國立中興大學科技管理研究所
Graduate Institute of Technology Management
National Chung Hsing University

碩士學位論文
A Thesis Submitted in Partial Fulfillment of the
Requirement for Degree of Master

探討跨領域科技演進的技術發展趨勢

Investigating the Trend of Cross-Disciplinary Evolution in Technology Development

指導教授：蘇信寧 Hsin-Ning Su, Ph.D.
研　究　生：郭權瑋 Chuan-Wei Kuo

中華民國一百零五年六月

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105 年 六月

摘要

目前世界正邁向全球化的經濟體持續發展，市場對於跨領域技術的需求亦日益上升，許多文獻也針對跨領域技術的發展進行了相當豐富的研究，但目前對於分析跨領域技術發展的演進趨勢，較缺乏系統化的研究分析及方法，為了填補此研究缺口，本研究以各類專利指標(專利數量、專利引證、專利引用、非專利科學引用文獻及訴訟專利)作為初步研究工具，除了探討技術是如何由傳統單一的功能型態逐漸地朝向跨領域技術的多功能型態發展外，研究亦使用專利特徵(十年專利被引證數量、專利所有權人數量、專利所有權人國家數量、專利發明人數量、專利發明人國家數量、專利引證數量、國際專利分類數量、美國訴訟專利、非專利引用文獻、國外引證專利及技術分類數量)分析跨領域技術相較傳統單一功能型態之技術，兩者的價值差異。時間序列分析及數理統計分析為觀察技術發展的主要分析工具。研究結果顯示跨領域技術對於產業而言已成為一種趨勢，對於產業未來發展，本研究建議應著重於研發跨領域之技術，以提高研發所產生的價值，因應全球化經濟體需求的同時，更可提高產業之核心競爭力。

關鍵字: 跨領域;專利

Abstract

In the globalized economy, cross-disciplinary technologies have been gradually developed to meet market demands. However, cross-disciplinary technology evolution has not been well investigated with systematic approaches. This study aims to fill the gap by using patent indicators, i.e. patent count, patent citation, patent reference, non-patent reference, and patent litigation, to explore how conventional technologies have evolved into cross-disciplinary ones in the industry. Longitudinal analysis and negative binomial regression analysis was conducted to observe how technology evolved as a function of time by using patent characteristics, i.e. ten year patent's time cited count, assignee count, assignee country count, inventor count, inventor country count, reference count, International Patent Classification (IPC) count, US litigation, non-patent reference count, foreign reference count, and number of technology field. These results showed that cross-disciplinary trends had been observed in a significant number of industries. Firms are encouraged to develop cross-disciplinary technologies in order to strengthen the value of R&D, and to respond to the requirements of modern globalized economy.

Keywords: Cross-disciplinary;Patent

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I. Introduction

Over the past few decades of research on the process of technological development, a number of issues have appeared(Gerybadze & Reger, 1999; Hsu, Lien, & Chen, 2015), some of which remain controversial in spite of reams of data on technological development. Moreover, some empirical studies have been showing that cross-disciplinary technology have a positive impact to economic and can promote technological progress(Hunter, Perry, & Currall, 2011), but there has only a few systematic approach to demonstrate the technology evolution. This paper aims to fill the gap by using the patent citation analysis and patent indicators. Because of we are life in the globalized knowledge economy, intellectual property becomes a very popular issue(Schmiele, 2013), and many empirical studies have proved that patent citation analysis and patent indicators can observe the economic activity comprehensively(Cho & Shih, 2011; Dubarić, Giannoccaro, Bengtsson, & Ackermann, 2011; Griliches, 1998). Cross-disciplinary collaboration usually needs to combine the different technology to get a new valuable technology. This paper used patent citation analysis to understand the knowledge flow of the process of technological development. Some research found that litigation patents are more valuable patent than the non-litigation patent(Su, Chen, & Lee, 2012), so this study also used litigation patent to do the analysis. The quality of a new technology has tested by using patent indicators to do a time serious analysis in this paper. A growing number of research studies are now available to shed some light on the evolution of the technology(Amesse & Cohendet, 2001, 2001; Etzkowitz & Leydesdorff, 2000, 2000; Guan & Zhao, 2013; Hunter et al., 2011; Kaplan & Tripsas, 2008; Murmann & Frenken, 2006). The paper in Hunter (2011) (Hunter et al., 2011)provide extensive discussions of the applications of patent activities. The paper in Amesse (2001) (Amesse & Cohendet, 2001)proposes a framework for understanding and analyzing the process of technology transfer in the perspective of the knowledge-based economy (KBE)(Amesse & Cohendet, 2001). Litigation patent has been proving is more valuable patent than non-litigation patent(Su et al., 2012). Seminal work on calculating litigation probability was carried out by Hsin-Ning Su (2012)(Su et al., 2012). Frietsch

