Innovation
Organization & Management

ISSN: 1447-9338 (Print) 2204-0226 (Online) Journal homepage: http://www.tandfonline.com/loi/rimp20

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To cite this article: Igam M. Moaniba, Hsin-Ning Su & Pei-Chun Lee (2018): Knowledge recombination and technological innovation: the important role of cross-disciplinary knowledge, Innovation, DOI: 10.1080/14479338.2018.1478735

To link to this article: https://doi.org/10.1080/14479338.2018.1478735

INNOVATION: ORGANIZATION & MANAGEMENT, 2018
https://doi.org/10.1080/14479338.2018.1478735

Knowledge recombination and technological innovation: the important role of cross-disciplinary knowledge

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ABSTRACT

Literature on innovation strategy has increasingly highlighted the vital role of cross-disciplinary knowledge in the development of important inventions. However, a number of recent studies have shown contradicting results. For this reason, this study aims to explore deeper into the concept through the use of an extended citation analytical approach and a broader data-set of patents granted by US Patent and Trademark Office from 1976 to 2016. Taking patent forward citation count as a proxy for how technologically important an invention is, the study finds a strong positive relationship between cross-disciplinary knowledge and the technological value of an invention. In particular, cross-disciplinary knowledge, acquired through a recombination of prior technological knowledge from more diverse International Patent Classification (IPC) sections, tends to have the highest positive impact on patent value compared with knowledge sourced from more diverse IPC classes or subclasses. The empirical findings of this study provide new evidence that important inventions involve recombination of technologically diverse knowledge. Based on this finding, certain policy and management implications are presented and discussed.

ARTICLE HISTORY
Received 21 December 2017
Accepted 10 May 2018

KEYWORDS
Cross-disciplinary knowledge; knowledge flow; knowledge recombination; invention; patent value

Introduction

Over the past decades, unprecedented growths in some economies, such as China, have been results of pragmatic policies aimed at fostering production and innovation systems (Gu & Lundvall, 2016). Modern technology, achieved through a series of breakthrough innovations, has changed society in many different ways (Utterback, 1994; Castells, 2014; Kazmeyer, 2016). In fact, a number of major technological advancements have revolutionised ways businesses work (Satell, 2013; Vitez, 2016). Business transactions and processes are more digitalised than ever, resulting in dramatic changes in people's social lifestyles, such as changes caused by online shopping (Díaz, Gómez, & Molina, 2017) and a major impact upon criminality related to fraud, pornography, and paedophilia (Wall, 2015). The adoption of modern technology by firms has provided many significant benefits such as lower operational costs, higher revenues, increased productivity and improved customer

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relationships. It also gives small startup businesses ways to level up their competitive advantages and allows big companies to expand their potentials (Vitez, 2016). Moreover, it removes business boundaries and makes outstanding inventions appear not only within a single technological domain but also between multiple domains (Duysters & Hagedoorn, 1998; Hacklin, Marxt, & Fahrni, 2009). To stay ahead of the competition and to consistently generate increasing revenues, businesses need to continue to develop and adopt advanced technologies. To do this, they need to rely heavily on knowledge and information (Roper & Hewitt-Dundas, 2015).

As an important driver of successful innovation, knowledge needs to be stocked and managed efficiently. Existing knowledge stocks can contribute directly to the novelty or complexity of a new innovation (C.-Y. Lee, 2010). Understanding the flow of knowledge within or across organisations is imperative to achieving the successful design and development of an important invention. Numerous studies have investigated different forms of knowledge flows (and diffusions) in order to understand how they can contribute to a firm's productivity or an organisation's performance (Chang Lee, Lee, & Kang, 2005; Decarolis & Deeds, 1999; Erden, Klang, Sydler, & von Krogh, 2014; Jifeng, Peng, & Love, 2008). Knowledge sharing between different organisations is one form of knowledge flow that has been found to bring huge benefits to organisations (Du, Ai, & Ren, 2007; Hsu, 2008; Law & Ngai, 2008; Lin, 2007; Wang & Wang, 2012). Knowledge transfer is a term used to encompass a broad range of activities that support innovation through different types of beneficial collaborations between organisations such as universities, businesses and the public sector (Minshall, 2009), and even between businesses and their clients (He & Wong, 2009). The choice of collaboration is determined by several factors including public financial support, internal and external R&D acquisitions, and the scientific sector or business group to which organisations belong (Barzi, Cortelezzi, Marseguerra, & Zoia, 2015). However, knowledge transfer is not a sufficient condition for effective knowledge diffusion. Diffusion of knowledge is complete only when transferred knowledge is internalised and translated into the capability of local suppliers (Ernst & Kim, 2002). Both terms, knowledge flow and knowledge transfer, are often used interchangeably.

The term 'cross-disciplinary knowledge', as defined in this study, refers to knowledge acquired through recombination of prior knowledge from two or more technological domains. The higher range of technological domains involved (i.e., the higher diversity of technological knowledge), the more cross-disciplinary knowledge is. The perceived importance of cross-disciplinary knowledge in technological innovation builds upon the notion that technologies are developed through combinations of existing components (Usher, 1954), and that entrepreneurs contribute as a function to the economy through 'combinations' (Schumpeter, 1934) of technical, organisational, and market knowledge (Nelson & Winter, 1985). Moreover, most important inventions are believed to be shaped by social demands from both within and outside product domains (Arthur, 2007), and thus can have implications across multiple industries (Mowery & Rosenberg, 1999). Understanding the essential role of cross-disciplinary knowledge in technological innovation is imperative for industrial firms and innovators alike. Cross-disciplinary knowledge can help firms identify the complimentary relationships between different knowledge areas. These relationships, in turn, may provide them with directions on internal knowledge investments and external knowledge search, so that they can achieve the most efficient combinations and be able to maximise their innovation outputs (Arora & Gambardella, 1990; Cassiman & Veugelers, 2002). In other words, firms will be equipped with better knowledge on implementing (or avoiding) particular technological knowledge fusions (Wu & Shanley, 2009).

Cross-disciplinary knowledge has been one of the hot knowledge flows research topics in innovation management over the last decade. However, although a number of previous related studies have been conducted, the consensus on the role of cross-disciplinary knowledge and how it contributes to the developments of important inventions is far from being reached. Previous studies (Mowery & Rosenberg, 1999; Arthur, 2007; Nemet, 2012) found evidence that important inventions involve the transfer of knowledge across different technologies. Yet, similar studies have provided contradicting results. For instance, a study by Nemet and Johnson (2012), which used patent forward citation as an indicator of the importance of an invention, found that increasing citations to external prior art is a significantly less important predictor of forward citation frequency than citing prior art that is technologically closer. Note, despite the popular use of patent forward citation as a measure of invention value, it indicates the technological importance of an invention rather than its economic worth (Squicciarini, Dernis, & Criscuolo, 2013).

Owing to the contradicting findings of prior studies investigating the role of cross-disciplinary knowledge in innovation, it is essential that further studies be carried out. In fact, this present paper is a deeper exploration or extension to previous studies investigating the notion that a patent's value increases if it cites a precedent patent from an outside technological domain (Nemet, 2012; Nemet & Johnson, 2012). The main difference though, is that this study measures the cross-disciplinarity of a patent in terms of the diversity of technological domains cited, regardless of whether the cited patents are from the same or different technological domain as the citing patent. Prior studies, on the other hand, considered cited patents from different technological domains only. In particular, they tended to explore the effects of knowledge flows across different technological domains on patent value, whereas this study examines the effect of the technological diversity of recombined knowledge on the value of an invention. However, analysing the flows of knowledge across many fields entails the risk of an increased variance in terms of the outcomes and boundaries. This in turn could easily lead to overestimating (or underestimating) the effect of cross-disciplinary knowledge. For example, failed projects might not receive a patent or are aborted before filing for a patent (Ferguson & Carnabuci, 2017). To address this risk, several approaches have been proposed in the past such as the use of certain methods to separate the effects on the mean and the variance of the forward citations distribution (Fleming, 2001; Verhoeven, Bakker, & Veugelers, 2016). Such studies found no positive effects on the mean, but positive effects on the variance.

