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Measuring technological performance of assignees using trace metrics in three fields

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Abstract The study establishes three synthetic indicators derived from academic traces—assignee traces T_1, T_2 and ST—and investigates their application in evaluating technological performance of assignees. Patent data for the top 100 assignees in three fields, "Computer Hardware & Software", "Motors, Engines & Parts", and "Drugs & Medical", were retrieved from USPTO for further analysis. The results reveal that traces are indeed valid and useful indicators for measuring technological performance and providing detailed technical information about assignees and the industry. In addition, we investigate the relationship between traces and three other indicators: patent citation counts, Current Impact Index and patent h-index. In comparison with the three other indicators, traces demonstrate unique advantages and can be a good complement to patent citation analysis.

Keywords Academic trace · Assignee trace · Patent trace · h-Index · CII

Introduction

Number of patents is the most widely used indicator in patent analysis to evaluate the innovative competitiveness of patent assignees. However, it has been much criticized for ignoring the great heterogeneity between patents (Griliches et al. 1988; Karki 1997). Patent

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citation analysis is therefore adopted and frequently used in evaluation (Karki 1997; Trajtenberg 1990; Wang 2007). The basic idea is that highly cited patents are likely to contain significant technological advances that many later patents are built upon, thus more citations may indicate that patents are of higher technological quality and impact (Hall et al. 2005; Harhoff et al. 1999; Trajtenberg 1990). Accordingly, assignees with more highly cited patents are more competitive in the industry. Numerous studies have confirmed the positive relationship between patent citations and corporation performance (Banerjee et al. 2000; Chang et al. 2012; Deng et al. 1999; Narin et al. 1987).

With the development of patent citation analysis, several quality-oriented indicators have been developed (Chen et al. 2007). Current Impact Index (CII) is one of the most representative of these, which shows how often the patents the company has been issued over the last 5 years are cited in the current year. The idea of CII is essentially the same as IF5 (impact factors for 5-year time windows) in bibliometrics, and both are commonly used in assessment. CII is sensitive to companies' current technology, and high CII implies high patent quality and technological impact for the company (Breitzman and Narin 2001). Hirschey and Richardson (2001) and Hirschey et al. (2001) have confirmed that there is a positive relation between market value and CII in the high-tech industries in Japan and USA. Additionally, the empirical findings of Thomas (2001) have further confirmed that the higher CII is, the better stock performance (market-to-book ratio) is.

The patent h-index, borrowed from bibliometrics, was developed as a new indicator for assessing technological performance of assignees (Chang et al. 2012; Guan and Gao 2009). The h-index was originally proposed to evaluate the productivity and impact of scientists, which was defined as follows: "A scientist has index h if h of his or her Np papers have at least h citations each and the other $(Np - h)$ papers have $\leq h$ citations each" (Hirsch 2005). Due to its simplicity and validity, the h-index has become a *de facto* scientometric indicator for research performance evaluation (Kuan et al. 2011a). Guan and Gao (2009) were the first to introduce h-index into patent citation analysis and propose the patent h-index as a measure of corporation performance. Their study of the top 20 firms in the area of semiconductors showed that patent h-index of assignees correlates positively with patent citation counts while not correlates significantly with patent counts. They concluded that patent h-index, which takes both of productivity and impact into consideration, can effectively reflect assignees' innovative performance.

Recently in bibliometrics, Leydesdorff and Bornmann (2011) proposed the Integrated Impact Indicator (I3), which was based on normalization in terms of percentile ranks of the distribution. Combing the idea of I3 with the h-index, Ye and Leydesdorff (2014) constructed a new measure of academic performance: matrix $V = (X, Y, Z)^T$, in which X, Y, Z were three vectors indicating publication distribution, citation distribution and the difference between citations and publications respectively. The trace of matrix V was then proposed to summarize academic achievements, and can be regarded as a single and unique synthetic indicator for measuring total academic performance. This indicator was called "academic trace" of the "performance matrix", and is proven to be able to evaluate journals, universities and authors effectively.

Since papers and patents share many analogous features (Meyer 2000; Meyer and Bhattacharya 2004), many indicators in bibliometrics have been introduced into patentometrics and applied successfully to evaluate the technological capacity of assignees. As such, this paper aims to introduce traces as useful indicators for measuring and ranking the technological performance of patent assignees. The data set used in the research was obtained from USPTO and covers three industrial sectors: "Computer Hardware & Software", "Motors, Engines & Parts", and "Drugs & Medical". The study also investigates the relationship between traces and three other patent citation indicators—patent citation counts, current impact index, and patent h-index—to test the validity of the indicators.

Methodology

Since the academic traces of an academic person or group denote the overall academic performances of the individual or group, traces of an assignee can measure the overall technical performances of the assignee, where the traces can be called as "assignee traces".

Method

Figure 1 shows the general citation distribution curve of an assignee's patent portfolio, in which the y axis represents the citations received by a patent and the x axis corresponds to the patent ranking arranged by citations in descending order. The area under the curve can be divided by the h-index into two areas: the h-core area (Kuan et al. 2011b) and h-tail area (Ye and Rousseau 2010). The h-core area can be further divided into the h-area and the e-area (Ye and Rousseau 2010; Zhang 2009). The h-tail can be further divided into two subsets: the lowly cited patents and the uncited (zero citations) (Kuan et al. 2011b). Let's call the former subset of h-tail the t-area and the later the uncited area. Thus the whole area under the curve is divided into four parts: the h-area, the e-area, the t-area and uncited.

On the basis of the distribution of citations of an assignee's patents portfolio, three vectors X, Y, Z are proposed by Ye and Leydesdorff (2014) indicating patent distribution, citation distribution and the difference between citations and patents respectively. They are defined as follows:

$$X = (X_1, X_2, X_3) = \left(\frac{P_\mathrm{c}^2}{P}, \frac{P_\mathrm{t}^2}{P}, \frac{P_\mathrm{z}^2}{P}\right) \quad (1)$$

$$Y = (Y_1, Y_2, Y_3) = \left(\frac{C_\mathrm{c}^2}{C}, \frac{C_\mathrm{t}^2}{C}, \frac{C_\mathrm{e}^2}{C}\right) \quad (2)$$

$$Z = (Z_1, Z_2, Z_3) = \left(\frac{C_\mathrm{c}^2}{C} - \frac{P_\mathrm{c}^2}{P}, \frac{C_\mathrm{t}^2}{C} - \frac{P_\mathrm{t}^2}{P}, \frac{C_\mathrm{e}^2}{C} - \frac{P_\mathrm{z}^2}{P}\right) \quad (3)$$

where $P_\mathrm{c} = h$ stands for the number of patents in the h-core, P_t the number of patents in the t-area, P_z the number of uncited patents, and $P = P_\mathrm{c} + P_\mathrm{t} + P_\mathrm{z}$ indicates the total

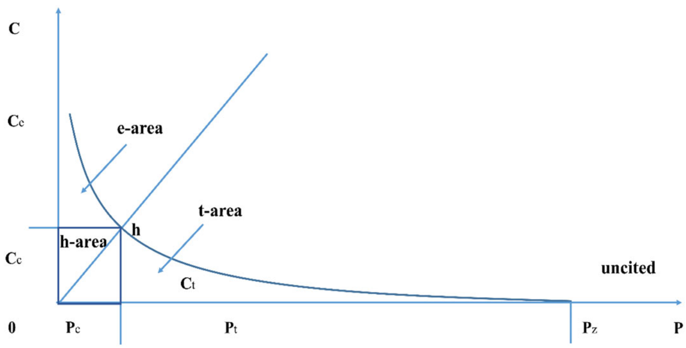

Fig. 1 Citations distribution curve of patents

number of patents. $C_{\mathrm{c}} = h^2$ denotes the number of citations in the h-area, C_t the number of citations in the t-area, C_{e} the number of citations in the e-area, $C_{\mathrm{h}} = C_{\mathrm{c}} + C_{\mathrm{e}}$ indicates the total number of citations in the h-core, and $C = C_{\mathrm{c}} + C_{\mathrm{t}} + C_{\mathrm{e}}$ the total number of citations. Two unique matrices V_1 and V_2 for measuring the total distribution of technological performances can be constructed as:

$$V_1 = \begin{pmatrix} Y \\ X \\ Z \end{pmatrix} = \begin{pmatrix} Y & X & Z \end{pmatrix}^T == \begin{pmatrix} Y_1 & Y_2 & Y_3 \\ X_1 & X_2 & X_3 \\ Z_1 & Z_2 & Z_3 \end{pmatrix} \tag{4}$$

$$V_2 = \begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \begin{pmatrix} X & Y & Z \end{pmatrix}^T == \begin{pmatrix} X_1 & X_2 & X_3 \\ Y_1 & Y_2 & Y_3 \\ Z_1 & Z_2 & Z_3 \end{pmatrix} \tag{5}$$