(2014) (Frietsch, Neuhäusler, Jung, & Van Looy, 2014) shows that patent has strongly correlated with export performance. Jiancheng Guan (2013)(Guan & Zhao, 2013) shows that members going in for alliance networks will obtain more patent value than members in networks without alliance networks. Kesidou (2012) and Nemet (2012) provide an excellent review of the methods, findings and instructional issues related to statistical calculate and selection of objects (Kesidou & Demirel, 2012; Nemet & Johnson, 2012). Given the theoretical positions taken for the study and the status of the field as briefly reviewed above, the study aimed to provide an answer to the following question: 1) Whether the combination of different technologies is the trend of industrial development?, 2) Whether the cross-disciplinary technology is more valuable technology?, 3) Whether industry decides to develop a cross-disciplinary technology is good or not? Technological innovation is usually accompanied by very large cost. Unless it can accurately predict technology trends to avoid worthless innovation (Albright, 2002). This paper also wants to know whether is worth to develop a cross-disciplinary. Because the cost of development a new technology is very high, and different degree of cross-disciplinary needs different cost. If we can prove the value of a cross-disciplinary technology, it will have a positive impact on innovation. Moreover, we distinguished the technology depend on the different degree of cross-disciplinary to classify the strength of development comprehensively. It can even accelerate industrial development. Although substantial studies have been performed on the critical factors that affect the technological evolution of technological development (Corredoira & Banerjee, 2015; J. Kim, Lee, & Cho, 2016; Leoncini, 1998), those of systematic investigation the technology trends are still critically lacking. While most of the literature on technological evolution treats only complex technical development process, we intend to introduce the notion of systematic observation and forecasting the trends of the evolution of technology by solving the problems we already mention in this paper. In answering these questions we hope to gain a better understanding of the nature of technological evolution and, most particularly, to be able to decide what kinds of the method can observing and forecasting the technological evolution comprehensively. A number of studies have been conducted using patent information as technology characteristic (B. Kim, Kim, Miller, & Mahoney, 2016; Patel & Ward, 2011; Su et al., 2012). This paper used patent information to do the data analysis and observed the trend of technological evolution. Moreover, this paper classifies the patent by different degree of cross-disciplinary. Different degree of the cross-disciplinary patent will be observed by using the different patent information. This paper clearly solve the problem by the method described above. Experimental results are of great interest both for application and scientific research. Through solving the problems, we may have a contribution to make to unravel the mystery of technological evolution. This study may be critically important in laying the groundwork for systematizing study of science and technology trends. While research on these questions is still at a beginning stage, findings will have broad implications in a number of areas as follows: 1) Innovation policies and systems, 2) Patent informatics, big data and data mining, 3) Open innovation and value co-creation. It would seem advisable to make an effort to identify technological evolution through various research methods (Frietsch et al., 2014; Kesidou & Demirel, 2012; Nemet & Johnson, 2012).

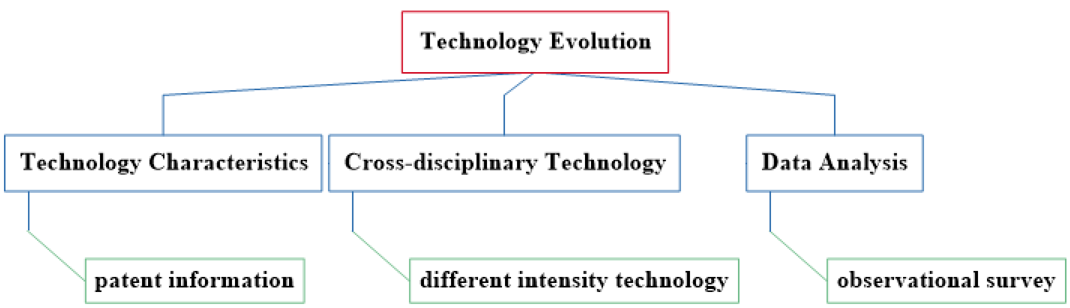

Fig. 1 The structure of this study

The structure of this paper is illustrate in Fig. 1. This paper used the different technology characteristics, i.e. patent information (patent count, patent litigation, patent assignee, patent inventor, patent reference, International Patent Classification and non-patent reference), three framework in Figs. 2, 4 and 10 as cross-disciplinary technology, and data analysis to investigate the trend of cross-disciplinary technology comprehensively.