The novelty of this present study lies mainly in its methodological approach, specifically, in addressing the aforementioned risk through the use of patent backward and forward citation data, and the structure of the International Patent Classification (IPC). Patent activity has been proved to be a reliable indicator of technological activity in the past and has been used in many previous studies (Wu & Shanley, 2009; Nemet & Johnson, 2012; Durán-Romero & Urraca-Ruiz, 2015; Su, 2017; Su & Moaniba, 2017; Lee & Kim, 2010; Tseng & Ting, 2013). Although this study's methodology was based on Nemet and Johnson's (2012) approach, the measures used in this study are constructed to capture a wider range of cross-disciplinarity scenarios, and therefore should reduce the risk of overestimation. These cross-disciplinarity measures were analysed to determine their influences on a patent's forward citation count. Taking patent forward citation count as a proxy for how technologically valuable (or important) an invention is and the constructed patent backward citation variables as proxies for the different measures of cross-disciplinary knowledge, the study finds strong positive relationships between cross-disciplinarity variables and the proxy for invention value, forward citation count. In doing so, it provides new empirical evidence that cross-disciplinary knowledge is a key contributing factor to the development of important inventions.

In summary, this paper aims to contribute to the innovation management and business strategy literature by providing empirical evidence on how vital cross-disciplinary knowledge is to the design and development of important inventions. This is done by bringing in new insights on the role of cross-disciplinary knowledge in technological innovation through the use of patent citation information and some estimation techniques from the perspective of knowledge recombination.

The remainder of the paper is organised as follows. The conceptual basis for the analysis is discussed, drawing on the literature on the importance of knowledge in the contexts of technological innovation, technological fusion through knowledge recombination, knowledge flows analysis using patent citation information and the use of IPC in patent citation analyses. Then, the data are described, the methodological framework and statistical methods employed in this study are discussed, the empirical results are presented, and finally conclusions are presented.

Conceptual background

Why knowledge is important for technological innovation

Major developments in the global economy over the past few decades have been largely associated with the non-stop technological advancements (Satell, 2013; Vitez, 2016). For instance, with the introduction of personal-computers in the 1970s, the outburst adoption of the Internet, and the increasing dominance, integration of mobile technology in many business processes and governments' pragmatic policies on innovation systems, economic growth in most parts of the world have shown steep rises as a result, e.g., in China (Gu & Lundvall, 2016). The new business environments created by these technological changes have led to the emergence of new business markets and opportunities as well as the loss of some old ones (Vitez, 2016). Technology has been recognised as one of the important ingredients to the sustained increases in economic productivity (Romer, 1990, 1994; Solow, 1956). Firms, through the adoption of new technologies, are able to produce far beyond their normal production limits, and within shorter time periods (Solow, 1956). Furthermore, business processes have become more efficient than ever leading to dramatic changes in social lifestyles (Díaz et al., 2017; Wall, 2015). To keep up with the growing demands from the society, businesses need to constantly improve on their productions and performances, and therefore their technologies. As one of the important drivers of technology development, knowledge needs to be stocked, managed and transformed into an organisational capability.

As defined by the concept of resource-based view, a firm's knowledge is a unique bundle of its idiosyncratic resources and capabilities, and the strategic combinations needed to achieve competitive advantage (Barney, 1991; Mahoney & Pandian, 1992; Rumelt, 1997; Wernerfelt, 1984). A firm's knowledge stock accumulates or de-accumulates over time with the strategies and choices it made. Therefore, expenditures associated with strategised effort to manage these knowledge stocks should be considered important investments (Hall, Griliches, & Hausman, 1986; Telser, 1961). Furthermore, the influential work of Decarolis and Deeds (1999) had led to an extension of the resource-based view and the growing academic interest in the knowledge-based view perspective of the firm. Being a strategically important intangible resource, firms should consistently create, transfer and use knowledge to improve their performance and ability to compete (Grant, 1996; Nonaka, 1994; Spender, 1996; Spender & Grant, 1996).

A firm's ability to create, use and manage knowledge has a huge influence on its performance and its competitive advantage (Grant, 1996; Nonaka, 1994; Spender, 1996). The differences in firms' abilities to stock, manage and transfer their knowledge efficiently contribute largely to the reasons why some firms are successful, while others are not. The relationship between transferred knowledge and product innovation can be positively moderated by a firm's macro-institutional environment (Gao, Yang, Gao, Page, & Zhou, 2014). These facts signify the imperative role knowledge plays as a firm-specific asset, which is neither easily imitated nor tradable in factor markets (Barney, 1986). For this reason, firms must make tremendous efforts to accumulate knowledge over time (Dierickx & Cool, 1989).

Technological fusion through knowledge recombination

In a world where the old maxim 'one technology–one industry' no longer applies, a singular breakthrough strategy is inadequate; companies need to include both the breakthrough and fusion approaches in their technology strategies (Kodama, 1992). This implies that technological breakthroughs (or major advancements) alone are no longer enough and yet are very expensive. From a business point of view, a technological breakthrough tends to affect a single market. This in turn can mean limited demands and complete product failure. By contrast, technology fusion has been known to be more effective in the sense that it widens the use and purpose of an invention by targeting not only one but multiple technological domains. In fact, it is increasingly perceived as one of the key contributors to the development of an important invention. It is becoming a popular approach to developing new inventions (Jin, Park, & Pyon, 2011; Kodama, 1986). According to the findings of prior studies investigating knowledge flows and technology fusion (Kodama, 1992; Nemet, 2012; Nemet & Johnson, 2012; No & Park, 2010), on which this present study is built, technological fusion seems to originate from the flows of knowledge through known mechanisms such as knowledge recombination. The key advantage of knowledge recombination is that it removes barriers to technological domains by creating outstanding inventions that no longer appear within a single technological domain only but also between multiple domains (Duysters & Hagedoorn, 1998; Hacklin et al., 2009). Despite this, recombination can be counterproductive when local search is needed to identify anomalies (Kaplan & Vakili, 2015). These advantages and disadvantages indicate that understanding the dynamics of technology fusion and the trajectories of knowledge recombination is vital for recognising the important emerging trends. Such trends can help provide the direction and map on how new important inventions can be developed through converging important technologies without restrictions to industrial boundaries. This in turn can bring many benefits and opportunities for technological innovations.

Relying on technological innovation requires an effective way of selecting and integrating the right technologies. This is necessary to ensure the most successful and cost-effective combinations are achieved. Although it would be easy for firms and innovators to come up with a mix of technologies they want, it is important to know that not all combinations can lead to outstanding inventions or even profitable ones. This is where prior knowledge plays a fundamental role. Technology is built on knowledge and therefore to achieve an outstanding invention through technology fusion, firms need knowledge recombination. One way to analyse the trajectories of technology fusion is by following the flows of technological knowledge through knowledge recombination, acquisition or diffusion. Frequent flows of knowledge across certain technological fields indicate the presence of technology fusion between such technology fields. In this kind of analysis, patent data have been widely adopted for such purpose (Hu & Jaffe, 2003; Jaffe, Trajtenberg, & Fogarty, 2000; von Wartburg, Teichert, & Rost, 2005). This is because data on patents are often well maintained and updated regularly and, in most cases, are provided to the public free of charge. Therefore, information on patents is generally considered reliable to reflect the rapidly changing technological developments (S. Choi, Park, Kang, Lee, & Kim, 2012; Cong & Tong, 2008; Griliches, 1990; J. Yoon & Kim, 2012a). In addition, patent analysis can help firms identify essential implications of technology fusion, and thus can be used as a basis of establishing a systematic approach towards designing and developing a technological fused invention (Park, Ree, & Kim, 2013).

Existing literature on technology trend analysis has heavily focused on identifying major important technologies and potential future technologies often within a single technological domain (Hullmann & Meyer, 2003; Kajikawa, Yoshikawa, Takeda, & Matsushima, 2008; No & Park, 2010). Among these were time-series studies that tried to analyse technological trajectories over time (C. Choi & Park, 2009; Hillman & Sandén, 2008; Verspagen, 2007). Other studies tried to use text-mining techniques to pick out keywords from patent documents in order to generate patent maps (Lee, Kim, Cho, & Park, 2009; Lee, Yoon, & Park, 2009; Son, Suh, Jeon, & Park, 2012; Yoon, 2008; Yoon & Kim, 2012b). Most of these studies seemed to focus within single technology industries rather than multiple or cross-industry. This restriction could limit their contributions to facilitating and providing directions towards technology fusion.

