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MEASURING INNOVATION PERFORMANCE.

ALSO

USING PATENT DATA TO MEASURE INNOVATION PERFORMANCE

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Bibliography:

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Abstract

Technologically radical innovations are a key success factor in many high technology industries. This study examines how firms can measure performance on this key dimension. I ask two questions: 1. How can patent data be used to measure innovation and its radicality?, and, 2. What are some of the empirical shortcomings with the current methods using patent data? These research questions are examined through a longitudinal data of 100 biopharmaceutical companies. Two main conclusions are drawn. First, patents and the subsequent patents that cite them provide a useful way to measure innovation performance. Patent data can be used to monitor activities of competitors, form a performance evaluation system in R&D organizations, and identify a specific technological trend. Second, in prior research, patent citation lags used to distinguish between innovations of different quality have been too short to distinguish between incremental and radical innovations. Lags of ten years and longer are recommended. Short lags may obscure patent-based comparisons of firm innovativeness.

Key words: innovation performance, patents, biotechnology industry.

INTRODUCTION

This study examines measurement of innovation performance and its radicality. I show how patents can be used to evaluate the innovation productivity of firms and divisions, and how patent data provides a way to distinguish the quality, i.e. the *radicality*, of innovations. Studying measurement of innovation radicality is important for at least four reasons. First, radical innovations increase *firm performance* and competitive advantage. In many high-technology industries industry leaders often produce incremental improvements and follow their core technologies to obsolescence and obscurity, while companies that are able to produce radical innovations become the new leaders (Mitchell, 1989). Consequently, accurate and objective measurement and monitoring of radical innovation becomes important. Second, what gets measured often *drives behavior*. Focusing attention on qualitative differences in innovation can potentially enhance the quality of the organization's innovation output.

Third, from the researcher's point of view the study of radical innovations is motivated by the observation that the concept of radicality is increasingly used in *new contexts*. Previously, radical innovation has been a widely-used construct in industrial organization economics and strategy studies. The general conclusion of this prior work is that incumbents have a somewhat reduced incentive to innovate radically because of their existing interests in the technology and market (Henderson, 1993). Recently, researchers on technological collaboration, for example, have also started to measure radicality, and ask how the incumbents' lack of incentives to innovate radically affects the radical innovation performance of collaborative relationships the incumbents are involved in. Fourth, despite the importance of the concept of radical innovation, and its wide use in the literature, there is relatively *little guidance on how to measure* radical innovation. Both the theoretical and the practical importance of radical innovations motivate the study of reliable and valid operationalizations of this construct.

I begin the paper with defining, and categorizing the definitions of radical innovation, and discuss prior work on measuring such innovations. I then present a study of biotechnology companies using patent-based measures of innovation. In the remaining of the paper the results of this study are further analyzed from the point of view of radical innovation measurement. Based on this analysis, several recommendations for future work are given. Implications for theory and practice conclude the paper.

RADICALITY OF INNOVATION

Definitions of radical innovation

Before discussing the measurement of radicality in more detail it is important to establish what we wish to measure; i.e. how we define innovation radicality. There is no commonly accepted definition of the radicality [1] of innovation. I propose that previous definitions of radical innovation can be arranged in four broad categories; organizationally, industry-, user- and technologically radical; each addressing a different dimension of radicality. Below I briefly discuss each of the four categories of radicality. This study focuses on technologically radical innovations using patent data to operationalize this construct.

The first category of radical innovations defines radical as new to the *organization*. Organizationally radical innovation may be defined as innovation which incorporates a technology that is new to the firm, but may be well understood by others (Green, Gavin and Aiman-Smith, 1995). Organizational radicality has also been described as a degree of change the innovation makes in the existing practices of the organization. The second category of radical innovations defines radical as new or disruptive to the *industry*; radical new products dominate and make obsolete the previous products in established markets and can give rise to new industrial sectors (Achilladelis, Schwarzkopf and Cenes, 1990). The third category defines radical as providing relative advantage to the *users*; user-radical innovations appear in fundamentally different product forms that command a decisive cost, performance, or quality advantage over prior forms (Anderson and Tushman, 1990).

