CAUSES, CONSEQUENCES AND DYNAMICS OF 'COMPLEX' DISTRIBUTIONS OF TECHNOLOGICAL ACTIVITIES: THE CASE OF PROLIFIC INVENTORS

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CAUSES, CONSEQUENCES AND DYNAMICS OF 'COMPLEX' DISTRIBUTIONS OF TECHNOLOGICAL ACTIVITIES: THE CASE OF PROLIFIC INVENTORS

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1. INTRODUCTION

In this chapter individuals constitute the unit of analysis. Individuals must be considered because innovation is not simply a product of firms and organizations, it requires individual creativity. A century ago Schumpeter clearly identified the individual entrepreneur as essential to technological development. We follow this Schumpeterian notion that innovation, a form of creativity very much like entrepreneurial activity, is fundamentally individual in its genesis. Firms and organizations can create conditions that enhance or detract from the innovative activity of individuals, but it is the individuals who innovate. Yet we also know that not all individuals innovate (or invent) equally. Among individuals, even among individual entrepreneurs or firm innovators, innovation is not uniformly distributed. This heterogeneity among individuals is, of course, not unrelated to the existence of technological gaps across firms and organisations as far as innovation activities are concerned. This variation across firms is especially important in evolutionary economics and was recognized explicitly by Alfred Marshall. It a natural outcome in a world marked by competition where organizations have heterogeneous bases of competences, different sets of strategies and, as a consequence, perform differently (c.f., Metcalfe, 1995). In other words, we are in Antonelli’s world of “organized complexity” as he describes it in the Introduction to this book.

Figure 1 illustrates heterogeneity among inventors using the distribution of U.S. patents for the most productive French inventors (those with 15 or more inventions) over the period from 1975 to 2002. The distribution is characterized by heterogeneity and skewness. The distributions for the other countries that we have examined, as expected, appear to be quite similar. The most noticeable

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1 The authors thank L'Agence nationale de la recherche, Paris for funding our research on prolific inventors regarding the characteristics, the productivity distributions, and the time paths of the careers of prolific inventors in the five largest countries in terms of overall technological activity (See Le Bas et al., (2009) and Latham et al., (2009). Christian Le Bas acknowledges the funding and support of the International Center for Economic Research, Torino where he was a Fellow in 2008 and 2009. We also thank Riad BoukliHassan, Naciba Haniba and Dmitry Volodin for their valuable research assistance.

2 The distribution shown is truncated because our data set has no information before 1975 or after 2002 and thus we do not have completed information for inventors who were at mid-career at the beginning and the end of our data. However, we have also examined the distribution for inventors whose entire careers begin and end within the data and know that the truncation does not affect the fundamental characteristics of the distribution.
and significant characteristic of these "long-tailed" distributions is that high-frequency or high-amplitude populations are followed by low-frequency or low-amplitude populations whose frequencies or amplitudes "tail off" asymptotically to zero.

This chapter provides an understanding of the causes and the consequences of the particular shapes of the distributions of individual inventors' productivities that have been observed. It has long been acknowledged that technological activities are characterized by asymmetrical distributions. The basic question underlying this paper is this: What can we learn about individual innovation from the analysis of similar phenomena observed in scientific productivity? In Section 2 we review a literature that begins with Lotka's (1926) "law" regarding his observations about the persistence of diversity in scientific productivity at any point in time and also over time. We note that Lotka's model has been extended to technological activities and has proved useful for describing and understanding inventor productivity distributions. In Section 3 we survey...
empirical work regarding the utility of the "power law" and the Pareto distribution to describe and explain empirically observed distributions. Section 4 is devoted to the economics of "prolificness." Here we are especially interested in the highly productive, or more “prolific,” inventors from the upper parts of the frequency distributions for inventors. While the identifying characteristic of a prolific inventor is that he individually contributes to the production of more than the average number of patents (which can be termed “quantity” productivity), we hypothesize that prolific inventors also contribute to the production of patents having greater than the average values (which can be termed “value” productivity). Our focus on "prolificness" allows us to explore the processes underlying knowledge accumulation at the individual level including its features, characteristics, and structural trends. We show that “prolificness” is a dual process: First, we show, as has been shown in numerous empirical studies, that some inventors are able to reach the upper end of the “quantity” productivity distribution by accumulating much larger than the average numbers of patents. Second we explore the specific processes by which these individuals create, maintain, and increase knowledge accumulation as their careers evolve.

2. "LOTKA" WORLD: A COMPLEX SYSTEM OF CREATIVITY

The Lotka world simply generalizes to more activities the highly skewed distribution of productivity among scientists first identified by Lotka (1926). The first work to extend the "Lotka model" to the productivity of inventors was Narin and Breitzman’s (1995) paper on prolific inventors. They found a "Lotka-like distribution" in the semi-conductor sector, and suggested that the same type of "law" governs the productivity distribution for the creation of new ideas in science and in technology\(^3\).

