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Exploring patent performance and technology interactions of universities, industries, governments and individuals

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Abstract In the era of the fast-paced knowledge economy, patent data may be analyzed to measure technological competitiveness. This paper aims to explore patent performance by indicators and technology interactions based on patent citation of assignee types. This study involved four types of patent assignees (i.e. universities, industries, governments, and individuals) in five technological fields (i.e. computers and communications; drugs and medical; electrical and electronics; chemical; and mechanical) over three periods (i.e. 1997–2001, 2002–2006, and 2007–2011). Four indicators were chosen for analysis of patent performance; they included, patent share, science linkage, current impact index, and citation density. The findings of this study show that among all four assignee types, industries had the highest patent productivity in all fields, and universities had the highest impact in all fields except for drugs and medical. Other interesting phenomena were also observed. Examples include reciprocal technology interactions between universities and governments; low technology interactions of industries in each field; individuals' higher patent performance and technology interactions in the field of drugs and medical.

Keywords Patent performance · Technology interactions · Patent bibliometrics · Patent citation analysis · Technological competitiveness

Introduction

In the era of the fast-paced knowledge economy, patent data may be analyzed to measure technological competitiveness. According to Narin (1994), patent bibliometrics is "for the

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use of patents, and patent citations in the evaluation of technological activities." The measure of patent performance is of use for understanding the technological development of countries, organizations and individuals respectively. In addition, patent data are viewed as one of the widely-accepted valid measures for a company's technological activities (Ma and Lee 2008) or a company's innovation performance (Griliches 1990). Quantitative indicators of the patent performance of individual companies would be an important addition to the financial and economic data used in competitor assessments, merger/acquisition analyses, investment decisions, and corporate planning and management (Narin et al. 1987). The indicators developed by CHI Research Corp. (e.g. current impact index, technology cycle time, science linkage, etc.) are most commonly used to measure patent performance (Chang et al. 2012; Hagedoorn and Cloodt 2003; Narin and Frame 1989; Tseng et al. 2011). Another indicator, essential patent index, is also approved by Chen et al. (2007) in advance.

Patent citation further helps us understand technology interactions among organizations. Analyzing patent data—for instance citing and cited relationships between countries, organizations, companies, inventors and technological fields—helps understand technology interaction among entities (Trajtenberg et al. 1997; Hall et al. 2000). Patent citations have been commonly used as a medium for measuring flows of knowledge as technology interaction in recent years. Examples of this include: strategic alliances and intercompany technological knowledge transfer (Mowery et al. 1996), international technological knowledge flows (Jaffe and Trajtenberg 1999), and knowledge interaction between science and technology (Chen and Hicks 2004). Despite some criticisms (see Kostoff 1998), patent data and patent citation data provide a vehicle for studying technical change, and examining and analyzing the innovation process (Engelsman and van Raan 1994).

Hence, this paper aims to explore patent performance and technology interactions of universities, industries, governments and individuals. In order to achieve this aim, the following objectives need to be met:

- Observation of patent performance of universities, industries, governments and individuals in five technological fields over three periods of time; and
- Comparison of technology interactions between university, industry, government and individual patents in five technological fields over three periods of time.

Literature review

Patents as indicators for measuring technological competitiveness

Evidence of using patent indicators to measure technological competitiveness as patent performance is substantial in the literature. For instance, Hagedoorn and Cloodt (2003) utilized a variety of indicators, including patent counts and patent citations, to study innovative performance of international companies in high-tech industries. Chen et al. (2007) utilized the number of patents, current impact index (CII), essential patent index (EPI) and essential technological strength (ETS) to evaluate technological innovation competitiveness of three high-tech industries in Taiwan.

A review of the literature summarizes two major trends in analyzing patent indicators. First, recent research has drawn upon both quantitative and qualitative patent indicators to measure technological competitiveness. As explained by Hagedoorn and Cloodt (2003), raw counts of patents produce a purely quantitative measure, whereas patent citations include a measure of the quality of patent. It is observed that both quantitative and qualitative indicators have been utilized to serve various purposes, such as tracing knowledge flows (for instance Meyer 2002) and studying the relationship between science and technological development (for instance Acosta and Coronado 2003). Second, recent studies have employed multiple patent indicators. Compared with using a single indicator, Hagedoorn and Cloodt (2003) justified the advantage of analyzing multiple indicators as "measuring innovative performance through a more complex, more informative, composite measure". Bearing the above-mentioned trends in mind and taking the complexity of technological competitiveness into account, this study also adopts multiple patent indicators and studies patent performance from both quantitative and qualitative perspectives.

A number of patent indicators were developed and defined by CHI Research (Narin 2000); examples include: the number of patents, cites per patent, CII, technology strength (TS), technology cycle time (TCT), science linkage (TS), and science strength (SS). In addition to the most commonly-used indicators, e.g. patent counts and patent citations (as in, for instance, Trajtenberg 1990; Jaffe et al. 1993; Stuart 2000), other indicators are also considered in this study in order to help investigate the technological competitiveness of different assignee types. For example, SL is used to indicate how leading edge the company's technology is, and CII is used to indicate patent portfolio quality (Narin 2000).