The fourth category of radical innovations, which is in more detail examined in this study, defines radical as *technologically* new and significant. Technologically radical innovations draw on new or different science bases, require development of qualitatively new technological capabilities and incorporate technology that is a significant departure from existing technology (Henderson and Clark, 1990). Rosenbloom and Christensen (1994) argue that radical innovations disrupt the established trajectories of technical advance and introduce a discontinuity in performance evaluation.

Measurement of radical innovation

Although both industrial and academic researchers have tried to measure significance or radicality of innovations using several methods, there is no commonly accepted way to measure radical innovation. In this sub-section several measures used in prior work are discussed. I discuss the strengths and weaknesses of these measures, and specifically address how patent-based operationalizations can address some of the central weaknesses of the other measures.

Radical innovation has been operationalized using several methods. Some authors have used qualitative data such as expert or manager interviews to determine the most radical innovations in the industry (see for example Achilladelis et al., 1990; Green et al., 1995; Henderson, 1993). Anderson and Tushman (1990) combine qualitative methods with quantitative data. They operationalize a radical design as an innovation which improves the current performance “frontier” by a significant amount; for example a significant improvement in the CPU speed of the computer. Also Christensen and Rosenbloom (1994) use performance improvement data to draw technological trajectories and to operationalize radical innovation.

These previous operationalizations of radical innovation have three main weaknesses. First, in many studies evaluation of radicality is based on subjective assessments by managers, industry experts, or customers. Reliability of these measures is context-dependent. Second, collecting this qualitative data is time- and resource-consuming. Third, prior operationalizations of radicality rarely distinguish between the four types of radicality discussed earlier in this paper. Many of the above-mentioned radical innovation studies also use a binary categorization of radicality: innovations are either incremental or radical. Most authors, however, acknowledge that radicality as a theoretical construct is a continuum (Green et al., 1995).

The three weaknesses of radical innovation measures discussed above can be, however, addressed by patent-based measures as described in this study. First, by definition, patents provide a relatively objective measure of new knowledge. Patents are required to describe something novel and not obvious; to be patented "an invention must be something not already known from prior publication, or not a part of the experience of those skilled in the art" (Walker, 1995: 83). Patents thus provide a good measure of technologically new knowledge as defined above. Several studies have recently used patents as a measure of innovation performance (e.g., Dutta and Weiss, 1997; Henderson and Cockburn, 1994). Hall, Griliches and Hausman (1985: 265) conclude that patents are measuring something “above and beyond R&D inputs, a creation of an underlying knowledge stock”.

Second, in addition to the methodological strengths of patent-based measures, also the availability of patent data motivates the use and research on patent-based measures of innovation. Electronic access to patent data through for example EPO and US Patent and Trademark Office databases has increased the use of patents in industrial and academic research (Pavitt, 1988; Walker, 1995). Arora and Gambardella (1994) further argue that the importance of patents as innovation appropriability mechanisms will be increasing in many industries in the future as several technological disciplines become more universal and the knowledge will be easier to articulate for patenting. Thus, patents are even more likely to be used as measures of innovation in future research. The third motivating factor identified above, continuous measurement of technological radicality, is discussed in more detail next.

Citation-weighted patents as a measure of innovation radicality

Several authors (see for example Jaffe et al., 1993; Patel and Pavitt, 1995; Trajtenberg, 1990) have argued that patents can vary enormously in their importance and value. In the context of radical innovation measurement, comparing simple patent counts is unlikely to totally capture the qualitative differences in innovative output between for example two departments, or two competing firms. Consequently, Henderson and Cockburn (1994) use granting in two of the three major geographical markets as an indicator of the patent's importance. Other authors have added citations to patent counts, i.e. citations that the focal patent receives in subsequent patents, to get a continuous measure of the qualitative differences in innovation performance. If a patent is cited in numerous subsequent patents, the technology revealed in that patent document is apparently used in many subsequent developmental efforts (Trajtenberg, 1990). These citations are thus argued to indicate the technological value of the innovation (Albert et al., 1991; Dutta and Weiss, 1997). See Figure 1 for an example of the difference between raw and citation-weighted patent counts.