II. Literature review

2.1 Technological Development

Arthur (2007) and Nemet (2012) proposed the framework for investigating technological development that has withstood the test of time (Arthur, 2007; Nemet & Johnson, 2012). Several studies (Chen, 2007; Xiang, Cai, Lam, & Pei, 2013; Yoon & Park, 2007) have noted that technology development and R&D (Research and Development) have a strong correlation. Theoretical models of new product development such as (Frankort, 2016) need to be confirmed and modified through empirical evidence. The findings of studies examining the use of various forms of research and development have been mixed. An increasing number of recent publications and empirical studies have reassessed the positive contribution that technical cooperation between the different areas can make to technology development (Herstad, Aslesen, & Ebersberger, 2014; Maietta, 2015). Under the globalized knowledge environment, many industries are cooperation each other in order to reduce the cost like R&D alliance(Narula & Santangelo, 2009). This kinds of strategic alliance can effective integration of research and development capabilities between different industries, it can also develop a more innovative and having more value of a new product. Because of the science and technology for human needs are constantly evolving also(Plotkina & Munzel, 2016). In recent years, the company can't rely on a single technology or a single product to survive, it usually need to sustainable development a new technology(Christensen, Olesen, & Kjaer, 2005). In other words, scientific and technological development is moving forward diversified technology. In this paper, the technology development of different intensity classified into different technical development strength. This paper distinguished the different degrees of cross-disciplinary cooperation, it can observing and understanding the technological development trend comprehensively.

Technological development often require a very large resource. Some empirical studies mention that industry-university collaboration can not only reduce the cost but also stimulate more excellent innovation, and many industries cooperated with university for many years. There have been a number of studied that have investigated industry-university collaboration of the impact on innovation(Bodas Freitas, Marques, & Silva, 2013; Etzkowitz & Leydesdorff, 2000; Maietta, 2015), and these studies provides a very good research direction. Industry-university collaboration performance is also a very good subject to observe the technological development. The patent information non-patent reference count (NPRCNT) in this paper used to representative the characteristic of industry-university cooperation. Because of this paper also want to observe the effect of industry-university collaboration in technological development (Sung, Wang, Huang, & Chen, 2015).

For the reasons given above, this paper will illustrate the process of technological development by using different degree of cross-disciplinary technology. In addition, this paper also used patent information to analysis the relationship between industry and university. Because this paper want to use these scientific method to understand the effect of different degree of cross-disciplinary technology (Frietsch et al., 2014; Kesidou & Demirel, 2012; Nemet & Johnson, 2012).

2.2 Evolution of Technology

Technological change is a critical determinant of the evolution of technology, and technological innovation builds upon prior existing knowledge. In general, the knowledge produced in a technology remains within the same technology. But for some special technology, knowledge spillovers across technologies also occur(Battke, Schmidt, Stollenwerk, & Hoffmann, 2016). This kinds of special technology reinforcing the existing technological trajectories, and has the potential to increase technological variety(van den Bergh, 2008). Successful innovation depends on knowledge – technological, strategic and market related(Roper & Hewitt-Dundas, 2015). From the technically perspective, new technology usually accompany a new technical. There are a lot of new product combines many different technologies, for example: 3D-printing machine, telemedicine machine and wearable electronics(Gebler, Schoot Uiterkamp, & Visser, 2014). From the strategic perspective, there have some kinds of new alliance appeared over the past decades, for example: R&D alliance and Strategic Alliance for Industries(Frankort, 2016). From the market perspective, product managers must constantly trade-off the level of customer satisfaction to meet their requirements(Chiang, Che, Wang, & Chen, n.d.).

