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Technology policy for a world of skew-distributed outcomes

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Abstract

This paper draws implications for technology policy from evidence on the size distribution of returns from eight sets of data on inventions and innovations attributable to private sector firms and universities. The distributions are all highly skew; the top 10% of sample members captured from 48 to 93 percent of total sample returns. It follows that programs seeking to advance technology should not be judged negatively if they lead to numerous economic failures; rather, emphasis should be placed on the relatively few big successes. To achieve noteworthy success with appreciable confidence, a sizeable array of projects must often be supported. The outcome distributions are sufficiently skewed that, even with large numbers of projects, it is not possible to diversify away substantial residual variability through portfolio strategies. © 2000 Elsevier Science B.V. All rights reserved.

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During the past several years the authors have been compiling data on the size distribution of financial returns within samples of significant technological innovations. Our uniform finding is that the returns are skew-distributed. Most innovations yield modest returns, but the size distribution has a long thin tail encompassing a relatively few innovations with particularly high returns. In this paper, we review earlier research, summarize our new evidence, and suggest implications for technology policy.

1. Prior research

Until recently there has been relatively little systematic empirical research on the statistical distribution properties of the returns from invention and innovation. Drawing upon a small sample survey of US patents, co-author Scherer (1965) (p. 1098) discovered a distribution of estimated profits from patented inventions so skew that ‘‘patent statistics are likely to measure run-of-the-mill industrial inventive output much more accurately than they reflect the occasional strategic inventions which open up new markets and new technologies. The latter must probably remain the domain of economic historians.’’ A second line of investigation differentiated the value of patents by the time when their holders chose not to pay the annual renewal fees imposed in some nations. The pioneering article in this tradition, overlooked by subsequent investigators, was by Dernburg and Gharrity (1961–1962). Leading examples of later investigations using more powerful econometric techniques include Pakes and Schankerman (1984), Pakes (1986), Schankerman and Pakes (1986), and

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Lanjou et al. (1996). These studies confirmed that the size distribution of patent values is indeed quite skew, most likely conforming either to a log normal or Paretian distribution law. A third line of research by Grabowski and Vernon (1990; 1994) used the particularly rich data available on sales of individual ethical drugs throughout the world to estimate the distribution of profits (or more exactly, quasi-rents) attained by samples of new drugs approved by the US Food and Drug Administration (FDA). Again, a skew distribution was found, leading inter alia to the conclusion that heavy-handed price controls could jeopardize the continued vitality of new drug discovery and testing efforts (see e.g., Grabowski and Vernon, 1996; Scherer, 1996).

2. The new evidence

Altogether, we have assembled eight data sets, seven of which are new to the literature. Table 1 describes the samples and provides a simple indicator of distribution skewness — the fraction of total sample profits, royalties, or stock market value contributed by the 10% of the sample members realizing the highest absolute or relative rewards.

In the most ambitious of our efforts, we collected survey and interview evidence on 772 German- and 222 US-origin inventions, on all of which German patent applications were filed in 1977, leading to issued German patents considered sufficiently valuable by their holders to warrant paying annual renewal fees totalling DM 16,075 until their expiration at full term in 1995. These are called the ‘‘German patents’’ and ‘‘US patents’’ in Table 1. [1] Fig. 1 shows the distribution of summed German patent values by value class intervals, with the number of patents in each value category given in parentheses above the bars. Fifty-four percent of the value is concentrated in the five inventions with values of DM 50 million or more.

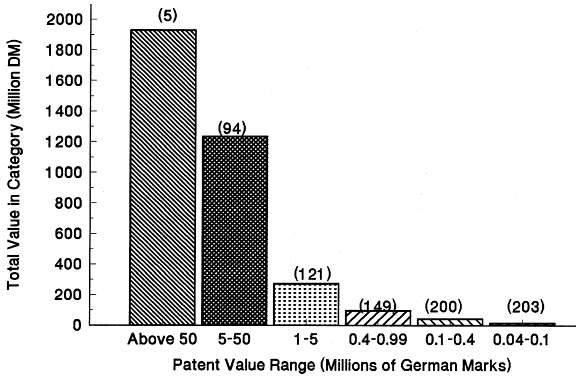

Fig. 1. Distribution of German patent values.