The citation-based patent measure is examined in more detail in this study. Much in the same way as scholarly articles cite previous work in the area, patent documents record the previous knowledge (patents) upon which the idea is based and out of which it grew. However, patent citations differ from journal citations in one important way: references to previous literature are made by both the inventor as well as by the patent office examiner - expert in the field of invention (Walker, 1995). Thus, the citations in patent documents may actually be a more reliable and powerful measure of the idea's contribution to subsequent work than those found in journals. Note, however, that patent citations as a measure of innovation radicality are limited to the technological radicality aspect of innovation, as explained above. Still, patent citations provide one of the best sources of technological radicality measure available to us (Patel and Pavitt, 1995).

Several studies provide evidence that citations are a good measure of the quality of innovation. Carpenter et al. (1981) show that patents that were the basis of radical innovations (radical innovation measured by IR-100 award; 100 most significant new technical products) received more than twice as many citations as a matching sample of random patents. Also Trajtenberg (1990) demonstrates that citation-weighted patents are a valid measure of radicality of innovation: he finds a significant relationship between citation-weighted patent counts and independent measures of economic and social value of these same innovations. Also a study by Eastman Kodak and CHI Research confirms that high patent citations were associated with technological importance as evaluated independently by knowledgeable peers.

While citation-weighted patent studies are becoming more common, few studies have explored the issues relating to the construct validity of this measure. This study examines the citation-based measure of technological radicality (sum of patents and citations) used by Dutta and Weiss (1997). I focus on two measurement issues: the correct citation lag and the differences in citation patterns between incremental and radical innovations; and formulate recommendations on how to increase validity on these dimensions.

SAMPLE STUDY - BIOTECHNOLOGY COMPANIES AND RADICAL INNOVATION PERFORMANCE

In this section I present a more hands-on example on how to use patent and citation data in performance measurement. Empirical data on biotechnology collaborations and their innovation performance is examined. I test the effects of R&D collaborations on radicality of innovation performance. A sample of 100 biotechnology companies is examined. Since the main focus of this paper is in innovation performance measurement, I concentrate on patents and patent citations, and I only briefly summarize the hypotheses of the sample study and the empirical results. In the following sections this sample data is further examined to test how well the patent-based measures measure innovation radicality.

Patenting in biotechnology

The importance of patenting differs greatly across industries. In this subsection I discuss a special case of biotechnology patenting, and how patents provide a good measure of innovativeness in this industry. While patents on microorganisms have been granted for many decades, the patent offices generally rejected patent applications on biotechnology until the early 1980s. However, in 1980, the US Supreme Court determined that genetically engineered organisms are patentable under the US patent law (The Chakrabarty case). Since the 1980 Chakrabarty decision, the governments all over the world have revised patent policy on several occasions to facilitate biotechnology patenting (Walker, 1995).

Several factors indicate that since the early 1980s patents have provided a good measure of innovative output in biotechnology. First, both Arundel and Kabla (1998) and Levin et al. (1987) find that the effectiveness of pharmaceutical and biotechnology patents is the best of all industries. Second, several authors have used patents to operationalize the innovative output of biotechnology companies (see for example Shan, Walker and Kogut, 1994). Third, popular press provides evidence that patents are also relevant in practice; patent output is used as an indication of the biotechnology company's innovativeness in making decisions about collaboration relationships. Patents provide external visibility and legitimacy for newly established organizations that seek collaborative partners. Patents as a measure of innovation output in collaborative relationships is examined in more detail with a sample study that follows.