Patent citations as an indicator of technology impact and interaction

Patent citations are viewed as an indicator of technology impact and interaction among organizations. According to Karki (1998) "patent citation analysis has been used as a measure of technological quality and influence and in studying diffusion of technological information." Similarly, Hagedoorn and Cloodt (2003) also stated "the validity of patent citations as an indicator of the quality of innovations, in terms of correlation between the inter-subjective assessment of the importance of patents by technical specialists and the number of citations." For example, Narin et al. (1987) employed patent citations as indicators of corporate technological strength. Albert et al. (1991) validated citation counts as indicators of industrially important patents.

Furthermore, patent citations also enable researchers to assess the linkages between cited and citing entities, such as countries, companies, and scientific and technological areas (Karki 1998). Consequently, patent citations made by and received from different types of patent assignees are analyzed in this study to explore their impact on each other, which in turn helps explore their technology interactions, as discussed next.

Technology interactions of different types of patent assignees

Technology interactions such as technological knowledge flow can be measured by means of patent citation analysis (Meyer-Krahmer and Schmoch 1998; Meyer 2000a, b; Tijssen 2001). Research using patent citation data to investigate technology interaction between different inventors or assignees is evident in the literature. For example, Jaffe and Trajtenberg (1999) explored the patterns of patent citations to study international technology interaction. Lim (2000) measured companies' science and technology interaction by patent-to-patent and patent-to-paper citation counts in the semiconductor industry. Meyer (2000a, b) also employed the tool of patent citation analysis to investigate the intensity of knowledge flows as interactions between science and technology. Agrawal (2001), summarizing empirical literature on university-to-industry knowledge transfer and interaction, observed that a heavy focus is placed on patents as a technology-transfer mechanism and reasoned that this is because the accessibility of patent data lends itself well to quantitative analysis.

A review of the patent-related literature observes that attention has been paid to the roles of universities (e.g. Henderson et al. 1998; Rosell and Agrawal 2009; Bacchiocchi and Montobbio 2009) and governments (e.g. Jaffe et al. 1998; Okada et al. 2006) respectively. Furthermore, papers have discussed the technology interaction between different inventors or assignees, university-industry in particular. For example, Tijssen (2006) focused on university-industry interactions to explore the connectivity between academic science and industrial research. Petruzzelli (2009) conducted a joint-patents analysis to investigate university-industry research and development (R&D) interactions. It is also observed that more attention is centered on the Triple Helix model of university-industry-government interactions in terms of the process of technological innovation (for example Leydesdorff and Etzkowitz 2001; Etzkowitz 2003; Leydesdorff and Meyer 2003).

Based on the Triple Helix model (Etzkowitz and Leydesdorff 2000), Leydesdorff (2012) further proposed that Quadruple Helix and even an *N*-tuple of Helices can be envisioned. As he justified, systemness of innovation patterns can be expected to remain in transition because of integrating and differentiating forces, which therefore requires three or more dimensions for the explanation of complex development (Leydesdorff 2012). For the Quadruple Helix model, the fourth dimension could be: the media-based and culture-based public (Carayannis and Campbell 2009), civil society (Carayannis and Campbell 2012), local–global (Leydesdorff 2012), private–public (Leydesdorff 2012) and so forth. For example, Carayannis and Campbell (2012) saw 'civil society' as a fourth dimension, in addition to government, academia and industry, in order to promote a democratic approach to innovation. Leydesdorff (2012) took the case of Japan as an example, explaining "the addition of a fourth helix to the model was needed because along with university-industry-government relations, internationalization also played an important role during the 1990s".

Influenced by the conception of the Quadruple Helix model, patent data of individuals, in addition to the most commonly-discussed assignee types, i.e. universities, industries and governments, are also gathered for analysis in this study. The rationale behind this decision was that the number of patents granted to individuals (cumulative up to 2011) is close to that of governments' as indicated in the United States Patent and Trademark Office (USPTO). Therefore, four assignee types, including universities, industries, governments, plus individuals, are analyzed, in terms of their patent performance and technology interactions.

Methodology

In this study, patent data were collected from the USPTO, which is accessible to researchers. A review of the literature observed different background factors in relation to patent analysis, including: patent assignee types, technological fields, and time periods. Four types of patent assignees, including universities, industries, governments and individuals, were classified by the definition of the assignee role in XML files of USPTO patent grant full text. According to the US NBER categories as in Hall et al. (2001), this study looked at five main technological fields: computers and communications (C&C); drugs and medical (D&M); electrical and electronics (E&E); chemical; and mechanical. In order to observe the recent development of patent performance, this study covered the past 15 years, divided into three periods, that is, 1997–2001, 2002–2006, and 2007–2011. Therefore, a total of 1,972,297 patents were gathered for analysis (see Table 1).