2.1. Empirical issues related to the Lotka model

2.1.1. Introduction to the issues

Among the well-known examples of skewed distributions of human creative activity that we will describe are the following: (1) the small proportion of individuals who ever patent an invention, (2) the extremely highly concentrated nature of eminence in science as described by Dereck Solla Price (1965), (3) the fact that only a small fraction of patents receives most citations while most patents receive few citations, (4) and the same citations pattern is observed for academic publications as for patent citations. All of these frequency distributions - of patents per inventor, publications per academic, citations per patent, and citations per academic publication, as well as many others - are not

\(^3\) See also Göktepe (2007).
symmetric but highly skewed. We refer to them as "complex" distributions because the observed varieties in individual creative capacity are the product of complex forces involving individuals, firms, organizations, and external effects across space and time. We contrast these skewed distributions with the assumption of normal (Gauss-Laplace) distributions for the characteristics and behaviours of the agents implicit in much of standard neo-classical economics. In the latter framework, the law of large numbers applies, and thus the mean is often a suitable representation for an entire distribution. By contrast, in complex technological-economic systems we show that understanding the nature of long-tail distributions, those that are highly right-skewed (such as the Pareto, log-normal, and others) is crucial. The "long-tailed" distributions describe a kind of diversity in their asymmetric shapes: a high-frequency population is followed by a low-frequency population which "tails off" asymptotically to zero.

Since Lotka’s seminal work on the subject many additional works in different disciplines and over varied time periods have confirmed this long-tailed form for the distribution of creativity. It has been shown that the distribution is even more skewed when the scientific productivity is measured by patent citations. For us the significant feature of the Lotka world is simply the highly-skewed distribution of productivity among scientists and inventors.

2.1.2. Detailed explanation of the Lotka Law.

Lotka's law of scientific productivity states that the number of scientists $y_x$ each having produced $x$ number of papers, is inversely proportional to $x$, which is the output of each individual author. The relation may be expressed as:

$$x^n y_x = C$$

where $n$ and $C$ are two constants that can be estimated with data on the numbers of scientific publications by author. Lotka's own calculations gave values to $C$ of 0.61 and 0.57 for $n = 2$ and $n = 1.888$, respectively. Thus in Lotka’s distribution 6% of scientist publishers produce half of the papers (Stephan, 1996). Some authors claim that a generalised form of Lotka's law is the “inverse power law” discussed in the next section below (Bookstein, 1976). Since the publication of Lotka's paper many studies have tested the existence of Lotka's law on particular samples. There have been too many studies for us to report on the results of each one in this chapter. For our purposes it is sufficient to note that some of these works have shown that Lotka's law does not apply to specific data sets. Nevertheless the nature of the distributions found remain the same: all are very skewed to the right with a long tail.
We note that the research program on Lotka’s distribution is not really complete. We find in the recent literature a large number of papers that continue to deal with it\(^4\). Efforts to explain why Lotka’s Law “works” to the extent that it does constitute another branch of research relative to the Law. For instance Huber (2002) develops a new model for a process that generates Lotka's Law. He shows that four relatively mild assumptions create a process that fits five different “informetric” distributions: rate of production, career duration, randomness, and Poisson distribution over time, as well as Lotka's Law. By simulation, he obtains good fits to three empirical samples that exhibit the extreme ranges of the observed parameters. The overall error is 7% or less. An advantage of this model is that the parameters can be linked to observable human factors. The model is not merely descriptive, but also provides insights into the causes of differences between samples. Furthermore, the differences can be tested with powerful statistical tools\(^5\).

2.1.3. Explanatory frameworks

We contrast two older proposed explanations or “frames of thinking about” the observed asymmetric distributions of innovative productivity: (1) the "sacred star" and (2) the "cumulative advantage" hypotheses of Allison and Stewart (1974). These two remain the most acknowledged explanatory frames. We discuss the supporting evidence for each hypothesis including empirical findings.

The first, the "sacred star," refers to the hypothesis that differences in creative productivities of scientists are largely determined before theirs careers even begin. For instance the productive capacity might be linked to the formation of the scientist, to his/her motivation and to general ability. Many academics are reluctant to consider this hypothesis because, in general, measures of intellectual ability have low correlations with creative productivity. David (1994) has identified another limit of this first approach: if a pre-determined distribution of abilities can perhaps explain the static cross-sectional distribution of productivity, it does not explain why the dispersion of productivity appears to increase over the life of cohorts of scientists.

The second explanation for asymmetry, "cumulative advantage,” is much better known. It has been proposed as an explanation by Allison and Stewart:

\(^4\)Two illustrative papers showing the kind of interest in the topic that is on-going are: Kretschmer and Kretschmer (2007) and Morris and Goldstein (2007). See Egghe (2005) as well.

\(^5\)Note that the Lotka’s analysis does not deal with the “value” of publications (which has been measured with citations).
“First, scientists who have been recognized as having significant advances will be motivated by additional publications, and will be influenced by their colleagues’ expectations that they repeat or exceed those achievements. Second beyond these direct effects, recognition usually implies increased access to resources which facilitates research, …..” (Allison and Stewart, 1974, p 597).

So they conclude that cumulative advantage is the relevant explanation for the increase in productivity inequality. Cole and Cole (1973) have assembled some positive evidence in favour of this approach. Moreover they note that the cumulative advantages thesis is strongest where individuals are rewarded according to their merits (in this case, the “Matthew effect” (the phenomenon where "the rich get richer and the poor get poorer") is particularly important). One point remains obscure and consequently would deserve more attention: is this cumulative advantage approach compatible with the pre-existing differences approach (which is the foundation of the “sacred stars” hypothesis? Surely, “yes” in theory, but perhaps it is less so in practice. All these issues are discussed in detail by Allison and Stewart (1974) and Cole and Cole (1973). Turner (2003) explicitly considers three laws of scientist productivity: 1) uneven distribution of productivity, 2) persistence of the hierarchy, and 3) reinforcement of the productivity gap (Turner, 2003).