Knowledge flows analysis using patent citation information

Patent citation information has been used in many knowledge flow studies to illustrate how knowledge is transferred across various technology domains (Lai & Wu, 2005; Lee, Kim et al., 2009; Lee, Yoon et al., 2009; Stuart & Podolny, 1996). Interest in the importance of patent citation information as a fundamental instrument to tracking the flow of knowledge has been stimulated by the sharp global increase in patenting activity over the past few decades. Patent citation analysis in general is very similar to the more popular literature citation analysis in academic writing. In fact, the uses of both in knowledge flows analysis have been very similar as well. The reason is that patent bibliometrics and literature bibliometrics have striking similarities (Narin, 1994). Patent citation information such as the technological antecedents and descendants of both the citing and cited patents can help provide means for analysts to track the flow of knowledge (Trajtenberg, Henderson, & Jaffe, 1997). Consequently, it has been widely used in analysing the spillover effects of technology classes on others through identifying citation links between certain technological sources and targets (Narin, 1994; Tseng, 2014).

Communication of different kinds of knowledge between organisations – through formal and informal ties – creates different knowledge flows that produce different types of networks (Xue, 2017). The complex networks of patents are often used to illustrate such flows of knowledge by studying the relationships between the citing and the cited patents, commonly known as citation pairs. The advantage of using a patent network lies in the fact that it not only shows the direction of the flow between a pair of technological classes but also can illustrate the strength of such flow. This is done by interpreting the number of times a citation pair is counted or frequently appeared as the strength (or density) of a certain knowledge flow (Xue, 2017). Once such network is established, it is then easier to analyse the flows of knowledge based on the identified trends, directions and densities of each link in the network. In addition, patent citation information has also been a key instrument in analysing the flow of knowledge across institutions and national boundaries (e.g., Breschi, Lissoni, & Malerba, 2003; Ho & Verspagen, 2006; Shin & Park, 2007) and the similarities between different technological domains (Nakamura, Suzuki, Sakata, & Kajikawa, 2015). Other studies tried to investigate the role of knowledge intermediaries in facilitating the flow of knowledge within a given technological domain, as in the role of brokers (e.g., Burt, 1976; Galaskiewicz & Krohn, 1984; Lim & Park, 2010). However, the main disadvantage of this approach is related to the fact that older patents tend to get higher counts of forward citations than do newer patents. This is in the sense that older patents have been available for much longer than newer patents. In light of this problem, some knowledge-flow studies have used restrictions on citation periods (such as the 10-year window in this study) to keep the data consistent and minimise truncation bias (e.g., in Mariani, 2004; Nemet, 2009; Nemet & Johnson, 2012).

In spite of the popular use of patents citation information, there is still criticism in the way they are applied in analyses that involve considerations of legal and economic issues. This criticism is based on the argument that citation behaviours for academic journals and patents are different, and that citation analysis relies heavily on the use of links in documents (Kostoff, 1998; Leydesdorff, 2008; Meyer, 2000; Michel & Bettels, 2001). Furthermore, patent citation information does not reflect aspects of how economically valuable a (patented) invention is, such as how widely adopted or advanced it is. For example, there are patents for some technologies that received few citations even though they have been widely adopted or are very advanced in providing state-of-the-art solutions to sophisticated problems such as a cure for a very complicated disease. This lack of citation attention does not mean that the patented technologies are not valuable. In general, patent citation analysis is often used to indicate a technological value of an invention, rather than an economic one (Squicciarini et al., 2013). Among other known indicators of patent value, the patent's private value on a real-world auction marketplace, such as Ocean Tomo, offers a more reliable economic measure, since it provides a direct observation of the market demands for patents, whereas originality index and patent's family size provide more technology-oriented measures of how popular a patent is to inventors. Moreover, a recent study (Fischer & Leidinger, 2014) showed that (forward) citation is a reliable predictor of a patent's private value in the auction marketplace. Their empirical findings also provided support for the patent's family size as a good indicator of patent value. However, both forward citation and patent's family size explain only a small variance in patent value.

The bulk of previous knowledge-flow studies that utilised patent citation information are in the area of identifying knowledge intermediaries in different domains and the roles they play in facilitating the flow of knowledge. Despite the growing interests in the effects of cross-disciplinary knowledge resulting from technological fusions, knowledge recombination and other forms of knowledge flows, the inconsistency in the results of related studies justifies the need for further investigations – with different approaches or from different perspectives. On the other hand, knowledge-flow studies based on non-patent data are also quite common (Casas, 2005; Dolińska, 2015; Gerke, 2016).

IPC and knowledge flow patent analysis

Patent classifications have been used extensively in scientific studies for many different reasons. For instance, Nemet and Johnson (2012) investigated the impacts of knowledge transfer across different technological domains on the important inventions. They utilised the IPC to construct indicators for different levels of intertechnology knowledge flows. Frietsch, Neuhäusler, Jung, and Van Looy (2014) examined the linkage between patenting and export performance for selected countries in different technology fields using the classification in the IPC as a way to categorise the different technology fields. Similarly, Grimaldi, Cricelli, Di Giovanni, and Rogo (2015) used the IPC to develop a practical and reproducible framework for scholars to leverage the value of patents and to extract all possible strategic information from patent portfolios. Other types of patents classifications such as the cooperative patent classification have also been used in past studies.

IPC is a hierarchical patent classification system currently used by more than 100 countries. It was introduced by the Strasbourg Agreement in 1971 and was designed based on the different broad areas of technology (WIPO, 2016). It uses a tree-like structure by which patents are categorised in hierarchical levels. The first level, known as a 'section', has eight groups of broad technical fields. Each section is divided into 'classes'. Class is the next hierarchical level in an IPC classification and is subdivided into 'subclasses'. Many past related studies utilised these top three IPC hierarchical classification levels to understand the flows of knowledge. These flows are often based on the citation intensities and the links between these hierarchical levels. Some of these studies include those by Wu and Shanley (2009) and Nemet and Johnson (2012).

Cross-disciplinary knowledge, in the context of this study, is defined as the knowledge acquired through recombination of technologically diverse prior art (i.e., cited patents or references from a variety of technological domains). Using the three IPC classifications (i.e., IPC sections, classes and subclasses) to represent categories for technological domains, cross-disciplinary knowledge can therefore be measured or defined as the resulting knowledge from a recombination process that involves one of the following scenarios:

(i) when a patent cites previous patents from more than one distinct IPC section;
(ii) when a patent cites previous patents from more than one distinct IPC class;
(iii) when a patent cites previous patents from more than one distinct IPC subclass.

Note, the higher the number of distinct IPC sections (or IPC classes or IPC subclasses) cited the higher the degree of knowledge cross-disciplinarity.

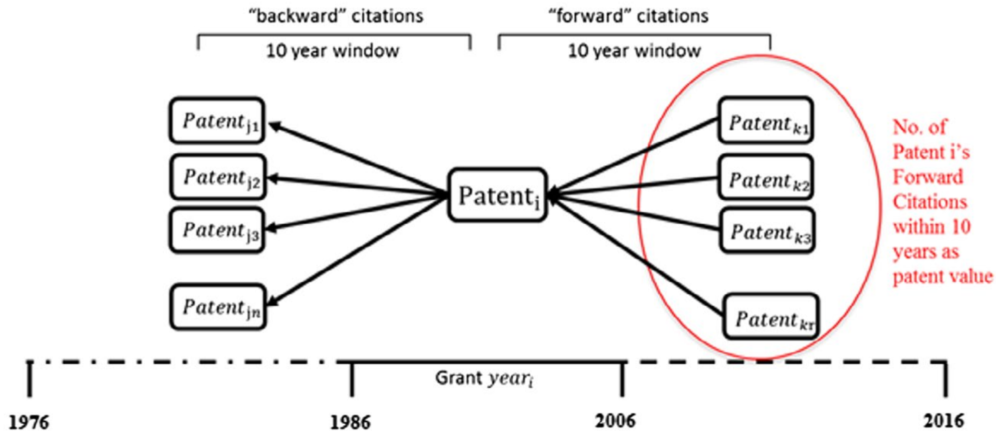

Figure 1. Cross-disciplinary knowledge recombination framework.