Table 1
Proportion of innovation samples' total value realized by the most valuable 10% of innovations

Data set	Number of observations	Percent of value in top 10%
German patents	772	84
US patents	222	81–85
Harvard patents	118	84
Six university patents		
1991 royalties	350	93
1992 royalties	408	92
1993 royalties	466	91.5
1994 royalties	411	92
Venture Economics startups	383	62
Horseley–Keogh startups	670	59
Initial public stock offerings (IPOs) — 1995 stock value	110	62
Grabowski–Vernon		
1970s drugs	98	55
1980s drugs	66	48

Our first-stage patent survey methodology asked company respondents to answer a single counterfactual question, phrased as follows in the US survey.

> If in 1980 you knew what you now know about the profit history of the invention abstracted here, what is the *smallest* amount for which you would have been willing to sell this patent to an independent third party, assuming that you had a bona fide offer to purchase and that the buyer would subsequently exercise its full patent rights?

In the first-stage survey, respondents were asked to place each sample patent in one of five value cate-

[1] A detailed analysis is found in Harhoff et al. (1997). The monetary patent value estimates are linked to subsequent patent citations in Harhoff et al. (1999).

gories ranging from less than DM 40,000 to more than DM 5 million. Fifty-six on-site interviews were held with companies reporting patents valued at more than DM 5 million, making it possible to elicit more detailed discounted profitability and invention value estimates. Because selling full rights meant that the patent holder could be enjoined from using its invention or forced to pay royalties reflecting the invention's value, the survey responses elicited private value estimates (grouped in value class intervals) corresponding most closely to the discounted present value of profits that would be foregone by not having the invention *and* its accompanying patent protection. As such, the estimates are roughly two orders of magnitude higher than those obtained in statistical studies of patent renewal, which implicitly assess only the value of patent protection, given disclosure and non-patent barriers to imitation, not the value of the invention per se, and which estimate the value of the presumptively most valuable full-term patents only by extrapolation.

Two other data sets also focused on invention patents, one tallying the royalties received between 1977 and 1995 on 118 patent ''bundles'' covering inventions made by Harvard University employees and licensed by the Harvard Office of Technology Licensing, the other analogous royalties received during the years 1991 through 1995 on inventions made at six research-oriented US universities. These are called the ''Harvard patents'' and ''six university patents'' in Table 1. The ''Venture Economics startups'' and ''Horsley–Keogh startups'' samples in Table 1 evaluated the asset value appreciation (or loss) experienced on a total of 1053 investments in startup companies by US venture capital firms between 1969 and 1988. The ''IPOs'' sample measures the appreciation of common stock values as of 1995 for 131 high-technology companies which made IPOs between 1983 and 1986. Finally, we take advantage of the data compiled and analyzed previously by Grabowski and Vernon (1990; 1994) on the discounted present value of quasi-rents realized on new pharmaceutical entities marketed in the United States — 98 of them introduced during the 1970s and 66 between 1980 and 1984.

In all cases, a relatively small number of top entities were responsible for most of the total value realized from the full cohort of innovations. The highest concentration of value is found for the patents, which tend to cover the narrowest range of innovative subject matter. The fraction of total portfolio value attributable to the top 10% of startup business investments is quite similar for the two sets of venture fund-backed companies and for the IPO companies (whose value gains occur at a later life cycle stage, since venture funds typically liquidate their positions shortly after the companies they have backed float IPOs). The least skewness is found for the new drug entity samples, perhaps in part because the samples include only products that had passed through rigorous FDA approval regimens.

For the German patents, Harvard patents, IPOs, and Grabowski–Vernon drug products, the data were of sufficient richness that we could statistically test alternative distribution form hypotheses (see Harhoff et al., 1997; Scherer, 1998; Scherer et al., 1999). For all five samples, the best-fitting distribution was the log normal (surpassing, e.g., Pareto–Levy, Weibull, negative exponential, and Maddala–Singh alternatives). The Grabowski–Vernon drug distributions, with the lowest fraction of value residing in the most valuable 10% of observations, were discernibly less skew than the log normal, but clearly more skew than alternatives such as the Weibull. This finding will be important at a subsequent stage of the argument.

