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Exploring paper characteristics that facilitate the knowledge flow from science to technology

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ABSTRACT

In this study, we explore paper characteristics that facilitate the knowledge flow from science to technology by using the patent-to-paper citation data. The linear growth trajectory of the number of patent citations to a scientific paper over time is used to measure the dynamism of its utilization for technology applications. The citation data used were obtained from the USPTO database based on two 5-year citation windows, 2001–2005 and 2009–2013. The former included patent citations to the publications in the Thomson Reuters Web of Science in 1998, and the latter included those in 2006. Only the publications in the top ten most frequently cited subject categories in the Web of Science were selected. By using growth modeling, we have found that the mean slope of the trajectory is significant. Moreover, the paper citation count, the ranking factor of the journal in which the paper was published, whether the paper is an industrial publication, and whether it is a review article have been identified to exert significant effects on the growth of the citation of scientific literature by patented inventions. Some policy implications are discussed.

1. Introduction

The importance of science to support technological development has been highlighted. In knowledge-intensive industries, scientific knowledge has significant impacts on technology innovation. Citation to scientific publications is an important driver that accelerates the rate of technological innovation (Sorenson & Fleming, 2004). Patents are considered representations of technologies, while papers are viewed as representations of science (Meyer, 2002). Patents also show the interest in commercial exploitation of a new technology (Schmoch, 1997; Trajtenberg, Henderson, & Jaffe, 1997). Although there are some problems regarding the use of patents—not all inventions are patentable, not all of those that are patentable are patented, and patents differ greatly in their commercial significance and value, patent data have long been used as a measure of innovative activity and technological development because patents cover the majority of technological fields and the major patent systems such as the United States Patent and Trademark Office (USPTO) cover all countries (Debackere Veugelers, Zimmermann, Van Looy, Andries, & Callaert, 2001; Tijssen, 2001).

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Citations to non-patent references (NPRs) in patent documents signal a direct influence of science on technology (Narin, Hamilton, and Olivastro, 1995, Narin, Hamilton, & Olivastro, 1997). NPRs constitute prior scientific knowledge or ideas to which a patent is related (Trajtenberg et al., 1997). However, some scholars argue that patent-to-paper citations should not be interpreted as a direct link or influence from science to technology (e.g., Callaert, Pellens, & Van Looy, 2014; Meyer, 2000). Fleming and Sorenson (2004) argue that science alters inventors' search processes by leading them to useful combinations, eliminating fruitless paths of research, and motivating them to continue. Patent citations to NPRs can be interpreted as exchange processes (Meyer, 2006) or relevance or relatedness (Callaert, Van Looy, Verbeek, Debackere, & Thijs, 2006; Tijssen, 2001) between science and technology. The number of NPRs is used as a measure of technological opportunity (Von Graevenitz, Wagner, & Harhoff, 2013). A greater number of NPRs is associated with higher technological opportunities.

The front page of a patent issued by USPTO provides patent and non-patent references. As pointed out in Hicks, Breitzman, Hamilton, and Narin (2000) and Tijssen (2001), patent applicants are legally obliged to state prior knowledge related to the invention. US patent law requires that the patent examiner determines the novelty and uniqueness of an invention claimed by the patent application. The invention is reviewed and additional important references could be added by the examiner. Therefore, the NPRs on the front page are supplied by inventors, patent attorneys, and/or the examiner. The links to the scientific literature reflect the association between science and technological development.

Because knowledge flow is a process over time, it should be measured in a dynamic rather than static way. As suggested by Callaert et al. (2006), the introduction of a time dimension can uncover the development of science intensity. Thus, regardless of whether the number of patent citations to NPRs represents a direct link between science and technology or just a measure of relevance, the focus should be placed on the growth of citation over time rather than just citation frequencies at specific points of time. Although there exist many empirical studies using citation data, few articles addressed the change in citation over time. Hung, Ding, Wang, Lee, and Lin (2015) evaluate and compare the university performance in knowledge utilization by analyzing the growth trajectories of patent citations to scientific publications produced by individual universities. Moreover, the factors that influence the growth of the patent-to-paper citation remain unclear.

For each published article, the data of patent citations to the paper after its publication need to be obtained over time. The panel data showing the time series of the number of patent citations for individual articles are formed. As can be seen later in Section 3, the majority of scientific papers were not cited, consistent with the fact mentioned in Aksnes (2003) that the large majority of the scientific papers are never or seldom cited in the subsequent scientific literature. Therefore, we focus only on the domains whose papers were more frequently cited by patents. By using growth modeling, an application of hierarchical linear models for the analysis of trajectory (e.g., Raudenbush & Byrk, 2002), we can assess the knowledge flow from science to technology by analyzing the change in patent-to-paper citation over time (its growth trajectory) and further identify paper characteristics that influence the growth pattern to have a deeper understanding of the knowledge flow in those domains. The results obtained are informative for paper authors, patent inventors, and policy makers.

2. Paper characteristics

The paper characteristics that influence the paper-to-paper citation have been widely discussed in the literature. They may also influence the patent-to-paper citation. In this section, we give a brief review.

The number of citations can be used as an indicator of the level of impact or performance for an individual publication or a journal that aggregates publications (Wilson, 1999). It is used as a measure of research excellence (Hicks et al., 2000). Citation-based impact indicators are considered objective because they reflect the evaluations by subsequent researchers (Van Raan, 2004). It is generally accepted that the paper citation count of an article is an effective measure of its importance (the degree of impact) (Onodera & Yoshikane, 2015). Hicks et al. (2000) find that US papers that are highly cited by other papers are much more likely to be cited in a US-invented patent. They concluded that research excellence and innovation are firmly linked, and that American technology draws on the best of American science.

Prestigious journals attract potentially influential papers and articles published in prestigious journals tend to receive more citations (Van Dalen & Henkens, 2001). The impact factor is used to measure the impact of a journal. Alternatively, the ranking factor could be used as the impact factor varies considerably among disciplines. The ranking factor of a journal is the relative rank of the journal in a subject category based on the impact factor. The lower the ranking factor in the subject category, the higher the journal's impact. While the paper citation count is used to measure a paper's research impact, the ranking factor is used to measure the impact of the journal in which the paper was published.

Callaert et al. (2006) suggest drawing attention to authors as well as affiliations of the authors to gain more insight about knowledge flow. Co-authorship is a frequent and reliable measure for collaboration in scientometric studies (Glänzel & Schubert, 2004). Minguillo and Thelwall (2015) find that high quality research institutions are much more likely to establish strong links in the form of co-authorships. The number of authors would positively affect the number of citations (Aksnes, 2003; Bayer, 1982; Franceschet & Costantini, 2010; Gazni & Didegah, 2010; Sooryamoorthy, 2009; Stewart, 1983). Research collaboration generates benefits which could not have been attained if the researchers had worked on their own and enhances the quality of research, leading papers to being cited more often (Katz & Martin, 1997; Narin, Stevens, & Whitlow, 1991; Van Dalen & Henkens, 2001). Collaboration enhances the visibility of research results (Franceschet & Costantini, 2010). The article is brought to the attention of a larger number of researchers through authors' personal network. The knowledge is more likely to be disseminated to the scholars inside the network than to those outside the network (Van Dalen & Henkens, 2001).