Data

Patent data used in this empirical study were retrieved from the US Patent and Trademark Office (USPTO) database. The data covered all patents granted by the office between 1976 and 2016. Patent litigation data and International Trade Commission (ITC) data were obtained from the LITALERT database (LITALERT, 2015) and US International Trade Commission website (US ITC, 2015). The analytical approach undertaken in this study was based on analysing the relationships between the constructed indicators of cross-disciplinary knowledge and the importance (or value) measure of a patent. The primary objective of the analysis is to examine how each of the different indicators of cross-disciplinary knowledge contributes to the perceived importance of a technology. Following Nemet and Johnson's (2012) approach, both forward and backward patent citation information are used to indicate the flow of knowledge and knowledge recombination. A patent forward citation count was used as a measure for how important or valuable a patent is, whereas the three constructed measures based on patent backward citation counts were used to represent the different levels (or types) of cross-disciplinary knowledge. Forward citation count has been considered and used as a good indicator for the quality or value of a patent (Nemet & Johnson, 2012) and an excellent measure of technological impact and performance (Albert, Avery, Narin, & McAllister, 1991; Y. Lin & Chen, 2014). Similar to Nemet and Johnsons' study, a 10-year window was imposed on both forward and backward citation pairs to minimise truncation bias (Nemet & Johnson, 2012). This leaves a period of 1986 to 2006 for investigation which consists of a total of 2,559,343 patents. The three indicators of cross-disciplinary backward citations were constructed based on the IPC classification system and patent backward citation information. Before illustrating how these indicators are computed, it is important to understand first the IPC classification system.

Variables and the construction of the cross-disciplinary knowledge indicators

Consider this typical patent citation scenario in Figure 1, where patent$_i$ is cited by a total of *r* subsequent patent$_k$(s). From patent$_i$'s point of view, this type of citation is called a forward citation. A variable called FWDCIT records the total counts of forward citations a patent has and is used in this study as the dependent variable. In the example in Figure 1, patent$_i$

Table 1. Descriptive statistics.

Variable	Description	*N*	Mean	Std. dev.	Min	Max
YEAR	Year of patent issue	2,559,343	–	–	1986	2006
FWDCIT	Forward citation count within 10-years	2,559,343	8.55788	13.95442	0	1966
ORIG	Originality index of a patent	2,559,343	0.5979975	0.2977711	0	0.9866561
SECCIT	Number of distinct sections backward cited (10-year window)	2,559,343	1.458668	0.8729031	0	8
CLSCIT	Number of distinct classes backward cited (10-year window)	2,559,343	1.856212	1.408239	0	28
SBCCIT	Number of distinct subclasses backward Cited (10-year window)	2,559,343	2.216892	1.859954	0	40
REFCNT	Number of references per patent	2,559,343	12.71393	14.15038	0	189
CLMCNT	Claim count per patent	2,559,343	15.39459	13.03622	0	887
USLIT	US litigation dummy	2,559,343	0.01141	0.1062063	0	1
ITC	ITC dummy	2,559,343	0.0004333	0.0208117	0	1
FATYPE	First assignee type	2,559,343	1.941708	0.5736036	1	7
TECSEC	Technology sector	2,559,343	2.845967	1.311777	1	5

has an FWDCIT = *r*. To avoid truncation bias, forward citation counts are restricted to a 10-year window (i.e., only citing patents granted within 10 years after the issue year of patent$_i$ are counted). And suppose patent$_i$ cites a total of *n* previous patent$_j$(s). These citations are called backward citations. In this study, a variable called BCKCIT is used to count and record the total number of backward citations a patent has. In the example in Figure 1, patent$_i$ has a BCKCIT = *n*[1].

In addition, three cross-disciplinary independent variables are constructed to indicate the different forms of cross-disciplinary knowledge measures across IPC sections, IPC classes and IPC subclasses. First, SECCIT denotes the number of distinct IPC sections a patent cites from. For instance, if a patent$_i$ backward cites three patent$_j$(s), each from a different IPC section, then in this case SECCIT = 3. And suppose another patent$_i$, cites four patent$_j$(s) of which two are from one IPC section, and the other two are from another IPC section, the total number of different sections cited in this case is 2, and therefore SECCIT is now 2. Similarly, the other two disciplinary variables CLSCIT and SBCCIT denote the number of distinct IPC classes and IPC subclasses a patent cites from, respectively. The calculations for the backward citation counts are again restricted to a 10-year window (i.e., counting only cited patents issued within the 10-year prior period to the issue year of patent$_i$ – see Figure 1).

Table 1 lists all the variables used in this study. The dependent variable is the number of forward citations a patent has within a 10-year period after it was first published. Forward citation has been used in many previous studies to indicate how valuable a patent is, i.e., the more a patent is cited, the more value it has. The independent variables are the SECCIT, CLSCIT, SBCCIT and BCKCIT. To control for the effects of other major known factors of forward citation, five additional independent variables are created: the CLMCNT variable, which represents the number of claims a patent has; a dummy binary variable USLITG, which indicates whether or not a patent has been litigated at the US court; a dummy binary variable ITCCNT, which indicates whether or not a patent has been disputed at the International Trade Commission; FATYPE, which denotes the first assignee type; and TECSEC, which indicates each of the five types of technology sectors (Figure 2). To check that all predictor variables are not highly correlated, a pairwise correlation test was conducted. The results are reported in Table 2.

Table 2. Pairwise correlation matrix.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	Forward citation	1.000											
2	Originality	0.144***	1.000										
3	Sections cited	0.119***	0.536***	1.000									
4	Classes cited	0.129***	0.535***	0.857***	1.000								
5	Subclasses cited	0.171***	0.547***	0.777***	0.920***	1.000							
6	Reference count	0.143***	0.405***	0.399***	0.484***	0.556***	1.000						
7	Claim count	0.189***	0.159***	0.138***	0.156***	0.183***	0.223***	1.000					
8	US litigation	0.096***	0.023***	0.029***	0.034***	0.042***	0.057***	0.052***	1.000				
9	ITC	0.030***	0.009***	0.005***	0.007***	0.009***	0.015***	0.016***	0.128***	1.000			
10	Technology sector	−0.059***	0.001**	0.054***	0.044***	0.017***	0.062***	−0.056***	0.018***	−0.004***	1.000		
11	Assignee	0.034***	0.024***	0.018***	0.019***	0.028***	−0.005***	0.061***	−0.019***	0.003***	−0.225***	1.000	
12	Country id	0.123***	0.121***	0.132***	0.149***	0.165***	0.139***	0.119***	0.052***	0.006***	0.001**	−0.061***	1.000
	$N = 2{,}559{,}343$												

*Significant at $p < 0.10$; **Significant at $p < 0.05$; ***Significant at $p < 0.01$.

