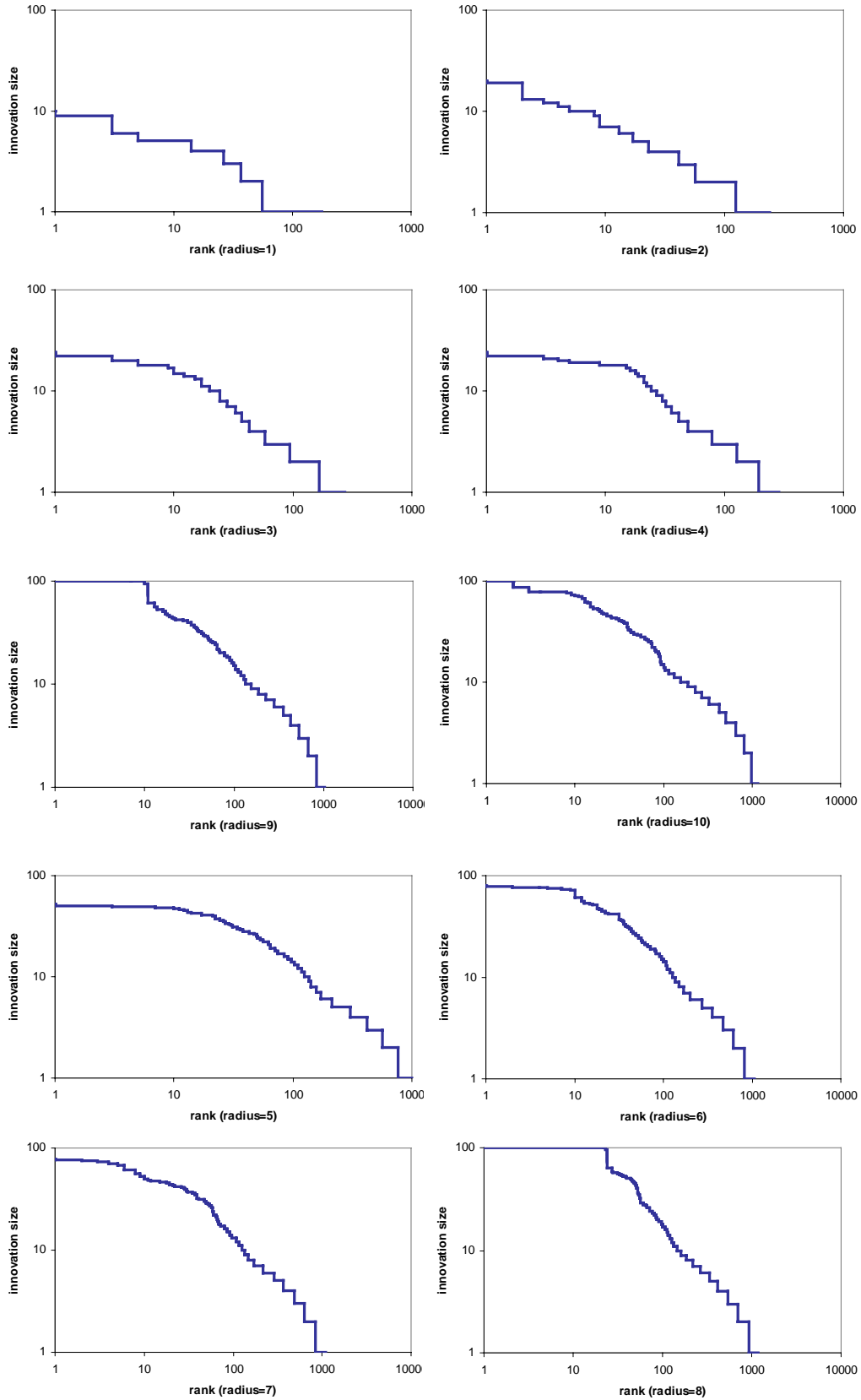


Figure 12. Rank-order distributions of innovation size for increasing search radius ($q=0.603$).