Main hypotheses

Main hypotheses of the sample study, and the empirical methods used, are summarized below. This sample study examines R&D collaborations between small and large biotechnology companies. The study hypothesizes that collaboration can have negative effects on innovation performance. More specifically, it proposes that with whom you collaborate matters. Collaboration with dissimilar partners -- with older, larger and foreign partners -- is hypothesized to have a negative effect on the radicality of the innovation output of the smaller partner. A more detailed description of the theoretical arguments leading to the hypotheses is available from the author, and similar arguments can also be found in other studies on R&D collaboration (for example Katila, 1997; Lane and Lubatkin, 1998; Shan et al., 1994).

Three main hypotheses are examined:

> *Hypothesis 1*. Number of collaborative partners has a curvilinear (inverted u) relationship with the radicality of innovation output of the smaller partner. Radicality of innovations increases up to point, but after this optimal point has been reached, additional increases in the number of partners is negatively related with the radicality of innovation output.
>
> *Hypothesis 2a.* The size and experience of the R&D collaborative partner have a negative effect on the radicality of innovation output of the smaller partner.
>
> *Hypothesis 2b.* Foreign R&D collaborative partners have a negative effect on the radicality of innovation output of the smaller partner.

Hypothesis 3. Complementarity in the resources of the collaborative partners, such as complementary marketing and technological capabilities, has a positive effect on the radicality of innovation output.

Methods

To test these hypotheses, data on a sample of 100 biotechnology firms founded between 1980 and 1988 were gathered. As discussed previously, the starting point of the study, year 1980 is a significant milestone in the US biotechnology industry; a first genetically engineered organism was patented in that year. Because patents are important and widely used in the biotechnology industry, and my study is also based on patent data, 1980 is a natural starting point for the analysis. The sample includes biotechnology companies listed in *PaineWebber* and *Genguide* biotechnology-specific directories and of which sufficient data was available during the period of study. Only biotechnology firms concentrating on human therapeutics and in-vivo diagnostics were included. This way the underlying technological setting and expertise requirements are relatively constant and the innovation output of the sample firms is comparable.

The operationalizations of the study variables are introduced below. Different aspects of patent data are used to operationalize the dependent variable, radicality of innovations, as well as one of the independent variables, technological capabilities.

Dependent variable; radical innovation. Radicality of innovation output is measured by citation-weighted patent counts (*Patents*) in this study. To distinguish between companies that produce incremental improvements and those that focus on more radical innovations, I weight the number of patents with the citations the patents received during six years after the application for the patent, or until the end of year 1997. Self-citations are excluded from this data. Patent information was obtained from the U.S. Patent and Trademark Office documents and it includes yearly counts of patents that the sample firms had applied for each year.

Independent variables. There are five independent variables in the study that measure different characteristics of biotechnology firms' collaboration behavior. The first independent variable, resource complementarity, measures the fit between the collaboration partners' resources. Resource complementarity is operationalized as an interaction between the partner's marketing capabilities (*Partner sales*) and the start-up's research capability (*Patents*). Start-up's research capability is measured as the cumulative number of its citation-weighted patents in three past years (years t-3 through t-1; see Henderson and Cockburn, 1995). The remaining partner characteristic variables are partner experience (*Partner age*), partner size (*Partner sales*), a binary variable indicating a foreign partner (*Foreign partner*), and the count of R&D collaborative partners (*Number of R&D partners*). Due to the time-series nature of the data, a lagged-variable design is used: data for the independent variables were collected a year before the dependent variable values.

Control variables. Following the Schumpeterian hypothesis of the effects of firm size on innovation, I control for each biotechnology firm's sales (*LogSales*) and yearly R&D expenditures (*LogRD*). Sales and age asymmetry was calculated by controlling for start-up's own sales (*Logsales*) and age (*Firm age*), respectively. Finally, a control for the calendar year (*Year*) is included. Although firms established in the late 1980s had shorter periods for their patents to be cited, these effects are expected to be minimal. As an additional safeguard, I controlled for the year.

