Technological Forecasting & Social Change 122 (2017) 12–23

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Investigating the dynamics of interdisciplinary evolution in technology developments

Hsin-Ning Su*, Igam M. Moaniba

Graduate Institute of Technology Management, National Chung Hsing University, 250 KuoKuang Road, Taichung 402, Taiwan

A R T I C L E I N F O

Keywords:
Interdisciplinary
Patent
Technology
Innovation

A B S T R A C T

In a global economy where technology plays a vital role, technology fusion is important for developing designs of outstanding innovations. These designs often involve the transfer of knowledge between different technological industries, a term known as "interdisciplinarity." This paper aims to contribute to the literature on interdisciplinary innovation by using a novel methodological approach to explore how conventional technologies have evolved into interdisciplinary technologies in different industries. The new methodological approach was based on patent citation analysis and negative binomial regressions conducted to: 1) observe the dynamics and evolution of interdisciplinary technologies, and 2) explore how interdisciplinary knowledge influences technology developments. The study found that interdisciplinary knowledge plays a significant role in the development of valuable technologies in all investigated industries. An important managerial implication from this is that firms should consider developing interdisciplinary technologies whenever possible.

1. Introduction

Interdisciplinarity is a popular concept in the literature on innovation and management. However, it is often used interchangeably with "cross-disciplinarity" by academic researchers. In fact, the two words have been interchanged so often that it becomes difficult to understand their differences. Interdisciplinarity involves integrating knowledge and methods from different disciplines using a real synthesis of approaches, whereas cross-disciplinarity refers to viewing one discipline from the perspective of another (Jenseius, 2012; Stember, 1991). In the context of technological innovation, interdisciplinarity is defined as the merging or combination of knowledge from various technical industries in order to create new technologies, products, or processes. In most cases, R & D collaborations are the primary movers behind this concept. These occur as firms working together share their knowledge, with the objective of enabling them to bring new products to the market (Hagedoorn, 1993).

One popular research stream that has emerged from the concept of interdisciplinarity has concentrated on the dynamics of technology development through organizational collaborations and other networking strategies. Findings from studies in this area have highlighted the important role of alliances in acquiring interdisciplinary knowledge (Frankort, 2013; Frankort et al., 2012; Gomes-Casseres et al., 2006; Mowery et al., 1996; Oxley and Wada, 2009; Rosenkopf and Almeida, 2003). By comparison, another popular research stream has focused on the role of interdisciplinarity in new technology or product development (Chen and Li, 1999; Decarolis and Deeds, 1999; Deeds and Hill, 1996; Kotabe and Swan, 1995; Rothaermel and Deeds, 2004). However, the linkage between the two research areas has not been adequately investigated by researchers.

Understanding the relationship between interdisciplinary dynamics and new product development is essential. Over the past few decades, a lot of studies have investigated different characteristics and dynamics of knowledge flows, mostly through the use of patent data (Gerybadze and Reger, 1999; Hsu et al., 2015; Su et al., 2012). Since then, a number of important findings and managerial implications have emerged. For instance, a firm's competitive advantage was found not to be entirely dependent on acquiring important knowledge, but also through translating such knowledge into new products as well (e.g., Blundell et al., 1999; Sorescu and Spanjol, 2008).

One of the longstanding and still-debated research gaps is the need to understand how interdisciplinary knowledge contributes to the development of new inventions. While the bulk of empirical studies have provided evidence that important inventions involve the transfer of knowledge across technological domains (e.g. Arthur, 2007; Hunter et al., 2011; Nemet, 2012), other studies found that such knowledge transfers have no significant impacts on important inventions (e.g. Nemet and Johnson, 2012). Because of these inconsistencies, a consensus on the role of interdisciplinary knowledge in the development of important inventions is far from being reached. This indicates the need

* Corresponding author.
E-mail addresses: ning@nchu.edu.tw (H.-N. Su), imoaniba@gmail.com (I.M. Moaniba).

http://dx.doi.org/10.1016/j.techfore.2017.04.024
Received 6 January 2017; Received in revised form 26 April 2017; Accepted 27 April 2017
Available online 09 May 2017
0040-1625/

for further investigation.

To fill the above described research gap, this paper aims to explore the role of interdisciplinary knowledge in technological innovation using a new approach. This is important for firms as it can help them find ways to maximize their technological capabilities by facilitating their knowledge search and acquisition. That outcome, in turn, may provide them with efficient product designs and improved productivities (Arora and Gambardella, 1990; Cassiman and Veugelers, 2002; Wu and Shanley, 2009).

The originality and contribution of this study to the innovation literature lies mainly in its methodological approach. The approach employed is novel in the sense that it constructs and measures the interdisciplinarity of a patent in a way that has never been done before. This unique method is based on the IPC classification and the idea that a patent citing patents from multiple technology sectors is interdisciplinary in nature. The more technology sectors cited, the more interdisciplinary a patent is. The first step in this approach utilized patent citation data to show the evolution of interdisciplinary patents, and the second analyzed the impacts of the constructed indicators of interdisciplinary knowledge on patent value. By utilizing patents' citation data and IPC classification, different levels of interdisciplinary measures were constructed and analyzed. Using patent forward citation count as a proxy for how valuable (or important) a technology is, the study found strong positive relationships between interdisciplinary variables and the development of important technologies. In doing so, it has provided new empirical evidence that interdisciplinarity is a relevant contributor to the development of important technologies.

In a nutshell, this paper is designed to contribute to the innovation literature by exploring the dynamics and trends of interdisciplinary knowledge, and how they influence the development of new technologies, using a novel methodology. Moreover, this involves a first-time systematic analysis of citation data on a complete range of patents granted by USPTO over a long period of time, the years 1983 to 2013.

The rest of the paper is organized as follows. Section 2 reviews the existing literature on the technology development, why it is important, and recent related research findings; the evolution of interdisciplinary technologies; and the use of patent data to explore knowledge flows and innovative performances. Section 3 presents the data and methodological approach employed in this study. Section 4 presents and discusses the empirical results, while Section 5 concludes the paper.

2. Literature review

2.1. The role of R & D in science and technology developments

Science and technology play important roles in the business world (Castells, 2014; Kazmeyer, 2016; Utterback, 1994). In fact, important scientific discoveries over the past decades have led to major technological breakthroughs. These technological advancements have in turn caused dramatic changes in the ways businesses operate (Satell, 2013; Vitez, 2016). For instance, since the scientific discovery of the binary number system by Gottfried Wilhelm Leibniz from as long ago as the 17th century, a series of breakthrough technologies based on the binary number system have emerged. These include the first-generation computers by IBM in the 1950s as well as the advent of the Web in the 1990s. Due to the widespread use of such technologies, most business transactions and processes have become digitized. This clearly demonstrates how such breakthrough technologies have brought significant changes to the ways businesses operate. These digital technologies bring immense benefits not only to businesses but also to users, in both commercial and social settings (Vitez, 2016). As a result, most outstanding technologies no longer appear within a single technological area but rather between multiple areas (Duysters and Hagedoorn, 1998; Hacklin et al., 2009). Moreover, small businesses are becoming more efficient and thus able to withstand competition from big companies. Many of the developments in science and technology have been attributed to improvements in knowledge and skills through R & D.

The findings of past studies examining the use of various forms of R & D have been mixed. However, an increasing number of recent publications and empirical studies have provided support for the positive contribution of technical cooperation in science and technology developments (Herstad et al., 2014; Maietta, 2015). In addition, studies such as Roper and Hewitt-Dundas (2015) have provided empirical evidence on strong and positive relationships among R & D, knowledge, and firm performance. Furthermore, in a global knowledge environment, many countries are collaborating with each other, with the hope of reducing their R & D costs (Narula and Santangelo, 2009). This kind of strategic alliance can lead to an effective integration of R & D capabilities between different industries and, in turn, to the creation of a more innovative and valuable new product. In the early years of the "one technology-one industry" era, firms often focused their R & D and production in a single technology area (Christensen et al., 2005; Kodama, 1992). Knowledge transfer and product diversification were rarely practiced. Over the years, knowledge transfer across different technological domains became popular and quickly led to product diversification. Soon, the one technology-one industry business strategy no longer applies. Now, relying on a technological breakthrough alone is not sufficient any more. Firms must also consider diversifying and expanding their product domains through knowledge and technology fusion strategies.

Technology fusion often requires some form of knowledge and skills sharing. This can include research collaborations either between organizations or across national boundaries. Some empirical studies have found that industry-university collaborations may not only lead to cost efficiencies but also to improved innovations (Bodas Freitas et al., 2013; Etzkowitz and Leydesdorff, 2000; Maietta, 2015). This type of collaboration has been around for quite a long time and the rate at which it is adopted is still growing. Consequently, industry-university collaboration became one of the indicators of technology developments (Sung et al., 2015).

2.2. Measuring interdisciplinarity of research publications

Interdisciplinary research is a popular phenomenon in scientific studies. For decades, scholars have tried to measure the scientific outputs of interdisciplinary researches through the use of bibliometric approaches. The term "bibliometrics" was first coined and defined by (Pritchard, 1969) as the application of mathematics and statistical methods to books and other media of communication. There are two main bibliometrics research approaches that have emerged from the core literature – the structuralist approach and the spatial approach (Wagner et al., 2011). While the former mainly uses citation analysis based on the structure of science (characterized by authors, articles, and disciplines), the latter uses the disciplinary distance between authors or journals. Some of the recent studies employing spatial distance approaches to investigate interdisciplinary research include (Boyack, 2004; Leydesdorff, 2007a,b; Leydesdorff and Schank, 2008; Porter and Rafols, 2009; Rafols and Meyer, 2010; Stirling, 2007; Van den Besselaar and Heimeriks, 2001; van Raan, 2005). Three of the most common methods used in spatial analysis are based on the concepts of diversity, entropy, and betweenness centrality.