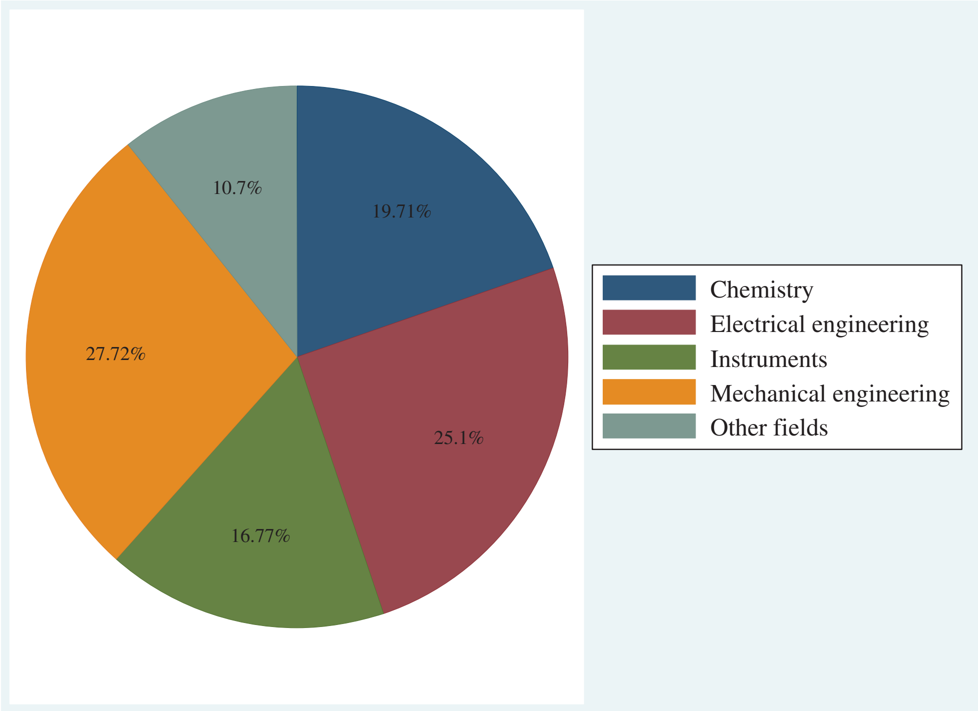

Figure 2. Shares of technology sectors as percentages.

Methodology

Estimation approach

To examine the effect of cross-disciplinary knowledge on invention value (indicated by patent value), the relationship between the forward citation variable, FWDCIT (used as a proxy for patent value) and each of the three cross-disciplinary variables discussed in the previous section, a regression analysis was conducted. In this case, the dependent variable is the forward citation count variable (FWDCIT), and the independent variables of interest are the three cross-disciplinary measures – SECCT, CLSCIT and SBCCIT. Note, the dependent variable has discrete and non-negative values (i.e., of count data). Non-negative discrete data are not linear in nature. This is shown graphically by the nonlinear plots of FWDCIT in the scatter diagrams when plotted against each of the cross-disciplinary variables in Figure 3. In such a case, standard linear regression is not applicable. Instead, the generalised linear models that use link functions to transform the nonlinear relationships between the dependent and independent variables into linear relationships are more appropriate. For count data, this comes in the form of exponential regression models such as Poisson (Cameron & Trivedi, 2013).

However, it is important to note that the variance of FWDCIT (equivalent to its squared standard deviation) is much larger than its mean, as shown in Table 1, indicating the existence of over-dispersion. Theoretically, this violates one of the restrictive conditions of the Poisson model, which requires the mean and variance of the dependent variable to be equal. This violation implies that Poisson regression could be problematic, and therefore another count data regression model known as the Negative binomial estimator, which is more appropriate in this case, should also be considered. In addition, the number of zeros in the FWDCIT dependent variable is quite low (only 9.7%) as shown in Figure 4. This

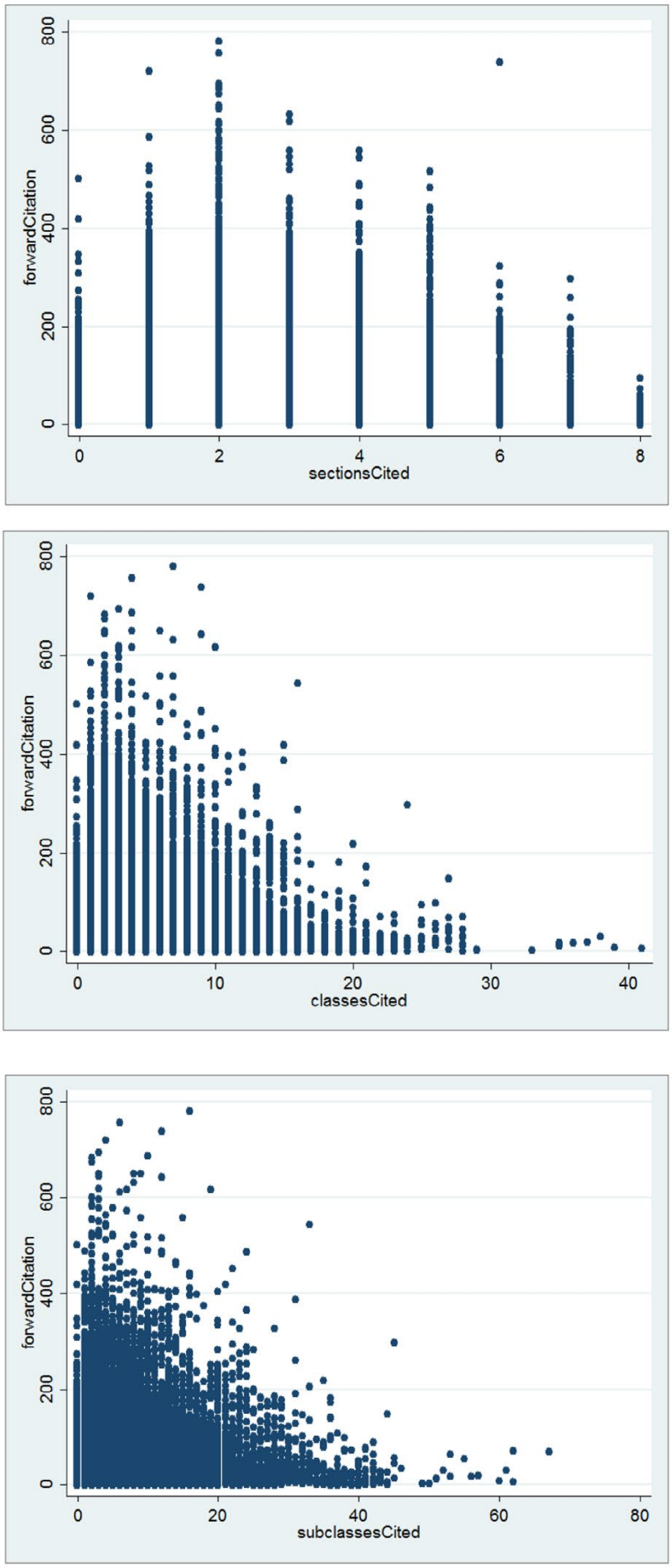

Figure 3. Scatter plots for forward citation against the cross-disciplinary variables.

indicates that problems related to excess zeros are not issues here and thus convey that the standard Negative binomial regression model is also more suited for the data than the zero-inflated Negative binomial version. This in turn confirms that Negative binomial

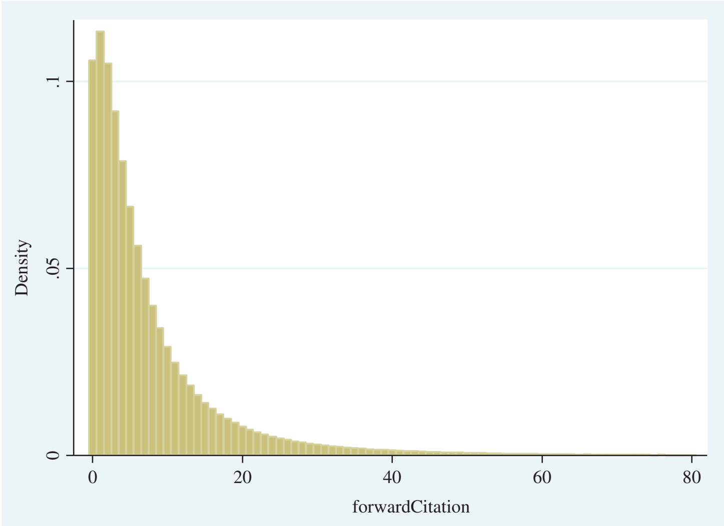

Figure 4. Distribution of values for dependent variable (Forward Citations). Only 1% of the observations have forward citations above 80 (not shown in graph). The number of patents in the data with zero forward citations within 10-years accounts for only 9.7%.

regression is a more appropriate method in this case compared with other popular count data models – the Poisson and zero-inflated Negative binomial regression. However, to ensure robustness and consistency in the results, both Poisson and the Negative binomial regressions are used in this study.