Inter-organizational co-authorship and international co-authorship are indicators for collaborative R & D activities. The former involves researchers from different organizations, and the latter involves researchers from different countries. The strength of inter-organizational co-authorship is positively related to citation impact (Gazni & Didegah, 2010; Sooryamoorthy, 2009). The strength of international co-authorship is generally thought and often found to have positive effects on the citation rate of scientific publications (Aksnes, 2003; Didegah & Thelwall, 2013; Ma & Guan, 2005; Schmoch & Schubert, 2008; Sooryamoorthy, 2009).

Academia-industry collaboration can lead to more citations due to the following reasons. First, academia-industry collaboration might imply the accessibility to complementary tangible and intangible assets needed to turn innovation projects into a commercial success (Hagedoorn, 1993; Teece, 1986). It is a means for knowledge transfer (Ahuja, 2000; Doz & Hamel, 1997). Second, it may help create interdisciplinary knowledge, one major issue in the 'knowledge-based society' emphasized by Gibbons, Limoges, Nowotny, Schwartzman, Scott, and Trow (1994) that can lead to applicable results (Schmoch, Breiner, Cuhls, Hinze, & Münt, 1994) since interdisciplinary knowledge is a more friendly problem-solving approach (Foray & Gibbons, 1996). Third, academia-industry collaboration could combine ideas from academic and industrial perspectives. Public–private research cooperation, measured by jointly authored research articles, is an important element in science-based technological innovation (Tijssen, 2012).

The length of an article also influences citation. As longer articles have more content that can be cited than shorter articles, the length of an article influences whether it is cited (Hudson, 2007). Research notes, comments and replies, whose contributions usually make small points, receive less attention than the regular journal articles (Van Dalen & Henkens, 2001).

Firms have incentives to publish their work. Hicks (1995) indicates that publishing signals the presence of tacit knowledge and helps build the reputation needed for the barter-governed exchange of scientific and technical knowledge. Additional incentives, as reviewed in Tijssen (2004), include increasing visibility, linking up to the scientific community, and attracting private capital, public research funding, and first-rate researchers and technicians. Citation counts of papers written by a firm's research team appear to be positively related to the firm's performance (Decarolis & Leeds, 1999). Because more insight about the application of science to industrial development may be obtained from the publications by the authors working in firms, industrial publications are attractive for patent inventors.

Review articles are cited more frequently than other publication types (Aksnes, 2003; MacRoberts & MacRoberts, 1996). Although such articles usually do not contain new material, reading review papers is a convenient way and save the time to dig into original research papers for inventors.

We will empirically examine for all of the paper characteristics mentioned above if they have significant effects on the growth of the number of patent citations to scientific publications.

3. Methods

Many types of documents are referenced in USPTO patents, but not all these documents are considered as scientific output. Callaert et al. (2006) indicate that the most widely adopted publication database is the Thomson Reuters Web of Science (WoS), covering many scientific disciplines, and find that 50% to 55% of NPRs are journal references covered by the database. In this study, NPRs are restricted to the publications (including articles, reviews, and letters) in the database. The scientific papers with at least one U.S. author[1] were considered. As indicated in Hung et al. (2015, pp. 1271–1272), "After 2000, the emergence and convergence of nanotechnology, biotechnology, information technology, and new technology based on cognitive science bring opportunities and challenges. These technologies absorb a lot of knowledge from science, leading to typical high-tech products such as gene-chips, wireless network, and smartphone," stimulating more scientific research papers. It appears that the number of patents issued by USPTO, the number of publications in WoS, and the total number of patent citations to NPRs all display increasing trends during 1998–2013 (See Fig. 1). Moreover, there is a sharp increase in the total number of patent citations to NPRs after 2005. In bibliometric analyses, the 5-year citation interval is often used (Aksnes, 2003). Thus, the analysis of citation growth in this study is based on two 5-year citation windows. The first one deals with the patent citations to the publications in 1998 (before 2000), and the second one to those in 2006 (after 2005). Two citation windows are used for checking the robustness of the results. We consider only granted patents (patent applications not included). Since the time between when US patents are filed and when they are issued is generally between 24 and 36 months, the citation starts from the fourth year after publication. Specifically, we used the citation data for the years of 2001–2005 in the first window and those for the years of 2009–2013 in the second window. Patent-to-paper citations were counted for each paper in each of the five consecutive years.

The growth trajectory of the number of patent citations to a scientific paper over time is used to measure the dynamism of its utilization for technology applications. The data for patent-to-paper citations were obtained from the USPTO database, widely used in previous research (e.g., Narin et al., 1997; Roach & Cohen, 2013). As for scientific papers to be cited, we identified the articles published in the target year with at least one U.S. author in the WoS. The number of total publications with at least one U.S. author in the WoS is 383661 in 1998 and 451200 in 2006, occupying 32.58% and 31.33% of the total publications in 1998 and 2006, respectively. The number of publications in 1998 cited at least once by patents by the end of

[1] Since the U.S. is a well representative country for the development of science and technology, this study restricts the scientific papers to the U.S.-affiliated papers.

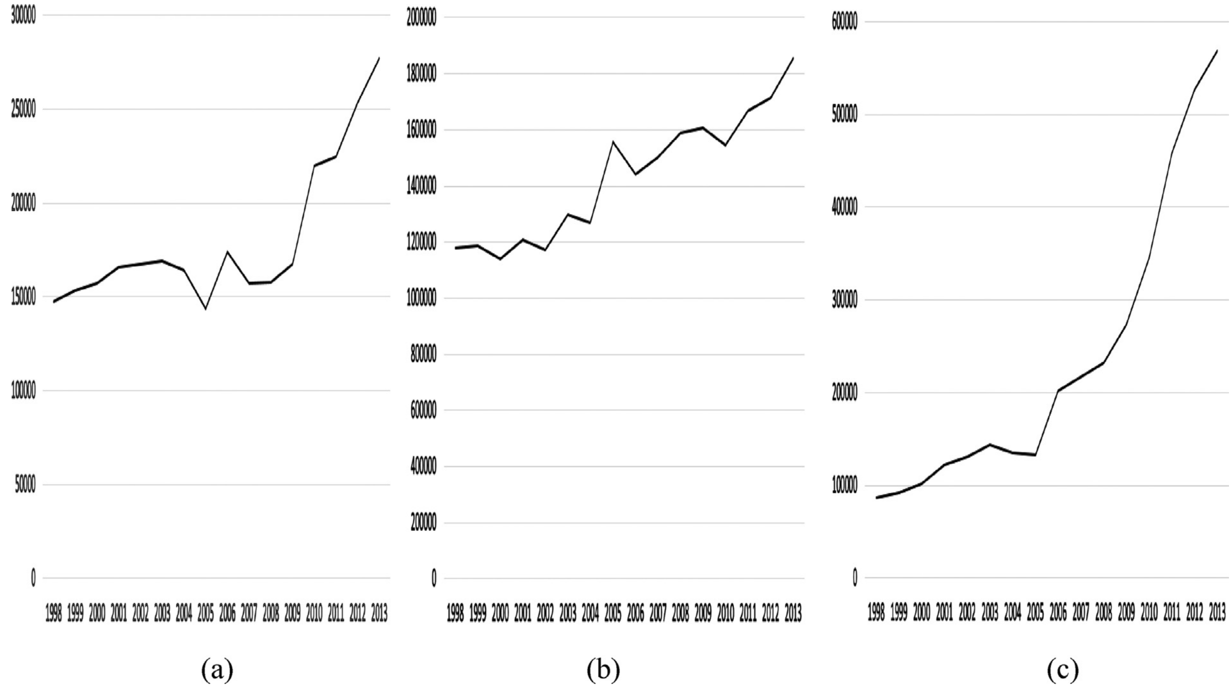

Fig. 1. The growths of (a) the number of patents issued by USPTO, (b) the number of publications in WoS, and (c) the total number of patent citations to NPRs during 1998–2013.