A number of papers have proposed indicators of interdisciplinarity based on diversity measures. Some of these include (Stirling, 1998, 2007); (Porter and Rafols, 2009); and, (Rafols and Meyer, 2010). (Stirling, 2007) provided a general framework for understanding diversity in a range of different contexts by recognizing it as a function of three necessary but individually insufficient properties: variety; balance, and disparity. (Porter and Rafols, 2009) used bibliometric indicators, the RaoStirling diversity index, and a visualization method based on overlay science maps (Leydesdorff and Rafols, 2009) to show how the degree of interdisciplinarity has changed between 1975 and 2005. Their study covered six research domains including long-established areas such as Math and relatively newly formed ones like Neurosciences. (Rafols and Meyer, 2010) proposed a conceptual framework that aims to capture interdisciplinarity using the concepts of diversity and coherence. They developed their disciplinary diversity indicators from ISI Subject Categories to describe the heterogeneity of a bibliometric set viewed. This is a top-down approach that locates the set on the global map of science.

By comparison, entropy is a particular case of the general concept of diversity (Stirling, 2007). It is drawn from a mathematical concept commonly used in areas such as thermodynamics, statistical mechanics, and information theory. In this context of diversity, it is a measure of disorder or uncertainty in a system of science. Entropy can be used to measure either inputs, such as a disciplinary indicator of knowledge stream intensity between research fields (Van den Besselaar and Heimeriks, 2001), or outputs, such as in most other studies involving the system of network citations coming from multiple fields to one field.

Another commonly used publication interdisciplinary measure is based on the concept of betweenness centrality. The betweenness centrality is defined as the number of the shortest paths that go through an edge in a graph or network (Girvanand Newman, 2002). In the context of interdisciplinarity, it refers to the shortest discipline paths between journals (Leydesdorff, 2007a) or between authors (Schummer, 2004). (Schummer, 2004) employed a new visualization method based on co-author analysis to analyze over 600 papers published in “nano journals” in 2002 and 2003. This was done in order to compare the patterns of research collaboration with those of classical disciplinarity.

2.3. From interdisciplinary knowledge to technology fusion

Technology fusion, through the combination of various technologies, is increasingly becoming a popular approach to successful innovation (Caviggioli, 2016; Jin et al., 2011; Kodama, 1986). Firms engaging in technology fusion are most likely to have the flexibility to switch between multiple technological domains or to operate in all simultaneously. As a result, technologies have become boundary-free and products no longer appear within a single technological industry but rather between them (Duysters and Hagedoorn, 1998; Hacklin et al., 2009). This highlights the importance of understanding the dynamics of technology fusion and the trajectories of interdisciplinary knowledge in order to identify the trends of emerging technologies. This understanding is necessary, as it can help provide firms with early precautionary warnings on how and whether they should continue to engage in their existing product lines or start switching to others. Because of these, technology fusion has become one of the key indicators of important technology development. However, the linkage between technology fusion and interdisciplinary knowledge remains a phenomenon.

Due to the close relationship between technology fusion and interdisciplinary knowledge, researchers have been using interdisciplinary knowledge as an indicator of technology fusion. This allows them to analyze the trajectories and dynamics of technology fusion through the use of patent data (e.g. (Hu and Jaffe, 2003; Jaffe et al., 2000; von Wartburg et al., 2005). In this type of analysis, the most frequently occurring citation between certain pairs of patents is perceived as an indication of the presence of technology fusion. With the spike in patenting activity over the last couple of decades and the reliability of patents databases, patent data have become the main source of technological knowledge flows and interdisciplinary knowledge (Choi et al., 2012; Cong and Tong, 2008; Griliches, 1990; Yoon and Kim, 2012a). In addition, a lot of systematic designs and strategies for technology fusion have been developed based on the implications and findings of patent data analyses. These designs often lead to improved inventions and products (Park et al., 2013).

The bulk of innovation literature on technology trend analysis has been mainly focused in the area of identifying existing and emerging influential technologies, mostly in a single technological domain (Hullmann and Meyer, 2003; Kajikawa et al., 2008; No and Park, 2010). Some of these analyzed the technological trajectories over time (Choi and Park, 2009; Hillman and Sandén, 2008; Verspagen, 2007) while others used patent maps to examine the linkages and network relationships between certain technologies (Lee et al., 2009a,b; Son et al., 2012; Yoon, 2008; Yoon and Kim, 2012b). These patent maps were developed based on text mining techniques and patent citations. Unfortunately, not many of these studies investigated the trends in interdisciplinary knowledge and their impacts on technology developments.

2.4. Analyzing the dynamics of interdisciplinarity using patent data

Patent data has been used in many innovation and economic studies to analyze the dynamics of and trends in technology developments (e.g. Lai and Wu, 2005; Lee et al., 2009a,b; Stuart and Podolny, 1996). In fact, patent data use has escalated with the sharp global increase in patenting activity over the past decades. The use of citation data in a patent analysis is similar to the use of literature references in an academic review paper. This similarity in use is due to the fact that patent bibliometrics and literature bibliometrics have striking similarities (Narin, 1994). In a patent analysis, the flow of knowledge is often characterized by the relationship or link between a citing and a cited patent (Trajtenberg et al., 1997). This means that interdisciplinary knowledge flow occurs when both the citing and cited patents are not from the same technology field – a concept that has been widely adopted in the investigations of spillover effects between technology classes (Narin, 1994).

Patent citation has been proved to be a reliable indicator of technological activity in the past and has been used in many similar studies (Nakamura et al., 2015; Nemet and Johnson, 2012; Wu and Shanley, 2009). Furthermore, the links within the citing-cited patent pairs have become the basis of complex patent network analyses. The reason is that the links do not only allow tracing the flow of knowledge from one technology field to another but also provide a way to measure the intensity of knowledge flow. This is done by taking the number of times a citation pair occurs as the strength (or intensity) of the knowledge flow. The use of patent citation linkages provides an indication of whether interdisciplinarity has succeeded in being effective and, if so, where it has succeeded. Moreover, data on patent citations has been widely used as well in studies that involve investigating knowledge flows across institutions and national boundaries (e.g. (Breschi et al., 2003; Ho and Verspagen, 2006; Shin and Park, 2007).

Despite its advantages, patent citation data is time sensitive and therefore can easily cause truncation bias in the analysis if not controlled properly. Older patents are often available longer than newer patents and therefore can cause comparison bias between citation pairs from either group. To solve this problem, a number of studies have used year restrictions on citations, such as the 10-year citation window (e.g. in Mariani, 2004; Nemet, 2009; Nemet and Johnson, 2012). Nevertheless, the use of patent citation data has received criticism when used in studies that involve legal considerations and economic issues. This criticism is based on the argument that citation behavior for academic journals and patents is not the same, and that citation analysis relies heavily on the use of links in documents (Kostoff, 1998; Leydesdorff, 2008; Meyer, 2000; Michel and Bettels, 2001).

Finally, the majority of previous related studies that have used patent citation data involved identifying knowledge intermediaries and examining their roles in the flow of knowledge. In spite of the increasing number of studies in the area of interdisciplinarity and its impacts on technology developments, the inconsistencies in the results have proved the need for further investigation.

3. Data and methodology

3.1. Variables

The data set used in this empirical study contains data on patents granted by the US Patent and Trademark Office (USPTO) in the years 1983 to 2013. It covers a total of around 4.2 million patents. Adopting a similar approach to Nemet & Johnson (2012b), patent citation was used as a proxy for the flow of knowledge in which forward citation counts were taken as measures for how valuable patents are, and the different constructed patent backward citation counts as proxies for the different levels (or types) of interdisciplinary innovation. A 10-year citation window was imposed on both forward and backward citations to minimize truncation bias (Nemet and Johnson, 2012). The lower-end window is for the years 1983 to 1992, and the upper-end window covers 2004 to 2013. The different indicators of interdisciplinarity are constructed based on the IPC classification system and the patent backward citation information.

IPC (International Patent Classification) is a hierarchical patent classification system now used by more than 100 countries. The system was introduced and designed by the Strasbourg Agreement in 1971 based on the different broad areas of technology. IPC has been used as a primary way to search and classify patent documents according to the technical fields to which they pertain. Because of this, IPC has become the basis for investigating the state of the art in many fields of technology (WIPO, 2016).

IPC classification uses a tree-like structure by which patents are categorized in hierarchical levels. The first level known as a “section” has eight groups of broad *technical fields*. It uses a single English letter between A and H to represent each group – the letter A stands for Human Necessities; B for Performing Operations and Transporting; C for Chemistry and Metallurgy; D for Textiles and Paper; E for Fixed Constructions; F for Mechanical Engineering, Lighting, Heating and Weapons; G; for Physics; and H for Electricity. Each section is divided into “classes.” Classes are the next IPC hierarchical level that contains 120 groups. Each class is labeled by a two-digit number. Classes are often used to describe the *type* of technology in a given section. For example, C21 deals with the Metallurgy of iron. Classes are further subdivided into more than 640 “subclasses”. These subclasses often describe the *feature* of a given type of technology class. Similarly, a single English letter is added to the different combinations of a section and class to get subclass labels. For example, A43B is a subclass that represents a certain feature of a selected shoe type. The subclasses are divided into the next hierarchical level called “main group.” Each main group is represented by a three-digit number and often relates to the *use* of a given feature. For example, A21C5/00 is a main group that deals with “Dough-diving machines.” The lowest hierarchical level, “sub-group,” is characterized by number of two or more digits and is designated by dots preceding the titles of the main groups. Altogether, there are around 70,000 IPC identified entries that can be allotted to patent documents (WIPO, 2016).

The use of IPC classification in this study is necessary because of the incredible range and coverage of patents per IPC category. According to our data, there are a total of 637 different IPC subclasses. The number of patents in each category ranges from 1 to 251,490 with the average of 6639 patents per subclass. There are three IPC subclasses having only one patent - H02S, F99Z and B99Z. The IPC subclass category with the highest number of patents of 251,490 is H01L. Unlike the ranges described in previous studies such as (Kay et al., 2014), the difference is mainly related to the type of IPC classification used. While IPC 7 was used in (Kay et al., 2014), the data for this study was based on an IPC 8 classification.