Then, the traces T_1 and T_2 of the performance matrices V_1 and V_2 can be naturally obtained, providing two scalar measures that summarize technological performance as:

$$T_1 = tr(V_1) = Y_1 + X_2 + Z_3 = \frac{C_{\mathrm{c}}^2}{C} + \frac{P_{\mathrm{t}}^2}{P} + \left(\frac{C_{\mathrm{e}}^2}{C} - \frac{P_{\mathrm{z}}^2}{P}\right) \tag{6}$$

$$T_2 = tr(V_2) = X_1 + Y_2 + Z_3 = \frac{P_{\mathrm{c}}^2}{P} + \frac{C_{\mathrm{t}}^2}{C} + \left(\frac{C_{\mathrm{e}}^2}{C} - \frac{P_{\mathrm{z}}^2}{P}\right) \tag{7}$$

Traces T_1 and T_2 could be interpreted as follows. In T_1, Y_1 provides a normalized citation measure for the h-area, while X_2 is a normalized patent score for the t-area. And in T_2, X_1 is a normalized patent score for the h-area, while Y_2 provides a normalized citation measure for the t-area. The last component Z_3 provides the fraction of excess citations minus the fraction of uncited patents, which is relatively more complicated because we consider the additional impact of excess citations as a possible compensation for the uncited patents. Positive and high Z_3 indicates that the assignee has high excess citations and overall patent quality, while negative Z_3 suggests that the assignee owns a large number of uncited patents which greatly drag down its overall performance. It should be pointed out that two indicators—Z_1 representing the difference between normalized citation score and patent score for the h-area, and Z_2 donating the difference between normalized citation score and patent score for t-area—are not included in our traces. Higher and positive values of Z_1 and Z_2 also imply higher patent quality and technological performance of the assignee.

Thus both T_1 and T_2 construct synthetic measures which cover all information of the four sectors—the e-area, the h-area, the t-area, and the uncited area—in the citation distribution. They reflect the patent-citation distribution in the core-tail plane of Fig. 1 and provide scalar measures for total technological performance. The larger the values of T_1 and T_2 are, the more technological accumulation is measured.

Meanwhile, when we ignore the uncited patents and focus on cited ones, core-tail distribution can be represented as a sub-matrix:

$$\mathrm{SV} = \begin{pmatrix} C_{\mathrm{h}}^2/C & C_{\mathrm{t}}^2/C \\ P_{\mathrm{c}}^2/P & P_{\mathrm{t}}^2/P \end{pmatrix} \tag{8}$$

Then the sub-trace becomes:

$$\mathrm{ST} = tr(\mathrm{SV}) = \frac{C_{\mathrm{h}}^2}{C} + \frac{P_{\mathrm{t}}^2}{P} \tag{9}$$

The sub-trace ST will always remain positive, as $C > C_{\mathrm{h}} > 0$ and $P > P_{\mathrm{t}} > 0$. In ST, C_{h}^2 provides a normalized citation measure for the h-core, while P_{t}^2 is a normalized patent score for the t-area.

T_1, T_2 and ST have their independent values and can provide different information about assignees. T_1 tends to strengthen h-area citation information. We assume that as the scores of h-area citations (Y_1) will match that of t-area patents (X_2), T_1 gives an almost balanced value for both h-area and t-area. And T_2 trends to strengthen t-area citation information. As h-area patents account for only a small portion (X_1) of total patents, most values of T_2 are occupied by scores of t-area citations (Y_2). Meanwhile, since new patents always supply zero or small amount of citations, they usually located in the h-tail area. In order to protect and encourage new patents, ST provides a good indicator for measuring total output and impact with ignoring new zero-cited patents. Accordingly, we suggest to define T_1 as the main trace or first trace, T_2 as the associate trace or second trace and ST as the sub-trace, which can be explained in component analysis.

In order to test the validity of the traces, we choose three other widely used indicators—patent citation counts(C), current impact index (CII), patent h-index (H)—to measure assignees' technological strength as well. By comparing their evaluation results, we can better understand the relationships between assignee traces and the other indicators, and the unique role that assignee traces can play in assessment.

An assignee's number of citations (C) is a single and basic measure which can be calculated by adding together all the citations the assignee has.

The CII of an assignee is "calculated based upon the number of times patents issued this year cite the patents issued to the selected assignee in each of the previous 5 years. The number of citations is then divided by the number of patents issued to the assignee in each of those 5 years in order to produce an average citation rate. This rate is then divided by the average citation rate for all U.S. patents issued in each year during the same time period" (Breitzman and Narin 2001). The computational formula of an assignee's CII is as follows:

$$\mathrm{CII}_{ij} = \frac{C_{ij}/K_{ij}}{\sum_i C_{ij}/\sum_i K_{ij}} \tag{10}$$

where C_{ij} represents the cited number of patents in a certain year assignee i produced in field j in the past 5 years, and K_{ij} is the number of patents assignee i produced in field j during the past 5 years.

On the basis of the definition of a scientist's h-index (Hirsch 2005), one can define the h-index of an assignee thus: an assignee has index h if h of its Np patents have at least h citations each and the other $(Np - h)$ patents have less than or equal to h citations each.

Data

Based on the reorganization of USPC (United States Patent Classification)—NBER Patent Data Technological Classification, we selected three independent fields—"Computer Hardware & Software", "Motors, Engines & Parts", and "Drugs & Medical"—for investigation. "Computer Hardware & Software" is a sub-field of "Computer

& Communications", which includes "Data processing", "Electrical computers and digital processing systems", "Error detection", and so forth. "Motors, Engines & Parts" belongs to "Mechanical", consisting of "Rotary kinetic fluid motors or pumps", "Rotary expansible chamber devices", "Endless belt power transmission systems or components", and so forth. Drugs & Medical includes "Drugs", "Surgery & Medical Instruments", "Biotechnology" and "Miscellaneous—Drugs & Medical". The three fields were chosen because they each belong to different industries: "Motors, Engines & Parts" thrived in the second industrial revolution, "Computer Hardware & Software" stands for the rise of the third industrial revolution, and "Drugs & Medical" represents advanced technology for the pharmaceutical industry. Additionally, we only focus on utility patents in our study since they are the key category of patents which can reflect assignees' technological capability.

The patent data for this study was retrieved from the USPTO database and downloaded in August 2014, and includes all utility patents issued between 2003 and 2012. Expired patents which have fallen into public domain or have not been renewed were not removed in this study. Although the legal status of patents potentially influence the results of technological performance evaluation, this is an issue which has not been addressed much in the literature, and most previous studies opted against removing expired patents (Chen et al. 2007; Hagedoorn and Cloodt 2003; Narin et al. 1987; Tseng et al. 2011).

In order to use the latest data for research and to evaluate the most current technological capacity of assignees, we collected patent citations from 2008 to 2013 instead of using a fixed citation window. Though older patents do have longer citation windows and logically are more cited than younger ones, this will not cause bias when we compare technological performance of assignees using the same citation window. We do not distinguish between self-citations to patents belonging to the same assignee and non-self-citations by other assignees, although they do have different meanings: self-citations represent internalized transfer of knowledge, whereas non-self-citations represent pure spillovers and competitiveness (Hall et al. 2001). Sapsalis et al. (2006) suggested that self-citations would not reflect corporations' value but rather a particular strategy. However, according to Hall et al. (2000, 2005), self-citations are positively correlated with firms' market value, though the relevance declined with firm size. As we endorse the opinion of Hall et al. (2000, 2005), that self-citations suggest a firm has a strong competitive position in their industry and has internalized knowledge spillovers, we chose not to remove self-forward citations.