Strangely, there are only a few studies that provide empirical support for either of the two theses. On the one hand Allison and Stewart (1974) confirmed the relevance of “accumulative advantages.” They show, with cross-sectional data for chemists, physicists and mathematicians, that the distribution of productivity becomes increasingly unequal as a cohort ages. Resources and esteem increase too as career age increases. Levin and Stephan (1991) analyzed scientist productivity in terms of career life-cycle (see also Stephan, 1996). After controlling for motivation and ability, they show that, in general, life-cycle has effects on productivity. As a consequence, this approach confirms and expands the Allison and Stewart (1974). But, by contrast and much more recently, empirical work by Mairesse and Turner (2002) gives different results. They have a data set on physicists from the French CNRS. They do not confirm that the thesis of “accumulative advantages” applies.

Six issues need to be considered in discussing the two approaches:

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6 Cumulative advantage is a general mechanism for inequality across any temporal process in which a favorable relative position becomes a resource that produces further relative gains. DiPrete and Eirich (2006) show that the concept of cumulative advantage has developed multiple meanings in the sociological literature, in particular in the areas of education, careers, and related life course processes. It is a well known in economics, explaining, for example, the productivity gap between individuals (inventors), firms, regions, and nations.

7 Recently this approach has been challenged by Harhoff and Hoisl (2006). They note that pre-existing differences and cumulative advantages affect differences in output not in quality.

8 Some of them are reviewed by David (1994).
(1) The "accumulative advantages" hypothesis is sometimes considered as a generalization of the Matthew effect, built on two feedback loops through recognition and resources. Although a variety of factors are at work in the process, the "winner-take all" manifestation in the reward structure in science translates small differences in human capital endowments into large differences in the economic reward (Stephan, 1996).

(2) An important contribution is the idea that the two theses ("sacred star" and "accumulative advantages") might be two special cases of a more general approach based on heterogeneity and stochastic reinforcement models (mathematical formulations of which were proposed by Simon, 1957). By contrast David (1994) has shown how Polya Urn schemes (processes first identified by Polya in probability theory in which a winning draw is reinforced) can be used for analysis of the cumulative advantages process, an idea first suggested by Price (1965).

(3) Interestingly, with both these approaches we are entering into the working of complex systems. The heterogeneity hypothesis tells us that individuals perform tasks differently (for instance inventive productivities differ). The reinforcing process delineates how the propensity to perform changes over time and, especially how, according to the "accumulative advantages" thesis, small differences may become large.

(4) It may be that the studies reviewed here do not sufficiently account for the characteristics of the modern process of invention in science and in technology: the production of new ideas is done by teams. Some studies have tested Lotka's law with institutional productivity data, where the institutions are viewed as teams. In general negative binomial distributions fit these data better than Lotka's distribution. Of course this type of research opens the way to bibliometric studies and the ranking of institutions. These works are different from Shockley (1957) who analyzed the distribution of publications among scientists in a particular institution and found them to be distributed in a lognormal way. From this point of view the work by Mairesse and Turner (2002) fills a gap. They include in their models variables measuring the influence of research teams. The size of the team, its productivity and the quality of publications of the team

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9 Nearly identical results are obtained from the analysis of the productivity of industrial firms in terms of patents.
are found to be positively related (although the size of the team only has a weak impact on the other variables). We note with the that team interactions takes place within “local or global networks”, in small worlds, where scientists are mobile and collaboration between individuals is common (Fleming and Marx, 2006). This last behaviour, collaboration, is more prevalent for inventors than for scientists.

(5) Often the productivity of scientists is defined equivalently by either the quantity of publications or by their quality (as measured by the number citations they receive). We believe it is necessary to distinguish explicitly between the quantity of publications and their quality as researchers do with patented inventions.10

(6) An intriguing question is posed by the empirical literature: does the same law that describes scientists’ productivity also apply to inventors “in technology” as well. In others words are scientists and inventors in the same Lotka world? After Lotka himself the works by Shockley (1957), Price (1976) and Seglen (1992) tend to confirm the main findings of the seminal Lotka study. But all these studies have been confined to the creative productivity of scientists. To our knowledge the first work that tries to extend the “Lotka world” to the productivity of inventors is Narin and Breitzman (1995) who focused on prolific inventors. They found that in the semi-conductor sector a “Lotka-like distribution” of the number of patents per inventor: a relative small number of highly productive inventors and a large number of inventors having only one patent. In brief they suggest that the same type of “law” governs the productivity distribution in the activity of creation of new ideas in science and in technology.11

2.2. A competitive explanation of the distribution of creativity: an evolutionary model of breakthrough inventions.

Fleming and Szigety (2006) provided a fascinating model that enables us to understand the creation process at the core of Lotka’s law but which is general enough to be applied to contexts other than scientific discovery.