A pooled time-series model tested in this sample study is:

$$Patents_{it} = \alpha + \beta_1 Number\_of\_RDpartners_{it-1} + \beta_2 Number\_of\_RDpartners^2_{it-1} + \beta_3 Partner\_age_{it-1} + \beta_4 Partner\_sales_{it-1} + \beta_5 Foreign\_partner_{it-1} + \beta_6 Partner\_sales_{it-1} * Patents_{it-1-3} + \beta_7 Patents_{it-1-3} + \beta_8 LogRD_{it-1} + \beta_9 LogSales_{it-1} + \beta_{10} Year_{t-1} + \beta_{11} Firm\_age_{it-1} + \beta_{12} Partner\_sales_{it-1} * Firm\_age_{it-1} + \varepsilon_{it}$$

where firms are indexed i, and time t.

Poisson regression analysis was used to test the hypotheses. Poisson regression models have a number of attractive features for innovation performance measurement: these models are appropriate for integer data (counts of events), and they also account counts that are aggregated over time periods (McCullagh and Nelder, 1989). In this study, the dependent variable, *Patents*, is a non-negative count of patents, and observations are combined to a time-series panel (nine yearly observations for each firm). Poisson regression is thus an appropriate method to use.

Innovative output of the sample companies was highly diverse: on average, these companies applied for 1.3 patents yearly, although some had no patents in any year (8 companies), and one organization applied for 18 patents in a single year. On average, companies in the sample had a total of 2.5 technological collaboration partners during their first nine years. 246 R&D collaborations were examined in this study, and yearly data for the companies was collected in 1980-1990, including patent citations until the end of year 1997. The data for this study were collected from several biotechnology-specific databases and directories, 10-Ks and annual reports of these companies, as well as for the *US Patent Office* database. *Predicasts*, and various news databases were the sources of the cooperation data. Data regarding the collaborative partners were drawn from *Compustat* database, annual reports of the companies, and news articles in *Lexis Nexis*.

Results

The results of the tests of the hypotheses are presented in Table 1. I summarize the results briefly below, and then discuss the patent-measurement issues in more detail. In Table 1 the hypothesized relationships are supported with significant main effects. Model 1 includes the control variables, and independent variables for testing the research hypotheses are added one at a time in subsequent models. Models 2a and 2b test for the effect of the number of R&D collaborative partners (*Number of R&D Partners*). As proposed in Hypothesis 1, I expect a curvilinear relationship between the number of technological partners and radical innovation output, and this prediction is born out. As shown in Model 2b, the number of technological collaborative partners is nonlinearly related to radicality of innovation (inverted U).

In Models 3 and 4 the measures of partner age and size are introduced. We expect a negative relationship between partner's experience (*Partner_age*) and size (*Partner_sales*) asymmetry, and radical innovation (*Patents*) (Hypothesis 2a). Once we control for the start-up's own size and age (*Logsales* & *Firm_age*), respectively, we find that both larger and older partners affect start-up's radical innovative output negatively. Although the coefficient estimates are small, inclusion of these variables results in a significant increase in the model fit. The *Foreign* coefficient does not reach significance in Model 5. However, this coefficient is negative and significant, as expected, in the full model. Models 6 and 7 include the test for the resource complementarity argument given in Hypothesis 3. We find that start-ups with increased technological capabilities (*Patents*) are better able to benefit from the marketing resources of the larger partner, thus giving some support for the complementarity hypothesis. Model 8 includes the full model. In all, these results imply that unbalanced combinations between collaborative partners can lower the radicality of the smaller partner's innovation output.

The above-discussed study provides an example of how to use patent data in performance measurement. Further analysis of the results demonstrates that the effects on innovation output are strongest when we distinguish the quality of innovation output by using citations. Significantly weaker results emerge as raw patent counts, instead of citation-weighted counts, are used (see also Trajtenberg, 1990 for a similar result). Thus, if the organization wants to measure both the quality as well as quantity of its innovation output, both raw and citation-weighted patent counts should be used. These results, as well as descriptive statistics are available from the author.