As illustrated in the example in Fig. 1, the number of subsequent patents citing patent α is counted and recorded in a variable called FWDCIT. In this example, FWDCIT = r. This variable was used in the regression as the *dependent variable* and it is a proxy for the value of patent α. In addition, three *independent variables* were constructed based on the backward citation data. The first variable, SECCIT, denotes the number of distinct IPC sections cited by patent α. In the example in Fig. 1, patent α cites a total of n previous patents. These patents are from a total of five different IPC sections – A, C, D, F and H; hence SECCIT in this case is equal to 5. Similarly, the second variable, CLSCIT, represents the number of distinct IPC classes cited by patent α; and the third constructed variable, SBCCIT, denotes the number of distinct IPC subclasses cited by patent α. In this given example in Fig. 1, CLSCIT = 6 and SBCCIT = 3. These three independent variables are used as indicators of the different levels of interdisciplinary citations.

Nevertheless, it is important to know that there have been many other types of indicators used in previous studies to trace the flow of knowledge in innovation and measure innovative performances (Hagedoorn and Cloodt, 2003). To this date, there is still no standard way of measurement, and therefore the use of new interdisciplinary indicators in this paper will contribute to understanding the evolution of interdisciplinary technologies, the role of knowledge flow in technology developments, and the collective efforts of previous indicators of interdisciplinarity.

Finally, to control for the effects of other major known determinants of forward citation count, one additional independent variable and one categorical independent variable are added. The first is the CLMCNT variable which represents the number of claims a patent has. The number of claims in a patent has been found to strongly influence its citation value and therefore has been used a lot as a control in past similar studies (Nemet and Johnson, 2012). Additionally, categorical dummies for the time variable YEAR are also used in the regressions to control for the unobserved time-related disturbances such as huge inflation spikes and other macroeconomic shocks.

3.2. Statistical approach and model specifications

In this study, a two-step approach was employed to analyze the trends and impacts of interdisciplinary knowledge on patent value. 1) The first step in the analysis was designed to examine the trends or evolution of the interdisciplinary knowledge and their dynamics in terms of patent value (proxied by forward citation counts) over the years. In such cases, the lower-end citation window was not applicable. As a result, a total of around 2.7 million patents (i.e., from 1976 to 2003) were analyzed in this step. 2) The second step estimated the impacts of the constructed interdisciplinary indicators (built on the basis of backward citations) on technology development (proxied by forward citation counts). Using information on both backward citations and forward citations requires both 10-year citation windows at the lower and upper end of the period. This leaves a period of 1993 to 2003 for estimation that comprises of a total of 1.4 million patents.

In the first step, the primary goal is to understand how interdisciplinary inventions or technologies have evolved over time. To accomplish this, the total number of patents and the average counts of the forward citations for the different categories of interdisciplinary variables are plotted as functions of time. This allows visualizing the forward citation trends of each interdisciplinary variable over the investigated years. The average annual forward citation count for each of the interdisciplinary variables was computed using the formula:

$$\text{Avg. Forward Citation} = \frac{1}{M}\sum_{i=1}^{M}\text{FWDCIT}_i$$

that is, the annual sum of all forward citations received by patents in a given interdisciplinary group divided by the number of patents in that group, M.

In the second step, a negative binomial regression was employed to estimate the relationships between the constructed indicators of interdisciplinary citations and the forward citation. Negative binomial regression was used due to the fact that the forward citation outcome

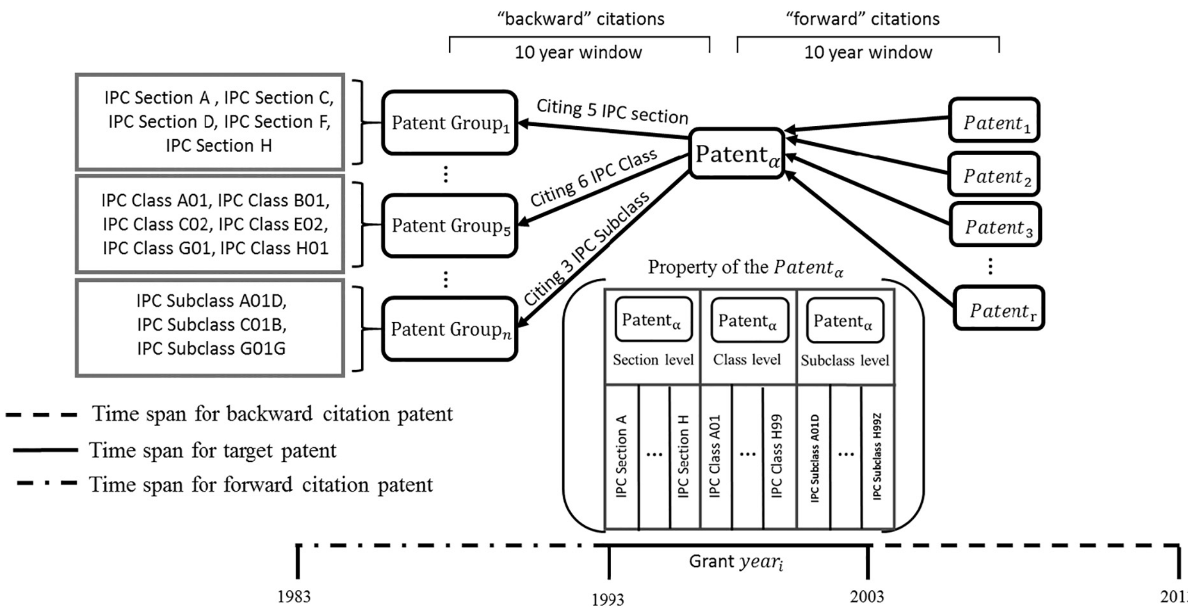

Fig. 1. Schema for patent citations showing how the variables are constructed; arrows indicate the directions of the flow of knowledge.

Table 1
Descriptive statistics.

Variable	Description	N	Mean	Std. dev.	Min	Max
YEAR	Year of patent issue	1,476,509	1998.64	3.085552	1993	2003
FWDCIT	Forward citations within 10 years	1,476,509	10.92975	18.94712	0	780
SECCIT	Number of sections bkwd cited	1,476,509	1.494327	0.902911	0	8
CLSCIT	Number of classes bkwd cited	1,476,509	1.948118	1.513268	0	41
SBCCIT	Number of subclasses bkwd cited	1,476,509	2.368852	2.081099	0	67
CLMCNT	Claim count	1,476,509	15.71645	12.97515	0	683
TECSEC	Technology industry	1,476,509	2.819201	1.312866	1	5

variable has non-negative integer values only and therefore cannot be estimated with linear models. Moreover, the mean of this outcome variable is much smaller than the variance, indicating the existence of over-dispersion. With overly dispersed data, negative binomial regression is more appropriate and reliable as compared to the other popular count data Poisson regression. In addition, using negative binomial on models that have high numbers of independent categorical variables (i.e., 41 class variables or 67 subclass variables – see maximum values of CLSCIT and SBCCIT variables in Table 1) does not require censoring. The advantage of this use, as compared to those in popular censoring regression models, is the fact that all information or data are used. With censoring or truncated techniques, some information or data are either grouped together or discarded.

The baseline specification model used in this step is shown below. This is a standard functional form for Poisson and negative binomial regression models:

$$E\,[y_i \mid x_i, \varepsilon_i] = \exp(\alpha + x_i\beta + \varepsilon_i) = h_i\lambda_i$$

where:

○ $h_i = \exp(\varepsilon_i)$ and $\lambda_i = \exp(\alpha + x_i\beta).x_i$ represents one of the independent interdisciplinary variables – SECCIT, CLSCIT, or SBCCIT;

○ y_i denotes the dependent forward citation variable – FWDCIT;

○ $E[y_i|x_i,\varepsilon_i]$ is the expected conditional mean of forward citation value for given sets of values of the independent interdisciplinary variable x_i and error term ε_i.

To estimate the relationships between each of the constructed interdisciplinary indicators and the forward citation count, three model specifications below (based on the baseline specification above) are devised and regressed. The first model contains only the first interdisciplinary variable SECCIT as the independent variable of interest. Similarly, the second model consists of the second interdisciplinary variable only (CLSCIT) whereas the third model has the third interdisciplinary variable only (SBCCIT). The main advantage of doing this is that it prevents possible collinearity and correlation issues from distorting the results.

$$E\,[y_i \mid x_i, \varepsilon_i] = \exp(\alpha + z_i\Omega + \varepsilon_i) = h_i k_i \quad \text{(Model I)}$$

$$E\,[y_i \mid x_i, \varepsilon_i] = \exp(\alpha + q_i\phi + \varepsilon_i) = h_i l_{i_i} \quad \text{(Model II)}$$

$$E\,[y_i \mid x_i, \varepsilon_i] = \exp(\alpha + w_i\gamma + \varepsilon_i) = h_i m_{i_i} \quad \text{(Model III)}$$

where:

○ z_i is the first interdisciplinary variable SECCIT$_i$; and $k_i = \exp(z_i\Omega)q_i$ is the second interdisciplinary variable CLSCIT$_i$; and $l_i = \exp(q_i\Phi)$

○ w_i is the third interdisciplinary variable SBCCIT$_i$; and $h_i = \exp(w_i\gamma)$.

4. Results

This section presents and discusses the empirical results in two parts: 1) the longitudinal dynamics of the interdisciplinary patents; 2) the results of the negative binomial regressions of the three models discussed in Section 3.2.