They start their study with a psychological model first elaborated by Simonton (1999). Inventors generate new ideas through combinatorial thought trials subject to psychological and social selection processes (see also Fleming, 2007).
They note that individuals who simultaneously juxtapose, combine, and evaluate a stream of uncombined inputs will be more creative. The generative creativity is an assemblage or rearrangement of new combinations. The more the inventor tries recombinant actions the more he/she increases the likelihood of a productive hit. As a consequence we hypothesize a correlation between an inventor’s total output and the likelihood that he/she finds inventions with high impact (“a one-hit wonder is very unlikely” Fleming and Szigety, 2006: 340). “The most prolific inventor is the one most likely to invent a breakthrough” (ibid.: 340). A scientist who has produced very highly cited publications has probably also published a lot of papers that are poorly cited, as Simonton (1999) noted. If we rank scientists (inventors) according to their productivity in terms of total number of papers (patents) we will find the “genius creators” with the most influential ideas are in the extreme right tail of the distribution of productivity.

Simonton (1999) has framed creativity as an investigation of the distributional moments of inventive output. He noted that the ratio of the number of major works to the number of minor works remained constant over a productive career. Fleming and Szigety (2006) make an inventory of the factors (technological and social-psychological variables) that have an influence on “the second moment of the creative outcome distribution” and consequently also affect the propensity to create breakthroughs. For example, among the important variables that have an expected positive impact on the variance of the distribution are: diversity of collaborators, dissolution of collaborative relationship, and changes of creative fields: as has been noted by many researchers an inventor cannot invent alone, he/she invents collectively and within an “ecological context.” As a consequence there are organizational influences on the evolution of the distribution of inventive behavior as well. In another paper Fleming (2007) finds empirical results in favour of his thesis. However, Mairesse and Turner (2002) find evidence contesting the trend for scientists (they investigate French physicists). They find that at some point in time there seems to be a substitution between the quantity of publications and their quality. That is not in accordance with the law pictured by Fleming and Szigety (2006).

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12 This point is controversial. Recent work on the private value of patents confirms the existence of a significant relationship between inventor productivity and value of inventions. The characteristics of the inventor, in particular his past number of patents, is the main determinant of this value, even more important than the characteristics of the organization in which he is employed (Gambardella et al., 2006).

13 It appears that for Fleming and Szigety the same mechanisms of creativity apply both in science and in technology.

14 Analysis of “stars scientists” such as those in Zucker, Darby and Torero (2002) is relevant in this context. “Stars scientists” have high-quality intellectual capital (measured in terms of number of citations) and make major discoveries (Zucker and Darby, 1996, 2001). The stars are also in the extreme upper tail of the productivity distribution. The observation that, in the biotechnology sector, “the labour of the most productive
We have reviewed theoretical and empirical analyses reported in the literature relating to scientists’ productivity distributions. These analyses led us into the workings of complex systems. The heterogeneity hypothesis tells us that individuals perform tasks differently; for example, inventive productivities differ. The Reinforcing processes hypothesis provides the dynamics in the system, delineating how the propensity to perform changes over time and how, according to the "accumulative advantages" hypothesis, small differences may become larger.

3. THE "LONG TAIL" STORY: THE POWER LAW AND THE PARETO DISTRIBUTION IN TECHNO-ECONOMIC SYSTEMS

The “long tail” is the name for a long-known feature of some statistical highly right-skewed distributions. The feature is also known as "heavy tails", "power-law tails", or "Pareto tails." The main characteristic of "long-tailed" distributions is that a high-frequency or high-amplitude population is followed by a low-frequency or low-amplitude population which gradually "tails off" asymptotically. Some authors have also noted that this long tail is also bigger (higher). The events at the far right end of the tail have extremely low probabilities of occurrence but these probabilities are nonzero, as emphasized by Taleb (2007). This type of distribution often follows a power law qualitatively quite different from the "normal" or "Gaussian" type distributions (which are narrower, symmetric and peaked) used to describe phenomena such as histograms of people's heights. A vast range of natural and social phenomena follow such distributions.\textsuperscript{15}

For a distribution having the power law general form, the power law can be expressed as

\begin{equation}
(1) \quad p(x) = C \cdot x^a,
\end{equation}

where \( a \) is the exponent and the constant \( C = e^c \). In the case of a cumulative distribution, the exponent of the power law will be \( (1 - a) \).

To check if an empirical distribution fits a power law, we can simply plot the data on a log-log scale. A power law distribution appears as a straight line. (Because \( \log_e [p(x)] = c + a \cdot \log_e (x) \) is a straight line.) Equivalently we can plot the cumulative distribution and it will give a straight line as well. We will

utilize these characteristics of power laws to represent the distribution of numbers of patents by inventors.

### 3.1. Variety in highly right-skewed distributions: some definitions

Newman (2006) uses the distribution of the population of all U.S. cities to illustrate the power law. The right-skewed form of the distribution indicates that most U.S. cities have small populations while there are a small number of very large cities. Price (1965) finds that the numbers of citations received by scientific papers can be described as a power law distribution.

Many skewed distributions are well-known. They include power law cumulative distributions that are sometimes called "Pareto distributions," a type of continuous power law distribution first identified by Pareto (also known as the "80-20" distribution because 80% of the total density is accounted for by 20% of the range of values). Pareto observed that 80% of Italy's wealth was owned by 20% of the population. He then carried out surveys on a variety of other countries and found that a similar distribution applied. The 80-20 Pareto principle states that, for many events, 80% of the effects come from 20% of the causes. It has many applications beyond world of economics, especially in engineering and business management. An advantage of the Pareto power law is that the exponent \( \alpha \) offers a measure of the concentration. There is a direct (and clear) relationship between it and the Lorenz concentration index (Bouget and Viénot, 1995).