3. Implications for R&D funding agencies

Our research reveals that the lion's share of the privately appropriated value through investments in innovation comes from roughly 10% of the technically successful prospects. This is true for patents, which typically cover quite narrow slices of technology, for discrete products (i.e., new drug chemical entities), and for whole firms securing venture capital or new public issue financing. Our study of high-technology startup firms' stock market performance over roughly 10 years reveals in addition that it is difficult to predict in advance *which* of the prospects considered attractive enough to warrant investment will pay off most lucratively.

A further, less fully documented, step must be taken to draw implications for technology policy, as implemented by governmental organizations. None of our data sets attempted to measure the *social* returns realized through technological innovation. However, there is no reason to suppose that the size distribution of payoffs from government research and/or development projects is qualitatively different from what we have observed for our samples of private sector and university projects. Fragmentary evidence suggests that the social returns from private investments and the returns from government projects are similarly skew-distributed. Thus, one cannot reject even at the 20% confidence level the hypothesis that the social rates of return calculated by Mansfield et al. (1977) on 16 private-sector innovations were log-normally distributed. [2] Similarly, crude data on the number of combat vehicles produced following government R&D programs in the fighter aircraft, bomber, and guided missile fields reveal a skew distribution. [3] Thus, for the inferences made in the next two paragraphs, we assume that the size distributions of returns from government projects have skewness properties similar to those we have observed in our more thoroughly analyzed private sector data sets.

Legislators and senior government leaders are likely to view government technology programs in which half the supported projects fail to yield appreciable returns and only one in 10 succeeds handsomely as a rather poor track record when in fact, by the standards of private sector markets, it is quite normal. [4] Those who are responsible for the allocation of financial resources to support the advance of technology should adjust their expectations accordingly. Similarly, researchers who seek to assess the success of government technology programs should focus most of their effort on measuring returns from the relatively few projects with clearly superior payoffs, not on projects in the heavily populated low-value distribution tail.

Our results also suggest the wisdom for technology policy in Mao Tse-Tung's aphorism, ''Let one hundred flowers bloom'' — implemented, to be sure, with greater discrimination and consistency than Chairman Mao exhibited in propagating his Great Leap Forward. Among other things, technology policies that concentrate government subsidies on a relatively few national champion enterprises may fail through insufficient statistical diversity, even if (as is debatable) leading firms embrace new technological opportunities as enthusiastically as their smaller counterparts. [5] Rather, from our findings one gains enhanced appreciation of the US venture funding system, under which private risk capital flows each year to thousands of high-technology startup companies in the hope that the returns from a handful will compensate, or more than compensate, the investors. Most industrialized nations have been slow in imitating that institution, which was almost surely the principal basis of US success in high-technology industries during the past decade. [6]

4. The efficacy of portfolio strategies

All this suggests the need for both nations and firms to pursue a portfolio approach to backing new technology, recognizing that only a few of the projects supported will pay off on a large scale and hoping that generous returns from the relatively few successes will also cover the cost of the many less successful projects. One should not, however, exaggerate the efficacy of portfolio strategies as a means

[2] One negative observation was excluded, leaving 16 useable observations, whose distribution in the logarithms had a skewness coefficient of 0.05 and a kurtosis coefficient of 2.53. The values for a perfect log normal distribution would be 0 and 3.0, respectively. For the 16 observations before logarithmic transformation, the skewness coefficient was 1.83, which differs from normality at the 0.01 significance level. Mansfield et al. (1977) estimated internal rates of return rather than undiscounted or discounted total returns, as in our samples. The distributions of internal rates of return are intrinsically less skew than present values of absolute payoffs, calculated at conventional discount rates, because the polynomial deflation carried out to determine internal rates of return tends to suppress very large values.