Table 1 Patent data gathered for analysis

	C&C	D&M	E&E	Chemical	Mechanical	Total
Universities	5,765	21,857	8,182	11,254	2,304	49,362
Industries	606,725	203,912	485,631	276,964	322,846	1,896,078
Governments	2,682	2,878	3,014	2,842	1,820	13,236
Individuals	2,344	2,833	2,487	2,334	3,623	13,621
Total	617,516	231,480	499,314	293,394	330,593	1,972,297

After setting the scope of this study, various aspects, i.e. patent productivity, attributes and impact, were selected to help explore patent performance. Additionally, patent citations made by and received from four assignee types were used to enable discussion of their technology interactions. For the purpose of this study, the following indicators were employed; definitions of each indicator were borrowed from CHI research (Narin 2000).

Patent share: indicates the productivity of assignees' patents

Patent share was employed as a proxy variable for the number of patents in this study. The number of patents was defined as "a count of patents issued in the US patent system" (Narin 2000). The number of patents is of use for measuring the technological productivity of countries or inventors (Narin 1994). Correspondingly, patent share was used to indicate the productivity of assignees. The higher the percentage of the patent share is, the higher the productivity of the assignee type's patents is.

Science linkage (SL): indicates the attribute of assignees' patents

SL was defined as "the average number of science papers referenced on the front page of the assignee's patents" (Narin 2000). In this respect, Karki (1998) stated that patent citations also show how near a set of patents is to scientific/basic research. Indeed, SL is viewed as an indicator of how closely the assignee's patents are linked to scientific/basic research.

In this study, SL was used to indicate the attribute of the assignee type's patents. With higher SL values, it suggests that the assignee builds its technology based on advances in science. In other words, assignees at the forefront of a technology tend to have higher SL than their competitors. The SL formula is as below:

$$SL = \frac{\text{Total research paper citations in granted patents}}{\text{Number of patents granted}} \tag{1}$$

Current impact index (CII): indicates the impact of assignees' patents

CII was defined as "the number of times a company's most recent 5 years of patents are citied in the current year, relative to the entire patent database" (Narin 2000). In other words, CII provides an indicator of "how often patents are cited in other patents, which shows how frequently they are used as the foundation for other inventions" (Karki 1998). Indeed, CII is a normalized indicator of the number of times a group of patents are cited by another patent; it measures the extent to which current technology is built on a group of patents, and provides an indicator of the quality of an assignee's patent portfolio in a particular field.

The key characteristic of CII is that it is a synchronous indicator, looking backwards from the current year to the previous 5 years. As a result, it changes with financial indicators and is sensitive to an assignee's current technology. Having 10- or 15-year-old extremely highly cited patents, for example, does not influence the value of CII, but having the patents granted to an assignee over the past 5 years does. Essentially, CII is a weighted sum of the citation ratios for each of the past 5 years' patents, as cited by all other patents in the current year.

This study adopted CII to indicate the impact of assignees' patents. According to Narin (2000), a value of 1.0 represents average citation frequency; a higher value is indicative of higher citation frequency, which in turn suggests higher impact. The CII formula is as follows:

$$\mathrm{CII}_n = \frac{\sum_{i=n-6}^{n-1}\left(\frac{\mathrm{CR}_i^n}{\mathrm{TCR}_i^n} \times P_i\right)}{\sum_{i=n-6}^{n-1} P_i} \qquad (2)$$

where CII_n represents the current impact index of an assignee in year n; P_i denotes the number of patents granted to the assignee in year i; CR_i^n denotes the average citation rate in year n of the patents granted to the assignee in year i; and TCR_i^n denotes the average citation rate in year n of the patents granted to all assignees in year i.

Citation density: indicates the technology interactions of assignee types

In graph theory, the density is the ratio of the actual number of lines in a graph to the number which would be presented when all points are connected to all others. The 'density' is one of the most widely used concepts in graph theory, which describes the linkage among the points in a graph. A 'complete' graph refers to one in which all the points are adjacent to one another: each point is connected directly to every other point. Such completion is very rare, even in very small networks. Also, the concept of density attempts to summarize the overall distribution of lines in order to measure how far from this state of completion the graph is. The more points that are connected to one another, the more dense will the graph be (Scott 2000). The density of a graph (network) is defined as the number of lines in a graph, expressed as the proportion of the maximum possible number of lines. This measure can vary from 0 to 1, the density of a complete graph being one.