ANALYSIS OF PATENT-BASED MEASURES

The above-discussed study on biotechnology patenting gives an example of the use of patent data in measuring innovation performance. However, the use of citation-weighted patent measures raises two measurement issues which have not been discussed in the prior literature. First, it is not clear whether the citation lag of five or six years, a lag customarily used in patent studies (see for example Dutta and Weiss, 1997), is long enough to capture the value of radical innovations, which possibly receive citations that are unevenly distributed over time. While the length of the citation lag may not be an important issue in operationalizing innovative performance in general, the potentially different citation patterns of incremental and radical innovations make the correct length of the citation lag important for measuring radicality of innovation. I know of no other work that has examined the effects of citation length on the validity of the empirical results.

Second, consequently, we do not know whether citation-weighted patents can be used to compare innovativeness of companies or business units. Since receiving more citations is proposed to reflect the radicality of the patent, and the value of radical innovations is likely to be acknowledged relatively late after their introduction (Trajtenberg, 1990; Utterback, 1994), it is likely that patents which get most citations are cited relatively late. Short lags would not thus capture the majority of the citations radical innovations receive, and thus would not accurately reflect radicality of innovation.

To address these questions on measurement validity, two preliminary tests were conducted. First, I compare innovation radicality of the above-discussed biotechnology companies by using two citation-lag periods. In Table 2 the first list of the most innovative biotechnology companies (and respective years) was compiled using five years of subsequent citations. The second list was prepared using a period of ten years. Comparison of the twenty most innovative companies in both lists leads to the conclusion that the length of the citation period indeed has an effect. Although many of the top companies change relatively little in positions as compared to their competitors as the citation period is extended, some company years such as Cytogen in 1982 (5^{th} in 0-10 years vs. 72nd in 0-5 year list) and Amgen in 1985 (13^{th} in 0-10 years vs. 32nd in 0-5 year list) “become” fundamentally more innovative when the longer citation period is used. This preliminary test gives an indication that the citation-weighted measure is possibly sensitive to the citation period, and that five years may not be a long enough citation period in many cases.

The second illustration of the importance of the citation period was conducted by selecting a subset of the patents for each firm (1980-1987) and testing the average length for these patents to receive all their citations. The sample was split in two based on the number of citations received. The test was conducted to find out whether patent portfolios that had received above-average number of citations were cited slower. I first tested how long it took on average for 80% of the total citations to be received. Indeed, it took significantly (p=0.019) longer for the above-average cited portfolios to receive 80% of the citations than for the less-cited. On average, it took 9.5 years and 10.4 years for the less and more cited portfolios, respectively, to receive 80% of the total citations. This result well supports the findings of the prior literature: technologically radical (most cited) innovations tend to be recognized later than technologically incremental. I also tested the sample for 30% of the received citations. Surprisingly, at first, less cited patents were cited slower (3.7 years) than the more cited patents (2.48 years) (p=0.001).

In all, these observations add useful information for correct use of citation-based measures. Preliminary results show that in most cases, a citation lag of five years is not adequate to reliably measure innovation performance. In the case of a sample of 100 biopharmaceutical companies in 1980-1997 it took companies on average ten years to receive 80% of the citations for a year’s patents. Furthermore, I found that radical innovations are cited slower than more incremental innovations. The results indicate that using short citation periods may result in exclusion of radical innovations from the sample. Consequently, researchers need to both assure that the length of citations used is long enough, as well as to experiment with the effects of different citations lags on the results. Figure 2 has a summary of the above-mentioned recommendations.

DISCUSSION

This chapter has four main implications. First, this study contributes to the increasing literature on how to use patents to measure innovation performance. Recently several authors have argued that patent documents represent one of the best sources of both historical and current technical information available to both corporate and academic researchers. Patents are a unique data source: a) patent documents deal exclusively with new and useful ideas, b) patents include a detailed description of the patented invention, and, c) analysis of patents can give early signals of technological change - trend indicators frequently appear in patent data before they are reported in trade or technical journals (Walker, 1995). Thus, patent measurement should be an integral part of innovation performance measurement in large corporations. This study contributes by distinguishing the quantity and quality in patent measurement, and pointing out pitfalls to be avoided.