There are 250,042 patents and 1,307,884 citations belonging to 7630 assignees in "Computer Hardware & Software"; 85,342 patents and 214,590 citations from 3896 assignees in "Motors, Engines & Parts"; and 173,067 patents and 995,911 citations from 2702 assignees in "Drugs & Medical". In each field, assignees are ranked according to total citation numbers and the top 100 assignees of each field are then chosen for further analysis. The top assignees and their countries are listed in "Appendix". In all of the three fields, US companies account for the largest single percentage of the top assignees: 67 % in "Computer Hardware & Software", 45 % in "Motors, Engines & Parts", and 81 % in "Drugs & Medical". The majority of other top assignees are from Japan and Germany, with a few are from Canada, South Korea, and Switzerland etc. The citation attributes of the top 100 assignees in the three fields are shown in Table 1.

Table 1 Citation attributes of first 100 assignees in three fields

Items	Computer Hardware & Software	Motors, Engines & Parts	Drugs & Medical
Maximum number of citations	105,967	9592	22,197
Average of number citations	7640	982	792
Minimum number of citations	1879	214	164
Standard deviation	14,226	1669	2447

Table 2 Portion of assignees with negative value of traces in top 100

Traces	Computer Hardware & Software (%)	Motors, Engines & Parts (%)	Drugs & Medical (%)
T_1	0	7	6
T_2	0	0	4

Results and discussion

Analyzing assignees in different technical fields

On the basis of Eqs. (1–9), we calculate the values of X_1, X_2, X_3, Y_1, Y_2, Y_3, Z_1, Z_2, Z_3 and T_1, T_2, ST of top 100 assignees in the three fields.

Table 2 shows the proportion of assignees with a negative value for traces in top 100 in the three fields. As asserted above, traces are measures of the overall technological accumulation in the core-tail plane of an assignee. Higher traces imply higher technological performance of the assignee. Thus, assignees with positive T_1 and T_2 make effective contributions in the field, while assignees with negative T_1 and T_2 make trivial contributions. According to Eq. (6), the value of T_1 is decided by the normalized patent score for the t-area (X_2), the normalized citation score for the h-area (Y_1) and the difference between fraction of excess citations and fraction of uncited patents (Z_3). According to Eq. (7), the value of T_2 is decided by the normalized patent score for the h-area (X_1), the normalized citation measure for the t-area (Y_2) and Z_3. For both T_1 and T_2, the fraction of uncited patents is the only element that could diminish their values. Therefore, traces <0 means the assignee has a large number of poor patents which drag down its overall performance remarkably and make its contribution insignificant.

As shown in Table 2, all the negative proportion of T_1 and T_2 are not particularly high in all three fields. There are no negative T_1 or T_2 existing in the field of "Computer Hardware & Software", showing all top 100 assignees in this field make positive contributions. The proportion of negative T_1 is highest in "Motors, Engines & Parts", while the proportion of negative T_2 is highest in "Drugs & Medical". It can be therefore inferred that several top companies in these two fields perform poorly due to a large number of low-quality patents.

The average values and standard deviations of traces in the three fields are shown in Table 3. For T_2 ($X_1 + Y_2 + Z_3$), we have assumed in the foregoing that most values of T_2 will be occupied by scores of t-area citations (Y_2). It can be observed that indeed in the area of "Computer Hardware & Software" and "Motors, Engines & Parts", the t-area accounts for the largest portion of citations in all fields on average, so the value of Y_2 is always the highest. Since Y_2 is much higher than X_1 and Z_3, the value of T_2 is largely decided by Y_2.

Table 3 AVG and SD parameters of assignees in the three fields

Technical field	Computer Hardware & Software (%)		Motors, Engines & Parts (%)		Drugs & Medical (%)	
	AVG	SD	AVG	SD	AVG	SD
X_1	2.60	3.81	1.15	1.13	1.72	1.71
X_2	364.25	688.60	80.88	156.40	13.40	40.48
X_3	202.70	429.05	48.92	74.40	33.71	50.61
Y_1	237.06	249.19	36.29	39.80	45.02	133.25
Y_2	3167.88	9316.36	411.71	1037.48	128.57	728.92
Y_3	563.02	740.07	69.07	85.79	191.34	215.86
Z_1	234.46	248.55	35.14	39.61	43.30	132.78
Z_2	2803.62	8635.17	330.83	882.36	115.17	689.01
Z_3	360.32	886.23	20.14	122.89	157.63	208.57
T_1	961.64	1002.90	137.31	153.05	216.05	311.67
T_2	3530.80	8998.78	433.00	970.90	287.91	823.98
ST	1782.72	1661.49	261.46	246.12	382.90	592.13

AVG average value, *SD* standard deviation

However the situation in the area of "Drugs & Medical" is different than anticipated: the average value of Z_3 is even higher than Y_2. We suggest that top assignees in this area have high patent quality since their difference between additional impact of excess citation (Y_3) and the uncited patents (X_3) on average is large. In all three areas, the value of X_1 is so small that it can hardly have any influence on T_2, which indicates that the proportions of patents located in the h-area are small in all three fields.

For $T_1(X_2 + Y_1 + Z_3)$, comparing with the gap between X_1, Y_2 and Z_3 in T_2, the difference between X_2, Y_1 and Z_3 in three fields are smaller, which proves our assumption that T_1 gives a balanced value for both h-area and t-area.

In addition, we note that the average numbers and standard deviations of all metrics in "Computer Hardware & Software" are higher than those in the other two fields. This shows that the top 100 assignees in "Computer Hardware & Software" generally adopt a more active approach in patenting, and their technological performances vary greatly.

Computer Hardware & Software industry

The top ten assignees ranked by the main trace T_1 in the field of "Computer Hardware & Software" are shown in Table 4 and Fig. 2.

From Table 4 and Fig. 2, we see that Microsoft and IBM have similar patent portfolios and seem to have created a duopolistic market structure in "Computer Hardware & Software". The values of T_2 ($X_1 + Y_2 + Z_3$) of Microsoft and IBM are much higher than those of other assignees. The excellent performance of the two assignees is mostly owed to their extremely high citations in the t-area (Y_2). In addition, their ST values are very high, which again shows their outstanding performance. The value of T_1 ($Y_1 + X_2 + Z_3$) of Microsoft is the highest in the field and while the T_1 of IBM is eighth highest. Their high T_1 values are due to high patent score in the t-area (X_2). Since patents in the t-area may contain important technology and have the potential to become patents in h-core, they can

Table 4 Top ten assignees of "Computer Hardware & Software"

Assignee	X_1	X_2	X_3	Y_1	Y_2	Y_3	Z_1	Z_2	Z_3	T_1	T_2	ST
Microsoft	1.13	4577.11	1199.25	1381.66	64,175.42	1226.85	1380.52	59,598.31	27.60	**5986.36**	64,204.14	**9789.52**
RSA	15.21	0.21	0.00	15.10	0.02	4951.16	−0.12	−0.19	4951.16	4966.46	4966.39	5513.23
Digimarc	13.96	116.25	17.78	1690.85	653.82	2753.52	1676.88	537.57	2735.74	4542.84	3403.52	8876.07
Commvault	14.06	57.51	0.44	504.20	207.48	2843.54	490.13	149.97	2843.09	3404.79	3064.63	5799.98
Apple	2.31	560.64	202.98	715.55	4325.32	1769.38	713.23	3764.68	1566.39	2842.58	5894.02	5295.96
Exbiblio	12.07	0.07	0.00	9.10	0.00	2809.10	−2.97	−0.07	2809.10	2818.27	2821.17	3138.07
Voicebox	16.00	1.00	0.00	49.67	1.52	2349.58	33.67	0.52	2349.58	2400.26	2367.10	3083.52
IBM	0.45	5028.91	3892.64	687.40	67,662.81	511.03	686.95	62,633.89	−3381.61	2334.70	**64,281.65**	7412.72
Cisco	1.56	922.18	244.57	622.46	7282.92	854.69	620.90	6360.74	610.12	2154.76	7894.60	3858.10
Google	2.08	692.61	190.67	780.68	5161.86	844.38	778.59	4469.25	653.71	2127.00	5817.65	3941.47