Information can be expected to flow more freely among members of a higher density network than a lower one. Haythornthwaite (1996) stated that information in a low-density graph can flow through a few routes, whereas information in a high-density graph can flow from and to a number of different actors. Actors in a high-density network are more in touch with all others in the same network than in a low-density network. Kenis and Knoke (2002) also stated the speed with which information may be transmitted to/from the corporate members of a field varies directly with the density of the communication ties. Meagher and Rogers (2004) analyzed the network density and R&D spillovers, and found that increasing the network density (i.e. the inter-connectedness of firms) improves aggregate innovation. The nature of innovation spillovers depends upon the network density, the commonality of knowledge between firms, and the learning capability of firms. As the size of the network density increases (i.e. the neighborhood expands), a firm is exposed to knowledge from a greater number of firms.

In this study, the citation density, the same as graph (network) density, is defined as the proportion of present dyadic citations to all potential citations between patents of any two assignee types. The formula is shown as below:

$$\text{Citation\_Density}_{i\cdot j} = \frac{C_{i,j}}{P_i \times P_j} \tag{3}$$

where $C_{i,j}$ represents the citation count of group i cited by group j. P_i represents the patent count of group i, and P_j represents the patent count of group j. The denominator (the maximum number of lines) could be calculated from the number of patents that two assignee types contain. Each patent of group i may be cited by patents of group j, so a directed graph with groups i and j can contain a maximum of $P_i \times P_j$ distinct lines. Lower citation density implies that technology information flows less from group i to group j, for relatively fewer patent citations are available to connect the groups. Set the threshold = 0.005 ‰ to extract technology interactions.

Results

Data collected from the USPTO showed the recent 15-year trend of university, industry, government and individual patents in terms of their performance (including productivity, attributes and impact), and their technology interactions. In this section, the results are discussed under the structure of the five main technological fields. These fields, addressed in this order: C&C; D&M; E&E; chemical; and mechanical.

Computers and communications (C&C)

Figure 1 shows four assignee types' patent performance (as indicated by patent share, SL and CII) and their technology interactions (as indicated by citation density) in the field of C&C.

In terms of productivity, industries were granted far more patents than universities, governments and individuals. In fact, the percentage of patents granted to industries was higher than 95 %. In terms of attributes, universities as indicated in the SL curve diagram appeared more active in conducting basic research than industries, governments and individuals, the SL values of which were very close to each other and lower than that of universities. In terms of impact, the CII value of industries was close to 1.0 over the three periods, which was indicative of an average citation frequency. While the CII value of universities was higher than 1.0 during the previous two periods, it declined to approximately 1.0 in the third period. Contrarily, while the CII value of individuals was lower than 1.0 during 1997–2001, it increased to about 1.0 in the final two periods. It was also observed that the government remained at the lowest value of approximately 0.60 in C&C.

The citations made by and received from the four types of patent assignees were indicative of how they interacted to each other over the three selected periods. While there was evidence of the four assignee types citing each other, the extent to which they cited each other was not as strong as self-citations.[1] In fact, it was obvious that individuals, particularly universities and governments, worked independently: individuals citing individuals, governments citing governments, and universities citing universities, in C&C. However, a declining tendency was observed in self-interaction made by both universities and individuals. The extent to which industries interaction within them, meanwhile, was

[1] In this study, self-citations were understood as one type of assignees cited previous inventions patented by the same type of assignees, rather than patents of other assignee types. For example, universities cited previous inventions patented by universities.