2005 is 11792 and the number of publications in 2006 cited at least once by patents by the end of 2013 is 14580. Because the majority of the publications were not cited by patents, the publications selected were restricted to those cited at least once by patents. Moreover, we focus our attention on the papers receiving more patent citations and investigate how they were cited over time. Specifically, we chose those in the top ten most frequently cited subject categories in the WoS and explored the factors influencing their citation growth. The numbers of selected publications in 1998 (cited by patents until 2005) and 2006 (cited by patents until 2013) are 5479 and 6885, respectively (see Table 1 for details[2]). They occupy more than 45% (5479/11792 for 1998 and 6885/14580 for 2006) of the total publications cited at least once by patents. Table 2 displays the shares of articles, reviews, and letters by subject category for the selected publications in 1998 and 2006. We counted patent citations to each of the papers selected for every year in the citation window. Then, we performed growth analyses for the window based on the data obtained. The process was repeated for the citation windows of 2001–2005 and 2009–2013.

As we have reviewed, paper characteristics that may exert influence on the growth trajectory of the number of patent citations to a paper include the paper citation count (PCC), the ranking factor (RF) of the journal in which the paper was published, the number of authors (NA), the strength of inter-organizational co-authorship, the strength of international co-authorship, the paper length (PL), whether it results from academia-industry collaboration (AICOLL), whether it is an industrial publication (IP), and whether it is a review article (RA). PCC includes the 2001–2005 paper citations to the 1998 publications and the 2009–2013 paper citations to the 2006 publications in the WoS. RF in 1998 or 2006 is the relative rank of the journal based on the impact factor in a subject category for the same year. If a journal was included in more than one subject category, the lower RF was selected. NA indicates the number of authors participating in the work. The strength of inter-organizational co-authorship is measured with the number of affiliations of authors (NAFF). The strength of international co-authorship is measured with the number of nationalities of authors (NNAT). PL is measured by the number of article pages (word count data are unavailable in the database). AICOLL means whether the paper results from the collaboration between one or more universities and one or more industrial enterprises. IP means whether the authors are all researchers or employees in industrial enterprises. RA means whether the paper is a review article according to the classification in Web of Science. AICOLL, IP, and RA are dummy-coded in such a way that AICOLL is set to 1 if the paper is produced by academia-industry collaboration, AICOLL is set to 1 if the paper results only from industrial enterprises, and RA is set to 1 if the paper is a review article; they are set to zero otherwise.

Since the citation over time is a process, attention is given to the growth trajectory of the number of citations. Growth modeling is an effective analytical tool to meet the research need. Growth modeling consists of two sub-models. The level-1 sub-model is an individual growth model. The level-2 sub-model expresses the random growth coefficients as linear

[2] The top ten subject categories most frequently cited by papers in the WoS in 1998 and 2006 are provided in the Appendix.

Table 1
Top ten most frequently cited (by patents) subject categories in the WoS in 1998 and 2006.

Rank	Subject category	Number of 1998 publications	Number of patent citations until 2005	Rank	Subject category	Number of 2006 publications	Number of patent citations until 2013
1	Biochemistry & Molecular Biology	1714	3540	1	Biochemistry & Molecular Biology	1392	3238
2	Multidisciplinary Sciences	429	2436	2	Chemistry, Organic	717	3088
3	Engineering, Electrical & Electronic	764	2272	3	Oncology	895	2634
4	Physics, Applied	614	1746	4	Engineering, Electrical & Electronic	1068	2561
5	Biotechnology & Applied Microbiology	389	1118	5	Pharmacology & Pharmacy	625	1689
6	Oncology	496	991	6	Chemistry, Multidisciplinary	668	1620
7	Immunology	514	938	7	Immunology	568	1493
8	Cell Biology	532	924	8	Physics, Applied	689	1467
9	Chemistry, Multidisciplinary	330	884	9	Cell Biology	612	1305
10	Pharmacology & Pharmacy	425	848	10	Optics	429	1121
Total		5479	14407	Total		6885	18807

Since a publication may belong to more than one subject category, the totals of the numbers of publications in the ten subject categories (6207/7663) for 1998 and 2006 are greater than the numbers of publications included for the same year (5479/6885), and the totals of the numbers of patent citations in the ten subject categories (15697/20216) are greater than the corresponding numbers of patent citations included (14407/18807).

Table 2
Shares of articles, reviews, and letters by subject category for the selected publications in 1998 and 2006.

Rank	Subject category	Article	Review	Letter	Rank	Subject category	Article	Review	Letter
1	Biochemistry & Molecular Biology	0.9031	0.0792	0.0022	1	Biochemistry & Molecular Biology	0.8384	0.1343	0.0014
2	Multidisciplinary Sciences	0.8636	0.0435	0.0348	2	Chemistry, Organic	0.9177	0.0418	0.0014
3	Engineering, Electrical & Electronic	0.9597	0.0138	0.0164	3	Oncology	0.8078	0.1497	0.0045
4	Physics, Applied	0.9791	0.0162	0.0029	4	Engineering, Electrical & Electronic	0.9728	0.0197	0.0019
5	Biotechnology & Applied Microbiology	0.8844	0.0712	0.0013	5	Pharmacology & Pharmacy	0.6416	0.2848	<0.0001
6	Oncology	0.8863	0.0927	0.0035	6	Chemistry, Multidisciplinary	0.9132	0.0838	<0.0001
7	Immunology	0.8845	0.0928	0.0021	7	Immunology	0.8046	0.1655	0.0035
8	Cell Biology	0.8665	0.0898	0.0045	8	Physics, Applied	0.9710	0.0189	<0.0001
9	Chemistry, Multidisciplinary	0.9000	0.0942	<0.0001	9	Cell Biology	0.7680	0.1830	0.0033
10	Pharmacology & Pharmacy	0.7760	0.2063	0.0049	10	Optics	0.9814	0.0163	<0.0001

functions of covariates showing paper characteristics. In other words, growth modeling can characterize the growth pattern of the patent-to-paper citation for each paper after its publication and examine how the growth patterns differ.

The level-1 sub-model in linear growth modeling is given by

$$Y_{it} = \beta_{0i} + \beta_{1i}\mathrm{Time}_t + \varepsilon_{it}, i = 1, 2, \ldots, n; t = 1, 2, \ldots, T, \tag{1}$$

where Y_{it} is the number of patent-to-paper citations for paper i at time t, Time_t represents the time variable (the explanatory variable), n is the total number of papers in the sample, T is the total number of time points (five in this study), and ε_{it} is the error associated with paper i at time t, reflecting the departure from the linear trajectory for paper i. Time points are assumed to be equally spaced. β_{0i} and β_{1i} denote, respectively, the intercept and the linear slope of the trajectory for paper i. The values of the T time points are usually set as 0, 1, 2, . . ., $T-1$, and therefore β_{0i} represents the initial citation status. β_{0i} and β_{1i} are random coefficients because papers differ in their initial status and growth rates of citation. ε_{it}'s are serially correlated for paper i. The autocovariance structure of ε_{it}, assumed to be identical for all papers, needs to be specified. Although AR(1) (the first-order autoregressive) may be the most commonly used one (Murphy & Pituch, 2009; p. 256), ARH(1) (heterogeneous AR(1)) is more appropriate because error variances may not be homogeneous. The error covariance matrix for $T = 5$ based on ARH(1) is given by (e.g., Ding & Jane, 2012)