4.1. The evolutionary trends and dynamics of interdisciplinary patents

Fig. 2 shows the trends of the number of patents citing different counts of distinct IPC sections. For instance, the top line represents the number of patents that cite previous patents from the same group of IPC section (i.e., the number of distinct IPC sections cited = 1). The next highest line denotes the number of patents that cite previous patents from two distinct groups of IPC sections (i.e., the number of distinct IPC

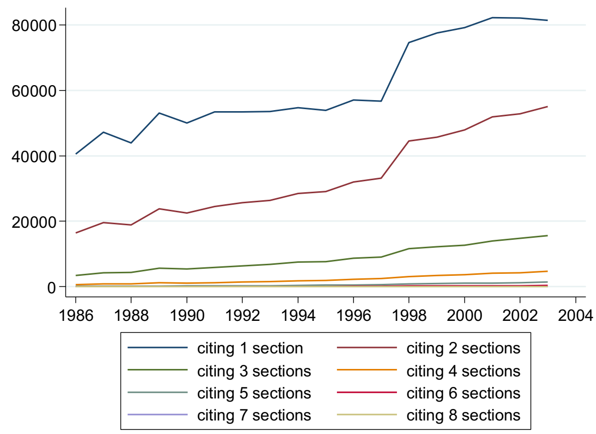

Fig. 2. Total number of interdisciplinary patents using cross-IPC section citations.

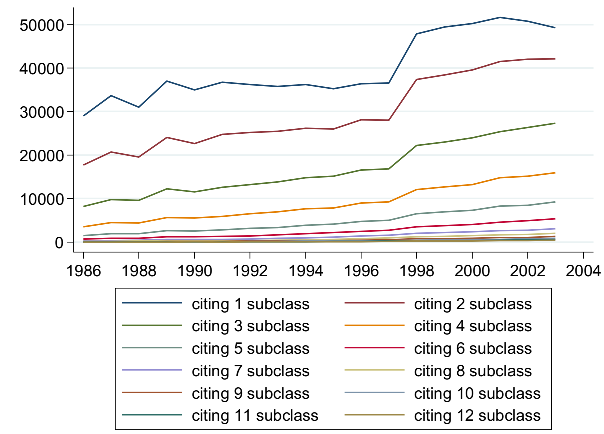

Fig. 4. The number of interdisciplinary patents using cross-IPC class citations.

sections cited = 2). It can be observed that the number of patents decreases with the increase in the number of distinct IPC sections cited. This indicates that the proportion of patents citing a higher number of distinct IPC sections is much smaller than that of patents citing fewer number of distinct IPC sections. Despite this, the number of patents in each category seems to increase gradually over the years.

Similar patterns and trends seen in Fig. 2 are also observed in the number of patents citing different counts of distinct IPC classes in Fig. 3. First, the proportion of patents citing fewer distinct IPC classes is much higher than that of patents citing more distinct IPC classes. Second, the number of patents engaging in interdisciplinary citations through cross-IPC class citation is generally lower than those in Fig. 2 but is increasing over the years. Note, for simplicity and readability, only the number of patents citing 10 or fewer distinct IPC classes are shown in this Fig. 2.

As observed in Fig. 4, the number of patents citing different counts of distinct IPC subclasses is also increasing in general but at different rates. The proportion of patents citing higher numbers of distinct subclasses is lower than the proportion of patents that cite fewer. For simplicity and readability, only the numbers of patents citing 12 or fewer distinct IPC subclasses are shown in Fig. 4.

Fig. 5 shows the plots of the average counts of forward citations for each group of interdisciplinary patents over the years. Note that the line plots include only the average counts of forward citations for patents citing up to 10 distinct IPC classes and 12 distinct IPC subclasses, instead of all 41 distinct classes and 67 subclasses cited respectively. Limiting the display of plots ensures readability. The important finding from these graphs is that although all these average forward citation counts fluctuate over time, they tend to increase gradually. These results clearly imply that firms' interests in interdisciplinary patents have been rising steadily over the years.

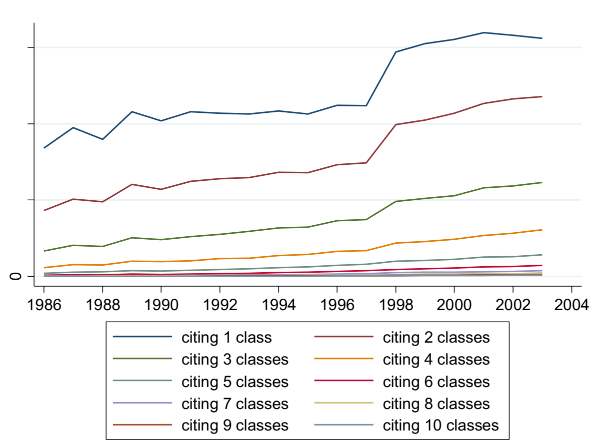

Fig. 3. Total number of interdisciplinary patents using cross-IPC class citations.

Fig. 6 depicts the distributions of the total forward citation counts for each group of interdisciplinary patents for the entire 1986 to 2003 period. The shaded blue boxes in the middle of each vertical line graph represent the 25th to the 75th percentiles of the distribution. The upper remaining part of the line represents the 75th to the 100th percentiles whereas the lower remaining part of the line shows the 0th to the 25th percentiles. The main important observation from this is that the number of forward citations received by a patent tends to increase with the number of distinct IPC sections, classes, or subclasses from which it cites. This clearly portrays a very important finding that the more the interdisciplinary a patent is, the more forward citations it receives.

The rapid increases in the number of interdisciplinary patents in 1998 (as depicted in Figs. 2, 3, and 4) are due to the steep increase in overall number of patents granted by the USPTO in 1998. "This is an increase of 31.5 percent over the 124,146 patents granted in 1997" (USPTO, O. of the C.C., 1999).

To statistically confirm the findings above, the number of distinct IPC sections, classes, or subclasses cited is regressed on the number of forward citations using negative binomial regression. The results are presented and discussed in the next subsection.

4.2. Regression results

The following are the negative binomial regression results of the three models explained in Section 3.2: 1) Model I: Impacts of backward citing distinct IPC sections on forward citation count, Table 2; 2) Model II: Impacts of backward citing distinct IPC classes on forward citation count, Table 3; and 4) Model III: Impacts of backward citing distinct IPC subclasses on forward citation count, Table 4.

Table 2 shows the results of the negative binomial regressions carried out to estimate the impacts of citing different numbers of distinct IPC sections on the forward citation count. Since all the independent variables are categorical dummy variables, the category 0.SECCIT (denoting patents that do not cite any previous patents) is used as a reference group and therefore not listed in the table. Patents backward citing zero previous patents are those that cited non-patent documents only such as academic papers. As shown in the table, almost all coefficients are significant and positive indicating that they have higher impacts on the forward citation count than the reference group. The important finding highlighted in these results is that the higher number of distinct IPC sections cited (e.g., compare 1.SECCIT to 7.SECCIT under All industries column) by a patent, the higher number of forward citations it receives. This is robust under all five different industries. Such finding strongly infers that the more interdisciplinary a patent is, the more valuable it is.

Table 3 lists the results of the negative binomial estimations carried out on the different numbers of distinct IPC classes cited against the

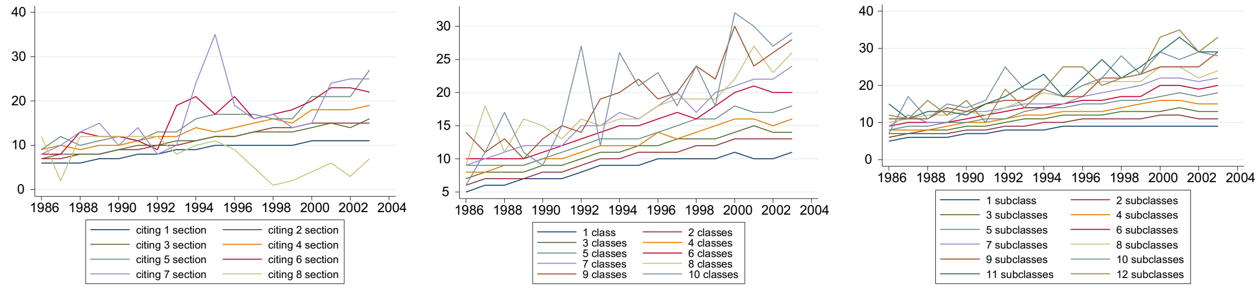

Fig. 5. Forward citation trends of interdisciplinary patents.

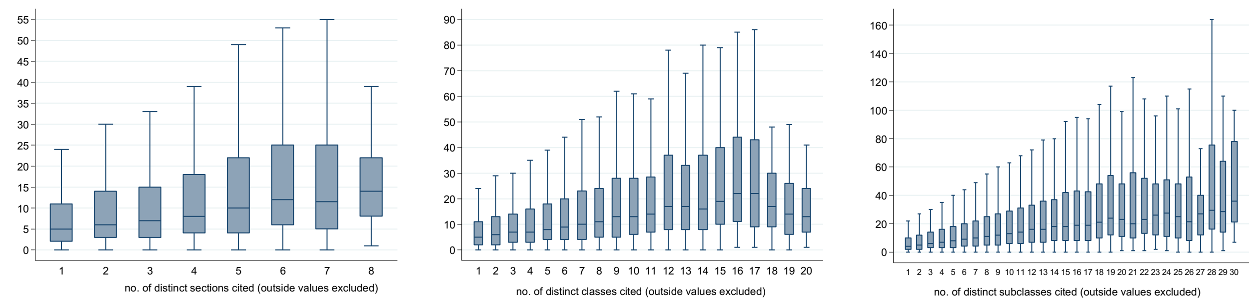

Fig. 6. Forward citation dynamics comparison between interdisciplinary variables.

forward citation counts. The category 0.CLSCIT (denoting patents that cited zero previous patents) is used as reference group and therefore again not shown in the results. Similar to the previous results, most of the coefficients are significant and positive indicating that they have higher impacts on the forward citation count than the reference group. It is also clear that the higher number of distinct IPC classes cited by a patent, the higher number of forward citations it receives. However, there seem to be certain limits before the coefficients start to decrease, and these are different under different industries. This finding implies that the more interdisciplinary a patent is in terms of cross-citing patents from other IPC classes, the more valuable it is – but to a certain extent. Note that even though the highest number of distinct IPC classes cited is 41, only the results for first 12 are shown in the table. The full results are provided in Table 5 in the Appendix A.