Specification models

Based on the reasons stated earlier, a baseline specification model, which is a standard functional form for nonlinear count data models such as Poisson and Negative binomial model (Greene, 2008), is set as follows:

$$E\left[y_i|x_i,\ \varepsilon_i\right] = \exp\left(\alpha + x_i'\beta + \varepsilon_i\right) = h_i\lambda_i \tag{1}$$

where = $\exp\left(\varepsilon_i\right)$ and $\lambda_i = \exp\left(\alpha + x_i'\beta\right)$. x_i' is a vector of explanatory variables of interest, which in this case represents the three cross-disciplinary indicator variables– SECCIT, CLSCIT and SBCCIT; y_i denotes the dependent forward citation variable – FWDCIT; $E\left[y_i|x_i, \varepsilon_i\right]$ is the expected conditional mean of y_i for each given value of x_i' and ε_i is the error term.

Given that the three cross-disciplinarity variables are highly correlated to each other, adding all of them to Equation (1) violates one of the important assumptions of Poisson and Negative binomial regressions. The standard way around this multicollinearity problem is to run estimations for each of these three cross-disciplinarity variables separately. Technically, this means having three separate specification models devised based on the baseline specification in Equation (1). The three separate models are expressed below:

$$E\left[y_i|x_i, \varepsilon_i\right] = \exp\left(\alpha_1 + TECSEC_i\beta_1 + z_i'\Omega_1 + TECSEC_i\phi_1 + \mathrm{FATYPE}_i\gamma_1 + \varepsilon_i\right) = h_ik_il_im_i\lambda_i \tag{1a}$$

$$E\left[y_i|x_i,\ \varepsilon_i\right] = \exp\left(\alpha_2 + CLSCIT_i\beta_2 + z_i'\Omega_2 + TECSEC_i\phi_2 + \mathrm{FATYPE}_i\gamma_2 + \varepsilon_i\right) = h_ik_il_im_i\lambda_i \tag{1b}$$

$$E\left[y_i|x_i,\ \varepsilon_i\right] = \exp\left(\alpha_3 + SBCCIT_i\beta_3 + z_i'\Omega_3 + TECSEC_i\phi_3 + \mathrm{FATYPE}_i\gamma_3 + \varepsilon_i\right) = h_ik_il_im_i\lambda_i \tag{1c}$$

where the added parameter: z_i' is a vector consisting of the following control variables – *CLMCNT* for claim count per patent *i*, *USLITG* dummy for whether patent *i* has been litigated in the US, and *ITCCNT* dummy indicating whether patent *i* has been litigated at ITC; $TECSEC_i$ is the first categorical control variable for the five technology sectors; $FATYPE_i$ is the second categorical control variable for the seven assignee types; and $\mathrm{k_i} = \exp\left(\mathrm{z}_\mathrm{i}'\Omega\right), \mathrm{l_i} = \exp(TECSEC_i\phi)$ and $\mathrm{m_i}=\exp(TECSEC_i\gamma)$.

For robustness check, the same set of explanatory variables on the right-hand side of Equation 1a to 1c is regressed on a different measure of patent value, the originality index, using an ordinary least-squares (OLS) estimator. The originality index was proposed by Trajtenberg, Henderson, and Jaffe (Trajtenberg et al., 1997) to indicate how original a patented technology is and has been considered a good indicator of patent value. The originality index is calculated using the formula:

$$\text{Originality index}_i = 1 - \sum_{j}^{n_i} SB_{ij}^2$$

where SB_{ij} is the share of previous patents cited by patent *i* belonging to patent class *j* out of $n_j = 35$ patent classes (see details of the 35 classes in the Appendix). The values of the originality index range from 0 to 1, where a low value indicates that a patent cites a number of prior patents belonging to the same technological field, and a high value indicates that most prior patents cited belong to many technological fields. A higher originality index implies that the patent in question is more original and not directly derived from prior patents.

The specified models used in estimating the impact of each of the three cross-disciplinary variables on patent value, respectively, are shown below:

$$E\left[o_i|w_i,\ \varepsilon_i\right] = \alpha_1 + TECSEC_i\beta_1 + z_i'\Omega_1 + TECSEC_i\phi_1 + \mathrm{FATYPE}_i\gamma_1 + \varepsilon_i \tag{2a}$$

$$E\left[o_i|w,\ \varepsilon_i\right] = \alpha_2 + CLSCIT_i\beta_2 + z_i'\Omega_2 + TECSEC_i\phi_2 + \mathrm{FATYPE}_i\gamma_2 + \varepsilon_i \tag{2b}$$

$$E\left[o_i|w_i,\ \varepsilon_i\right] = \alpha_3 + SBCCIT_i\beta_3 + z_i'\Omega_3 + TECSEC_i\phi_3 + \mathrm{FATYPE}_i\gamma_3 + \varepsilon_i \tag{2c}$$

where o_i denotes the new dependent variable, originality index (ORIG); the parameter: z_i' is a vector consisting of the following control variables – *CLMCNT* for claim count per patent *i*, *USLITG* dummy for whether patent *i* has been litigated in the US, and *ITCCNT* dummy indicating whether patent *i* has been litigated at ITC; $TECSEC_i$ is the first categorical

Table 3. (Poisson regression) effects of cross-disciplinary knowledge on forward citations.

	(1a)		(1b)		(1c)	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
No. of distinct sections cited	0.1133***	(0.0014)				
No. of distinct classes cited			0.0572***	(0.0009)		
No. of distinct subclasses cited					0.0593***	(0.0011)
Reference count	0.0068***	(0.0001)	0.0065***	(0.0001)	0.0048***	(0.0001)
Claim count	0.0067***	(0.0004)	0.0067***	(0.0004)	0.0066***	(0.0004)
US litigation	0.6271***	(0.0128)	0.6256***	(0.0126)	0.6198***	(0.0141)
ITC	0.3006***	(0.0378)	0.2968***	(0.0379)	0.3041***	(0.0380)
Technology sectors						
Electrical engineering	0.7196***	(0.0033)	0.7147***	(0.0033)	0.7034***	(0.0033)
Instruments	0.5190***	(0.0034)	0.5229***	(0.0034)	0.5113***	(0.0035)
Mechanical engineering	0.0432***	(0.0035)	0.0444***	(0.0035)	0.0457***	(0.0035)
Others	0.0943***	(0.0038)	0.1014***	(0.0038)	0.1102***	(0.0038)
Assignee type						
Individual	0.2312***	(0.0032)	0.2345***	(0.0032)	0.2332***	(0.0033)
Company	0.0544***	(0.0106)	0.0549***	(0.0106)	0.0499***	(0.0107)
Government	0.3546***	(0.0074)	0.3569***	(0.0074)	0.3482***	(0.0075)
University	0.2486***	(0.0327)	0.2587***	(0.0327)	0.2497***	(0.0325)
Hospital	0.0765	(0.0563)	0.0742	(0.0580)	0.0836+	(0.0485)
Private non-profit	0.0837***	(0.0223)	0.0868***	(0.0223)	0.0841***	(0.0222)
Country dummies	Yes		Yes		Yes	
Year dummies	Yes		Yes		Yes	
Constant	1.0268***	(0.0225)	1.0821***	(0.0225)	1.0886***	(0.0224)
N	2,559,343		2,559,343		2,559,343	

All robust standard errors are presented in parentheses.
***Significant at $p < 0.001$; **Significant at $p < 0.01$; *Significant at $p < 0.05$; +Significant at $p < 0.1$.

control variable for the five technology sectors; $FATYPE_i$ is the second categorical control variable for the seven assignee types. $E[o_i|w_i, \varepsilon_i]$ is the expected mean of o_i for given values of independent variables on the right-hand side of the equations (denoted by vector w_i'), and ε_i is the error term.

Results

In this section, the empirical results of all estimation models are presented and discussed. The tables are reported in Tables 3, 4 and 5. The first and second results (Tables 3 and 4) show the results of the Poisson regressions and Negative regressions for Equation (1), respectively, used to estimate how each of the cross-disciplinary variables influences the number of forward citations a patent receives while controlling for major known determinants of forward citation – the number of claims a patent has (CLMCNT), whether a patent has been litigated at US court (USLITG) or disputed at the International Trade Commission (ITCCNT), the different Technology sectors and the different assignee types. Table 5 reports the results of a robustness analysis using a different known measure of patent value i.e., originality index.