$$\boldsymbol{\Theta}_{\boldsymbol{\varepsilon}} = \begin{bmatrix} \sigma_{\varepsilon_1}^2 & \sigma_{\varepsilon_1}\sigma_{\varepsilon_2}\rho & \sigma_{\varepsilon_1}\sigma_{\varepsilon_3}\rho^2 & \sigma_{\varepsilon_1}\sigma_{\varepsilon_4}\rho^3 & \sigma_{\varepsilon_1}\sigma_{\varepsilon_5}\rho^4 \\ & \sigma_{\varepsilon_2}^2 & \sigma_{\varepsilon_2}\sigma_{\varepsilon_3}\rho & \sigma_{\varepsilon_2}\sigma_{\varepsilon_4}\rho^2 & \sigma_{\varepsilon_2}\sigma_{\varepsilon_5}\rho^3 \\ & & \sigma_{\varepsilon_3}^2 & \sigma_{\varepsilon_3}\sigma_{\varepsilon_4}\rho & \sigma_{\varepsilon_2}\sigma_{\varepsilon_4}\rho^2 \\ & & & \sigma_{\varepsilon_4}^2 & \sigma_{\varepsilon_4}\sigma_{\varepsilon_5}\rho \\ & & & & \sigma_{\varepsilon_5}^2 \end{bmatrix} \tag{2}$$

where ρ denotes the autoregressive coefficient. The error autocorrelation at lag k, $k = 1, 2, \ldots, 4$, denoted byρ_k, is given by$\rho_k = \rho^k$.

The level-2 sub-model in linear growth modeling is given by

$$\begin{aligned} \beta_{0i} &= \gamma_{00} + \zeta_{0i}, \\ \beta_{1i} &= \gamma_{10} + \zeta_{1i}, \end{aligned} \tag{3}$$

where γ_{00} and γ_{10} are the level-2 intercepts, representing the means of β_0 and β_1, and ζ_{0i} and ζ_{1i} are the corresponding errors. The covariance structure of ζ_0 and ζ_1 is always unstructured (freely estimated). The intra-paper errors over time and the inter-paper errors are conventionally referred to as level-1 and level-2 errors, respectively. Substituting Eq. (3) into Eq. (1) results in the following combined model:

$$Y_{it} = \gamma_{00} + \gamma_{10}\mathrm{Time}_t + (\zeta_{0i} + \mathrm{Time}_t \times \zeta_{1i} + \varepsilon_{it}). \tag{4}$$

An interesting question follows: How do growth trajectories differ? That is, what factors influence the growth trajectory? What paper characteristics can explain the random coefficients in Eq. (1)? Potential characteristics exerting influential effects include PCC, RF, NA, NAFF, NNAT, PL, AICOLL, IP, and RA, which are included in the level-2 sub-model as follows:

$$\begin{aligned} \beta_{0i} &= \gamma_{00} + \gamma_{01}\mathrm{PCC}_i + \gamma_{02}\mathrm{RF}_i + \gamma_{03}\mathrm{NA}_i + \gamma_{04}\mathrm{NAFF}_i + \gamma_{05}\mathrm{NNAT}_i + \gamma_{06}\mathrm{PL}_i + \gamma_{07}\mathrm{AICOLL}_i + \gamma_{08}\mathrm{IP}_i + \gamma_{09}\mathrm{RA}_i + \zeta_{0i}, \\ \beta_{1i} &= \gamma_{10} + \gamma_{11}\mathrm{PCC}_i + \gamma_{12}\mathrm{RF}_i + \gamma_{13}\mathrm{NA}_i + \gamma_{14}\mathrm{NAFF}_i + \gamma_{15}\mathrm{NNAT}_i + \gamma_{16}\mathrm{PL}_i + \gamma_{17}\mathrm{AICOLL}_i + \gamma_{18}\mathrm{IP}_i + \gamma_{19}\mathrm{RA}_i + \zeta_{1i}, \end{aligned} \tag{5}$$

where $\gamma_{01} - \gamma_{09}$ are the fixed effects associated with PCC, RF, NA, NAFF, NNAT, PL, AICOLL, IP, and RA, respectively, with respect to the random intercept β_0 and $\gamma_{11} - \gamma_{19}$ are those with respect to the random linear slopeβ_1. Eq. (3) and Eq. (5) are

Table 3
Descriptive statistics of the number of patent citations to the publications included in the two citation windows.

Year	Mean	S.D.	Min	Max
(1) Citations to the publications in 1998 (n = 5479)				
2001	0.26	0.81	0	21
2002	0.43	1.17	0	43
2003	0.59	1.22	0	36
2004	0.64	1.62	0	44
2005	0.65	1.48	0	41
(2) Citations to the publications in 2006 (n = 6885)				
2009	0.08	0.43	0	20
2010	0.22	0.71	0	21
2011	0.52	1.26	0	23
2012	0.83	1.50	0	29
2013	1.06	1.99	0	39

The publications in 1998 (or 2006) included only those in the top ten most frequently cited subject categories in the WoS. The articles were restricted to those with at least one U.S. author.

Table 4
Results based on the unconditional linear growth model for the number of patent-to-paper citations.

Independent variable	Citation window	
	2001–2005	2009–2013
Intercept	0.2706***	0.0766***
Time	0.1050***	0.2284***
Error variance/covariance		
$\hat{\sigma}^2_{\varepsilon_1}$	0.2543***	0.0883***
$\hat{\sigma}^2_{\varepsilon_2}$	0.9174***	0.3866***
$\hat{\sigma}^2_{\varepsilon_3}$	0.9230***	1.0833***
$\hat{\sigma}^2_{\varepsilon_4}$	1.5240***	1.3767***
$\hat{\sigma}^2_{\varepsilon_5}$	0.7016***	2.3066***
$\hat{\rho}$	0.3117***	0.1868***
$\hat{\sigma}^2_{\zeta_0}$	0.4020***	0.0974***
$\hat{\sigma}^2_{\zeta_1}$	0.0755***	0.0869***
$\hat{\sigma}_{\zeta_0\zeta_1}$	−0.0176*	−0.0021
Fit index		
AIC	79061	93232
BIC	79120	93294

* $p < 0.05$.
*** $p < 0.001$.

called unconditional and conditional growth models, respectively, and γ's are called growth parameters. Substituting the conditional level-2 sub-model (Eq. (5)) into the level-1 sub-model (Eq. (2)) leads to the following combined model:

$$
\begin{aligned}
Y_{it} &= \gamma_{00} + \gamma_{10}\mathrm{Time}_t + \gamma_{01}\mathrm{PCC}_i + \gamma_{02}\mathrm{RF}_i + \gamma_{03}\mathrm{NA}_i + \gamma_{04}\mathrm{NAFF}_i + \gamma_{05}\mathrm{NNAT}_i + \gamma_{06}\mathrm{PL}_i + \gamma_{07}\mathrm{AICOLL}_i + \\
&\gamma_{08}\mathrm{IP}_i + \gamma_{09}\mathrm{RA}_i + \gamma_{11}\mathrm{Time}_t \times \mathrm{PCC}_i + \gamma_{12}\mathrm{Time}_t \times \mathrm{RF}_i + \gamma_{13}\mathrm{Time}_t \times \mathrm{NA}_i + \gamma_{14}\mathrm{Time}_t \times \mathrm{NAFF}_i + \\
&\gamma_{15}\mathrm{Time}_t \times \mathrm{NNAT}_i + \gamma_{16}\mathrm{Time}_t \times \mathrm{PL}_i + \gamma_{17}\mathrm{Time}_t \times \mathrm{AICOLL}_i + \gamma_{18}\mathrm{Time}_t \times \mathrm{IP}_i + \gamma_{19}\mathrm{Time}_t \times \mathrm{RA}_i + \\
&(\zeta_{0i} + \mathrm{Time}_t \times \zeta_{1i} + \varepsilon_{it}),
\end{aligned}
\tag{6}
$$

which contains level-1 predictor Time, level-2 predictors PCC, RF, NA, NAFF, NNAT, PL, AICOLL, IP, and RA, their cross-level product terms, and level-1 and level-2 errors. $\gamma_{11} - \gamma_{19}$, the effects associated with the cross-level product terms of Time and level-2 predictors, are the cross-level interactions between Time and the level-2 predictors, indicating the influential effects of PCC, RF, NA, NAFF, NNAT, PL, AICOLL, IP, and RA on the growth trajectory of the number of patent citations.