[3] These estimates were made by co-author Scherer in a work done for the US Department of Justice in opposition to a merger between Lockheed–Martin and Northrop–Grumman.

[4] We owe this insight to Arati Prabhakar, former director of DARPA and then the US National Institute of Standards and Technology, from a discussion at a US Department of Defense Science Council meeting in 1993.

[5] Compare Scherer (1992) and Christensen (1997).

[6] For a comparative analysis of various leading nations' high-technology venture systems, see US National Science Board (1998) (pp. 6–30–33). For a comparison of US and German systems, see Kukies and Scherer (1998).

of hedging against the risks from investing in new technologies.

We began our research hypothesizing provisionally, based upon fragmentary earlier evidence, that the returns from investments in new technology adhered to a Pareto–Levy distribution. Where V is the value of profits from an innovation, N is the number of cases with value V or greater, and k and α are positive parameters, the simplest Pareto–Levy distribution is characterized by the equation:

$$N(V) = kV^{-\alpha}.$$

The equation is linear in the logarithms, with a long thin tail into the highest-value range of innovation profits. The Pareto–Levy distribution has the unusual property that when $\alpha < 1$, the weak law of large numbers fails to hold, so that neither the distribution's mean nor its variance is asymptotically finite. What this means in practical terms is that as one draws ever larger samples, there is an increasing probability that some extremely large observation will materialize, causing both the mean and the variance to explode upward rather than converging toward stable values. This in turn implies that it is difficult or impossible to achieve stable mean expectations and hence hedge against risk by supporting sizeable portfolios of projects.

Our research failed for the most part to support the Paretian hypothesis, pointing instead toward log normal distributions with better-behaved large-sample properties. That is good news for the users of portfolio strategies. However, the log normal distributions we observed were themselves quite skew and indeed hard to distinguish statistically in their extreme-value tails from Paretian distributions. As such, attempts to achieve stable mean returns through feasible portfolio strategies are likely to yield at best middling success.

To demonstrate this point, we report on a series of Monte Carlo experiments using the Grabowski–Vernon quasi-rent data for 98 new drugs that cleared FDA regulatory hurdles and were introduced into the US market during the 1970s. The distribution of 1970s drug quasi-rents, we recall from Table 1, was the second-to-least skew of any of the distributions on which we obtained data, and thus it provides a relatively optimistic test of the problems that attend portfolio strategies.

Each individual quasi-rent observation in the Grabowski–Vernon data set was replicated 10 times, and the observations were stored in a (figurative) computer urn, where their order was randomized. From supplementary data that underlay the Grabowski–Vernon quasi-rent estimates, it was assumed that the typical drug has a rent-earning life of 21 years following its introduction into the market. The rents for any given drug were assumed to be distributed triangularly over time, with peak rent-earning at year 10. During the period for which the Grabowski–Vernon data were collected, an average of 18 new drug chemical entities per year were approved by the FDA and introduced into the US market. Thus, for each year over a total of 70 years, 18 new drugs were drawn randomly from the computer urn. For each drug so drawn, its quasi-rents were spread over 21 years. When the sampling was completed, the quasi-rents of all drugs on the market in any given year (i.e., 18 drugs per year times 21 years = 378 rent-earning drugs) were summed. Because they included incomplete numbers of drugs, the totals for the first and last 20 years were deleted from the sample, leaving quasi-rent totals for 30 years, each year's total comprising the moving sum of 378 observations. After further randomizations, the experiment was repeated over a total of seven complete runs.

The results are summarized in Figs. 2 and 3. For all years and all simulations combined, mean annual

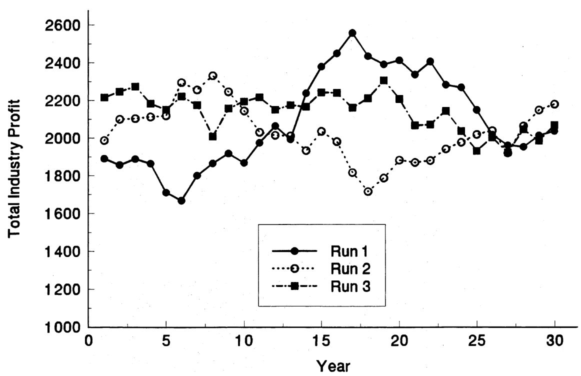

Fig. 2. Plot of drug industry profit simulations, runs 1, 2, and 3.