It is important not to confuse the general phenomenon of the long tail, the power law that provides the general mathematical structure for the long tail, and the Pareto distribution as a particular (and popular) type of power law distribution.

Zipf's law leads to one of a family of related discrete power-law probability distributions first proposed by Zipf (1935, 1949). If we rank a collection of individuals each having the rank \( r \), by the size of the individual \( z_r \), the following relationship defines Zipf's law:

\[
(2) \quad r^\beta z_r = C \quad \text{where} \quad \beta \text{ is Zipf's parameter}
\]

For the distribution of people by their wealth, we can rank the people beginning with the wealthiest person (rank = 1). The individual with the wealth, \( w_r \), has the rank \( r \). In this context the function shows how \( w_r \) is a power-law function of \( r \) (see, for example, Klass et al., 2007). Such power-law cumulative distributions are also call rank/frequency distribution (see Newman, 2006). For relevant applications in the field of economic phenomena see Axtell (2001) and Naldi (2003).

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16 Zipf's law refers to frequency distributions of "rank data," in which the relative frequency of the \( n \)-th-ranked item is given by the Zeta distribution that is the discrete form of the probabilistic Pareto law.
Note that, for small values of the variable being measured (i.e., for values of $x < x_m$), a distribution often may not follow a power law. Consequently estimating the value of the coefficient $a$ only for the values of $x > x_m$ requires making a judgment about the value of $x_m$.

Also note that a large number of highly right-skewed distributions do not follow power laws (Newman, 2006). There are other types of laws that can generate highly skewed distributions. Surprisingly, the second most popular distribution after Pareto’s law is not a general power-law distribution but is the so-called “Gibrat law”, the log-normal law, that describes the distribution of firms by size in particular industries. However, recent studies have shown that the parameters for Gibrat’s law in this situation are not stable (Sutton, 1997). In addition, it’s value as a descriptive device has been challenged by other laws.\textsuperscript{20} Pareto’s distribution and the log-normal law yield very similar distributions. In some cases it is impossible to choose between the two (Petruszewycz, 1972). It is acknowledged that the foundations in terms of probability are clear concerning the log-normal law and somewhat fuzzy for Pareto’s distribution (Bouget and Viénot, 1995).

3.2. The distribution of prolific inventors according their patents

We propose to illustrate these different types of distributions using data collected by Le Bas et al. (2009) and Latham et al. (2009) on the distribution of inventor productivity in terms of inventions patented.

For defining who is prolific inventor we decided to use the threshold of 15 U.S. patents granted over the time period under observation (1975-2002). We have examined the distributions for alternative numbers of patents. There is no large gap between the numbers of inventors having 13 or 14 patents and the (prolific) inventors having 15 or 16 patents. In other words, if we had fixed the threshold at 13 or 14 patents, the number of prolific inventors would have been larger, but this increase would not have been dramatic. We justify choosing 15 patents as our threshold for identifying prolific inventors as follows: Trajtenberg (2004), in his report on inventors in the U.S. patenting system, notes that in the period 1975-1999 the average number of patents per inventor was 2.74 (for all countries). Our period of observation is longer extending through 2002. We know that patenting strongly increased toward the end of the period under consideration. Thus we might expect that the average number of patents per inventor would have risen to about 3.00. It seems to us that a prolific inventor

\textsuperscript{17} Reed (2001) proposes a model that predicts there is a power law fitting the lower tail as well.
\textsuperscript{18} We already have noted it is closed the Pareto distribution.
\textsuperscript{19} Simon and Bonini (1958) show under some general conditions that this distribution might be a power law.
\textsuperscript{20} See in particular Dosi et al., (2007).
would be an individual with productivity (in terms of patents) at least five times higher than the average.\textsuperscript{21} We use data for U.S patents issued to more than 55,000 individual prolific inventors from five countries in our analysis. The countries are those with the largest numbers of patents in the US. Patent system: the U.S., Japan, Germany, France and the U.K.

We have calculated the distribution of this population of prolific inventors according to their individual levels of patenting. Figure 2 displays the relationship between the log of the number of patents per inventor (recall that the patenting begins at 15) and the log of cumulative decreasing frequency of individuals with the number of patents for France. For a large section of the observed distribution of points, a linear relationship fits well. As noted by many authors the right hand end of the distribution is noisy because of the sample size. So we are in the frame of a power law distribution. We could have used simple OLS regressions to calculate slope parameters for the linear functions for each of the five countries. However, Newman (2006) showed that this method of estimation is biased. Fortunately he derived an alternative way of estimating these slope coefficients. Using Newman’s method, we estimate the slopes as follows: Japan 1.5, Germany 1.4, U.S. 1.34, France 1.52, and U.K. 1.74.\textsuperscript{22} The larger is the value of the coefficient, the steeper the slope and the smaller is the skewness. The U.S. has the distribution that is the most skewed, and the U.K.’s is the least skewed. Surprisingly the U.S. has a much larger number of prolific inventors than the U.K. It may be the size of the sample (which is much larger for the U.S.) influences the results but more studies will be necessary to get the right explanation. Note that we could also perform this same analysis using the number of patents by technological fields or we could do it after pooling the data across all five countries.