According to the reviews given earlier, it is expected that the nine paper characteristics have positive effects on the growth of citation except RF, and RF has a negative effect on the growth. Thus, the right-tail test was conducted to test for the positive interaction effects associated with PCC, NA, NAFF, NNAT, PL, AICOLL, IP, and RA and the left-tail test for the negative interaction effect associated with RF.

4. Results

Descriptive statistics of the number of patent citations to the target year's publications in each of the two citation windows are presented in Table 3. Although the average numbers of citations are small in both windows, they increase with years. The results based on the unconditional linear growth model are reported in Table 4. It appears that the mean slope of the linear

Table 5
Means, standard deviations, and correlations for the paper characteristics used.

	PCC	RF	NA	NAFF	NNAT	PL	AICOLL	IP	RA
Mean									
1998	46.71	0.16	4.87	2.40	1.25	8.25	0.13	0.07	0.08
2006	53.07	0.19	5.83	2.81	1.32	8.56	0.12	0.04	0.11
S.D.									
1998	98.58	0.17	3.54	1.67	0.58	6.70	0.34	0.25	0.27
2006	100.34	0.19	6.29	2.41	0.71	4.83	0.32	0.21	0.32
PCC	1	−0.24	0.16	0.19	0.11	0.05	−0.01	−0.04	0.13
RF	−0.24	1	−0.10	−0.09	−0.01	0.15	0.03	0.06	0.00
NA	0.19	−0.12	1	0.72	0.44	0.01	0.16	0.01	−0.13
NAFF	0.16	−0.09	0.61	1	0.58	0.05	0.19	−0.12	−0.07
NNAT	0.09	−0.03	0.36	0.48	1	0.06	0.11	−0.07	−0.04
PL	0.06	0.10	−0.05	−0.00	0.20	1	0.05	0.03	0.34
AICOLL	−0.01	−0.03	0.18	0.21	0.13	−0.02	1	−0.08	−0.06
IP	−0.04	0.07	−0.04	−0.17	−0.10	0.05	−0.11	1	0.02
RA	0.14	0.02	−0.18	−0.08	−0.03	0.31	−0.04	0.01	1

PCC: paper citation count, RF: ranking factor, NA: number of authors, NAFF: the strength of inter-organizational co-authorship, NNAT: the strength of international co-authorship, PL: paper length, AICOLL: academia-industry collaboration, IP: industrial publication, RA: review article. PCC includes the 2001–2005 paper citations to the 1998 publications and the 2009–2013 paper citations to the 2006 publications in the WoS. n = 5479 for 1998 and n = 6885 for 2006. The correlations for 1998 are placed in the lower triangular matrix and the correlations for 2006 are placed in the upper triangular matrix.

trajectory of the number of patent-to-paper citations is significantly positive in each of the citation windows ($\hat{\gamma}_{10} = 0.105$ and 0.2284 ($p < 0.001$)).

It is of more interest to investigate the effects of paper characteristics on the trajectory of the number of patent-to-paper citations. Table 5 shows the means, standard deviations, and correlations of the nine paper characteristics for 1998 and 2006. The results based on the conditional linear growth model for the two citation windows are presented in Table 6. The size of the effect of the ith paper characteristic (denoted by X_i) on the slope, controlling for other paper characteristics, can be measured based on the pseudo-R^2 statistic (Peugh, 2010; Singer & Willett, 2003; p.104), and the effect size index is given by

$$\text{Pseudo-}R_i^2 = [\hat{\sigma}^2_{\zeta_1}(Reduced_i) - \hat{\sigma}^2_{\zeta_1}(\text{Full})]/\hat{\sigma}^2_{\zeta_1}(Reduced_i), \tag{7}$$

where $\hat{\sigma}^2_{\zeta_1}$ (Full) denotes the estimated variance of the level-2 error term ζ_1 for the full model (with all paper characteristics) and $\hat{\sigma}^2_{\zeta_1}(\text{Reduced}_i)$ denotes that for the reduced model (with all paper characteristics except X_i). The values for small, medium, and large effect sizes are 2%, 13%, and 26%, respectively, by following those based on the squared partial correlation (Cohen, 1992).

In Table 6, the linear fixed effect (associated with Time) is significantly positive in both citation windows. With the one-sided test, the paper characteristics showing significant interactions with Time in both windows include PCC ($\hat{\gamma}_{11} = 0.0004$ ($p < 0.001$) and 0.001 ($p < 0.001$)), RF ($\hat{\gamma}_{12} = -0.1157$ ($p < 0.001$) and -0.0595 ($p < 0.05$)), IP ($\hat{\gamma}_{18} = 0.0421$ ($p < 0.05$) and 0.0636 ($p < 0.01$)), and RA ($\hat{\gamma}_{19} = 0.0252$ ($p < 0.1$) and 0.0385 ($p < 0.01$)). PCC, IP, and RA exert positive influences on the slope of the citation trajectory while RF exerts a negative influence. NA shows a significant positive interaction with Time in the second citation window only ($\hat{\gamma}_{13} = 0.025$ ($p < 0.05$)). None of NAFF, NNAT, PL, and AICOLL significantly interacts with Time in either window. The positive effects associated with PCC and the negative effects associated with RF indicate that the more impact a paper has, the steeper the slope of the trajectory. Although joint research in terms of the number of authors seems helpful for the knowledge flow from science to technology, none of academia-industry collaboration, inter-organizational collaboration, and international collaboration is effective. Note that, regardless of whether an effect is statistically significant or not, the sizes of the effects of the paper characteristics are all very small (much less than 2%) except PCC, showing a small effect size (3.75%) in the first citation window and a near medium effect size (10.64%) in the second window.

5. Discussion

This study contributes to the literature by analyzing the growth trajectory of the number of patent-to-paper citations (i.e., the dynamic change in the number of patent-to-paper citations over time) and identifying the paper characteristics that influence the trajectory. The results obtained from the two citation windows are quite consistent (robust to different windows used). The paper characteristics showing statistically significant effects (i.e., significant interaction effects with Time) have been summarized in Table 7. If a paper characteristic significantly interacts with Time in both citation windows, the evidence is defined as a "strong evidence". If the interaction effect is significant in only one of the citation windows, the evidence is "weak". The paper characteristics showing strong evidence include the paper citation count, the ranking factor of the journal in which the paper was published, whether the paper is an industrial publication, and whether it is a review article. The paper characteristic with weak evidence is the number of authors. None of academia-industry collaboration, inter-organizational collaboration, and international collaboration exerts significant influence on the linear growth of the number of patent-to-paper citations, though they are helpful for the paper-to-paper citation. We conclude that, for the

Table 6
Results based on the conditional linear growth model of the number of patent-to-paper citations.