Bold: top trace metric value

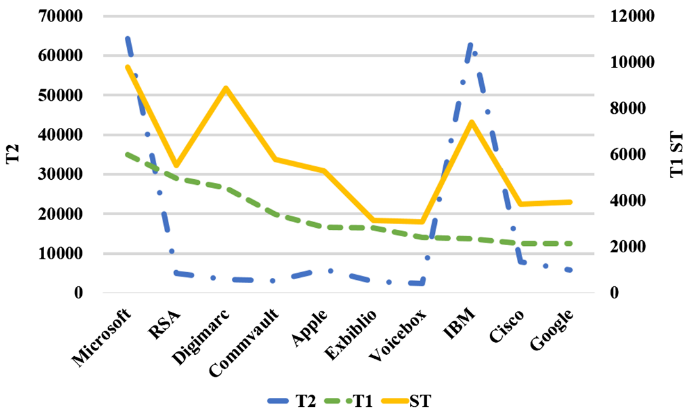

Fig. 2 Top ten assignees of "Computer Hardware & Software"

be considered "backup promising patents" of the assignees. For this reason, assignees like Microsoft and IBM who perform excellently in the t-area can be expected to have golden prospects for the future. On the other hand, though, their contribution by Z_3 to T_1 and T_2 is much lower than other top assignees. The Z_3 of IBM is even negative. It is notable that their uncited number of patents (X_3) is considerably high and the additional citation in e-area (Y_3) is not high and can hardly compensate for X_3. Thus, we may suggest that Microsoft and IBM are not so competitive in high quality patents, and their performances have been influenced by a great number of poor-quality patents.

The patent portfolios of RSA, Exbiblio and Voicebox are fairly different from those of Microsoft and IBM. Their high values of T_1 and T_2 are mostly contributed by Z_3. Their high Z_3 values are due to high citation scores in the e-area (Y_3) and zero uncited patents (X_3). Their X_2 and Y_2 values are fairly low, showing their low patent scores and citation scores in t-area. Therefore, we can infer that the overall patent qualities of these three assignees are quite good, and they may hold some patents containing significant techniques, which is the reason why they are at the forefront of the industry. Nevertheless, RSA, Exbiblio and Voicebox may not have heavy development potential since their performances in the t-area are poor, which means they are short of supplies of potential patents.

Among the other five top assignees, the patents profilos of Apple, Cisco and Google resemble those of IBM and Microsoft, whose advantages mainly depend on patents in the h-tail, whereas Digimarc and Commvault are are more like RSA, Exbiblio and Voicebox, paying more attention to patents in the h-core.

Motors, Engines & Parts industry

The top ten assignees ranked by the main trace T_1 in the field of "Motors, Engines & Parts" are shown in Table 5 and Fig. 3.

As indicated by Table 5 and Fig. 3, there is no obvious monopoly in the field. Ford, GE, Toyota and Honda are the top 4 assignees with the highest values of T_1, T_2 and ST. They have better performances than the other assignees, but their advantages are not so obvious. The four have similar patent portfolios. For $T_1(Y_1 + X_2 + Z_3)$, they have high patent scores in the t-area (X_2), low citation scores in the h-area (Y_1) and low Z_3. For

Table 5 Top ten assignees of "Motors, Engines & Parts"

Assignee	X_1	X_2	X_3	Y_1	Y_2	Y_3	Z_1	Z_2	Z_3	T_1	T_2	ST
Ford	1.05	596.10	136.16	249.54	3808.15	193.33	248.49	3212.04	57.17	**902.81**	3866.37	**1478.25**
GE	0.33	998.09	476.69	96.28	6600.69	47.36	95.95	5602.60	−429.33	665.04	**6171.69**	1276.79
Toyota	0.54	742.04	391.51	177.02	5129.27	51.08	176.49	4387.23	−340.43	578.64	4789.38	1160.32
Honda	0.42	745.49	332.38	103.73	4992.64	56.63	103.30	4247.16	−275.75	573.46	4717.31	1059.13
Paice	2.67	0.67	0.00	0.50	0.00	479.56	−2.17	−0.66	479.56	480.73	482.23	511.67
iRrobot	2.13	5.63	2.70	6.38	1.70	462.66	4.25	−3.94	459.96	471.97	463.79	583.33
Fallbrook	8.02	21.02	0.00	157.99	71.66	197.44	149.97	50.64	197.44	376.44	277.11	729.67
Nissan	1.13	237.83	48.81	127.70	1359.11	51.01	126.56	1121.28	2.19	367.72	1362.44	577.94
Boeing	0.68	261.95	71.33	86.21	1032.21	37.02	85.53	770.26	−34.31	313.84	998.58	498.17
Autoliv	1.22	172.65	22.88	96.28	764.88	55.89	95.06	592.22	33.01	301.94	799.11	471.53

Bold: top trace metric value

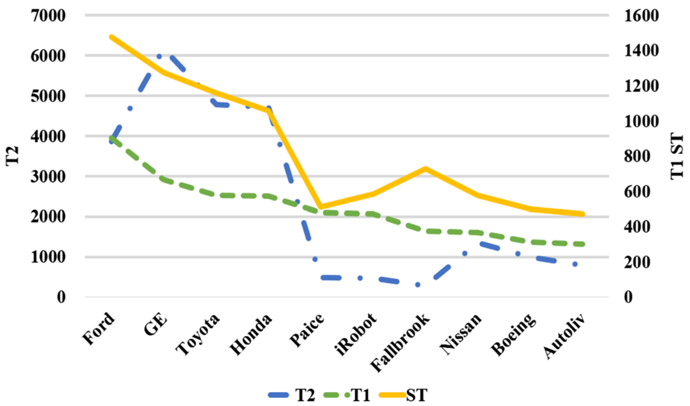

Fig. 3 Top ten assignees of "Motors, Engines & Parts"

$T_2(X_1 + Y_2 + Z_3)$, they have high citation scores in the t-area (Y_2), low patent scores in the h-area (X_1) and low Z_3. Of the four, three have negative Z_3, suggesting there are so many uncited patents (X_3) that the additional impact of excess citation (Y_3) on average can hardly compensate for them. It reveals that these four companies hold superiority in the t-area. Three other assignees in top 10—Nissan, Boeing and Autoliv—have similar patent structures to Ford et al.

The patent structures of Paice, iRobot and Fallbrook are distinctive among the top 10 assignees, and resemble RSA in "Computer Hardware & Software". Their T_1 and ST are in the top 10, but their T_2 are not in the top 20 in the field. They have quite high additional impact of excess citation (Y_3) and very low uncited number of patents (X_3), suggesting their great strength lies in superior patents in h-core, which may contain critical techniques. However, they do not have many patents and citations in the t-area (X_2 and Y_2). We may infer that they put more emphasis on high-quality patents, but may not be so promising in the future.

Drugs & Medical industry

The top ten assignees in the field of "Drugs & Medical" are shown in Table 6 and Fig. 4, ranked by the main trace T_1.

As indicated by Table 6 and Fig. 4, the Drugs & Medical's industry structure resembles an oligopoly structure. Monsanto have the highest T_1, T_2 and ST, and its T_2 and ST is much higher than that of the rest of the assignees, showing its monopolistic position. Furthermore, almost all the indicators of Monsanto rank first in the field, which demonstrates its superiority in all aspects. It has excellent citation scores for the h-area and the e-area (Y_1 and Y_3), and also excellent patent and citation scores for the t-area (X_2 and Y_2). We can see that Monsanto have quite a balanced patent portfolio, holding both highly cited important patents and backup promising patents.