\textbf{INSERT FIGURE 2 ABOUT HERE.}

\textsuperscript{21} Another option would have been to retain the top 1\% or top 5\% of patenting inventors. Tratjenberg (2004) observes that inventors present in 10 patents and more represent the top 5\% of the inventor population. We thus estimate that with our threshold of 15 patents we focus on the 3\% top inventors (in the U.S. patent system) and thus our figures can be compared with those cited in debates about top or star scientists.

\textsuperscript{22} The ranking of countries as far as this estimator is concerned is virtually identical to those obtained with the OLS estimates and the actual values of the estimated slopes are also very similar.
3. 3. The quest for explanation: the frameworks

We hypothesize that an empirical distribution fitting a power-law is stable (that the exponent $a$ is constant when we calculate it for different time periods or different economic entities). This stability means mechanisms exist working for maintaining the stability of distributions.

Many theoretical frameworks have been proposed to explain why stable power-law distributions arise in the natural and social worlds. From the point of view of mathematical structures, a combination of exponentials can be sufficient for producing power-law distributions. Regarding the basic mechanisms, some researchers have turned to the tools of “complex systems” such as “self-organised criticality” or “highly-optimized tolerance.” Other researchers hypothesize that the well-known Yule process\(^\text{24}\) can be applied to economic phenomena such as the growth of cities, the distribution of wealth, the number of citations to a paper, and so on. In these applications the probability of gaining a new member, or of increasing revenues, or of receiving a new citation is proportional to the number the object already has. The dynamic process is reinforcing.\(^\text{25}\) According to various researchers we have phenomenon such as

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\(^{23}\) In this section we follow Newman’s (2006) survey.

\(^{24}\) In a Yule process, entities get random increments of a given property in proportion to their present value of that property.

\(^{25}\) See Simon (1955). Recall that the power-law distribution has a “broad dynamic range.”
the Matthew effect and the cumulative advantage process, both of which we have discussed in previous sections.

4. ANALYZING THE UPPER END OF THE PERFORMANCE DISTRIBUTION: THE ECONOMICS OF "PROLIFICNESS".

Previous studies on prolific (or key) inventors have focused on firms or industries. For example Narin and Breitzman (1995) use four firms in one sector in their seminal work. Pilkington et al. (2009) use two industries. We have another perspective: we have adopted the individual inventor as the unit of analysis. We choose to focus our analysis around comparisons of individual inventors across countries, across technological fields, and across individuals. We use the empirical results and analysis summarized in the following four papers: Gay et al. (2008), Le Bas et al. (2009), Laredo et al. (2009) and Latham et al. (2009). As previously indicated we use a large database on U.S. patenting from 1975 to 2002, for the five largest countries in terms of scale of technological activities: France, Germany, the U.K., the U.S. and Japan. It contains more than 55,000 prolific inventors. This database provides systematic empirical evidence on the main trends concerning prolific inventors. First we summarize some salient stylised facts drawn from our previous studies. Then we will provide more details on the explanatory framework we propose for “prolificness.”

4.1. Some stylised facts on “prolificness”.

(1) Macro patterns
   (a) The size of the relative population of prolific inventors as a proportion of the total number of inventors, a first index of prolificness, and the number of their patents as the proportion of total patenting, a second index of prolificness, differ across countries (see Table 1). Note that there is a strong asymmetry between the proportion of prolific inventors and the proportion of their patenting. In fact, this asymmetry defines what we term “prolificness.”

(2) The country ranking in terms of “prolificness” according to the first index is: Japan, Germany, U.S., France, and the U.K. (the U.S. and France change places with the second index). The country ranking that we found is coherent (correlated) with what we know about the primary national technological indicators such as R&D expenditures funded by enterprises, triadic patents, and private industrial R&D.

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26 Triadic patents are those filed in the U.S., Japan and Europe.
We observe that prolific inventor patenting is distributed unevenly across technological fields in all countries. We also observe a close relationship between the degree of a country’s technological specialization and the importance of its prolific inventors (measured by their patents as a proportion of all of a country’s patents).

The significance of the correlation between technological specialization and prolificness is confirmed by a strong correlation between the Revealed Technological Advantages Index and the proportion of prolific inventor at technological subcategory level for 37 subcategories of technology. When we regress the RTA and the proportion of prolific inventors at the technological field level, we obtain an $R^2$ of 47.7%. In an expanded model dummy variables to control for country fixes are not significant and broad technological class fixed effects for six categories are significant only for Chemicals. This model has an $R^2$ of 53.3% (Adjusted $R^2 = 50.6\%$). The slope coefficient for the proportion of prolific inventors is significant at the 1% level.

From this last evidence it is possible to provide a tentative explanation. The evidence raises the following question: what is the relationship between country technological specialization and the technological importance of prolific inventors (measured here by their relative number)? It may be that the relationship is simultaneous. On the one hand as more R&D investments are made in the fields in which a country is specialized, there will be more inventions and consequently the more prolific inventors there will be (indirect effects). On the other hand, the strengths of each country are reflected in the presence of large nationally-based firms which are able to maintain their specialization persistently in the context of competitive pressures if they hire the best technological knowledge workers available (prolific inventors). Supporting this interpretation, Pilkington et al. (2009) have recently shown that key inventors are primarily located within a limited number of key firms that show real technological leadership (Pilkington et al., 2009). If this view is correct, we would have a “virtuous circle” linking national technological specialization and prolificness.