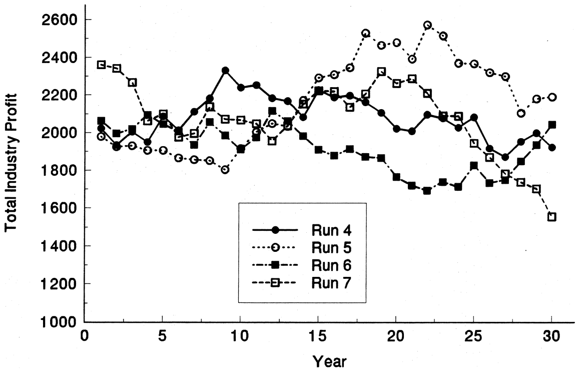

Fig. 3. Plot of drug industry profit simulations, runs 4, 5, 6, and 7.

quasi-rents amounted to US$2.07 billion. Total quasi-rents varied widely from year to year, however, from a minimum of US$1.55 billion (in run 7) to a maximum of US$2.57 billion (in run 5), with an average year-to-year standard deviation of US$168 million. Inspecting any given run's quasi-rent fluctuations without knowing that they were generated by a random sampling process, one might infer that they reveal systematic ''cycles'' quite like the cycles actually observed in total US drug industry profitability. But this would be wrong. Rather, the year-to-year and sample-to-sample variability is typical of what happens when one draws relatively large samples of individual values that are skew-distributed.

The annual quasi-rent totals presented in Figs. 2 and 3 stem from a methodology that in effect covers all the new products on the US market in any given year over the products' life cycles. Thus, they reflect portfolio averaging at the whole pharmaceutical industry level. Even with a skew log normal distribution, it remains true that the more observations over which one samples, the more stable the year-to-year averages (or totals) are. Thus, recent mergers among pharmaceutical companies, motivated in part by a desire to create larger portfolios spreading the risks of individual R&D project investments, undoubtedly do reduce the year-to-year variability of outcomes. But even at the extreme of merging the entire industry into one hypothetical firm, year-to-year standard deviations equal to roughly 8% of industry quasi-rent totals remain. For individual firms much smaller than the pharmaceutical industry aggregate, substantially larger year-to-year variations cannot be escaped through portfolio strategies. [7] Thus, given skew-distributed outcomes, appreciable risk-taking cannot be avoided. And in judging the innovative performance of individual firms, a long time perspective is essential, since short-run returns can be dominated by particularly favorable or unfavorable draws from a skew distribution.

5. Macroeconomic implications

The drug quasi-rent distribution used as the basis for our Monte Carlo analysis was, to reiterate again, less skew than all but one of the distributions summarized in Table 1. For the other more skew distributions, one would expect even more instability of means and totals for relatively large samples — e.g., extending to the whole-industry level. This raises the question, might the skewness of innovation outcome distributions contribute instability even when the individual effects are aggregated up to the level of a whole economy? In other words, might the real business cycles (more accurately, business fluctuations) to which macroeconomists have called attention be attributable in part to randomness in draws from a skew-distributed universe of innovative opportunities? A Monte Carlo experiment by Nordhaus (1989) suggests that they may be. He postulated that 99.99% of the tens of thousands of invention patents issued each year are worthless, but that the remaining 0.01% (i.e., three to eight inventions per year) have high values adhering to a Pareto distribution with a fairly conservative α coefficient of 1.3. The effects of those valuable inventions were assumed to seep into the economy slowly but persist indefinitely. Making random draws from his Pareto distribution and aggregating the effects, Nordhaus simulated year-to-year fluctuations in economy-wide productivity growth ranging from 0.5% to 3.5% per year in a seemingly cyclical pattern resembling the productivity growth fluctuations actually experienced by the US economy over the years 1900 through 1988.