We calculate estimates for the slope of the cumulative Pareto distribution α using the Hill estimator in Figures 13, 14, and 15 for different values of q and $m=5$. It is apparent that for lower values of q there is an intermediate range of k where the estimate converges to a value between 1 and 2. For $q=0.695$ convergence is to a value of around 2, indicating a log-normal distribution rather than a Pareto.

We also calculated LD plots, which are obtained by grouping the original observations into blocks of size b :

$$X_{t,b} = \sum_{i=(t-1)b+1}^{tb} X_i.$$

The right cumulative histograms are then plotted on double-log scales for different block sizes. If these curves are straight and parallel in the tails, then the data are in the domain of attraction of a Pareto-Levy stable distribution with $\alpha < 2$ (cf. Crovella, Taquu, and Bestavros 1998). If the curves seem to converge in the tails, this is an indication of a finite-variance distribution such as lognormal. Figures 16, 17 and 18 show the LD plots for the same runs as in Figures 13, 14, and 15. While they do not incontrovertibly demonstrate that the data are Pareto distributed, for $q=0.695$ the convergence of the curves is apparent, again indicating a finite-variance distribution. We have not calculated LD plots for the empirical observations because of the paucity of data points.

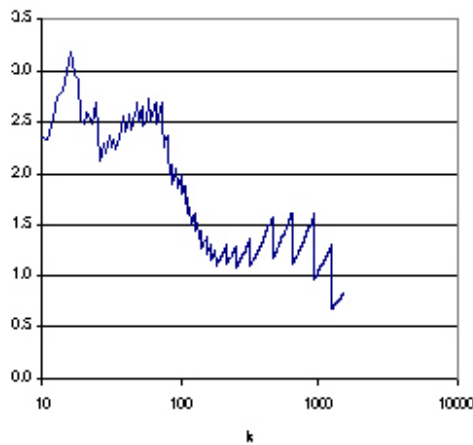


Figure 13. Hill estimator of Pareto α for innovation distribution generated with $q=0.6$ and $m=5$ plotted on a double-log scale for values of k up to 90% of number of observations.

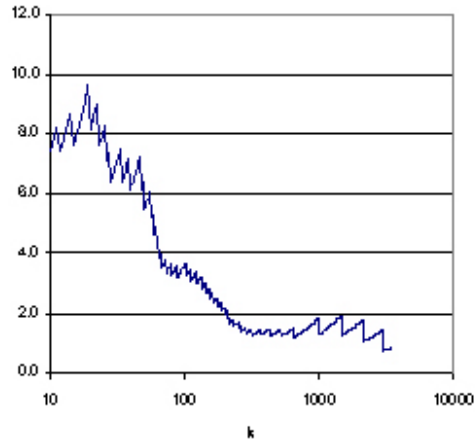


Figure 14. Hill estimator of Pareto α for innovation distribution generated with $q=0.645$ and $m=5$ plotted on a double-log scale for values of k up to 90% of number of observations.

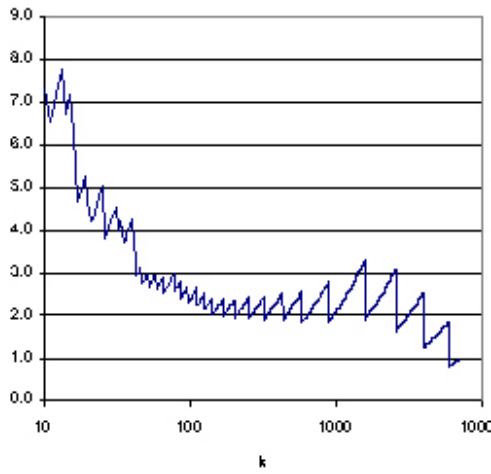


Figure 15. Hill estimator of Pareto α for innovation distribution generated with $q=0.695$ and $m=5$ plotted on a double-log scale for values of k up to 90% of number of observations.