Note that the lowest level of significance used in all these regressions is 0.001, instead of 0.01. This adjustment is required to ensure reliability and reproductivity of the study (Benjamin et al., 2018). According to Benjamin et al. (2018), associating statistically significant findings with $p < 0.05$, which is commonly used, results in a high rate of false positives even in the absence of other experimental, procedural and reporting problems. For this reason, they proposed the use of a much lower significant level of 0.005, instead

Table 4. (Negative binomial) effects of cross-disciplinary knowledge on forward citations.

	(1a)		(1b)		(1c)	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
No. of distinct sections cited	0.1298***	(0.0011)				
No. of distinct classes cited			0.0723***	(0.0007)		
No. of distinct subclasses cited					0.0738***	(0.0006)
Reference count	0.0074***	(0.0001)	0.0070***	(0.0001)	0.0052***	(0.0001)
Claim count	0.0142***	(0.0001)	0.0143***	(0.0001)	0.0141***	(0.0001)
US litigation	0.6319***	(0.0080)	0.6313***	(0.0080)	0.6240***	(0.0080)
ITC	0.3845***	(0.0410)	0.3812***	(0.0407)	0.3923***	(0.0409)
Technology sectors						
Electrical engineering	0.6946***	(0.0035)	0.6914***	(0.0035)	0.6776***	(0.0035)
Instruments	0.4989***	(0.0036)	0.4999***	(0.0036)	0.4866***	(0.0036)
Mechanical engineering	0.0626***	(0.0032)	0.0632***	(0.0032)	0.0643***	(0.0032)
Others	0.1184***	(0.0037)	0.1243***	(0.0037)	0.1331***	(0.0037)
Assignee type						
Individual	0.2047***	(0.0027)	0.2081***	(0.0027)	0.2069***	(0.0027)
Company	0.0675***	(0.0132)	0.0680***	(0.0134)	0.0649***	(0.0131)
Government	0.3108***	(0.0069)	0.3129***	(0.0069)	0.3049***	(0.0069)
University	0.2297***	(0.0304)	0.2391***	(0.0303)	0.2255***	(0.0300)
Hospital	0.0489+	(0.0276)	0.0489+	(0.0275)	0.0434	(0.0273)
Private non-profit	0.0435*	(0.0179)	0.0465**	(0.0180)	0.0448*	(0.0180)
Country dummies	Yes		Yes		Yes	
Year dummies	Yes		Yes		Yes	
Constant	0.9630***	(0.0197)	1.0147***	(0.0197)	1.0177***	(0.0197)
lnAlpha (constant)	0.0085***	(0.0015)	0.0109***	(0.0015)	0.0061***	(0.0015)
N	2,559,343		2,559,343		2,559,343	

All robust standard errors are presented in parentheses.
***Significant at $p < 0.001$; **Significant at $p < 0.01$; *Significant at $p < 0.05$; +Significant at $p < 0.1$.

Table 5. (OLS) Effects of cross-disciplinary knowledge on originality index.

	(2a)		(2b)		(2c)	
	coeff	s.e.	coeff.	s.e.	coeff.	s.e.
No. of distinct sections cited	0.1467***	(0.0002)				
No. of distinct classes cited			0.0897***	(0.0002)		
No. of distinct subclasses cited					0.0703***	(0.0001)
Reference count	0.0043***	(0.0000)	0.0035***	(0.0000)	0.0027***	(0.0000)
Claim count	0.0003***	(0.0000)	0.0003***	(0.0000)	0.0003***	(0.0000)
US litigation	−0.0088***	(0.0014)	−0.0095***	(0.0014)	−0.0140***	(0.0014)
ITC	−0.0035	(0.0067)	−0.0065	(0.0070)	−0.0056	(0.0071)
Technology sectors						
Electrical engineering	0.1093***	(0.0005)	0.1058***	(0.0005)	0.0969***	(0.0005)
Instruments	0.0620***	(0.0005)	0.0663***	(0.0005)	0.0579***	(0.0005)
Mechanical engineering	0.0416***	(0.0005)	0.0426***	(0.0005)	0.0472***	(0.0005)
Others	0.0024***	(0.0006)	0.0100***	(0.0006)	0.0198***	(0.0006)
Assignee type						
Individual	0.0349***	(0.0005)	0.0373***	(0.0005)	0.0385***	(0.0005)
Company	0.0083***	(0.0011)	0.0073***	(0.0012)	0.0065***	(0.0012)
Government	−0.0125***	(0.0011)	−0.0126***	(0.0012)	−0.0174***	(0.0012)
University	−0.0572***	(0.0052)	−0.0464***	(0.0055)	−0.0593***	(0.0054)
Hospital	0.0035	(0.0051)	0.0032	(0.0052)	0.0026	(0.0052)
Private non-profit	0.0149***	(0.0033)	0.0173***	(0.0034)	0.0177***	(0.0034)
Country dummies	Yes		Yes		Yes	
Year dummies	Yes		Yes		Yes	
Constant	0.1240***	(0.0034)	0.1730***	(0.0034)	0.1962***	(0.0034)
N	2,559,343		2,559,343		2,559,343	
Adj. R^2	0.378		0.361		0.355	

All robust standard errors are presented in parentheses.
***Significant at $p < 0.001$; **Significant at $p < 0.01$; *Significant at $p < 0.05$; +Significant at $p < 0.1$.

of 0.05 level. To ensure the regression results in this present study are adjusted for this correction, the lowest threshold of significance was changed to 0.001, which is lower than the recommended 0.005 level.

Poisson and Negative binomial analysis

Table 3 shows the results of the Poisson regressions for Equations (1a), (1b) and (1c). As reported in the table, all three cross-disciplinary variables – SECCIT, CLSCIT and SBCCIT – have positive and significant coefficients. These results suggest that the higher the number of distinct technological domains (in terms of IPC section, class or subclass) a patent cites from, the higher the value it receives. Among these results for the three cross-disciplinary variables, the coefficient for the number of distinct IPC sections cited by a patent [i.e., the estimated natural log increase in number of forward citations a patent receives owing to a one unit increase in the value of a cross-disciplinary variable (0.1133 under column 1a)] is higher than that for the IPC classes cited (0.0572 under 1b) and for IPC subclasses cited (0.593 under 1c). Based on these results, it is clear that cross-disciplinary knowledge acquired from a more diverse range of IPC sections produces more valuable patents than those obtained through a diverse range of IPC classes or IPC subclasses.

By contrast, the first three control variables (i.e., patent claim count, US litigation and ITC) also have positive and significant effects on a patent's citation value. The magnitudes of the coefficients of these control variables seem to be relatively close, though. All coefficients for the Technology sector dummies and assignee type dummies are also positively significant except for the Hospital assignee type in column 1a and 1b. Two additional sets of control dummies are included in all regressions to control for the unobserved year and country fixed effects.

Next, the results of estimating Equation 1a, 1b and 1c using Negative binomial regression are reported in Table 4. Similar to the previous results, all three cross-disciplinary variables – SECCIT, CLSCIT and SBCCIT – have positive and significant coefficients. These results strongly confirm the important finding from Table 3, that is, the higher the number of different technological domains a patent cites from, the higher the value it receives. In other words, a one unit increase in the number of distinct IPC sections cited by a patent will result in an exp(0.1298) increase (under 1a) in its value. This increase in patent value per estimated increase in the distinct number of IPC sections cited is higher than that for the number of distinct IPC classes cited (=0.0723 under 1b) and for the IPC subclasses cited (=0.0738 under 1c). As for the control variables, the first three (i.e., patent claim count, US litigation and ITC) again have positive and significant effects on a patent's citation value that are relatively similar in magnitudes. Like the results in Table 3, all coefficients for the Technology sector dummies and assignee type dummies are positively significant except for the Hospital assignee type in column 1c. The two additional sets of control dummies are again added to control for the unobserved year and country fixed effects.

The important thing to note from Tables 3 and 4 is that both the Poisson and Negative binomial estimations have very similar and stable results. Therefore, it is conclusive to say that, based on these empirical results, cross-disciplinary knowledge (acquired or combined from technologically diverse domains) has a positive and significant contribution to the quality or value of an invention (proxied by patent value).