The results of the negative binomial estimations for the third model (Model III – see Section 3.2) are shown in Table 4. The categorical independent variables in this case is the number of distinct IPC subclasses cited. The reference category is the 0.SBCCIT (denoting those patents that cited zero previous patents) which is again not shown in the results. Similar to the previous two tables, most of the coefficients are significant and positive indicating that they have higher positive impacts on the forward citation count than the reference group. Similarly, this indicates that the higher number of distinct IPC subclasses cited by a patent, the higher number of forward citations it receives, but to a certain limit that varies with the industries. This finding is consistent with the previous two and thus strongly confirms that the more interdisciplinary a patent is (in terms of cross-citing patents from different IPC subclasses), the more valuable it is (to a certain limit). Note the highest number of distinct IPC subclasses cited is 67 however only the results of the first 16 are shown in the table. The full results are provided in Table 6 in Appendix A.

5. Conclusion

This study explores how conventional technologies have evolved into interdisciplinary technologies in different industries. Patent citation analysis and negative binomial regression were conducted to observe the dynamics and evolution of interdisciplinary technologies and to investigate how interdisciplinary knowledge influences technology developments. The study found that interdisciplinary knowledge plays a significant role in the development of valuable technologies in all investigated industries. It is observed that interdisciplinary knowledge contributes positively to technology developments and that the use of interdisciplinary knowledge in technology developments (or inventions) has been increasing rapidly over the period.

Table 2
Model I: Impacts of backward citing distinct IPC sections on forward citation count.

	All industries	Chemistry	Electrical engineering	Optics	Mechanical engineering	Other industries
1.SECCIT	0.639***	0.353***	0.519***	0.531***	0.417***	0.424***
2.SECCIT	0.886***	0.650***	0.815***	0.797***	0.638***	0.671***
3.SECCIT	0.859***	0.873***	0.707***	1.021***	0.830***	0.780***
4.SECCIT	1.011***	1.106***	0.686***	1.245***	1.033***	0.872***
5.SECCIT	1.154***	1.356***	0.870***	1.415***	1.119***	0.976***
6.SECCIT	1.210***	1.276***	0.621***	1.516***	1.291***	1.112***
7.SECCIT	1.124***	1.372***	1.376	1.333***	1.448***	0.789***
8.SECCIT	0.805***	1.419***	0.983	0.629	1.323***	0.400**
CLMCNT	0.0215***	0.0187***	0.0212***	0.0179***	0.0172***	0.0187***
Constant	1.189***	1.191***	1.719***	1.529***	1.167***	1.215***
Alpha(ln) Cnst	0.223***	0.343***	0.141***	0.195***	− 0.0226***	-0.0244***
N	1,476,509	297,910	379,953	246,218	396,035	156,393

Note: ***, **, * indicate significance of the estimated coefficient at 0.1, 1, and 5% respectively.

Table 3
Model II: Impacts of backward citing distinct IPC classes on forward citation count.

	All industries	Chemistry	Electrical engineering	Optics	Mechanical engineering	Other industries
1.CLSCIT	0.617***	0.311***	0.508***	0.537***	0.380***	0.413***
2.CLSCIT	0.779***	0.552***	0.676***	0.687***	0.555***	0.591***
3.CLSCIT	0.863***	0.718***	0.751***	0.818***	0.702***	0.696***
4.CLSCIT	0.935***	0.838***	0.852***	0.938***	0.818***	0.739***
5.CLSCIT	1.014***	0.967***	0.901***	1.085***	0.914***	0.859***
6.CLSCIT	1.107***	1.099***	1.000***	1.185***	1.061***	0.995***
7.CLSCIT	1.199***	1.229***	1.048***	1.306***	1.197***	1.078***
8.CLSCIT	1.261***	1.378***	1.134***	1.328***	1.252***	1.183***
9.CLSCIT	1.326***	1.355***	1.187***	1.543***	1.366***	1.178***
10.CLSCIT	1.396***	1.399***	1.122***	1.646***	1.400***	1.388***
11.CLSCIT	1.333***	1.483***	0.931***	1.434***	1.440***	1.179***
12.CLSCIT	1.480***	1.593***	1.148***	1.540***	1.530***	1.594***
CLMCNT	0.0212***	0.0182***	0.0213***	0.0176***	0.0164***	0.0182***
Constant	1.196***	1.199***	1.713***	1.535***	1.182***	1.224***
Alpha(ln) Cnst	0.220***	0.338***	0.144***	0.196***	− 0.0328***	-0.0308***
N	1,476,509	297,910	379,953	246,218	396,035	156,393

Note: ***, **, * indicate significance of the estimated coefficient at 0.1, 1, and 5% respectively.

5.1. Contribution to theory

The empirical results of this paper bring new insights to the evolutionary dynamics of interdisciplinary knowledge and how it can contribute to technology developments. The contribution of this paper to the innovation and economic theories is based on the following. First, the empirical results provide support to the notion that knowledge fusion through interdisciplinary patent citations contributes positively to technology development. This implies that the more interdisciplinary a technology or invention is, the more valuable or influential it will be. Second, the paper provides a new methodological framework for identifying interdisciplinary patents and analyzing their impacts on patent value. This framework can allow researchers and analysts to trace the trends and evolution of interdisciplinarity in innovation.

5.2. Management implications

Some of the management implications that can be drawn based on the above stated findings include the following. First, the finding of strong positive relationships between interdisciplinary variables and the forward citation value clearly implies that interdisciplinarity plays a vital role in the development of an important technology. This means that managers and decision makers in firms should consider prioritizing their R & D projects that guarantee the use of interdisciplinary knowledge. Second, the higher number of claims is the indication of higher patent value; therefore firm managers should always try to have as many claims as they can per patent application. This should guarantee a high number of future citations to their patent as demonstrated by the findings of this study. Patents that are highly cited can be licensed out and become revenue sources to firms in terms of license fees. Third, firms should know that there is a limit or threshold to knowledge integration or interdisciplinarity. According to the findings of this study, there is an adequate level of interdisciplinarity. This means that, depending on the type of industry or product, there are certain limits to the number of classes or technological domains to acquire knowledge from; otherwise it may lead to excessive fusion and lack of technological or business focus.

5.3. Limitations

Despite its use in many research innovation and economic-related studies, there is still criticism that patent value cannot be explicitly

Table 4
Model III: Impacts of backward citing distinct IPC subclasses on forward citation count.

	All industries	Chemistry	Electrical engineering	Optics	Mechanical engineering	Other industries
1.SBCCIT	0.519***	0.287***	0.398***	0.364***	0.358***	0.405***
2.SBCCIT	0.716***	0.486***	0.615***	0.606***	0.507***	0.548***
3.SBCCIT	0.839***	0.626***	0.729***	0.780***	0.647***	0.637***
4.SBCCIT	0.952***	0.756***	0.860***	0.915***	0.751***	0.722***
5.SBCCIT	1.053***	0.881***	0.962***	1.051***	0.844***	0.780***
6.SBCCIT	1.138***	0.953***	1.064***	1.157***	0.962***	0.865***
7.SBCCIT	1.209***	1.064***	1.128***	1.220***	1.019***	1.030***
8.SBCCIT	1.308***	1.176***	1.215***	1.361***	1.164***	1.063***
9.SBCCIT	1.368***	1.213***	1.360***	1.374***	1.184***	1.155***
10.SBCCIT	1.422***	1.288***	1.324***	1.462***	1.291***	1.363***
11.SBCCIT	1.457***	1.379***	1.294***	1.486***	1.418***	1.303***
12.SBCCIT	1.522***	1.389***	1.308***	1.605***	1.500***	1.387***
13.SBCCIT	1.634***	1.569***	1.397***	1.670***	1.562***	1.634***
14.SBCCIT	1.584***	1.705***	1.428***	1.528***	1.447***	1.530***
15.SBCCIT	1.694***	1.777***	1.240***	1.758***	1.618***	1.689***
16.SBCCIT	1.711***	1.792***	1.533***	1.752***	1.590***	1.712***
CLMCNT	0.0197***	0.0178***	0.0198***	0.0161***	0.0159***	0.0174***
Constant	1.233***	1.209***	1.759***	1.587***	1.192***	1.239***
Alpha(ln) Cnst	0.199***	0.334***	0.120***	0.160***	− 0.0404***	-0.0407***
N	1,476,509	297,910	379,953	246,218	396,035	156,393

Note: ***, **, * indicate significance of the estimated coefficient at 0.1, 1, and 5% respectively.

reflected by forward citation. The quality of how USPTO categorizes a patent into multiple IPC sections, classes, and subclasses is unknown and scarcely investigated. In addition, there is also a concern about how sensitive forward citation is to time. It is highly possible that the number of forward citations a patent gets (e.g., $patent_i$) in a given year (e.g., $year_t$) is likely to influence the number of forward citations it will get in the subsequent year (i.e., $year_{t+1}$) and later years. This occurs as patents citing $patent_i$ in $year_t$ may help promote $patent_i$ to subsequent patents in $year_{t+1}$ and later years. This is known as the lag effect of a citation. Finally, there are also concerns about the use of a 10-year citation window. There is a high probability that citations outside the 10-year window, i.e., below the 10-year backward citation window or above the 10-year forward citation window, are significantly large enough for some patents. Ignoring them may lead to lower patent citation values and therefore distorted results.

5.4. Future research

Potential future research paths include: 1) To conduct a similar study that is based on CPC; 2) To investigate the dynamics of interdisciplinary evolution by using other patent databases such as EPO or JPO; 3) To investigate the interdisciplinary impact of a patent by analyzing the IPC sections, classes, subclasses of its forward citation patent; and 4) The lag effect of a forward citation and its impacts on subsequent citations.

Acknowledgements

The author would like to thank the Ministry of Science and Technology of Republic of China, Taiwan, for the financial support under the contract: MOST 103-2401-H-005-058-MY3.

Appendix A

Table 5
Full regression results of Model II.