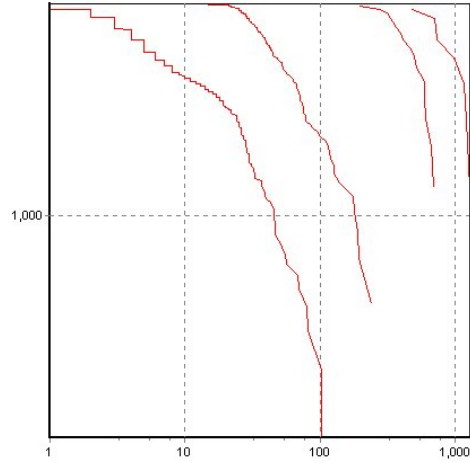


Figure 16. LD plot for innovation distribution generated with $q=0.60$ and $m=5$ (original data and aggregated data in blocks of 10, 100 and 200 observations).

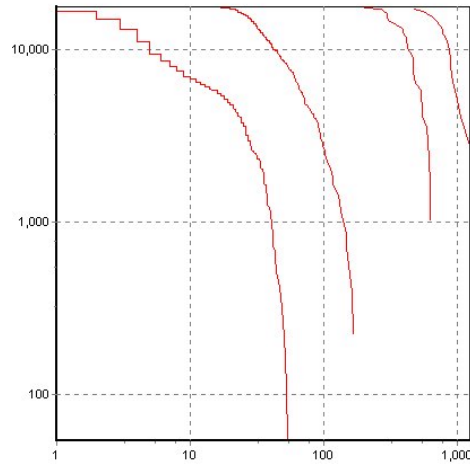


Figure 17. LD plot for innovation distribution generated with $q=0.645$ and $m=5$ (original data and aggregated data in blocks of 10, 100 and 200 observations).

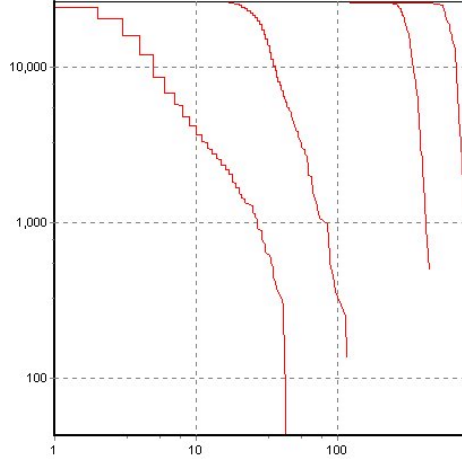


Figure 18. LD plot for innovation distribution generated with $q=0.695$ and $m=5$ (original data and aggregated data in blocks of 10, 100 and 200 observations).

5. Comparison of Simulated and Empirical Data and Conclusions

We have examined empirical and simulated data on innovations with respect to a number of characteristics of complex systems: temporal and spatial clustering, and highly skewed size distributions. In the temporal domain in particular the similarity of the results is striking. Time series of significant innovations are more highly clustered than Poisson, and the extent of clustering depends on the level of aggregation. While it has proven difficult until now to define the spatial clustering of technologies empirically because a natural topology first has to be defined, in our model spatial clustering and technological trajectories emerge naturally from the percolation structure and the assumed technological topology. Landscape models (cf. Frenken 2001) of technological evolution based on genetic algorithms provide one possible way of imposing a topology, although one very different from the lattice structure examined here. In any event, the generation of a technological space randomly is sufficient to create the minimal characteristics of order evident in the empirical data due to the necessity of building one technology on a preexisting neighboring technology.

Skewness of innovation size distributions is a natural feature of both empirical data and the model, whereby in both cases there seems to be a spectrum of results ranging from lognormal (and thus finite variance) to Pareto in the tails (and thus infinite variance, and possibly infinite mean as well). Whether this is an indication of the richness of the model or a lack of specification is unclear. Analysis of more extensive datasets derived from patent citation data might provide an avenue for more incontrovertible statistical hypothesis testing (cf. van Raan 1990).

The model still makes a number of simplifying assumptions that could be relaxed in future versions. First, the percolation probability q is now exogenous and must be set above the critical value to generate interesting results. The NIP perspective allows this crucial variable to be endogenized by allowing the aggregate level of R&D effort adjust to be just sufficient to produce further technological advances. We also assume that R&D effort is equally spread out along the BPF, whereas real agents would obviously tend to focus their effort at places where a higher reward is to be expected (and thus certainly not in front of demonstrable obstacles). An agent-based version of the model with agents which autonomously decide where to devote their resource might address this problem.

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