Robustness analysis

To reaffirm the above finding, the same set of regressors and control variables were regressed on a different, but also well accepted, measure of patent value (or quality), the originality index. Three OLS regressions were run for each of the three Equations 2a, 2b and 2c, respectively. Each regression was employed to estimate the impact of each of the cross-disciplinary knowledge variables. The results are reported in Table 5.

Like previous results, all three cross-disciplinary variables – SECCIT, CLSCIT and SBCCIT – as shown in Table 5, have positive and significant coefficients. These results provide, again, further evidence that the more diverse technological domains a patent cites from, the higher the value it receives. Although the coefficients for the three cross-disciplinary variables are slightly higher than those in the previous two tables (i.e., Tables 3 and 4), the other consistent finding is that the marginal effect of an increase in the number of (distinct) IPC sections cited on the number of forward citations a patent receives (0.1467 under column 2a in Table 5) is higher than that for IPC classes cited (0.0897 under column 2b) or for IPC subclasses cited (0.0703 under column 2c). In other words, these results confirm the two key findings from the previous tables that: (1) cross-disciplinary knowledge has a positive effect on patent (or invention) value, and (2) cross-disciplinary knowledge combined (or acquired) from technologically diverse IPC sections produces more valuable inventions than those produced from technologically diverse IPC classes or IPC subclasses.

Furthermore, the control variables, patent claim count and ITC again have positive and significant effects on a patent's citation value. US litigation, on the other hand, now has significant but negative results. This is the only main difference observed compared with the results of US litigation variable in the previous two tables. All coefficients for the Technology sector dummies and assignee type dummies are also positively significant except for the Hospital assignee type in column 1a and 1b. These results suggest that all technology sectors listed in the table have more significant influence on invention value than the reference sector, Chemistry. Two additional sets of control dummies are included in all regressions to control for the unobserved year and country fixed effects.

In brief, the study finds further empirical evidence that the higher the degree of cross-disciplinary knowledge a patent has, the higher its value. This finding is robust across three different sets of estimations in Tables 3, 4 and 5 – for Poisson regressions, Negative binomial regressions and OLS regressions, respectively. Previous findings of studies investigating the impacts of cross-disciplinary knowledge acquired through recombination (or other forms of knowledge flows) on patent value have been inconsistent. There have been studies that found a positive relationship between the flows or combinations of knowledge from various technological domains and patent value, whereas a number of other studies have found no correlation between the two. The findings of this present study provide new evidence in support of the positive and significant role cross-disciplinary knowledge plays in the development of important inventions.

Furthermore, the study finds that knowledge acquired (or combined) from a wider range of IPC sections tends to bring more positive impacts on the value of a patent (or invention) as compared with knowledge acquired from a wider range of IPC classes or IPC subclasses. This finding is shown by the fact that the variable SECCIT receives the highest significant coefficients in all three tables (Tables 3, 4 and 5) compared with the other two cross-disciplinary variables – CLSCIT and SBCCIT. According to the structure of the IPC classification system, an IPC section is the highest hierarchical level in the classification system signifying the furthest distance between two patents. However, it is important to know that the core purpose of this study is to investigate whether cross-disciplinary knowledge contributes positively or negatively to a patent value from the technological diversity of prior art (i.e., patent references) and knowledge recombination perspectives. Unlike previous studies (e.g., Nemet & Johnson, 2012), this study is not designed to examine whether the technological distance between the source of the flow and the destination affects the value of a patent.

Conclusion

The empirical results of this paper bring new insights into the concept of cross-disciplinary knowledge and its role in technological innovation. They provide the basis for the important contribution of the paper to the innovation management and business strategy literature in three ways. First, these results show new empirical evidence that knowledge recombination across a variety of technological domains contributes positively to the creation of an important inventions. Second, the findings of this study contribute to the literature by introducing a new methodological framework (or approach) to patent citation knowledge-flow analysis. This approach utilises the IPC classification system to construct measures of the intensity of cross-disciplinarity in a way that has never been done before. While previous studies (Nemet & Johnson, 2012) constructed their measures based on the technological distance between the citing and cited prior knowledge (i.e., patents), this present study built its measures based on the diversity of prior technological art cited. With this new approach, the study helps provide a stable mental framework for analysts to follow cross-disciplinarity trajectories and analyse the technological diversity of prior related knowledge across IPC sections, classes and subclasses. Lastly, the paper discusses some policy and managerial implications that can assist firms and institutions in their decisions related to technology developments.

The data set used in this study consists of data on patent citation information retrieved from the USPTO database. The data include forward citation counts, backward citation counts, computed cross-disciplinarity measures and other important patent information such as litigation and claims. The patents covered in the study were taken from a period of 1976 to 2016. However, the citation information only covered patents issued between the year 1986 and 2004 to allow a 10-year window for both forward and backward citations. This is done to ensure consistency in the data as well as to avoid truncation bias. After employing some econometric estimation methods on the data, the study found that all the constructed cross-disciplinary variables have positive and significant influences on the patent value (represented in this study by a patent's forward citation count). The major highlight of this finding is the fact that knowledge recombination from multiple IPC sections tends to have the highest positive impact on a patent value compared with that from multiple IPC classes or subclasses. By contrast, the effect of the number of backward citations on a patent value is also positive and significant however quite small compared with those of the cross-disciplinary variables. Some of the econometric methods employed in this study include the Negative binomial regression and some data tests needed to eliminate common bias issues such as those related to the correlations in the explanatory variables and the excessive number of zeros in the dependent variable data.

Furthermore, the study found that patents litigated in the US courts have significant and higher value compared with non-litigated patents. Patents that have been disputed at the ITC also seem to have a higher value than those that have not. Moreover, patents with a higher number of claims turned out to be more valuable. Technologywise, patents in the electrical engineering sector tend to receive the highest values, compared with those in other sectors. The next highest are those in the Instruments sector, while the lowest and second lowest are the Mechanical Engineering and Chemistry sectors respectively. In terms of assignees, patents assigned to universities have the highest incremental values, followed by those from the companies, and then those from hospitals. The least influential patents are those from governments.

Management implications and limitations

Based on the above findings, three important policy implications are drawn. First, the fact that strong positive relationships between cross-disciplinary variables and the forward citation value were found clearly implies that cross-disciplinary knowledge plays a critical role in the development of an important technology. A managerial implication from this is that firms and innovators should consider giving priority to their R&D projects that guarantee the use of knowledge from more technological domains. In particular, when searching for prior knowledge, they should refrain from researching patents on technologies similar to theirs only. Second, a higher number of claims, litigated patents and ITC disputed patents are some of the important characteristics of successful patents suggested by this study; therefore, firms should always take into account such information when developing a technology. A technology or invention based on these prior art characteristics is likely to get a higher value. Third, this study found that some technology sectors receive higher incremental patent citation values compared with others. This could indicate that perhaps firms should consider knowledge recombination across these technology sectors whenever they can.

Finally, like many other papers, this study has some limitations. First is the use of a patent activity as a proxy for the value or importance of an invention. As previously mentioned, patent information still receives criticism for its use in a citation analysis. The importance of an invention or technology cannot be reflected alone by the search for knowledge related to the underlying technology. There are many other factors that can determine the importance or value of a technology. For instance, how widely adopted the technology is, even if its corresponding patent is not receiving much attention, and how advanced the technology is in providing a cure for a very complicated disease. The latter example demonstrates how some advanced technologies, which are also very rare, often receive little citation attention owing to reasons related to their high costs. This does not mean that the technology is not important. Another concern is the use of a 10-year citation window. Despite its obvious purpose to prevent a data and analysis bias, there is still a possibility that citations outside the 10-year window are significant for some patents. This truncation approach can lead to misinterpretations on how active a patent is in both its backward and forward citations, and therefore can significantly affect the regression results. Last, it is also important to note that references added by the inventors and the USPTO examiners are both considered in this study.

Note

1. Note that BCKCIT is included in Figure 1 to help demonstrate the concepts of forward and backward citations only; however, it is not relevant to this study's purpose and therefore was not used in the analysis.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was funded by the Ministry of Science and Technology of Republic of China, Taiwan, under the contract: MOST 106-2410-H-005-040-MY2.

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