	All industries	Chemistry	Electrical engineering	Optics	Mechanical engineering	Other industries
1.CLSCIT	0.617***	0.311***	0.508***	0.537***	0.380***	0.413***
2.CLSCIT	0.779***	0.552***	0.676***	0.687***	0.555***	0.591***
3.CLSCIT	0.863***	0.718***	0.751***	0.818***	0.702***	0.696***
4.CLSCIT	0.935***	0.838***	0.852***	0.938***	0.818***	0.739***
5.CLSCIT	1.014***	0.967***	0.901***	1.085***	0.914***	0.859***
6.CLSCIT	1.107***	1.099***	1.000***	1.185***	1.061***	0.995***
7.CLSCIT	1.199***	1.229***	1.048***	1.306***	1.197***	1.078***
8.CLSCIT	1.261***	1.378***	1.134***	1.328***	1.252***	1.183***
9.CLSCIT	1.326***	1.355***	1.187***	1.543***	1.366***	1.178***
10.CLSCIT	1.396***	1.399***	1.122***	1.646***	1.400***	1.388***
11.CLSCIT	1.333***	1.483***	0.931***	1.434***	1.440***	1.179***
12.CLSCIT	1.480***	1.593***	1.148***	1.540***	1.530***	1.594***
13.CLSCIT	1.510***	1.633***	0.705***	1.781***	1.590***	1.617***
14.CLSCIT	1.489***	1.365***	1.023**	1.582***	1.743***	1.503***
15.CLSCIT	1.628***	1.387***	1.489***	2.066***	1.763***	1.392***
16.CLSCIT	1.718***	2.012***	1.093	2.077***	1.632***	1.297***
17.CLSCIT	1.516***	1.361***	0.655	1.942***	1.948***	0.724**
18.CLSCIT	1.286***	1.538***	0.691	1.617***	1.380***	0.766*
19.CLSCIT	1.137***	1.360***	–	1.513***	1.267***	0.731*
20.CLSCIT	0.832***	1.205*	0.473	0.846	1.503***	− 0.122
21.CLSCIT	1.749***	2.921***	–	1.461*	− 0.288	0.000261
22.CLSCIT	0.417*	0.373	1.403*	0.714	0.677	− 0.246
23.CLSCIT	0.0330	0.167	–	0.825	0.162	− 0.0244
24.CLSCIT	1.367***	1.527	–	–	2.428***	0.526
25.CLSCIT	1.197***	2.286***	–	0.824	–	0.170
26.CLSCIT	1.262*	2.056	–	–	2.350*	− 0.496
27.CLSCIT	1.911***	0.236	–	0.883	2.660***	–
28.CLSCIT	1.693***	2.001***	–	1.217	–	–
29.CLSCIT	− 0.708	–	–	–	− 0.368	–
33.CLSCIT	− 0.750	− 0.525	–	–	–	–
35.CLSCIT	0.779	0.993	–	–	–	–
36.CLSCIT	0.0803	–	–	–	–	0.304
37.CLSCIT	0.329	0.717	–	–	–	–
38.CLSCIT	1.137	–	–	–	–	1.318
39.CLSCIT	0.231	–	–	–	–	0.338
41.CLSCIT	− 0.613	–	–	–	–	− 0.422
CLMCNT	0.0212***	0.0182***	0.0213***	0.0176***	0.0164***	0.0182***
Constant	1.196***	1.199***	1.713***	1.535***	1.182***	1.224***
Alpha(ln) Cnst	0.220***	0.338***	0.144***	0.196***	− 0.0328***	− 0.0308***
N	1,476,509	297,910	379,953	246,218	396,035	156,393

Table 6
Full regression results of Model III.

	All industries	Chemistry	Electrical engineering	Optics	Mechanical engineering	Other industries
1.SBCCIT	0.519***	0.287***	0.398***	0.364***	0.358***	0.405***
2.SBCCIT	0.716***	0.486***	0.615***	0.606***	0.507***	0.548***
3.SBCCIT	0.839***	0.626***	0.729***	0.780***	0.647***	0.637***
4.SBCCIT	0.952***	0.756***	0.860***	0.915***	0.751***	0.722***
5.SBCCIT	1.053***	0.881***	0.962***	1.051***	0.844***	0.780***
6.SBCCIT	1.138***	0.953***	1.064***	1.157***	0.962***	0.865***
7.SBCCIT	1.209***	1.064***	1.128***	1.220***	1.019***	1.030***
8.SBCCIT	1.308***	1.176***	1.215***	1.361***	1.164***	1.063***
9.SBCCIT	1.368***	1.213***	1.360***	1.374***	1.184***	1.155***
10.SBCCIT	1.422***	1.288***	1.324***	1.462***	1.291***	1.363***
11.SBCCIT	1.457***	1.379***	1.294***	1.486***	1.418***	1.303***
12.SBCCIT	1.522***	1.389***	1.308***	1.605***	1.500***	1.387***
13.SBCCIT	1.634***	1.569***	1.397***	1.670***	1.562***	1.634***
14.SBCCIT	1.584***	1.705***	1.428***	1.528***	1.447***	1.530***
15.SBCCIT	1.694***	1.777***	1.240***	1.758***	1.618***	1.689***
16.SBCCIT	1.711***	1.792***	1.533***	1.752***	1.590***	1.712***
17.SBCCIT	1.648***	1.529***	1.272***	1.731***	1.719***	1.373***
18.SBCCIT	1.642***	1.736***	1.499***	1.526***	1.575***	1.808***
19.SBCCIT	1.873***	1.717***	1.765***	1.736***	2.066***	1.597***
20.SBCCIT	1.808***	1.656***	1.648***	1.800***	1.817***	1.939***
21.SBCCIT	1.800***	1.349***	1.405***	1.630***	1.934***	2.112***
22.SBCCIT	1.901***	1.514***	1.566***	1.898***	1.748***	1.981***
23.SBCCIT	1.931***	1.308***	1.113**	2.175***	2.144***	2.058***
24.SBCCIT	1.846***	2.056***	1.358***	1.768***	2.012***	1.880***
25.SBCCIT	1.825***	1.409***	1.037**	1.701***	2.272***	2.113***
26.SBCCIT	1.809***	1.801***	1.096***	1.955***	2.247***	0.480
27.SBCCIT	1.469***	1.265***	1.311**	1.760***	1.757***	1.743**
28.SBCCIT	2.225***	1.618***	1.374*	2.159***	1.972***	3.437***
29.SBCCIT	1.953***	1.940***	2.282***	1.992***	1.946***	0.420
30.SBCCIT	1.840***	2.149***	1.513***	1.562***	1.650***	1.822**
31.SBCCIT	2.180***	1.563**	2.196***	2.420***	2.109***	0.307
32.SBCCIT	1.532***	1.640	1.032	1.645***	2.083***	0.540
33.SBCCIT	2.466***	3.725**	–	2.671***	1.588**	1.139*
34.SBCCIT	1.272***	0.752	–	1.970*	1.329**	− 0.606
35.SBCCIT	1.427***	0.666	–	1.996**	1.499***	− 0.635
36.SBCCIT	1.950***	3.189***	–	–	1.815***	− 0.117
37.SBCCIT	0.663**	0.952	–	1.217	1.020*	− 0.415
38.SBCCIT	1.355***	− 1.444	–	1.557*	1.405*	0.815
39.SBCCIT	0.434	1.144	0–0.512	–	− 0.355	0.246
40.SBCCIT	0.784*	− 1.616	–	1.002	1.947***	− 0.0149
41.SBCCIT	1.182**	1.881	–	2.037**	0.227	− 0.583
42.SBCCIT	0.935**	1.713*	1.413*	–	− 0.131	− 0.572
43.SBCCIT	0.583	–	–	1.089	–	− 0.00640
44.SBCCIT	1.964***	–	–	–	2.840***	− 0.185
45.SBCCIT	2.060***	2.078	–	0.866	3.081***	− 1.484
CLMCNT	0.0197***	0.0178***	0.0198***	0.0161***	0.0159***	0.0174***
Constant	1.233***	1.209***	1.759***	1.587***	1.192***	1.239***
Alpha(ln) Cnst	0.199***	0.334***	0.120***	0.160***	− 0.0404***	− 0.0407***
N	1,476,509	297,910	379,953	246,218	396,035	156,393

References

Arora, A., Gambardella, A., 1990. Complementarity and external linkages: the strategies of the large firms in biotechnology. J. Ind. Econ. 361–379.

Arthur, W.B., 2007. The structure of invention. Res. Policy 36, 274–287. http://dx.doi.org/10.1016/j.respol.2006.11.005.

Blundell, R., Griffith, R., van Reenen, J., 1999. Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms. Rev. Econ. Stud. 66, 529–554. http://dx.doi.org/10.1111/1467-937X.00097.

Bodas Freitas, I.M., Marques, R.A., Silva, E.M. de P.e., 2013. University–industry collaboration and innovation in emergent and mature industries in new industrialized countries. Res. Policy 42, 443–453. http://dx.doi.org/10.1016/j.respol.2012.06.006.

Boyack, K.W., 2004. Mapping knowledge domains: characterizing PNAS. Proc. Natl. Acad. Sci. 101, 5192–5199.

Breschi, S., Lissoni, F., Malerba, F., 2003. Knowledge-relatedness in firm technological diversification. Res. Policy 32, 69–87. http://dx.doi.org/10.1016/S0048-7333(02)00004-5.

Cassiman, B., Veugelers, R., 2002. Complementarity in the Innovation Strategy: Internal R & D, External Technology Acquisition and Cooperation.

Castells, M., 2014. The impact of the internet on society: a global perspective [WWW Document]. MIT Technol. Rev(URL https://www.technologyreview.com/s/530566/the-impact-of-the-internet-on-society-a-global-perspective/ (accessed 9.20.16)).