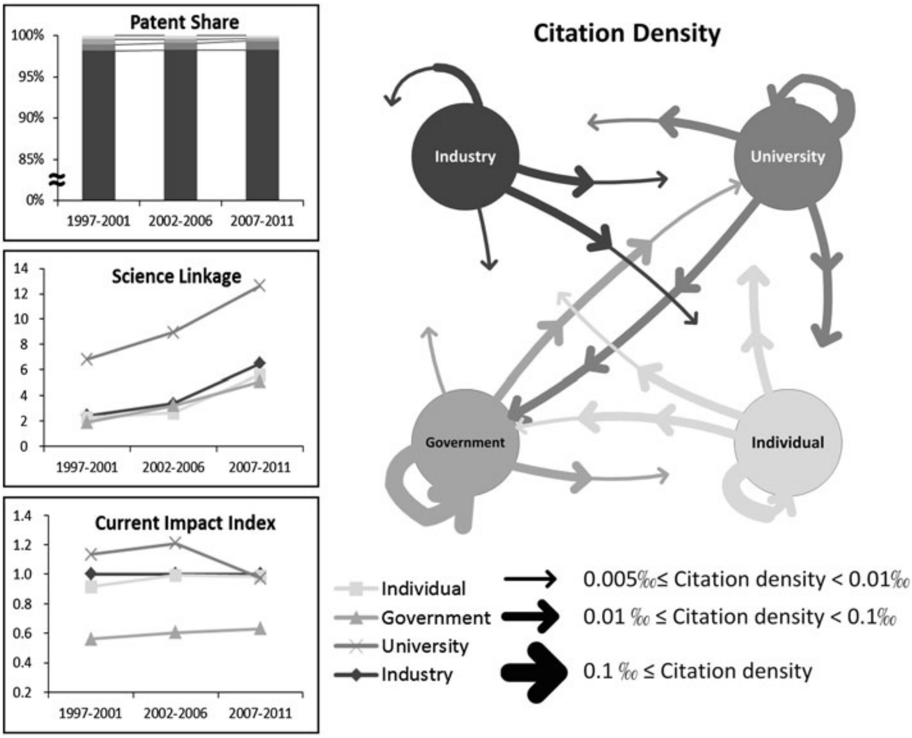

Fig. 1 Patent performance and technology interactions in the C&C field

relatively low, and there was no evidence of self-interaction in the third period. Furthermore, there was clearly some evidence of mutual technology interactions between universities and governments, and from individuals to governments, but with a slight decrease over the three periods.

Drugs and medical (D&M)

Figure 2 shows four assignee types' patent performance (as indicated by patent share, SL and CII) and their technology interactions (as indicated by citation density) in the field of D&M.

As for productivity, the patent share of industries in D&M remained the highest one among all four selected assignee types. What was different was the percentage of the patents granted to industries was less than 90 %, which was lower than that in C&C. Universities came second, accounting for nearly 10 % of the patents. As for attributes, universities clearly had the highest SL value (i.e. performing more actively in basic research), which was followed by governments, industries and then individuals respectively. As for impact, the CII value of industries was near 1.0, with a slight increase over the three periods. Contrarily, the CII values of individuals, universities and governments were lower than 1.0, and there was a decreasing tendency over the three periods. It is also worth noting for future research that individuals had higher impact than universities and governments in D&M.

Technology self-interactions made by the four types of patent assignees were also evidenced over the three periods in D&M. Based on the intensity of technology self-

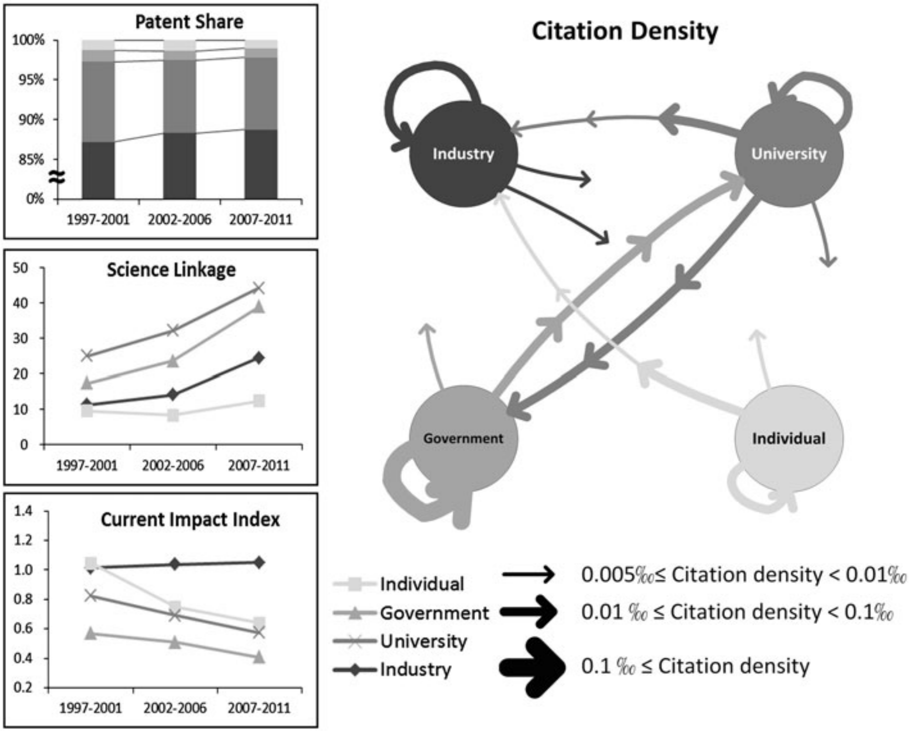

Fig. 2 Patent performance and technology interactions in the D&M field

interaction, governments came first, followed by individuals, universities and finally industries. As observed from the citations between the four assignee types, there were constant technology interactions between universities and governments, from individuals to industries and from universities to industries over the three periods. Fewer interactions were evidenced from the citations between governments and industries, and between individuals and universities; furthermore, there was no such evidence between governments and individuals.

Electrical and electronics (E&E)

Figure 3 shows four assignee types' patent performance (as indicated by patent share, SL and CII) and their technology interactions (as indicated by citation density) in the field of E&E.

Similar to the results shown in the field of C&C, industries accounted for the highest patent productivity in E&E (having more than 95 % of patents granted). Also, universities performed more actively in basic research, whereas the SL values of governments, industries and individuals were close to each other and lower than that of universities. In terms of impact, universities had a higher CII value (more than 1.0) than industries (around 1.0), followed by individuals (around 0.80) and then governments (around 0.60). That is, industries in E&E had average patent impact; universities had higher than average patent impact; and both individuals and governments had lower than average patent impact.