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27 We measure a country’s technological specialisation with an index of revealed technological advantage (RTA) as developed and used previously by many authors (see Le Bas and Sierra, 2002). Denoting $P_{ij}$ as the number of patents granted in technological field $j$ to country $i$, the RTA index is calculated on the sample of countries used in this study as follows: $RTA_{ij} = (P_{ij} / S_i P_{ij}) / (S_j P_{ij} / S_j S P_{ij})$. When $RTA_{ij} > 1$, technological field $j$ is revealed to be a strength for country $i$. 
specialisation (countries), technological leadership (firms) and highly productive human capital (inventors). Positive feedbacks stand at the core of the process and self-reinforcing processes are at work here. We find here many of the processes depicted by Antonelli in the introduction to this book, especially irreversibility due to path dependence or deterministic past dependence.

(2) Micro patterns

(a) Almost 30% of our population of prolific inventor got their first patent at the outset of the period of time under observation (1975). In the U.S. a high proportion of prolific inventors (20%) have their first patent after 1990. The variable patent duration (a proxy for the length of an inventor’s career) differs greatly across inventors (and countries). Some inventors are active over only 5 years, others are active for more than 35 years. Japanese inventors have shorter periods of activity, Germans have longer periods. This variable should be used for building a taxonomy of inventors: inventors who patent persistently becomes prolific overtime, others are prolific quickly (the study should control for inter-industrial differences).

(b) Inventor productivity. Negative binomial regressions explaining the inventor productivity (number of patents) show that interfirm and international mobility and technological variety (at the inventor level) positively affect inventor productivity after controlling for patent duration and time concentration. The overall results suggest that the same factors positively impact productivity across countries with few exceptions (Le Bas et al., 2009).

(c) Mobility. The “dominant design” as far as the effects of inventor mobility are concerned is based on knowledge spillovers. In standard microeconomics it is acknowledged that individual mobility is an important source of knowledge externalities (Griliches, 1992; Moen, 2005). Mobility is mainly a local phenomenon, in general knowledge flows between economic units are localized to the extent labour mobility also is (Breschi and Lissoni, 2003). We present evidence for national inter-firm mobility: around 20% of the prolific inventors do not move during the period under observation and international mobility of prolific inventors is very weak (all results shown by Le Bas et al., 2009). The mobility equations for the five countries (France, Japan, Germany, U-K, USA) show that

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28 We envisage here only inter-firm mobility. Latham et al. (2009) deals with geographic mobility and technological mobility (intellectual mobility).
productivity is positively associated with mobility. The more prolific an inventor is, the more mobile he/she is (in accordance with what the recent literature tells us).

(d) Patent value. Following Fleming and Szigety (2006) who described an evolutionary model of breakthrough invention directly linked to prolificness, we thought a priori that the more productive a prolific inventor is, the more valuable are his/her inventions would be. This follows directly from the idea that the most prolific inventor is the one most likely to invent a breakthrough. In fact, our findings do not confirm this implication of creativity. The regressions carried by Latham et al. (2009) for three countries (France, Germany, and the U.K.) show a consistent negative and significant relationship between value and inter-firm mobility. These results are surprising. A priori we expected that value would be enhanced by mobility. Instead we are left to conclude that while mobility may increase patenting, there is more value produced when inventors remain where they begin. The negative relationship with productivity lends credence to the idea of a trade-off for prolific inventors between value and productivity. At this stage of the research we have to remain cautious for two reasons: a) we measure value of patent by citations and numerous authors have emphasized that this measure may be misleading in particular for patents receiving high numbers of citations; and b) so far we have studied the relationship between productivity and value only for the population of prolific inventors. When we conduct a comparison between prolific and non-prolific inventors, as we did in a previous study, the evidence showed clearly that having prolific inventors in the team of inventors is a factor increasing the number of citations (Gay et al., 2008).

(3) Micro-Micro patterns.

(a) Gay et al. (2008) show that prolific inventors work with larger teams than others and produce inventions having more value after controlling for technological field effects.29 These results suggest that a prolific inventor can act as a “knowledge system integrator.” The “knowledge system integrator” (the prolific inventor) coordinates the competence and capabilities of the members of the team in order to increase the firms’ technological performance and its economic competitiveness. This view tends to confirm that human resources are the most important factor for R&D performance (and may be for

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29 This evidence is consistent with the hypothesis that firm size matters as well. Kim, et al. (2004) report that inventor productivity is higher in large firms.
scientific research as well), not only because of the individual talents and qualifications of scientists, but also because of their capacities to create and develop ties with other scientists, the scientific “communities” and networks (Laredo et al., 2009).

(b) Econometric analysis suggests that the presence of a foreign inventor (who may or may be not prolific) on the inventive team has a positive effect on the value of invention. This witnesses the actual importance of the international networks within which large, often multinational, corporations operate (Cantwell and Iammarino, 2003). Firms extend their knowledge activity abroad in order to extract local knowledge for their global production of new ideas.

4.2. Introductory general remarks on an explanatory framework for “prolificness”.

Our empirical findings to date have enabled us to propose a tentative explanatory framework. Our feeling is that there are two fundamental processes that explain the prolificness of inventors: First, prolificness is linked to the role of these inventors as gatekeepers for “science in the making” (in particular in science-based industries). Second, prolificness is linked to the capacity of inventors to aggregate resources, mainly human resources, for deploying their inventions to the extent that they can be patented (see Laredo et al., 2009), not only because of their individual talents and competence, but also because of their capacities to create and develop ties with other scientists, the scientific "communities" and networks. Their creativity tends to define, to some extent, a form of localized technological change (Antonelli, 2008) to the smallest level of analysis: an individual.