Independent variable	Citation window			
	2001–2005		2009–2013	
	Parameter estimate	Effect size	Parameter estimate	Effect size
Intercept	0.3289***		0.0607***	
Time	0.1212***		0.2212***	
PCC	0.0010***		0.0001	
RF	−0.0404		−0.0169	
NA	0.0035		0.0011	
NAFF	−0.0174†		−0.0080*	
NNAT	−0.0383*		0.0094	
PL	−0.0059***		0.0015	
AICOLL	0.1204***		0.0270†	
IP	0.0926*		0.1117***	
RA	0.0255		−0.0186	
Time × PCC	0.0004***	0.0375	0.0010***	0.1064
Time × RF	−0.1157***	0.0057	−0.0595*	0.0018
Time × NA	0.0022	0.0001	0.0025*	0.0015
Time × NAFF	−0.0074	0.0016	−0.0074	0.0018
Time × NNAT	0.0002	0.0001	−0.0066	0.0000
Time × PL	−0.0009	0.0008	−0.0033	0.0019
Time × AICOLL	−0.0234	0.0008	0.0162	0.0000
Time × IP	0.0421*	0.0019	0.0636**	0.0015
Time × RA	0.0252†	0.0001	0.0385**	0.0007
Error variance/covariance				
$\hat{\sigma}^2_{\varepsilon_1}$	0.2644***		0.0905***	
$\hat{\sigma}^2_{\varepsilon_2}$	0.9164***		0.3898***	
$\hat{\sigma}^2_{\varepsilon_3}$	0.9144***		1.0925***	
$\hat{\sigma}^2_{\varepsilon_4}$	1.5313***		1.3869***	
$\hat{\sigma}^2_{\varepsilon_5}$	0.7268***		2.2710***	
$\hat{\rho}$	0.3126***		0.1905***	
$\hat{\sigma}^2_{\zeta_0}$	0.3807***		0.0947***	
$\hat{\sigma}^2_{\zeta_1}$	0.0712***		0.0758***	
$\hat{\sigma}_{\zeta_0\zeta_1}$	−0.0194**		−0.0025	
Fit index				
AIC	78921		92849	
BIC	78981		92910	

PCC: paper citation count, RF: ranking factor, NA: number of authors, NAFF: the strength of inter-organizational co-authorship, NNAT: the strength of international co-authorship, PL: paper length, AICOLL: academia-industry collaboration, IP: industrial publication, RA: review article. The right-tail test was conducted to test for the interactions between Time and the paper characteristics except RF, whose interaction with Time is examined with the left-tail test. The size of the effect of the *i*th paper characteristic (denoted by X_i) on the slope, controlling for other paper characteristics, is measured byPseudo-$R_i^2 = [\hat{\sigma}^2_{\zeta_1}(Reduced_i) - \hat{\sigma}^2_{\zeta_1}(\text{Full})]/\hat{\sigma}^2_{\zeta_1}(Reduced_i)$, where$\hat{\sigma}^2_{\zeta_1}(\text{Full})$ denotes the $\hat{\sigma}^2_{\zeta_1}$ resulting from the conditional linear growth model with all paper characteristics and $\hat{\sigma}^2_{\zeta_1}(\text{Reduced}_i)$ denotes the $\hat{\sigma}^2_{\zeta_1}$ resulting from the conditional linear growth model with all paper characteristics except X_i.

† $p < 0.10$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 7
Summary of strong/weak/no evidence for the paper characteristics showing statistically significant influence on the growth of the patent-to-paper citation.

Paper characteristic	Evidence of the Influence on the growth trajectory
PCC	Strong
RF	Strong
NA	Weak
NAFF	No
NNAT	No
PL	No
AICOLL	No
IP	Strong
RA	Strong

PCC: paper citation count, RF: ranking factor, NA: number of authors, NAFF: the strength of inter-organizational co-authorship, NNAT: the strength of international co-authorship, PL: paper length, AICOLL: academia-industry collaboration, IP: industrial publication, RA: review article. Strong evidence: two statistical significances out of the two citation windows for the linear growth, weak evidence: one statistical significance out of the two citation windows.

Table 8
Regression results of the number of patent-to-paper citations on the paper characteristics.

Independent variable	Citation window			
	2001–2005		2009–2013	
	Parameter estimate	Effect size	Parameter estimate	Effect size
Intercept	3.0172***		2.5539***	
PCC	0.0094***	0.0325	0.0105***	0.0547
RF	−1.4094***	0.0022	−0.6753*	0.0009
NA	0.0330	0.0004	0.0302**	0.0010
NAFF	−0.1766	0.0020	−0.1134	0.0017
NNAT	−0.1793	0.0004	−0.0176	0.0000
PL	−0.0379	0.0026	−0.0267	0.0008
AICOLL	0.3929*	0.0007	0.3157*	0.0006
IP	0.8669***	0.0020	1.2200***	0.0035
RA	0.3331	0.0003	0.3152†	0.0005
R^2	0.0488		0.0692	

PCC: paper citation count, RF: ranking factor, NA: number of authors, NAFF: the strength of inter-organizational co-authorship, NNAT: the strength of international co-authorship, PL: paper length, AICOLL: academia-industry collaboration, IP: industrial publication, RA: review article. The right-tail test was conducted for the paper characteristics except RF, and the left-tail test was conducted for RF. The size of the effect of the *i*th paper characteristic on the number of patent-to-paper citations, controlling for other paper characteristics, is measured by the squared partial correlation.

† $p < 0.10$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

publications in the top ten subject categories frequently cited by patents, the mean slope of the growth trajectory of the number of patent citations is positive, and the characteristics of research impact and journal impact have positive effects on the growth. The growth can also be enhanced by the characteristics of being an industrial publication and being a review article. However, the effect sizes are mostly quite small.

In addition to identifying the paper characteristics that influence the trajectory of the patent-to-paper citation, we have also conducted static cross-sectional regression analyses to see if and how the paper characteristics are related to the number of patent-to-paper citations for each of the citation windows. The sum of the numbers of patent-to-paper citations across five years in the window was used as the dependent variable. The size of the effect of the *i*th paper characteristic (denoted by X_i) on the number of patent-to-paper citations (denoted by Y), controlling for other paper characteristics, can be measured with the squared partial correlation, denoted by $R^2_{YX_i\bullet Others}$, or $f_i^2 \left(= R^2_{YX_i\bullet Others} / \left(1 - R^2_{YX_i\bullet Others}\right)\right)$ (Cohen, 1988; pp. 410–414; Cohen, 1992). The values for small, medium, and large effect sizes based on $R^2_{YX_i\bullet Others}$ are 2%, 13%, and 26%, respectively.

The regression results, reported in Table 8, indicate that PCC, RF, AICOLL, and IP showed significant influence with strong evidence, NA and RA showed significant influence with weak evidence, and NAFF, NNAT, and PL showed no influence. Again, the effect sizes (based on the squared partial correlation) of the paper characteristics are all very small (much less than 2%) except PCC, showing small effect sizes (3.25% and 5.47%). The conclusions resulting from regression are slightly different from those obtained by using conditional growth modeling. Higher research impact, higher journal impact, and industrial publications can all lead to more patent citations as well as greater growth of the number of citations. Although academia-industry collaboration may increase the number of patent citations, it is not a facilitator of the knowledge flow. A review article may not be strongly related to the number of patent citations, but it is indeed a facilitator of the knowledge flow.