Second, this study contributes for the subsequent empirical work that measures radicality of innovation performance through patents. The main conclusion of my empirical analysis is that the length of the patent citation period can dramatically change the picture of the innovativeness of firms. Moreover, the study shows that radical innovations tend to be cited later than incremental. Consequently, short citation lags may not properly capture the value of radical innovations.

Third, from the theoretical standpoint, this study presents an overview and structures the previous literature on radical innovation. Four different categories of radicality, seen from the perspectives of organization, industry, users, and technology, are identified. This categorization is important for measuring radicality at the appropriate level of analysis that corresponds to the theoretical construct used. In this study technologically radical innovations are discussed, and measured through patent-citation measures. One interesting issue for future work would be to evaluate the interrelations between the four categories of radicality; for example, whether technologically radical innovations generally also disrupt industry order, and whether industry-radical innovations tend to be more successful if they are not organizationally radical at the same time (diversified companies).

Fourth, this study also has implications for technology managers in general. The sample study on biotechnology collaboration presents evidence of the negative effects of collaboration on the radicality of innovation output. From the managerial perspective, these results complement those of a more recent study by Lane and Lubatkin (1998) who find that the relative similarity in partner characteristics can enhance the smaller partner’s innovative performance. Taken together, this study emphasizes the need for small organizations to carefully select their partners to obtain maximum radical innovation performance. The measurement issues discussed in this study can help in further clarifying the sources of radical innovation performance for these companies.

FOOTNOTES

1. Radical innovations have also been called path-breaking, discontinuous, revolutionary, new, original, pioneering, basic or major innovations (Green et al., 1995).

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TABLE 1

Maximum-Likelihood Estimates in Poisson regression Analysis

Predicting *Patents* $_t$ Variable

Model

Variable	1	2a	2b	3	4	5	6	7	8
Intercept	529.7***	496.9***	490.9***	558.6**	494.8***	496.8***	551.37***	379.26***	551.77***
	[00.67]	[12.48]	[12.57]	[14.22]	[12.49]	[12.47]	[13.96]	[14.45]	[14.56]
Number of		0.133***	0.267***	0.227***	0.260***	0.154***	0.318***	0.232***	0.623***
R&D partners $_{t-1}$		[0.017]	[0.043]	[0.027]	[0.021]	[0.022]	[0.022]	[0.022]	[0.059]
Number of			-0.039***						-0.070***
R&D partners $^2{}_{t-1}$			[0.012]						[0.016]
Partner Age $_{t-1}$				-0.001**					-0.0006
				[0.0005]					[0.0005]
Partner Sales(M$) $_{t-1}$					-0.00004***		-0.0001***	-0.0001***	-0.0001***
					[0.0000]		[0.0000]	[0.0000]	[0.0000]
Foreign Partner $_{t-1}$						-0.088			-0.245**
						[0.059]			[0.059]
FirmAge $_{t-1}$				0.135***			0.133***		0.135***
				[0.013]			[0.014]		[0.014]
*Partner Sales*FirmAge* $_{t-1}$							0.00001***		0.00001***
							[0.0000]		[0.0000]
Patents $_{t-1}$								0.0196***	
								[0.0008]	
*Partner Sales*Patents* $_{t-1}$								-0.00001***	
								[0.0000]	
LogRD $_{t-1}$	0.714**	0.672***	0.669***	0.592***	0.684***	0.672***	0.536***	0.496***	0.585***
	[0.042]	[0.043]	[0.043]	[0.047]	[0.044]	[0.043]	[0.045]	[0.047]	[0.048]
LogSales $_{t-1}$	0.409***	0.372***	0.365***	0.282**	0.387**	0.375***	0.292***	0.274***	0.281***
	[0.032]	[0.032]	[0.032]	[0.033]	[0.032]	[0.032]	[0.033]	[0.033]	[0.033]
Year $_{t-1}$	-0.267***	-0.251***	-0.248***	-0.282***	-0.250***	-0.251***	-0.278***	-0.191***	-0.279***
	[0.006]	[0.006]	[0.006]	[0.007]	[0.006]	[0.006]	[0.007]	[0.007]	[0.007]
Scaled deviance	4258	4200	4189	3996	4094	4198	3954	3687	3822
dF	4	5	6	7	6	6	8	8	11
Log likelihood sign. tests		58***	69***	262***	164***	60***	304***	571***	436***

There were 100 firms, and 894 yearly observations in the sample.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (two-tailed tests)

The table gives parameter estimates; standard errors are in brackets.