Technological diversification has received substantial attention from studies, as many firms have increasingly diversified their technological resources(Piening, Salge, & Schäfer, n.d.). A substantial body of research documents our tendency to cross-disciplinary development (Etzkowitz & Leydesdorff, 2000; Guan & Zhao, 2013; Holgersson, 2013; Liew, Shahdan, & Lim, 2013), and provide an excellent review of the methods, findings and structural issues related to analysis technology evolution. The majority of research (Guan & Zhao, 2013; Y. Kim, Kim, & Yang, 2012; Motohashi, 2005) in evolution of technology has focused on university-industry Collaboration. (Battke et al., 2016) used the technological knowledge flow to explore the internal or external spillovers for the technologies. This paper considers not only industry-university cooperation but also consider the flow of technology between all sectors (Nemet & Johnson, 2012)(there all have 35 different kinds of sectors for the technology). Moreover, this paper aim to use technical knowledge flow to generate a systematical method to observe the technology evolution. Technological evolution typically accompany the Technological diversification (J. Kim et al., 2016; Wang, Ning, & Prevezer, 2015). In order to understanding how important of technology diversification, this paper used technology characteristic (i.e. patent information: non-patent reference count, reference count, patent litigation, patent assignee, patent inventor, IPC classification and technology fields) and technical knowledge flow (i.e. patent citation (Patel & Ward, 2011)) to observe the process of technological diversification by a data analysis.

There have many empirical studies have used the patent to illustrate a variety of technology-related phenomena(Frietsch et al., 2014; Hoenig & Henkel, 2015; B. Kim et al., 2016; Nam, Nam, & Kim, 2015; Roper & Hewitt-Dundas, 2015).

2.3 Systematic Study of Technological Evolution

In several empirical studies, it has been demonstrated that there are a close association and considerable correlation between Intellectual property and economic performance in international markets (Grupp & Schmoch, 1999; Ushijima, 2013; Yang & Kuo, 2008). Intellectual Property also is a major concern in a wide variety of applications such as economy growth (Gould & Gruben, 1996), the value of innovation (Greenhalgh & Rogers, 2006), technological capabilities (Fai, 2005), and market competition (Patel & Ward, 2011).

A lot of research shows patents are valuable indicators (Fischer & Leidinger, n.d.; Grimaldi, Cricelli, Di Giovanni, & Rogo, 2015; Harhoff, Hoisl, Reichl, & van Pottelsberghe de la Potterie, 2009; McQueen, 2005). This paper used patent characteristic to generate a systematic approach to observe the evolution of technology. Patent characteristic represent the technology characteristic for the research in this study. Some empirical studies have provided different kinds of systematic methods and structure for the research(Kesidou & Demirel, 2012; Nemet & Johnson, 2012). Frietsch (2014) provided a systematic analysis method to exploring the relationship between technology and economic performance (Frietsch et al., 2014). Ivanova (2014) provided a systematic structure to observe the innovation system of university–industry–government relations (Ivanova & Leydesdorff, 2014). Hagedoorn (2003) provided a systematic method to measure innovative performance. Combining the advantage above, this paper used a systematic approach to observe the trend of the evolution of technology (Hagedoorn & Cloodt, 2003). There also have some empirical studies have contribute the research of technology evolution such as Amess (2001) and Nemet (2012) enhance the previous studies' findings by providing a much more detailed examination of the trend of cross-disciplinary evolution (Amesse & Cohendet, 2001; Nemet & Johnson, 2012). Arthur (2007) need to be confirmed and modified through empirical evidence (Arthur 2007). The two studies and this paper can complement each other well, for each emphasizes a different aspect of the evolution of technological development. Moreover, there are many different points of view can be explained the evolution of technology, a systematic approach to observe the trend of the evolution of technology is very useful for future research. If the trend of technology evolution can be forecasting, there will have many advantage for different sectors such as industries and government. In addition to decrease the risk of development a new technology and also reduce the cost. For the policy, government can properly use resources. For industries, they may have more confidence in the development of cross-disciplinary technology and drive the industries to innovation (Piening et al., n.d.). For market, the right policies and healthy competitive environment between industries will drive the market active (Frankort, 2016). Table 1 descried the key paper which this study used.