Pioneer Hi-Bred, whose T_1 ranks third and T_2 and ST second, has a similar patent structure to Monsanto. It also has great performance both in the h-area and the t-area (see from high Y_1, X_2 and Y_2). The only difference is it doesn't have much additional excess citation for compensation (Y_3)—that is to say, highly cited critical patents.

Table 6 Top ten assignees of "Drugs & Medical"

Assignee	X_1	X_2	X_3	Y_1	Y_2	Y_3	Z_1	Z_2	Z_3	T_1	T_2	ST
Monsanto	3.38	365.01	292.68	1081.68	6408.67	1299.14	1078.29	6043.67	1006.45	**2453.14**	**7418.51**	**5116.68**
Dharmacon	11.57	0.32	1.75	63.12	0.06	1062.08	51.55	−0.26	1060.33	1123.78	1071.96	1643.38
Pioneer	2.73	181.41	267.63	659.71	3576.61	391.49	656.99	3395.21	123.86	964.98	3703.20	2249.02
Senomyx	5.58	6.70	15.51	114.47	10.57	743.60	108.89	3.87	728.09	849.26	744.24	1448.26
454 Life Sciences	3.00	3.00	0.00	1.44	0.36	792.25	−1.56	−2.64	792.25	796.70	795.61	864.36
Limagrain	5.14	0.14	0.00	1.70	0.00	693.70	−3.45	−0.14	693.70	695.54	698.84	764.14
Zymogenetics	7.50	9.08	27.08	455.31	23.16	256.87	447.81	14.09	229.80	694.18	260.46	1405.24
Lifescan	1.78	0.44	1.00	0.36	0.00	689.36	−1.42	−0.44	688.36	689.15	690.13	721.44
Stanford Univ	0.96	17.56	83.71	29.48	29.18	638.33	28.53	11.62	554.62	601.66	584.76	959.74
KWS	4.17	0.17	0.00	1.05	0.00	545.05	−3.11	−0.17	545.05	546.27	549.22	594.17

Bold: top trace metric value

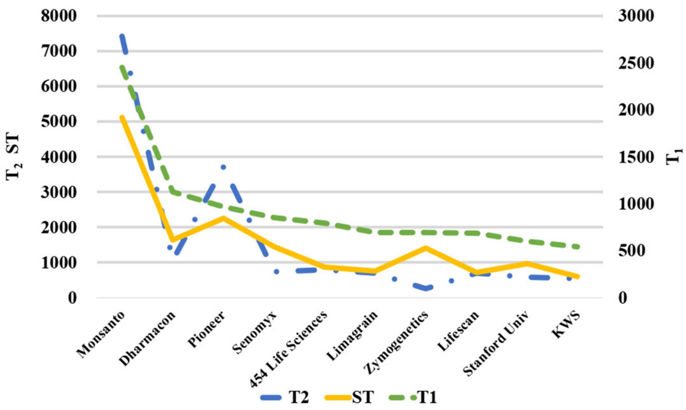

Fig. 4 Top ten assignees of "Biotechnology"

All the other top assignees show similar patent structure with RSA in "Computer Hardware & Software" and Paice in "Motors, Engines & Parts". Their patent scores in t-area (X_2) and citation scores in t-area (Y_2) are very low while the values of Z_3 are quite high. The high values of Z_3, which makes the greatest contribution to T_1 and T_2, are due to the very high additional impact of excess citations (Y_3) and little uncited patents (X_3). This suggests that the competiveness of these assignees originates from holding highly cited patents. However, these assignees' performances in the t-area are not good, indicating their worrying future.

From Tables 4, 5 and 6, we can see that different assignees have different trace values, indicating different contributions to technical patents of their fields. The values of traces vary considerably from field to field. For instance, Ford has the highest value of T_1 in the field of "Motors, Engines & Parts", whereas assignees with same T_1 value only rank 36th in "Computer Hardware & Software". Since patent and citation patterns differ wildly across fields, these differences will cause strong industry biases in Trace measures. So, normally, assignee traces can be only used to compare the technological capability of assignees within fields, and are inapplicable for direct comparison across fields.

The above analysis reveals three patent strategies of assignees—h-core oriented strategy, h-tail oriented strategy and balanced strategy. H-core oriented assignees lay more emphasis on high quality patents in h-core. Their T_1 and T_2 are mostly occupied by Z_3 whereas scores for the t-area (X_2 and Y_2) are poor. They hold core technologies, but may run into the trouble of losing potential for sustainable development. For h-tail oriented assignees, on the contrary, the patent scores of the t-area (X_2) account for the largest portion of T_1, the citation scores of the t-area (Y_2) account for the largest portion of T_2, and the values of Z_3 are low or even negative. Their strengths lie in patents in h-tail and have great potential for growth. Assignees with balanced strategy do well in both h-core and h-tail, and they are companies who are competitive and also promising.

It is worth noticing that the three industries demonstrate distinctive industrial structures and patterns of patents activities. The "Computer Hardware & Software" industry tends toward a duopoly, with Microsoft and IBM occupying a large part of the market. The structure of "Drugs & Medical" resembles an oligopoly in which Monsanto dominates the market, while the field of "Motors, Engines & Parts" has no clear monopoly characteristics. In addition, the assignees' strategy selections also show enormous industry differences. Most top assignees in "Motors, Engines & Parts" are h-tail oriented companies, most top assignees in "Biotechnology" are h-core oriented companies, while assignees in "Computer Hardware & Software" have various choices.

Comparing traces with *C*

We first examine the correlations between traces and C (number of citations), since the number of citations is a basic indicator for measuring assignees' technological capability.

To present the findings more clearly, we decided to take the logarithm of traces and C. Since negative trace metrics exist in our study, the data is preprocessed in order to avoid the influence of outliers. As mentioned above, there are negative T_1 in "Motors, Engines & Parts" and negative T_1 and T_2 in "Drugs & Medical". All of these three traces metrics will add the absolute value of the largest integer less than the smallest traces value in that field so that negative traces can be translated to positive values. For example, if the smallest T_1 in "Drugs & Medical" is -15.3, 16 will be added to all values of T_1 in that field. Such processing will not influence the distribution of data. The $\log(T) - \log(C)$ scatterplots of the three fields are shown in Figs. 5, 6, and 7. The correlations between $\log(T)$ and $\log(C)$ are computed by SPSS, as shown in Table 7.

As illustrated in Fig. 5, the scatterplots of T_2 and C for "Computer Hardware & Software" are almost linear, the scatterplot of ST and C is more or less a straight line, and the scatterplot of T_1 and C tends to be not linear. The Pearson's and Spearman's correlation coefficients in Table 7 indicate that T_1, T_2 and ST are all significantly positively correlated with C. The coefficients for T_2 versus C are extraordinarily high, showing a strong positive correlation. The coefficients for ST versus C, T_1 versus C show notable positive correlations.

The situation in "Motors, Engines & Parts" is almost the same with that of in "Computer Hardware & Software". As seen from Fig. 6, the scatterplot of T_2 and C approximates a straight line; though there are a few exceptional outliers, the scatterplot of ST and C is nearly linear, but that of T_1 and C is not linear. Statistics in Table 7 suggest strong positive correlations between T_2, ST and C, and a moderate positive correlation between T_1 and C.