TABLE 2. Citation lag matters. Most innovative biotechnology companies in 1980-1989 based on citation-weighted patent counts. A lag of five years is used in columns on the left, and the right columns use a lag of 10 years.

Firm	**Year**	**0-5 years**	**Firm**	**Year**	**0-10 years**
NeoRx	1989	97	Liposome Co.	1983	170
Liposome Techn.	1986	66	Liposome Techn.	1986	167
Liposome Techn.	1989	61	NeoRx	1989	131
Liposome Co.	1983	50	Liposome Co.	1985	128
Genetics Inst.	1987	50	Cytogen	1982	112
Genetics Inst.	1989	46	Genetics Inst.	1987	109
NeoRx	1988	42	Chiron	1984	108
Liposome Co.	1985	39	Genetics Inst.	1984	98
Genetics Inst.	1988	39	NeoRx	1988	90
Liposome Co.	1989	36	Liposome Techn.	1989	89
NeoRx	1987	35	Genetics Inst.	1986	85
Repligen	1986	33	Genetics Inst.	1983	79
Genetics Inst.	1986	32	Amgen	1985	77
Liposome Co.	1984	31	Genetics Inst.	1989	77
Chiron	1984	31	Liposome Co.	1989	77
ChemTrak	1989	31	Molecular Bios.	1987	74
Chiron	1989	30	Vestar	1985	73
TheraTech	1988	29	Chiron	1988	72
Immunex	1981	29	Genetics Inst.	1988	70
Liposome Techn.	1987	27	Cytogen	1984	68

FIGURE 1. Simple patent counts vs. citation-weighted patent counts. A hypothetical example of three firms and their innovation output. Although Firm A has the lowest number of patents, these patents are cited most. Firm A's R&D activities are thus evaluated as technologically most significant among the three companies.

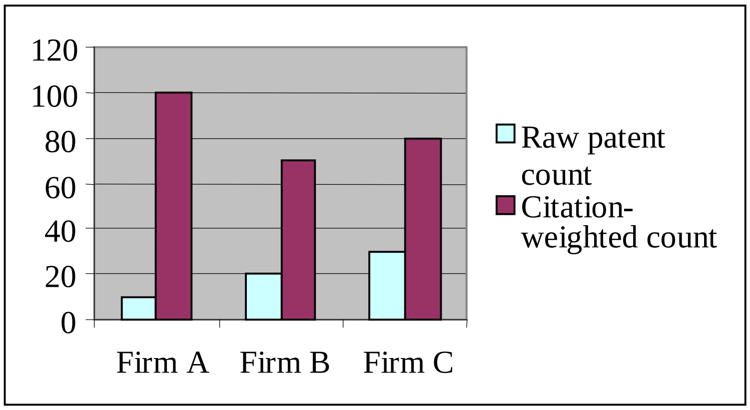

FIGURE 2. How to use patent data in performance measurement - Summary of recommendations.

1. Several electronic databases provide patent data for free. Define your questions and download data for several years: examine trends, changes and averages.

2. Weight patents by subsequent citations to capture qualitative differences between patents.

3. Use >10 years of subsequent citations.

4. Citation-weighted patents best capture technological radicality. Use other methods for industry- and user-radicality, for example.

5. Patent and citation-tendencies may differ across industries. Patent data best capture differences in innovation performance within the same industry.

6. Remember that patents only measure part of innovation output. Complement patent data with other measures of innovation such as new product counts, R&D expenditure, and trademarks.

List of titles

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