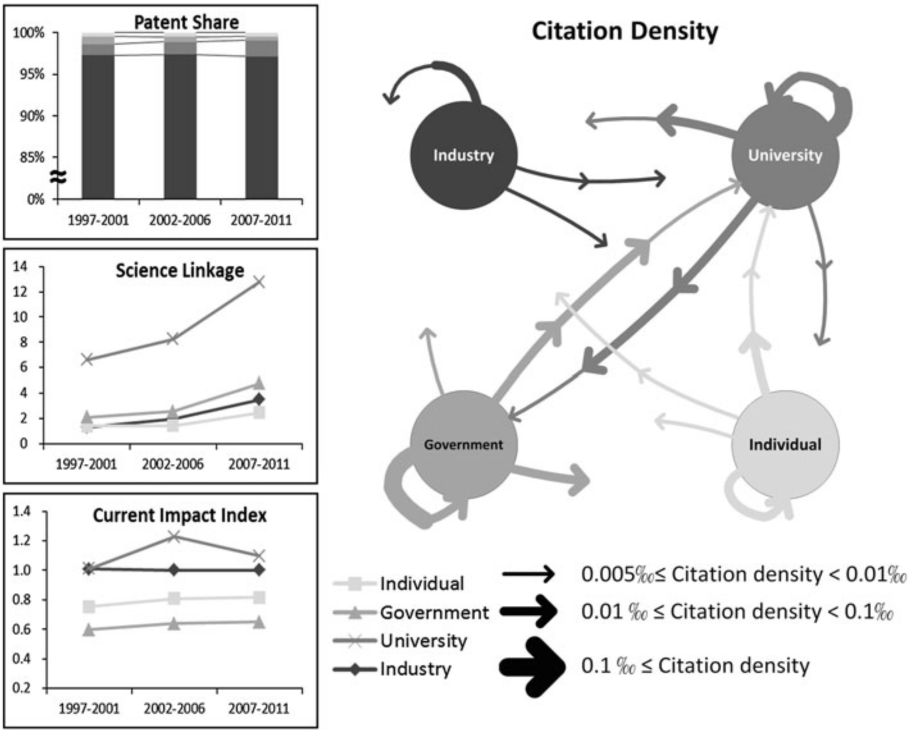

Fig. 3 Patent performance and technology interactions in the E&E field

Technology self-interactions made by the four assignee types were also evidenced over the three periods in E&E, but there was no evidence of self-interactions made by industries in the third period in E&E. Furthermore, there was evidence of technology mutual interactions between governments and universities, and from individuals to universities. Other technology interactions (e.g. governments-industries, governments-individuals, and industries-universities) appeared weak, and these kinds of technology interactions did not even exist during some periods.

Chemical

Figure 4 shows four assignee types' patent performance (as indicated by patent share, SL and CII) and their technology interactions (as indicated by citation density) in the chemical field.

Similar to the results shown in C&C and E&E, industries in the chemical field had the highest patent productivity (possessing more than 90 % of patents granted) and universities performed more actively in basic research. With regard to impact, universities had a higher CII value (more than 1.0) than industries (around 1.0), followed by individuals and then governments. That is, industries in the chemical field had average patent impact; universities had higher than average patent impact; and both individuals and governments had lower than average patent impact.

It was clear as evidenced in Fig. 4 that technology self-interactions made by the four assignee types existed in the chemical field throughout the three periods. This phenomenon