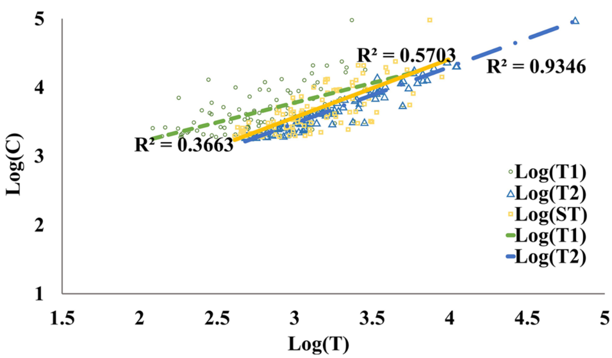

Fig. 5 The scatterplot of $\log(T)$ and $\log(C)$ for "Computer Hardware & Software"

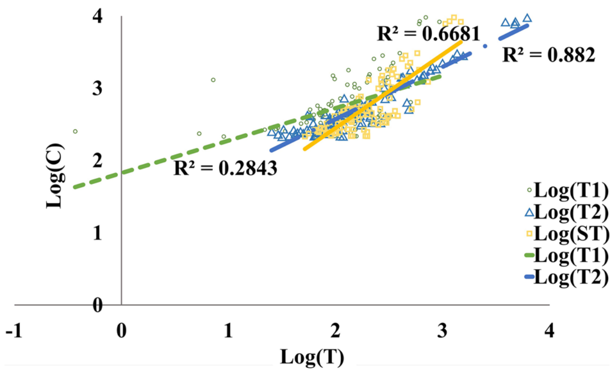

Fig. 6 The scatterplot of log(T) and log(C) for "Motors, Engines & Parts"

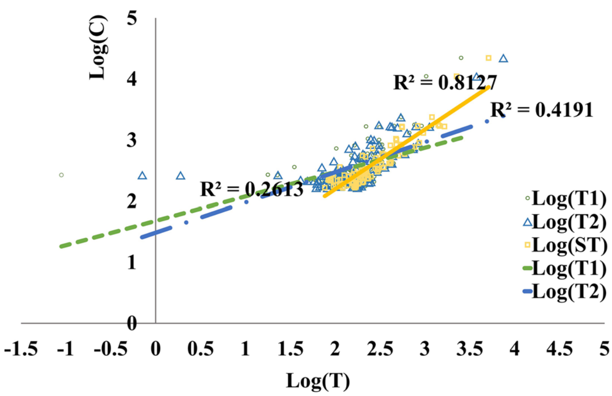

Fig. 7 The scatterplot of log(T) and log(C) for "Biotechnology"

Table 7 Correlation coefficients between log(T) and log(C)

Correlation coefficient	Computer Hardware & Software		Motors, Engines & Parts		Drugs & Medical	
	Pearson's	Spearman's	Pearson's	Spearman's	Pearson's	Spearman's
Log(T_1)	.605**	.593**	.533**	.573**	.511**	.639**
Log(T_2)	.967**	.947**	.939**	.878**	.647**	.668**
Log(ST)	.755**	.732**	.817**	.748**	.901**	.843**

* $P < 0.05$ (2-tailed); ** $P < 0.01$ (2-tailed)

In Fig. 7, we can see that the relationship between traces and C for "Drugs & Medical" are little different from the other two fields. The linear relationship between ST and C is strongest, the linear relationship between T_2 and C is not so obvious, while the relationship between T_1 and C is not linear. Statistics in Table 7 still show significant correlations between all traces and C: T_1, T_2 are notably correlative with and C, while ST are highly correlative with C.

In general, the analysis above reveals a significantly positive correlation between traces and C in all three fields, which means that an assignee's values of traces is highly dependent on its citation counts. The correlations between T_2 and C, ST and C tend to be strong and linear, while that of T_1 and C is not linear and is weaker than the other trace metrics. Compared with C, traces are multidimensional indicators, which can be analyzed from different aspects and used as effective indicators in patent citation analysis.

Comparing traces with CII

Since traces and CII are two indicators which can capture the overall technical performance of an assignee, a comparative analysis can be made to further investigate their relationship. The data is processed in the same way as described above. The log(T) − log(CII) distributive scatterplots for the three fields are shown in Figs. 8, 9, and 10. Then the correlations between log(T) and log(CII) are computed by SPSS and shown in Table 8.

As shown in Fig. 8, the scatterplot of T_1 and CII for "Computer Hardware & Software" is slightly linear, but the scatterplots of T_2 and ST are scattered and not linear. The Pearson's and Spearman's correlation coefficients in Table 8 show that T_1 and ST are positively correlated with CII, but T_2 is not correlated with CII. The correlation between T_1 and CII is strong, and the correlations between ST and CII are moderate.

In Fig. 9 for the field of "Motors, Engines & Parts", we can see that the scatterplots of all three traces and CII are irregular. The Pearson's and Spearman's correlation coefficients in Table 8 suggest that there are moderate positive correlations between T_1 and CII, ST and CII, and almost no correlation between T_2 and CII.

As shown in Fig. 10, the scatterplots of traces T and CII for "Drugs & Medical" are also quite scattered and not linear. Statistics in Table 8 still indicate that moderate positive correlations between T_1 and CII, ST and CII. Somewhat differently from the other two filed, T_2 in "Drugs & Medical" is also moderately associated with CII.

The result shows that T_1 and ST have positive, moderate, nonlinear correlations with CII, which means their evaluation results roughly accord with CII. Meanwhile the

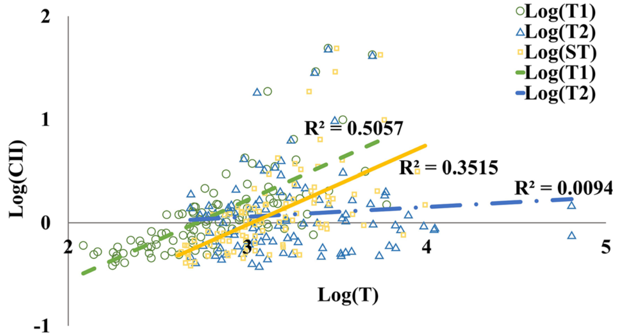

Fig. 8 The scatterplot of log(T) and log(CII) for "Computer Hardware & Software"

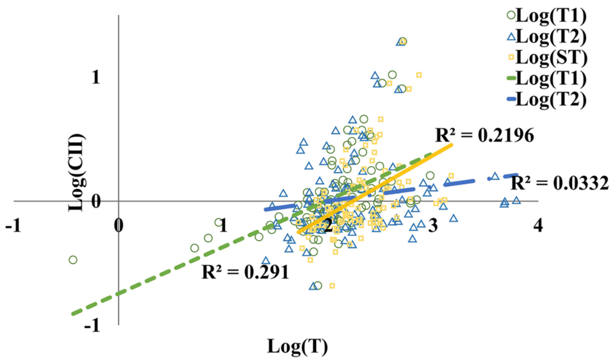

Fig. 9 The scatterplot of log(T) and log(CII) for "Motors, Engines & Parts"

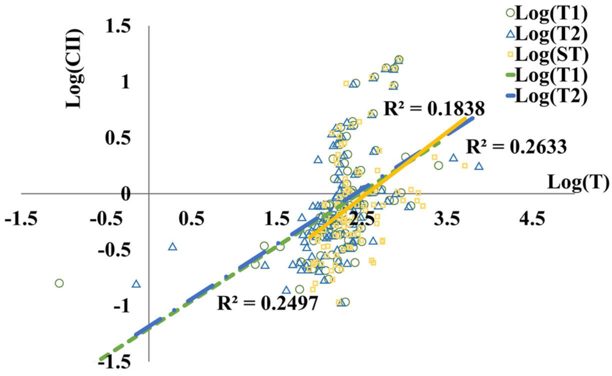

Fig. 10 The scatterplot of log(T) and log(CII) for "Biotechnology"

Table 8 Correlation coefficients between log (T) and log (CII)

Correlation coefficient	Computer Hardware & Software		Motors, Engines & Parts		Drugs & Medical	
	Pearson's	Spearman's	Pearson's	Spearman's	Pearson's	Spearman's
Log(T_1)	.711**	.789**	.539**	.660**	.500**	.610**
Log(T_2)	0.097	0.112	0.182	.250*	.513**	.594**
Log(ST)	.593**	.670**	.469**	.527**	.429**	.493**

* $P < 0.05$ (2-tailed); ** $P < 0.01$ (2-tailed)

correlation between T_2 varies from industry to industry. In the field of "Computer Hardware & Software" and "Motors, Engines & Parts", T_2 and CII are generally two distinct measures. But in the field of Drugs & Medical, T_2 has a notable correlation with CII.