Caviggioli, F., 2016. Technology fusion: identification and analysis of the drivers of technology convergence using patent data. Technovation 55–56, 22–32. http://dx.doi.org/10.1016/j.technovation.2016.04.003.
Chen, R., Li, M., 1999. Strategic alliances and new product development: an empirical study of the US semiconductor start-up firms. J. Compet. Stud. 7, 35.
Choi, C., Park, Y., 2009. Monitoring the organic structure of technology based on the patent development paths. Technol. Forecast. Soc. Chang. 76, 754–768. http://dx.doi.org/10.1016/j.techfore.2008.10.007.
Choi, S., Park, H., Kang, D., Lee, J.Y., Kim, K., 2012. An SAO-based text mining approach to building a technology tree for technology planning. Expert Syst. Appl. 39, 11443–11455. http://dx.doi.org/10.1016/j.eswa.2012.04.014.
Christensen, J.F., Olesen, M.H., Kjær, J.S., 2005. The industrial dynamics of open innovation—evidence from the transformation of consumer electronics. Res. Policy 34, 1533–1549.
Cong, H., Tong, L.H., 2008. Grouping of TRIZ inventive principles to facilitate automatic patent classification. Expert Syst. Appl. 34, 788–795. http://dx.doi.org/10.1016/j.eswa.2006.10.015.
Decarolis, D.M., Deeds, D.L., 1999. The Impact of Stocks and Flows of Organizational Knowledge on Firm Performance: An Empirical Investigation of the Biotechnology Industry. Strateg. Manag. J. 20, 953–968.
Deeds, D.L., Hill, C.W.L., 1996. Strategic alliances and the rate of new product development: An empirical study of entrepreneurial biotechnology firms. J. Bus. Ventur. 11, 41–55. http://dx.doi.org/10.1016/0883-9026(95)00087-9.
Duysters, G., Hagedoorn, J., 1998. Technological convergence in the IT industry: the role of strategic technology alliances and technological competencies. Int. J. Econ. Bus. 5, 355–368. http://dx.doi.org/10.1080/13571519884431.
Etzkowitz, H., Leydesdorff, L., 2000. The dynamics of innovation: from National Systems and "Mode 2" to a triple helix of university–industry–government relations. Res. Policy 29, 109–123. http://dx.doi.org/10.1016/S0048-7333(99)00055-4.
Frankort, H.T.W., 2013. Open Innovation Norms and Knowledge Transfer in Interfirm Technology Alliances: Evidence from Information Technology, 1980?1999. In: Collaboration and Competition in Business Ecosystems, Advances in Strategic Management. Emerald Group Publishing Limited, pp. 239–282. http://dx.doi.org/10.1108/S0742-3322(2013)0000030011.
Frankort, H.T.W., Hagedoorn, J., Letterie, W., 2012. R & D partnership portfolios and the inflow of technological knowledge. Ind. Corp. Change 21, 507–537. http://dx.doi.org/10.1093/icc/dtr045.
Gerybadze, A., Reger, G., 1999. Globalization of R & D: recent changes in the management of innovation in transnational corporations. Res. Policy 28, 251–274. http://dx.doi.org/10.1016/S0048-7333(98)00111-5.
Girvan, M., Newman, M.E.J., 2002. Community structure in social and biological networks. Proc. Natl. Acad. Sci. 99, 7821–7826. http://dx.doi.org/10.1073/pnas.122653799.
Gomes-Casseres, B., Hagedoorn, J., Jaffe, A.B., 2006. Do alliances promote knowledge flows? J. Financ. Econ. 80, 5–33. http://dx.doi.org/10.1016/j.jfineco.2004.08.011.
Griliches, Z., 1990. Patent statistics as economic indicators: a survey. J. Econ. Lit. 28, 1661–1707.
Hacklin, F., Marxt, C., Fahrni, F., 2009. Coevolutionary cycles of convergence: an extrapolation from the ICT industry. Technol. Forecast. Soc. Chang. 76, 723–736. http://dx.doi.org/10.1016/j.techfore.2009.03.003.
Hagedoorn, J., 1993. Understanding the rationale of strategic technology partnering: Nterorganizational modes of cooperation and sectoral differences. Strateg. Manag. J. 14, 371–385. http://dx.doi.org/10.1002/smj.4250140505.
Hagedoorn, J., Cloodt, M., 2003. Measuring innovative performance: is there an advantage in using multiple indicators? Res. Policy 32, 1365–1379. http://dx.doi.org/10.1016/S0048-7333(02)00137-3.
Herstad, S.J., Aslesen, H.W., Ebersberger, B., 2014. On industrial knowledge bases, commercial opportunities and global innovation network linkages. Res. Policy 43, 495–504. http://dx.doi.org/10.1016/j.respol.2013.08.003.
Hillman, K.M., Sandén, B.A., 2008. Exploring technology paths: the development of alternative transport fuels in Sweden 2007–2020. Technol. Forecast. Soc. Chang. 75, 1279–1302. http://dx.doi.org/10.1016/j.techfore.2008.01.003.
Ho, M., Verspagen, B., 2006. The role of national borders and regions in knowledge flows. Eur. Econ. Learn Coord. Compet. Models 50–73.
Hsu, C.-W., Lien, Y.-C., Chen, H., 2015. R & D internationalization and innovation performance. Int. Bus. Rev. 24, 187–195. http://dx.doi.org/10.1016/j.ibusrev.2014.07.007.
Hu, A.G.Z., Jaffe, A.B., 2003. Patent citations and international knowledge flow: the cases of Korea and Taiwan. Int. J. Ind. Organ. 21, 849–880. http://dx.doi.org/10.1016/S0167-7187(03)00035-3.
Hullmann, A., Meyer, M., 2003. Publications and patents in nanotechnology. Scientometrics 58, 507–527. http://dx.doi.org/10.1023/B:SCIE.0000006877.45467.a7.
Hunter, E.M., Perry, S.J., Currall, S.C., 2011. Inside multi-disciplinary science and engineering research centers: the impact of organizational climate on invention disclosures and patents. Res. Policy 40, 1226–1239. http://dx.doi.org/10.1016/j.respol.2011.05.024.
Jaffe, A.B., Trajtenberg, M., Fogarty, M.S., 2000. Knowledge spillovers and patent citations: evidence from a survey of inventors. Am. Econ. Rev. 90, 215–218. http://dx.doi.org/10.1257/aer.90.2.215.
Jenseius, A.R., 2012. Disciplinarities: Intra, Cross, Multi, Inter, Trans | ARJ.
Jin, J.H., Park, S.C., Pyon, C.U., 2011. Finding research trend of convergence technology based on Korean R & D network. Expert Syst. Appl. 38, 15159–15171. http://dx.doi.org/10.1016/j.eswa.2011.05.088.
Kajikawa, Y., Yoshikawa, J., Takeda, Y., Matsushima, K., 2008. Tracking emerging technologies in energy research: toward a roadmap for sustainable energy. Technol. Forecast. Soc. Chang. 75, 771–782. http://dx.doi.org/10.1016/j.techfore.2007.05.005.
Kay, L., Newman, N., Youtie, J., Porter, A.L., Rafols, I., 2014. Patent overlay mapping: visualizing technological distance. J. Assoc. Inf. Sci. Technol. 65, 2432–2443.
Kazmeyer, M., 2016. The importance of modern technology [WWW Document]. In: Our Everyday Life, (URL http://techin.oureverydaylife.com/importance-modern-technology-2077.html (accessed 9.20.16)).
Kodama, F., 1986. Japanese innovation in mechatronics technology. Sci. Public Policy 13, 44–51. http://dx.doi.org/10.1093/spp/13.1.44.
Kodama, F., 1992. Technology fusion and the new R & D [WWW document]. Harv. Bus. Rev(URL https://hbr.org/1992/07/technology-fusion-and-the-new-rd (accessed 11.9.16)).
Kostoff, R.N., 1998. The use and misuse of citation analysis in research evaluation. Scientometrics 43, 27–43. http://dx.doi.org/10.1007/BF02458392.
Kotabe, M., Scott Swan, K., 1995. The role of strategic alliances in high-technology new product development. Strateg. Manag. J. 16, 621–636. http://dx.doi.org/10.1002/smj.4250160804.
Lai, K.-K., Wu, S.-J., 2005. Using the patent co-citation approach to establish a new patent classification system. Inf. Process. Manag. 41, 313–330. http://dx.doi.org/10.1016/j.ipm.2003.11.004.
Lee, H., Kim, C., Cho, H., Park, Y., 2009a. An ANP-based technology network for identification of core technologies: a case of telecommunication technologies. Expert Syst. Appl. 36, 894–908. http://dx.doi.org/10.1016/j.eswa.2007.10.026.
Lee, S., Yoon, B., Park, Y., 2009b. An approach to discovering new technology opportunities: keyword-based patent map approach. Technovation 29, 481–497. http://dx.doi.org/10.1016/j.technovation.2008.10.006.
Leydesdorff, L., 2007a. Betweenness centrality as an indicator of the Interdisciplinarity of Scientific Journals. J. Am. Soc. Inf. Sci. Technol. 58, 1303–1319. http://dx.doi.org/10.1002/asi.20614.
Leydesdorff, L., 2007b. Mapping interdisciplinarity at the interfaces between the Science Citation Index and the Social Science Citation Index. Scientometrics 71, 391–405.
Leydesdorff, L., 2008. Patent classifications as indicators of intellectual organization. J. Am. Soc. Inf. Sci. Technol. 59, 1582–1597. http://dx.doi.org/10.1002/asi.20814.
Leydesdorff, L., Rafols, I., 2009. A global map of science based on the ISI subject categories. J. Am. Soc. Inf. Sci. Technol. 60, 348–362.
Leydesdorff, L., Schank, T., 2008. Dynamic animations of journal maps: indicators of structural changes and interdisciplinary developments. J. Am. Soc. Inf. Sci. Technol. 59, 1810–1818.
Maietta, O.W., 2015. Determinants of university–firm R & D collaboration and its impact on innovation: a perspective from a low-tech industry. Res. Policy 44, 1341–1359. http://dx.doi.org/10.1016/j.respol.2015.03.006.
Mariani, M., 2004. What determines technological hits?: Geography versus firm competencies. Res. Policy 33, 1565–1582. http://dx.doi.org/10.1016/j.respol.2004.08.004.
Meyer, M., 2000. What is special about patent citations? Differences between scientific and patent citations. Scientometrics 49, 93–123. http://dx.doi.org/10.1023/A:1005613325648.
Michel, J., Bettels, B., 2001. Patent citation analysis. A closer look at the basic input data from patent search reports. Scientometrics 51, 185–201. http://dx.doi.org/10.1023/A:1010577030871.
Mowery, D.C., Oxley, J.E., Silverman, B.S., 1996. Strategic alliances and interfirm knowledge transfer. Strateg. Manag. J. 17, 77–91. http://dx.doi.org/10.1002/smj.4250171108.
Nakamura, H., Suzuki, S., Sakata, I., Kajikawa, Y., 2015. Knowledge combination modeling: the measurement of knowledge similarity between different technological domains. Technol. Forecast. Soc. Chang. 94, 187–201. http://dx.doi.org/10.1016/j.techfore.2014.09.009.
Narin, F., 1994. Patent bibliometrics. Scientometrics 30, 147–155.
Narula, R., Santangelo, G.D., 2009. Location, collocation and R & D alliances in the European ICT industry. Res. Policy 38, 393–403. http://dx.doi.org/10.1016/j.respol.2008.11.005.
Nemet, G.F., 2009. Demand-pull, technology-push, and government-led incentives for non-incremental technical change. Res. Policy 38, 700–709. http://dx.doi.org/10.1016/j.respol.2009.01.004.
Nemet, G.F., 2012. Inter-technology knowledge spillovers for energy technologies. Energy Econ. 34, 1259–1270. http://dx.doi.org/10.1016/j.eneco.2012.06.002.
Nemet, G.F., Johnson, E., 2012. Do important inventions benefit from knowledge originating in other technological domains? Res. Policy 41, 190–200. http://dx.doi.org/10.1016/j.respol.2011.08.009.
No, H.J., Park, Y., 2010. Trajectory patterns of technology fusion: trend analysis and taxonomical grouping in nanobiotechnology. Technol. Forecast. Soc. Chang. 77, 63–75. http://dx.doi.org/10.1016/j.techfore.2009.06.006.
Oxley, J., Wada, T., 2009. Alliance Structure and the Scope of Knowledge Transfer: Evidence from U.S.-Japan Agreements. Manag. Sci. 55, 635–649. http://dx.doi.org/10.1287/mnsc.1080.0968.
Park, H., Ree, J.J., Kim, K., 2013. Identification of promising patents for technology transfers using TRIZ evolution trends. Expert Syst. Appl. 40, 736–743. http://dx.doi.org/10.1016/j.eswa.2012.08.008.
Porter, A., Rafols, I., 2009. Is science becoming more interdisciplinary? Measuring and mapping six research fields over time. Scientometrics 81, 719–745.
Pritchard, A., 1969. Statistical bibliography or bibliometrics. J. Doc. 25, 348.
van Raan, A.F., 2005. Measurement of central aspects of scientific research: performance, interdisciplinarity, structure. Meas. Interdiscip. Res. Perspect. 3, 1–19.
Rafols, I., Meyer, M., 2010. Diversity and network coherence as indicators of interdisciplinarity: case studies in bionanoscience. Scientometrics 82, 263–287. http://dx.doi.org/10.1007/s11192-009-0041-y.