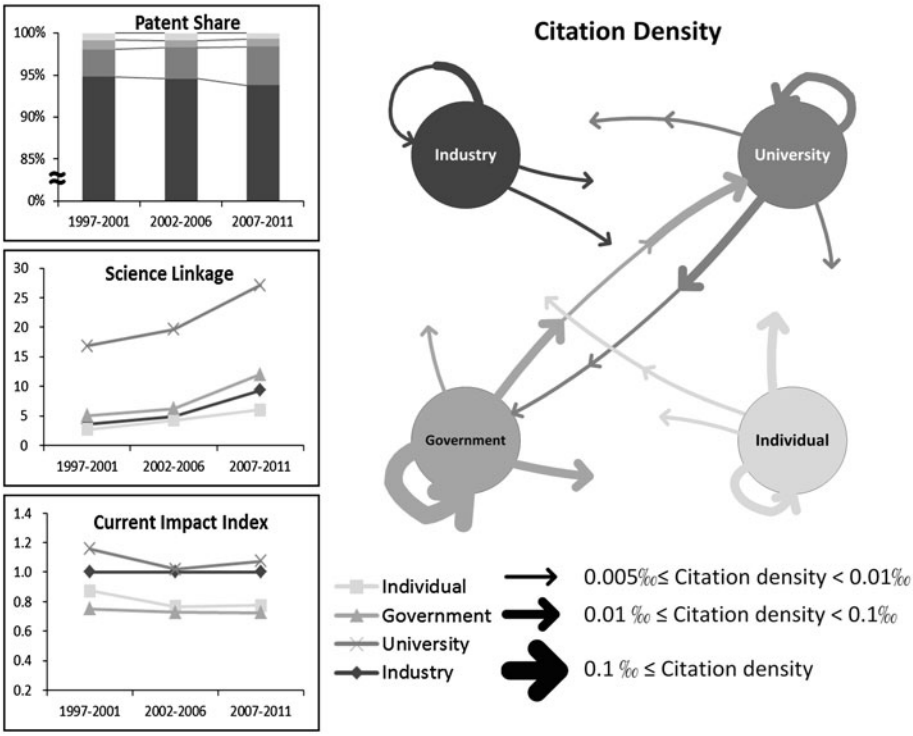

Fig. 4 Patent performance and technology interactions in the chemical field

was particularly evident within governments. While there appeared constant mutual technology interactions between governments and universities, other interactions (e.g. governments-industries, governments-individuals and individuals-universities) appeared fairly weak, and these kinds of technology interactions did not even exist during some periods.

Mechanical

Figure 5 shows four assignee types' patent performance (as indicated by patent share, SL and CII) and their technology interactions (as indicated by citation density) in the mechanical field.

Similar to the results obtained in the fields discussed above, except D&M, industries in the mechanical field had the highest patent productivity (accounting for more than 95 % of patents granted). Additionally, universities performed more actively in basic research, whereas the SL values of industries, governments and individuals were close to each other and lower than that of universities. With regard of impact, universities had a higher CII value (more than 1.0) than industries (around 1.0), which was followed by individuals and then governments. In other words, industries in the mechanical field had average patent impact; universities had higher than average patent impact; and both individuals and governments had lower than average patent impact.

It was clear as evidenced in Fig. 5 that technology self-interactions made by the four assignee types existed in the mechanical field throughout the three periods. According to

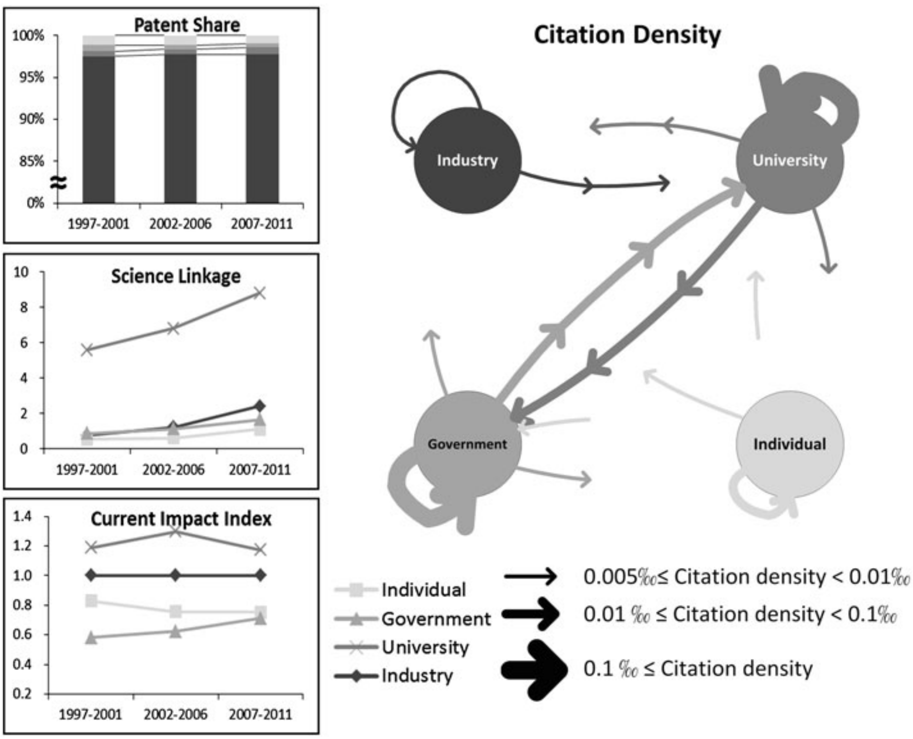

Fig. 5 Patent performance and technology interactions in the mechanical field

the intensity of self-interactions, universities came first, which was followed by governments, individuals, and finally industries. While there appeared to be constant technology mutual interactions between governments and universities, other interactions (e.g. governments-industries, governments-individuals and individuals-universities) appeared fairly weak, and such interactions did not even exist during some periods.