[7] Thus, for a drug firm one-fifth the size of the total industry, the year-to-year standard deviation (assuming log normality) would be on the order of 18%; for a firm one-tenth the size of the industry approximately 25%.

We had contemplated performing a similar analysis using our much richer data, but concluded that the additional assumptions required would overwhelm the empirical observations per se and therefore that the results would be too assumption-dependent to provide reliable insights. There were three problem clusters.

First, our data are uniformly for private economic values, whereas a proper macroeconomic analysis requires the use of social returns to innovation, taking into account unappropriated benefits and other externalities, not merely private returns. The translation from private to social returns must have large but poorly understood stochastic components. [8]

Second, our patented invention samples are limited to a single year's cohort, and hence may not have captured the most extreme private values. And for the US sample, the survey elicited value estimates only for discrete categories, including an open-ended category of US$100 million and more. We know from telephone interviews with respondents that some of the 18 estimates in the highest category were valued at more than US$1 billion, but the evidence is too incomplete to support a confident extrapolation. Assuming the categorical data to be Pareto-distributed and extrapolating linearly from the fitted US patent size distribution to the extreme tail, one finds the most valuable invention in our sample to have a private value of US$90 billion (see Harhoff et al., 1997). But given the more complete evidence from other samples, it is unlikely that the log linearity associated with a Pareto distribution persists into the extreme tail, and so the validity of this extrapolation is dubious. [9] If one ignores that hazard, crude simulations imposing minimal structure on the data reveal sufficient skewness to generate macroeconomic fluctuations of appreciable magnitude.

Third, too little is known about the detailed structure of individual innovations' macroeconomic effects. For any given innovation value, longer lag structures will produce smoother effects than short lags; Koyck-type lags will impart sharper fluctuations than, e.g., lag effects distributed in a bell-curve pattern over time. [10] Major innovations can generate positive multiplier effects, and reverse causality can also intrude as macroeconomic swings induce demand-pull effects on the supply of innovations (see Schmookler, 1966). Interactions among individual inventions also cannot be ignored. Simulation analyses suggest, for example, that both complementarities and competitive interactions among inventions with Pareto-distributed individual values lead to revised value distributions that are less skew than Pareto.

Given these difficulties, we chose not to attempt a full-scale Monte Carlo analysis of macroeconomic implications. The most that can be said is that the skew distribution of innovation values could in principle lead to noticeable macroeconomic fluctuations, and that must remain a tantalizing hypothesis for future research.

6. Conclusions

Our empirical research reveals at a high level of confidence that the size distribution of private value returns from individual technological innovations is quite skew — most likely adhering to a log normal law. A small minority of innovations yield the lion's share of all innovations' total economic value. This implies difficulty in averting risk through portfolio strategies and in assessing individual organizations' innovative track records. Assuming similar degrees of skewness in the returns from projects undertaken under government sponsorship, public sector programs seeking to support major technological advances must strive to let many flowers bloom. The skewness of innovative returns almost surely persists

[8] The most relevant analysis, focusing on internal rates of return rather than absolute magnitudes, is by Mansfield et al. (1977). The simple (Piersonian) correlation between their social and private rate of return estimates for 17 innovations was +0.47.

[9] To be sure, innovations with *social* payoffs of that magnitude (e.g., 3.2% of 1980 US GDP) undoubtedly exist. Probable examples include Alexander Graham Bell's telephone, Edison's electric light (see Nordhaus, 1997), the Otto internal combustion engine, television, integrated circuits and microprocessors, and the Cohen–Boyer gene splicing inventions (whose three patents are included in our six universities sample, yielding US$75 million in royalties from numerous non-exclusive licenses during 1991–1994). Most of these innovations were covered by multiple patents, some competing and some complementary.

[10] See e.g., Ravenscraft and Scherer (1982).

to add instability to the profit returns of whole industries and may extend even up to the macroeconomic level. Although much remains to be learned, some important lessons for technology policy have begun to emerge.

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