The paper characteristics related to the number of citations by papers are not necessarily related to the number of citations by patents or its growth trajectory. In the present study, we have found that research impact, journal impact, industrial publication, and review article are facilitators of the knowledge flow from science to technology. “Highly cited papers are much more likely to be cited in patents, which suggests that scientific excellence and contributions to innovation go hand in hand. In other words, agencies that support the best research will support the research most likely to contribute to innovation” (Hicks et al., 2000; p. 317). Patent inventors may be more familiar with prestigious journals, usually more frequently cited. They may select references from a few core journals only. Industrial publications tend to address the direct linkage to technology and are more practice-oriented. Patent inventors could benefit more from the perspective of industrial application. Review articles are useful for patent inventors to efficiently capture knowledge background. Although the learning literature argues that collaboration not only transfers existing knowledge among organizations but also facilitates the creation of new knowledge (Hardy, Phillips, & Lawrence, 2003), collaboration, regardless of academia-industry collaboration, inter-organizational collaboration, or international collaboration, have shown no significant positive influence on the growth of the patent-to-paper citation. Furthermore, paper length is also not related to the growth of the patent citation.

With a limited budget, policy makers are more interested in the criteria of setting the priority to grant. The growth facilitators identified in this study are informative for government and industries in choosing granting targets and further designing a mechanism to stimulate the research advancing patented inventions. The facilitators could also help patent inventors identify articles they need and guide article authors to develop those useful for technological development. When the knowledge flow from science to technology is of the main concern, policy makers should allocate more resources to its facilitators to accelerate the flow. More incentives are needed for producing high-impact research, industrial publications, and review articles.

There exist several research limitations. First, an earlier approval of a patent application would lead to the rejection of other parallel applications, especially in fields with a large number of patent applications. This might lead to the underestimation of the number of patent citations for some (highly relevant) papers cited in almost every patent application in a certain area. Second, scientific papers are restricted to the U.S.-affiliated articles in the WoS, and patented inventions are restricted to the patents in the USPTO database. Further studies may include more patent and publication data. Analysis can also be conducted by using the articles included in the Scopus database. Third, the effects sizes of the facilitators identified are mostly very small and show little practical significance. Fourth, more characteristics of papers and journals in which papers were published can be included in future research to see if and how they exert influence on the knowledge flow from science to technology. Those with larger effect sizes are particularly of interest. Fifth, we explore paper characteristics that facilitate the knowledge flow from science to technology in an overall way. The same approach can be used for individual subject categories and even for individual prestigious journals such as *Nature*, *Science*, *PNAS*, and *PLOS ONE* to gain more insight. Sixth, the 5-year citation window is too short to examine literature obsolescence. Longer-period citation windows are needed to explore, with higher-order growth modeling, patent-to-paper citation life-cycles.

Author contribution

Cherng G. Ding: conceived and designed the analysis, collected the data, performed the analysis and wrote the paper.
Wen-Chi Hung: Collected the data, performed the analysis.
Meng-Che Lee: Performed the analysis.
Hung-Jui Wang: Other contribution.

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Appendix A.

Top ten subject categories most frequently cited by papers in the WoS in 1998 and 2006.

Rank	Subject category	Paper citation count in 1998	Rank	Subject category	Paper citation count in 2006
1	Biochemistry & Molecular Biology	638511	1	Biochemistry & Molecular Biology	677755
2	Multidisciplinary Sciences	424099	2	Multidisciplinary Sciences	532224
3	Cell Biology	403101	3	Cell Biology	480816
4	Neurosciences	257734	4	Oncology	408691
5	Immunology	217597	5	Neurosciences	408022
6	Genetics & Heredity	194397	6	Chemistry, Multidisciplinary	276262
7	Oncology	187188	7	Immunology	271355
8	Medicine, General & Internal	166926	8	Medicine, General & Internal	268627
9	Medicine, Research & Experimental	127240	9	Genetics & Heredity	267536
10	Pharmacology & Pharmacy	105322	10	Chemistry, Physical	212454

Eight of the top ten subject categories most frequently cited by papers in 1998 also appear in the top ten subject categories in 2006. They include ‘Biochemistry & Molecular Biology’, ‘Multidisciplinary Sciences’, ‘Cell Biology’, ‘Neurosciences’, ‘Immunology’, ‘Genetics & Heredity’, ‘Oncology’, and ‘Medicine, General & Internal’. It can be further observed from Table 1 that, for those cited by patents, eight of the top ten most frequently cited subject categories in 1998 also appear in the top ten subject categories in 2006. They include ‘Biochemistry & Molecular Biology’, ‘Engineering, Electrical & Electronic’, ‘Physics, Applied’, ‘Oncology’, ‘Immunology’, ‘Cell Biology’, ‘Chemistry, Multidisciplinary’, and ‘Pharmacology & Pharmacy’. Therefore, the most frequently cited subject categories seem stable across time (with 80% agreement), regardless of whether they were cited by papers or by patents. However, comparing between the top ten subject categories frequently cited by papers and those frequently cited by patents for the same year, we found only 60% agreement for 1998 and 50% agreement for 2006. It is noteworthy that papers from the subject category of ‘Multidisciplinary Sciences’ stayed at the same high level of impact (ranked second) on scientific knowledge in 1998 and in 2006, but had less impact (did not show in the top ten) on patented inventions in 2006 than they had (ranked second) in 1998. Nevertheless, we have found (see Tables 7 and 8) that, regardless of the 1998 or 2006 publications, those with higher research impact and those with higher journal impact would lead to more patent citations as well as greater growth of the number of citations. Although the subject category of

'Multidisciplinary Sciences' include prestigious journals such as *Nature* and *Science*, high-impact papers and journals are not limited to this category.

References

Ahuja, G. (2000). Collaboration networks, structural holes: and innovation: A longitudinal study. *Administrative Science Quarterly*, *45*, 425–455.

Aksnes, D. W. (2003). Characteristics of highly cited papers. *Research Evaluation*, *12*, 159–170.

Bayer, A. E. (1982). A bibliometric analysis of marriage and family literature. *Journal of Marriage and the Family*, *44*, 527–538.

Callaert, J., Van Looy, B., Verbeek, A., Debackere, K., & Thijs, B. (2006). Traces of prior art: An analysis of non-patent references found in patent documents. *Scientometrics*, *69*, 3–20.

Callaert, J., Pellens, M., & Van Looy, B. (2014). Sources of inspiration?: Making sense of scientific references in patents. *Scientometrics*, *98*, 1617–1629.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates.

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*, 155–159.

Debackere, I. K., Veugelers, R., Zimmermann, E., Van Looy, B., Andries, P., & Callaert, J. (2001). *A longitudinal study into the science-technology-market interactions PBO-project (PBO99A/51/109)*. K.U. Leuven, Belgium: Department of Applied Economics.

Decarolis, D. M., & Leeds, D. L. (1999). The impact of stock and flows of organizational knowledge on firm performance: An empirical investigation of the biotechnology industry. *Strategic Management Journal*, *20*, 953–968.

Didegah, F., & Thelwall, M. (2013). Which factors help authors produce the highest impact research? collaboration, journal and document properties. *Journal of Informetrics*, *7*, 861–873.