As mentioned before, the idea of CII is the same as IF5 for papers in essence, and the assignee traces derive from the papers' academic trace proposed by Ye and Leydesdorff

(2014). In the previous study, academic trace, which is T_2 for scientific papers, correlated significantly with IF5, while in this study, trace T_2 in two fields did not show a correlation with CII. The similarities and differences between academic trace and patent trace can be explored in the future.

Comparing traces with h-index

We also made a comparison between traces and h-index, a very popular indicator in scientometrics. The same data processing is repeated, and the $\log(T) - \log(H)$ scatterplots of the three fields are shown in Figs. 11, 12, and 13. Then the correlations between $\log(T)$ and $\log(H)$ are computed by SPSS, as shown in Table 9.

As indicated in Fig. 11, the scatterplots of T_2 and H, ST and H are more or less linear, while the scatterplot of ST and H is not linear. The Pearson's and Spearman's correlation coefficients in Table 9 show significantly positive correlations between traces and H. The correlations between T_2 and H, ST and H appear to be strong, and that of between T_1 and H is moderate.

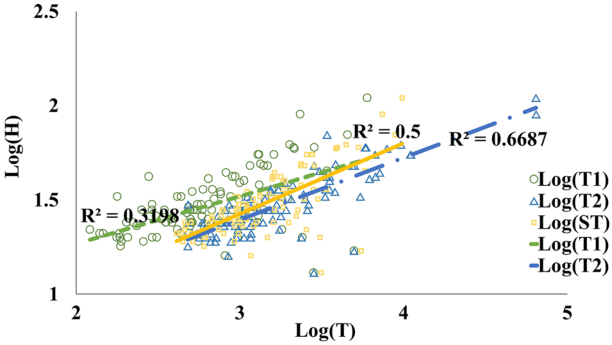

Fig. 11 The scatterplot of log(T) and log(H) for "Computer Hardware & Software"

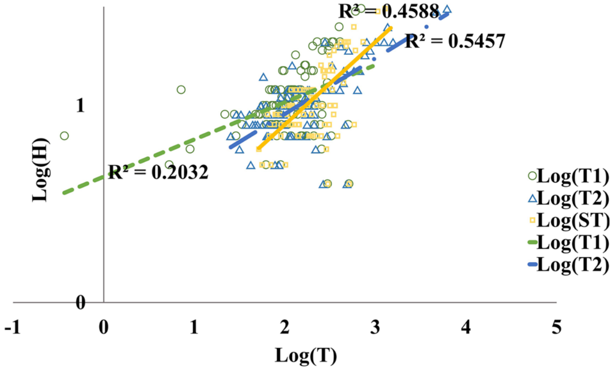

Fig. 12 The scatterplot of log(T) and log(H) for "Motors, Engines & Parts"

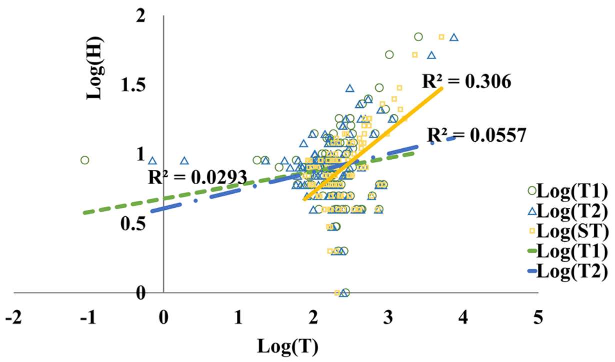

Fig. 13 The scatterplot of log(T) and log(H) for "Biotechnology"

Table 9 Correlation coefficients between log(T) and log(H)

Correlation coefficient	Computer Hardware & Software		Motors, Engines & Parts		Drugs & Medical	
	Pearson's	Spearman's	Pearson's	Spearman's	Pearson's	Spearman's
Log(T_1)	.566**	.545**	.451**	.409**	0.171	0.087
Log(T_2)	.818**	.763**	.739**	.630**	.236*	0.081
Log(ST)	.707**	.671**	.677**	.583**	.553**	.375**

* $P < 0.05$ (2-tailed); ** $P < 0.01$ (2-tailed)

The situation in "Motors, Engines & Parts" is similar to "Computer Hardware & Software". As shown in Fig. 12, the scatterplots for T_2 and ST tend to be more or lesslinear, and the scatterplots for T_1 is not linear. Statistics in Table 9 indicate strong positive correlations between T_2 and H, ST and H, and a moderate correlation between T_1 and H.

As seen in Fig. 13 for "Drugs & Medical", the scatterplots of traces and H are quite scattered and not linear. The Pearson's and Spearman's correlation coefficients suggest that T_1 is not associated with H, T_2 is very weakly associated with H at the level of 0.05, and ST is moderately associated with H.

According to the above analysis, traces in the field of "Computer Hardware & Software" and "Motors, Engines & Parts" are generally positively, nonlinearly and strongly/moderately correlated with H. This indicates that the evaluation result of traces is consistent with that of h-index. Both of the two indicators measure assignees' technological capability where productivity (number of patents) and impact (citation counts) are taken into consideration. While h-index offers a general overview of the assignee, traces can provide much more detailed and accurate information by summarizing and balancing the accumulation of publications and citations across the h-core, h-tail, and uncited areas in a reasonable way.

The field of "Drugs & Medical" again shows its particularity. The correlations between its T_2, ST and H are weaker than the other two fields, and its T_1 is not correlated with H at all.

Conclusion

The objectives of this paper are to introduce traces from bibliometrics into patent citation analysis and to investigate their application in measuring and ranking the technological performance of patent assignees. According to our empirical study of assignees from three different fields, assignee traces have proven to be effective and reliable indicators for capturing the total technological performance, and providing detailed information about the assignees' technology structure at the same time. On the basis of different contributions of individual components X_1, X_2, Y_1, Y_2 and Z_3, for instance, we can identify the technological strengths and weaknesses of a certain assignee, or even probe into its patent strategy. Moreover, with the help of traces, we can analyze monopolistic or duopolistic competitive situations and gain a broad overview of the technology landscape of a certain field.

Further comparative analysis illustrates that T_1 and ST in the fields of "Computer Hardware & Software" and "Motors, Engines & Parts" have positive, strong or moderate correlations with total citations, CII and h-index. T_2 in these two fields is highly linearly correlated with total citations, strongly correlated with h-index and not correlated with CII. This result may reveal that in these two fields the traces of an assignee are generally consistent with its patent citation counts and h-index, but T_2 and CII tend to be two distinctive indicators. Compared with the three other indicators, traces have shown unique advantages such as versatility, comprehensiveness and accuracy, making it a good complement to patent citation analysis.

Some phenomena ought to be noted in the "Drugs & Medical" industry. Most top assignees in this filed gain their competitive edge by holding highly cited patents, the high quality patents. While in the other two fields, more top assignees' strengths lie in patents in h-tail. In addition, the correlations between traces and three other indicators differ from that in "Computer Hardware & Software" and "Motors, Engines & Parts". T_2 is significantly correlated with CII but less correlated with C, and the correlations between traces and h-index are relatively weaker in "Drugs & Medical". The various characteristics of traces in different industries could be studied in the future to investigate the different patents strategies of assignees in those industries.

Assignee traces are derived from academic traces, but they show some characteristics that differentiate them from academic traces. Negative values of traces appeared for the first time in our study. Traces >0 indicates that an assignee has a positive contribution in the field, while traces <0 means the assignee has so many patents of poor quality that its contribution is redundant. Additionally, the correlation between T_2 and CII differs greatly from that between the academic trace and IF5. Further studies can focus on the comparison of the two indicators in a more detailed manner and investigate the similarities and differences between scientific papers and patents.

Acknowledgments The authors are grateful for financial support from NSFC Grant No. 71173187, and thank Ms. Huei-Ru Dong for data processing, and Ms. Wei-Tzu Huang for data collection.

Appendix

See Table 10.