These general remarks do not even begin to adequately explain the mechanisms that determine the precise levels of inventor productivity. Our basic hypothesis is that the models laid out in the previous section enable us to account for much of the upper end of the tail of the productivity distribution. But they can help us only to a limited extent. Both of the two main hypotheses regarding the productivity of prolific inventors, the "sacred star" and the "accumulative advantage" hypotheses, seem to be at work. We observe in some cases an inventor is immediately prolific. His/her level of patenting is high. In general he/she is productive over a short period of time. For example, the “star scientists,” when they patent, enter this category. We can think they have high capabilities in their academic and technological fields and stay strongly motivated. By contrast, some inventors patent a few patent per year but
persistently over a long time period. They accumulate knowledge step-by-step. The "accumulative advantage" hypothesis fits well their career or professional trajectory. But at this point of our own research we are not sure that a pattern of "increases in productivity inequality" really works. It sets out the limits of the comparison between inventors and scientists. A Matthews effect is not observed here, or if it is, only with special insights. Surely an inventor must receive financial incentives for researching, inventing, and accumulating knowledge but the incentives are not the same kind as the rules governing the awards system in science. It may be that the Matthews effect works since a good productive inventor will receive more money from the firm for developing his/her research program. Basically industrial firms are in a competitive environment, they have to survive and they search for new technological knowledge, not for the sake of increasing the current stock of knowledge but for innovating in a business environment (the users part of the knowledge economy). The recognition of the inventor is linked to a great extent to his/her capacity to produce new knowledge that is economically useful (innovation). The awards come from the market, not from the “community of inventors.” Of course, in science, the opinion of peers is of paramount importance.

5. CONCLUSION

The preceding discussion has placed the analysis of prolific inventors at the heart of understanding the dynamic complexity of innovation and technological change. Our analysis has been based on only preliminary analyses, ours and those of others that have been completed to date. We hope that those analyses and our discussion of them now provide guidance in the continuing development of empirical research programs on innovative productivity. We hope to contribute to the emergence of both a useful inventor productivity taxonomy and a coherent explanatory framework for the observed patterns of innovative behaviour.

We believe that the preliminary work suggests some implications for policy and management. Regarding the relations between mobility and productivity, the policy implications of our findings are clear but puzzling: more total value will be created in R&D if incentives are used to keep inventors where they are. It seems that the externality spillover losses from mobility in the firms from which inventors move are not offset by the gains in productivity in the firms to which inventors move. This is a classic example of private markets not being able to adequately balance private individual gains with global losses.
Prolific inventors make up a very special variety of human resources that require particular management. First, policies and incentives are needed in order to both motivate these productive people to share their knowledge and know-how and simultaneously discourage movements that are not likely to be productive or, at least, to discourage them from moving too quickly. Leonard and Swap (2005) have described some criteria for the management of “deep smarts,” the people who have a high level of expertise in all the areas of the industrial life. It may be useful to apply their analysis to prolific inventors.

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30 Inventor mobility must also now be understood as a component of the firm’s overall competitive strategy. High tech firms seek competitive advantages by actively encouraging defections among their competitors’ technological personnel (Kim and Marschke, 2004). See also Fleming and Marx (2006).
6. REFERENCES


Le Bas et al. (2009), Who are the prolific inventors? What data on US patents from five countries tell us, Paper for the LEFI and ESDES workshop, The role of inventors and patents: Analysis and methodological issues, Lyon.


Moen, J. (2005), Is mobility of technical personnel a source of R&D spillovers? Department of Economics Discussion paper 05/01, Norwegian School of Economics and Business Administration, Oslo.


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<th></th>
<th>GB</th>
<th>France</th>
<th>U.S.</th>
<th>Germany</th>
<th>Japan</th>
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<tr>
<td><strong>Total Number of Prolific Inventors</strong></td>
<td>813</td>
<td>1157</td>
<td>26279</td>
<td>5270</td>
<td>19418</td>
</tr>
<tr>
<td><strong>Index of prolificness (1)</strong></td>
<td></td>
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<tr>
<td>Number of Prolific Inventors / Total Number of Inventors</td>
<td>1.32</td>
<td>1.75</td>
<td>2.66</td>
<td>3.77</td>
<td>7.31</td>
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<tr>
<td><strong>Index of prolificness (2)</strong></td>
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<td></td>
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<td></td>
<td></td>
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<tr>
<td>Number of Prolific Inventors’ Patents / Total Number of Patents</td>
<td>20.27</td>
<td>34.62</td>
<td>33.72</td>
<td>40.02</td>
<td>66.61</td>
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<tr>
<td><strong>Average Number of Patents per Inventor for All Inventors</strong></td>
<td>2.34</td>
<td>2.38</td>
<td>2.80</td>
<td>3.49</td>
<td>4.94</td>
</tr>
<tr>
<td><strong>Average Number of Patents per Inventor for Prolific Inventors</strong></td>
<td>24.63</td>
<td>26.34</td>
<td>25.77</td>
<td>30.05</td>
<td>31.14</td>
</tr>
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Source: Le Bas et al. (2009)