Ding, C. G., & Jane, T. D. (2012). Using SAS PROC CALIS to fit level-1 error covariance structures of latent growth models. *Behavior Research Methods*, *44*, 765–787.

Doz, Y., & Hamel, G. (1997). The use of alliances in implementing technology strategies. In M. L. Tushman, & P. Anderson (Eds.), *Managing strategic innovation and change: A collection of readings* (pp. 556–580). New York: Oxford University Press.

Fleming, L., & Sorenson, O. (2004). Science as a map in technological search. *Strategic Management Journal*, *25*, 909–928.

Foray, D., & Gibbons, M. (1996). Discovery in the context of application. *Technological Forecasting and Social Change*, *53*, 263–277.

Franceschet, M., & Costantini, A. (2010). The effect of scholar collaboration on impact and quality of academic papers. *Journal of Informetrics*, *4*, 540–553.

Gazni, A., & Didegah, F. (2010). Investigating different types of research collaboration and citation impact: A case study of Harvard university's publications. *Scientometrics*, *87*, 251–265.

Gibbons, M., Limoges, C., Nowotny, H., Schwartzman, C., Scott, P., & Trow, M. (1994). *The new production of knowledge: The dynamics of science and research in contemporary society*. London: Sage.

Glänzel, W., & Schubert, A. (2004). Analyzing scientific networks through co-authorship. In H. F. Moed, W. Glänzel, & U. Schmoch (Eds.), *Handbook of quantitative science and technology research: The use of publication and patent statistics in studies of S&T systems* (pp. 257–276). Dordrecht: Kluwer.

Hagedoorn, J. (1993). Understanding the rationale of strategic technology partnering: Inter-organizational modes of cooperation and sectoral differences. *Strategic Management Journal*, *14*, 371–385.

Hardy, C., Phillips, N., & Lawrence, T. B. (2003). Resources, knowledge and influence: The organizational effects of interorganizational collaboration. *Journal of Management Studies*, *40*, 321–347.

Hicks, D., Breitzman, A., Hamilton, K., & Narin, F. (2000). Research excellence and patented innovation. *Science and Public Policy*, *27*, 310–320.

Hicks, D. (1995). Published papers: tacit competencies and corporate management of the public/private character of knowledge. *Industrial and Corporate Change*, *4*, 401–424.

Hudson, J. (2007). Be known by the company you keep: citations—quality or chance? *Scientometrics*, *71*, 231–238.

Hung, W. C., Ding, C. G., Wang, H. J., Lee, M. C., & Lin, C. P. (2015). Evaluating and comparing the university performance in knowledge utilization for patented inventions. *Scientometrics*, *102*, 1269–1286.

Katz, J. S., & Martin, B. R. (1997). What is research collaboration? *Research Policy*, *26*, 1–18.

Ma, N., & Guan, J. C. (2005). An exploratory study on collaboration profiles of Chinese publications in molecular biology. *Scientometrics*, *65*, 343–355.

MacRoberts, M. H., & MacRoberts, B. R. (1996). Problems of citation analysis. *Scientometrics*, *36*, 435–444.

Meyer, M. (2000). Does science push technology? Patents citing scientific literature. *Research Policy*, *29*, 409–434.

Meyer, M. (2002). Tracing knowledge flows in innovation systems. *Scientometrics*, *54*, 193–212.

Meyer, M. (2006). Measuring science-technology interaction in the knowledge-driven economy: The case of a small economy. *Scientometrics*, *66*, 425–439.

Minguillo, D., & Thelwall, M. (2015). Research excellence and university–industry collaboration in UK science parks. *Research Evaluation*, *24*, 181–196.

Murphy, D. L., & Pituch, K. A. (2009). The performance of multilevel growth curve models under an autoregressive moving average process. *Journal of Experimental Education*, *77*, 255–282.

Narin, F., Stevens, K., & Whitlow, E. S. (1991). Scientific cooperation in Europe and the citation of multinationally authored papers. *Scientometrics*, *21*, 313–323.

Narin, F., Hamilton, K. S., & Olivastro, D. (1995). Linkage between agency supported research and patented industrial technology. *Research Evaluation*, *5*, 183–187.

Narin, F., Hamilton, K. S., & Olivastro, D. (1997). The increasing linkage between U.S. technology and public science. *Research Policy*, *26*, 317–330.

Onodera, N., & Yoshikane, F. (2015). Factors affecting citation rates of research articles. *Journal of the Association for Information Science and Technology*, *66*, 739–764.

Peugh, J. L. (2010). A practical guide to multilevel modeling. *Journal of School Psychology*, *48*, 85–112.

Raudenbush, S. W., & Byrk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Thousand Oaks, CA: Sage.

Roach, M., & Cohen, W. M. (2013). Lens or prism? Patent citations as a measure of knowledge flows from public research. *Management Science*, *59*, 504–525.

Schmoch, U., & Schubert, T. (2008). Are international co-publications an indicator for quality of scientific research? *Scientometrics*, *74*, 361–377.

Schmoch, U., Breiner, S., Cuhls, K., Hinze, S., & Münt, G. (1994). *Interdisciplinary cooperation of research teams in science intensive areas of technology. Final report to the Commission of the European Union*. Karlsruhe, Germany: Fraunhofer Institute for Systems and Innovation Research.

Schmoch, U. (1997). Indicators and the relations between science and technology. *Scientometrics*, *38*, 103–116.

Singer, J. D., & Willett, J. B. (2003). *Applied longitudinal data analysis: Modeling change and event occurrence*. New York: Oxford University Press.

Sooryamoorthy, R. (2009). Do types of collaboration change citation? Collaboration and citation patterns of South African science publications. *Scientometrics*, *81*, 177–193.

Sorenson, O., & Fleming, L. (2004). Science and the diffusion of knowledge. *Research Policy*, *33*, 1615–1634.

Stewart, J. A. (1983). Achievement and ascriptive processes in the recognition of scientific articles. *Social Forces*, *62*, 166–189.

Teece, D. J. (1986). Profiting from technological innovation: Implications for integration, collaboration: licensing and public policy. *Research Policy*, *15*, 285–305.

Tijssen, R. J. W. (2001). Global and domestic utilization of industrial relevant science: Patent citation analysis of science–technology interactions and knowledge flows. *Research Policy*, *30*, 35–54.

Tijssen, R. J. W. (2004). Is the commercialisation of scientific research affecting the production of public knowledge?: Global trends in the output of corporate research articles. *Research Policy*, *33*, 709–733.

Tijssen, R. J. W. (2012). Co-authored research publications and strategic analysis of public?private collaboration. *Research Evaluation*, *21*, 204–215.

Trajtenberg, M., Henderson, R., & Jaffe, A. (1997). University versus corporate patents: A window on the basicness of invention. *Economics of Innovation and New Technology*, *5*, 19–50.
Van Dalen, H. P., & Henkens, K. (2001). What makes a scientific article influential?: The case of demographers. *Scientometrics*, *50*, 455–482.
Van Raan, A. F. J. (2004). Measuring science. In H. F. Moed, W. Glänzel, & U. Schmoch (Eds.), *Handbook of quantitative science and technology research: The use of publication and patent statistics in studies of S&T systems* (pp. 19–50). Dordrecht: Kluwer.
Von Graevenitz, G., Wagner, S., & Harhoff, D. (2013). Incidence and growth of patent thickets: The impact of technological opportunities and complexity. *Journal of Industrial Economics*, *61*, 521–563.
Wilson, C. S. (1999). Informetrics. *Annual Review of Information Science and Technology*, *34*, 107–247.