Table 10 Top 100 assignees with highest citations and their countries

No	Computer Hardware & Software		Motors, Engines & Parts		Drugs & Medical	
	Assignee name	Country	Assignee name	Country	Assignee name	Country
1	Microsoft	US	General Electric	US	Monsanto	US
2	IIBM	US	Toyota	JP	Pioneer Hi-Bred	US
3	Sony	JP	Ford	US	Dupont	US
4	Hewlett-Packard	US	Honda	JP	Zymogenetics	US
5	Intel	US	Nissan	JP	Ajinomoto	JP
6	Cisco Technology	US	Nippon	JP	Senomyx	US
7	Apple	US	Yamaha	JP	California University	US
8	Google	US	Boeing	US	Dharmacon	US
9	Oracle	US	Autoliv	US	Stine Seed Farm	US
10	Digimarc	US	Takata	JP	Stanford University	US
11	At&T	US	ZF Friedrichshafen	DE	Novozymes	DE
12	Samsung	KR	Mitsubishi	JP	Allergan	US
13	SAP	JP	Hitachi	JP	454 Life Sciences	US
14	Hitachi	JP	Hyundai	KR	Scripps Research	US
15	Sun Microsystems	US	Daimlerchrysler	GE	MIT	US
16	Symantec	US	Toyoda	JP	USA Department of Health and Human Services	US
17	Canon	JP	Airbus	FR	Limagrain	FR
18	Yahoo!	US	Robert Bosch	DE	Syngenta	GB
19	Fujitsu	JP	Delphi Technologies	US	Lifescan	US
20	Toshiba	JP	Fallbrook	US	California Institute Of Technology	US
21	Ricoh	JP	Aisin	JP	Cornell Research Foundation	US
22	Nokia	FI	Caterpillar	US	KWS Saat	DE
23	EMC	US	Honeywell	US	Sanofi Pasteur	FR
24	Commvault	US	Siemens	DE	Applied Biosystems	US
25	General Electric	US	Magna	CA	Wyeth	US
26	Siemens	DE	Mazda	JP	Seminis Vegetable Seeds	US
27	Cadence Design Systems	US	USA, Secretary Of Army	US	Ibis Biosciences	US
28	Amazon	US	Deere+	US	Martek Biosciences	NL
29	Research In Motion	CA	Kone Oy	FI	Texas University	US
30	American Online	US	Porsche	DE	University Of Pennsylvania	US

Table 10 continued

No	Computer Hardware & Software		Motors, Engines & Parts		Drugs & Medical	
	Assignee name	Country	Assignee name	Country	Assignee name	Country
31	Panasonic	JP	iRobot	US	Genencor International	US
32	Accenture	US	Rolls-Royce	GB	Amgen	US
33	Rsa Security	US	Lockheed Martin	US	Dow Agrosciences	US
34	Adobe Systems	US	United Technologies	US	Zea Chem	US
35	Broadcom	US	Trw Vehicle Safety Systems	US	Fluidigm	US
36	Honda	JP	Otis Elevator	US	Applera	US
37	Trading Technologies	US	Shimano	JP	Genentech	US
38	Xerox	US	Raytheon	US	Verdia	US
39	Lg Electronics	KR	BRP	CA	Cargill	US
40	Honeywell	US	Bayerische Motoren Werke	DE	Bayer	DE
41	Jpmorgan Chase Bank	US	Paice	US	Sru Biosystems	US
42	Xilinx	US	Jtekt	JP	3M	US
43	American Express Travel Related Services	US	Borgwarner	US	Harvard College	US
44	Fotonation	US	Kanzaki	JP	Gen-Probe	US
45	Texas Instruments	US	Inventio	CH	Anthrogenesis	US
46	Nvidia	US	Black & Decker	US	Isis Pharmaceuticals	US
47	Network Appliance	US	Jatco	JP	Illinois University	US
48	Bea Systems	US	Automotive	US	General Hospital	US
49	Alcatel	FR	Kawasaki Jukogyo	JP	Harris Moran Seed	US
50	NEC	JP	American Axle and Manufacturing	US	Human Genome Sciences	US
51	Seiko Epson	JP	Lg Electronics	KR	Mendel Biotechnology	US
52	Mcafee	US	Advics	JP	Commonwealth Scientific and Industrial Research	AU
53	Synopsys	US	Benteler	AUT	Florida University	US
54	Philips Electronics	NL	DEKA	US	Illumina	US
55	Micron Technology	US	Emerson	AU	Crucell Holland	NL
56	Marvell	US	Baxter	US	Wisconsin Alumni Research	US
57	Netapp	US	NSK	JP	USA, Secretary Of Army	US
58	Voicebox	US	CNH America	US	Basf	DE
59	National Instruments	US	Pride Mobility Products	US	Johns Hopkins University	US
60	Altera	US	Pratt & Whitney	CA	Kyowa Hakko Kogyo	JP
61	Nortel Networks	CA	Kubota	JP	Bavarian Nordic	DE

Table 10 continued

No	Computer Hardware & Software		Motors, Engines & Parts		Drugs & Medical	
	Assignee name	Country	Assignee name	Country	Assignee name	Country
62	Exbiblio	US	Hon Hai	TW	Mertec	US
63	Juniper Networks	US	Key Safety Systems	US	Novartis Vaccines and Diagnostics	CH
64	Boeing	US	Tk Holdings	US	D & Pl Technology	US
65	Vmware	US	Fuji Jukogyo	JP	Verenium	US
66	Computer Associates Think	US	Luk	DE	Minnesota University	US
67	Qualcomm	US	Link Treasure	VG	Sequenom	US
68	Donnelly	US	Harley-Davidson	US	Bristol-Myers Squibb	US
69	Rockwell Automation	US	Milliken & Company	US	Handylab	US
70	Matsushita Electric	JP	Eaton	US	A. Duda & Sons	US
71	Avaya Technology	US	Graco Children's Products	US	Iowa University	US
72	Sprint Communications	US	Kia Motors	KR	Geron	US
73	The Mathworks	US	Florida Turbine Technologies	US	Boehringer Ingelheim	DE
74	Sharp	JP	Invacare	US	Canon	JP
75	Ericsson	SE	Arvinmeritor	US	Genomatica	US
76	Fuji Xerox	JP	Wilhelm Karmann	DE	Duke University	US
77	Ebay	US	Goodyear Tire + Rubber	US	Danisco	DK
78	Toyota	JP	Chrysler Group	US	University of Michigan	US
79	Citrix Systems	US	NTN	JP	Zyomyx	US
80	Cummins-Allison	US	Wonderland Nurserygoods	TW	Biosite	US
81	Fujifilm	JP	Yanmar	JP	Hemogenix	US
82	Thomson Licensing	FR	Schaeff	US	University Of Utah	US
83	Nippon	JP	Hill-Rom	US	Vanderbilt University	US
84	Akamai	US	Knorr-Bremse	DE	Cytori Therapeutics	US
85	Dell Products	US	Snecma	FR	North Carolina University	US
86	LSI	US	89,908	US	Ethicon	US
87	Fisher Rosemount Systems	US	Lear	US	Pacific Biosciences of California	US
88	Ford	US	Mahle International	DE	Dako	DK
89	Eastman Kodak	US	Komatsu	JP	Merck+	US
90	Motorola	US	Polaris Industries	US	Abbott Laboratories	US
91	Mitsubishi	JP	International Truck Intellectual Property	US	Dsm Ip Assets	NL
92	Ntt Docomo	JP	Continental	DE	Regeneron Pharmaceuticals	US

Table 10 continued

No	Computer Hardware & Software		Motors, Engines & Parts		Drugs & Medical	
	Assignee name	Country	Assignee name	Country	Assignee name	Country
93	Sandisk	US	IBM	US	Centocor	US
94	Sony Ericsson	JP	Eurocopter Deutschland	DE	Agilent Technologies	US
95	Unisys	US	Ts Tech	JP	Rochester University	US
96	Stmicroelectronics	CH	Gates	US	Immunex	US
97	Novell	US	Canadian National Railway	CA	Cyterra	US
98	Advanced Micro Devices	US	Target Brands	US	Affymetrix	US
99	Robert Bosch	DE	Yokohama Rubber	JP	Millennium Pharmaceuticals	US
100	Silverbrook Research	AU	Michelin Recherche Et Technique	CH	Third Wave Technologies	US

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