To sum up, industries occupied the largest patent share in all five fields discussed above, which suggests that industries had the highest patent productivity. Generally, industries possessed more than 90 % of patents granted, except in the D&M field, where industries possessed approximately 85 % of patents granted. Nearly 10 % of patents were granted to universities in D&M. Another common thread running through the patent performance in all five fields is that universities had the highest SL value, which indicates that universities acted more actively in conducting basic research. It is also clear that governments performed more actively in conducting basic research than industries and individuals in D&M. When it comes to the patent impact of different assignee types, industries, whose CII value was equivalent to 1.0 had average patent impact in all five fields. Generally, universities had more than average patent impact, except in D&M. Also, the patent impact of governments remained the lowest one in all five fields.

Furthermore, evidence of technology self-interactions made by the four types of assignees existed in five main fields over three periods. The only exception is that there was no evidence of self-interactions by industries in C&C and E&E in the third period. The intensity of self-interactions was clearly higher than that of technology interaction with others. There was evidence of constant technology interactions between governments and universities in all five fields over three periods. In addition, constant interactions were found from individuals to governments in C&C; from universities to industries and from individuals to industries in D&M; and from individuals to universities in E&E over all three periods.

Discussion and conclusions

This study has met the aim and objectives set at the outset of this paper. Specifically, this study, drawing upon a very large amount of patent data, employed patent indicators (i.e. patent share, SL, CII, and citation density) to explore patent performance (i.e. productivity, attributes and impact) and their technology interactions in five technological fields (i.e. C&C, D&M, E&E, chemical, and mechanical) over three periods (i.e. 1997–2001, 2002–2006, and 2007–2011). The significant contribution of this paper is an identification of interesting phenomena regarding patent performance and technology interactions for future research.

There are clearly considerable differences in the pattern of technology interactions in different technological fields; however, specific reasons for these patterns remain fully unknown. This observation resonates with that of Jacobsson (2002), who suggested that the reasons could be found in a combination of knowledge and spatial specific features. Some interesting observations are made from the patent data and suggestions for future research are proposed, as discussed below.

Reciprocal technology interactions between universities and governments

There were reciprocal technology interactions between governments and universities in all fields over three periods; a possible explanation for this observation is that both parties' patent attributes are similar in terms of conducting scientific/basic research. Indeed, empirical data show that both governments and universities in particular tended to focus on basic research, which corresponds with the research findings of Trajtenberg et al. (1997) who concluded that "universities perform more basic research than corporations". The observation of reciprocal technology interactions between governments and universities also provides a reasonable justification for abundant research devoted to university-industry-government relations (for example, Leydesdorff and Etzkowitz 2001; Etzkowitz 2003; Leydesdorff and Meyer 2003). An area that may be worth exploring further is whether the technology self-interactions within governments and universities occur at an intra-organizational or inter-organizational level.

High patent productivity and low technology interactions of industries in each field

Whilst variances were observed in different fields, patenting in the D&M field has a very different pattern to that in the other four fields in terms of patent performance and technology interactions. For example, industries in D&M accounted for approximately 85 % of patents and universities accounted for approximately 10 %, whereas industries in other fields accounted for more than 90 %. The fact that universities and governments in D&M occupy larger patent shares than in other fields corresponds well with what is known about the field: it takes more time and higher expenditure to invest in the invention of new medicines.

While industries have the highest patent productivity among the four assignee types in all five fields over the three periods, it is interesting to find that technology interactions of industries are relatively lower than those of other assignee types. It is likely that the attributes of technological R&D conducted in industry differ somewhat from the attributes which tend to characterize the nature of universities' and governments' scientific/basic research. In addition, the lower self-interaction within industries may also be worth exploring further to see the extent to which it occurs at an intra-organization or inter-organization level.

Individuals' better patent performance and technology interactions in drugs and medical

The "individuals" assignee type drew attention due to its unexpected patent performance. For instance, industries possessed more than 90 % of patents granted, except in the D&M field, where they possessed approximately 85 % of patents granted. Also, individuals' impact was higher than that of universities and governments in D&M, but only higher than that of governments in C&C, E&E, chemical, and mechanical.

Moreover, there is evidence of constant technology interactions from individuals to governments in C&C, from individuals to industries in D&M, and from individuals to universities in E&E in the past 15 years. Investigation of the above-mentioned issues, and the possible role played by individuals in terms of both their patent performance and technology interactions with other assignee types, particularly with industries, is a fruitful area for future research.

Intense technology self-interactions of assignee type excluding industries

Strong evidence of self-citations made by all assignee types in all five fields is observed. Self-citations are indicative of technology interactions of the same assignee type. As suggested by Hall et al. (2001), self-citations represent transfers of knowledge that are mostly internalized. Empirical data show that self-interaction of industries did not occur as rapidly as those of the other three assignee types; in fact, the self-interactions of universities and governments were relatively high. It is therefore suggested that future research further investigate the phenomenon of self-interactions within different assignee types. For instance, whether the low density of self-citation implies low intra-organizational interactions or low inter-organizational interaction, which was not explored in this study.

It is to be hoped that future research could investigate the reasons behind those phenomena discussed above. In-depth qualitative research could serve to fulfill the research gaps.

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