Roper, S., Hewitt-Dundas, N., 2015. Knowledge stocks, knowledge flows and innovation: evidence from matched patents and innovation panel data. Res. Policy 44, 1327–1340. http://dx.doi.org/10.1016/j.respol.2015.03.003.
Rosenkopf, L., Almeida, P., 2003. Overcoming Local Search Through Alliances and Mobility. Manag. Sci. 49, 751–766. http://dx.doi.org/10.1287/mnsc.49.6.751.16026.
Rothaermel, F.T., Deeds, D.L., 2004. Exploration and exploitation alliances in biotechnology: a system of new product development. Strateg. Manag. J. 25, 201–221. http://dx.doi.org/10.1002/smj.376.
Satell, G., 2013. 4 Ways In Which Technology Is Transforming Business [WWW Document]. Forbes(URL http://www.forbes.com/sites/gregsatell/2013/04/02/4-ways-in-which-technology-is-transforming-business/ (accessed 9.20.16)).
Schummer, J., 2004. Multidisciplinarity, interdisciplinarity, and patterns of research collaboration in nanoscience and nanotechnology. Scientometrics 59, 425–465.
Shin, J., Park, Y., 2007. Building the national ICT frontier: the case of Korea. Inf. Econ. Policy 19, 249–277. http://dx.doi.org/10.1016/j.infoecopol.2007.01.003.
Son, C., Suh, Y., Jeon, J., Park, Y., 2012. Development of a GTM-based patent map for identifying patent vacuums. Expert Syst. Appl. 39, 2489–2500. http://dx.doi.org/10.1016/j.eswa.2011.08.101.
Sorescu, A.B., Spanjol, J., 2008. Innovation's Effect on Firm Value and Risk: Insights from Consumer Packaged Goods. J. Mark. 72, 114–132. http://dx.doi.org/10.1509/jmkg.72.2.114.
Stember, M., 1991. Advancing the social sciences through the interdisciplinary enterprise. Soc. Sci. J. 28, 1–14. http://dx.doi.org/10.1016/0362-3319(91)90040-B.
Stirling, A., 1998. On the economics and analysis of diversity. Sci. Policy Res. Unit SPRU Electron. Work. Pap. Ser. Pap. 28, 1–156.
Stirling, A., 2007. A general framework for analysing diversity in science, technology and society. J. R. Soc. Interface 4, 707–719. http://dx.doi.org/10.1098/rsif.2007.0213.
Stuart, T.E., Podolny, J.M., 1996. Local search and the evolution of technological capabilities. Strateg. Manag. J. 17, 21–38.
Su, H.-N., Chen, C.M.-L., Lee, P.-C., 2012. Patent litigation precaution method: analyzing characteristics of US litigated and non-litigated patents from 1976 to 2010. Scientometrics 92, 181–195. http://dx.doi.org/10.1007/s11192-012-0716-7.
Sung, H.-Y., Wang, C.-C., Huang, M.-H., Chen, D.-Z., 2015. Measuring science-based science linkage and non-science-based linkage of patents through non-patent references. J. Inf. Secur. 9, 488–498. http://dx.doi.org/10.1016/j.joi.2015.04.004.
Trajtenberg, M., Henderson, R., Jaffe, A., 1997. University versus corporate patents: a window on the basicness of invention. Econ. Innov. New Technol. 5, 19–50. http://dx.doi.org/10.1080/10438599700000006.
USPTO, O. of the C.C., 1999. U.S. Patents Up 31.5 Percent in 1998 [WWW Document]. USPTO - U. S. Pat. Trademark Off. URL https://www.uspto.gov/about-us/news-updates/us-patents-315-percent-1998 (accessed 3.13.17).
Utterback, J., 1994. Mastering the dynamics of innovation: how companies can seize opportunities in the face of technological change. In: Univ. Ill. Urbana-Champaigns Acad. Entrep. Leadersh. Hist. Res. Ref. Entrep.
Van den Besselaar, P., Heimeriks, G., 2001. Disciplinary, multidisciplinary, interdisciplinary: concepts and indicators. In: Presented at the ISSI, pp. 705–716.
Verspagen, B., 2007. Mapping technological trajectories as patent citation networks: a study on the history of fuel cell research. Adv. Complex Syst. 10, 93–115. http://dx.doi.org/10.1142/S0219525907000945.
Vitez, O., 2016. The Impact of Technological Change on Business Activity [WWW Document]. Chron - Small Bus(URL http://smallbusiness.chron.com/impact-technological-change-business-activity-2191.html (accessed 9.20.16)).
Wagner, C.S., Roessner, J.D., Bobb, K., Klein, J.T., Boyack, K.W., Keyton, J., Rafols, I., Börner, K., 2011. Approaches to understanding and measuring interdisciplinary scientific research (IDR): a review of the literature. J. Inf. Secur. 5, 14–26. http://dx.doi.org/10.1016/j.joi.2010.06.004.
von Wartburg, I., Teichert, T., Rost, K., 2005. Inventive progress measured by multi-stage patent citation analysis. Res. Policy 34, 1591–1607. http://dx.doi.org/10.1016/j.respol.2005.08.001.
WIPO, 2016. International Patent Classification: Frequently Asked Questions [WWW Document]. WIPO - World Intellect. Prop. Organ(URL http://www.wipo.int/classifications/ipc/en/faq/ (accessed 10.26.16)).
Wu, J., Shanley, M.T., 2009. Knowledge stock, exploration, and innovation: research on the United States electromedical device industry. J. Bus. Res. 62, 474–483. http://dx.doi.org/10.1016/j.jbusres.2007.12.004.
Yoon, B., 2008. On the development of a technology intelligence tool for identifying technology opportunity. Expert Syst. Appl. 35, 124–135. http://dx.doi.org/10.1016/j.eswa.2007.06.022.
Yoon, J., Kim, K., 2012a. An analysis of property–function based patent networks for strategic R & D planning in fast-moving industries: the case of silicon-based thin film solar cells. Expert Syst. Appl. 39, 7709–7717. http://dx.doi.org/10.1016/j.eswa.2012.01.035.
Yoon, J., Kim, K., 2012b. Detecting signals of new technological opportunities using semantic patent analysis and outlier detection. Scientometrics 90, 445–461. http://dx.doi.org/10.1007/s11192-011-0543-2.

Hsin-Ning Su is an Assistant Professor of Graduate Institute of Technology Management, National Chung Hsing University, Taiwan. He received Ph.D. in Material Science and Engineering from Illinois Institute of Technology and M.S. in Chemistry from National Taiwan University. His research interests are Science and Technology Policy, Innovation Management, Intellectual Property Management, Patent Big Data, aiming to understand evolutionary mechanism of Sci-Tech development and contribute to national level technology management.

Igam M Moaniba is a Graduate Institute of Technology Management Ph.D. student at National Chung Hsing University, Taiwan. He received his Master of Science degree from National Taiwan University in Agricultural Economics in Taiwan and a Bachelor of Art in Economics and Computer Science from the University of the South Pacific in Fiji. His research interests are Econometrics and Policy Analysis in: Innovation and Technology, Climate Change and Environmental Impacts, Economic Growth, Data Mining and Computer Language Programming.