Table 1 Descriptive the key paper in this study

Authors	Data	Method	Key findings
(Roper & Hewitt-Dundas, 2015)	1. Irish innovation panel 2. USPTO 3. PATSTAT	1. Questionnaires 2. Mathematical Statistics	1. Knowledge flows from internal investments will have a positive impact on innovation outputs. 2. Existing knowledge stocks will have a negative moderating effect on the innovation value of knowledge flows from internal investments.
(Nemet & Johnson, 2012)	1. USPTO 2. National Bureau of Economic Research Patent Citation Data File	1. Patent Citation 2. Mathematical Statistics	The additional flows of knowledge from distant technological domains are associated with fewer forward citations received relative to adding citations to more proximate knowledge.
(Hagedoorn & Cloodt, 2003)	1. USPTO 2. RDS Business & industry databank	1. Patent Granted 2. Mathematical Statistics	There is no major systematic disparity amongst R&D inputs, patent counts, patent citations and new product announcements
(Hoenig & Henkel, 2015)	187 individual venture capitalists from Germany and the United States.	1. Questionnaires 2. Mathematical Statistics	Add new insights to a recent stream of research on the role of signals in venture capital financing, and in particular of patents as signals
(Nam et al., 2015)	Lexis-Nexis news database	1. Event study 2. Mathematical Statistics	The announcement that a lawsuit been filed has a positive impact on the plaintiff firm and a negative impact on the defendant firm.
(Grimaldi et al., 2015)	1. Esp@cenet 2. Google patents 3. MyIntelliPatent 4. InfoPatent 5. Thomson Innovation	Patent Indicators : Technical scope, Forward citation frequency, International scope, Patenting strategy and Economic relevance	1. This paper develops a practical and reproducible framework that can support scholars and practitioners to leverage the value of patents and to extract all possible strategic information from patent portfolio. 2. This paper propose a framework to analyze and assess strategic information of patents.
(Frietsch et al., 2014)	1. PATSTAT 2. UN-COMTRADE 3. OECD databases	1. Patent Granted 2. Mathematical Statistics	1. Forward citations are a promising indicator of patent value at the country level. 2. Innovation, as measured by patent applications, actually drives a country exports.
(Guan & Zhao, 2013)	1. Derwent Innovation Index database 2. USPTO, JPO, EPO, WIPO and SIPO database	1. Patent Citation 2. Mathematical Statistics	Members going in for alliance networks that combine a high degree of clustering and reach will exhibit more patent value than members in networks without these characteristics.
(Arthur, 2007)	Empirical study	1. Event study 2. Literature integrate	This paper mention: invention is a recursive process: it repeats until each challenge or problem (and subproblem, and sub-subproblem) resolves itself into one that can be physically dealt with.

III. Research Method

A three-phase study was designed to explore the identification, classification, and application of cross-disciplinary technologies by three kinds of research frameworks. First, this paper observed the knowledge flow of technology activity and identified the cross-disciplinary technology by patent information in framework 1. Patent characteristic as an important element to identify the cross-disciplinary technology. We use patents granted by the Unite State Patent and Trademark Office from 1976 to 2013. Unite State Patent and Trademark Office database provided the data with different patent characteristics (i.e. time cited count, assignee count, assignee country count, inventor count, inventor country count, reference count, International Patent Classification (IPC) count, non-patent reference count, foreign reference count, number of technology field and litigation status).

Second, after identifying the cross-disciplinary technology, this paper used different degree of patent citations to classify the level of different cross-disciplinary technology in framework 2. Patent citation is the major patent indicator in this paper to explore the technology value comprehensively. In this part, we use patents granted by the EPO Worldwide Patent Statistical Database (PATSTAT) from 1976 to 2013. Because of the PATSTAT database provided the information of patent included an industrial sector and field information. In addition, this part we impose a 10-year-window—on both forward and backward citation pairs—to minimize truncation bias (i.e. the target patent was granted between 1993 and 2003).

Last but not least, in order to improve the robustness of the results in framework 2. We employed the International Patent classification system (IPC) to classify the technology with different degree of the patent citation in framework 3. We arrive at a comparable hierarchy of sections (8), classes (124) and sub-classes (1053) and code each citation pair according to these categories as well. It is the reason why this paper analysis the application of cross-disciplinary technologies by patent citation with IPC classification. Through the framework 3, this paper got the research results with different views (Kesidou & Demirel, 2012).

To ensure some homogeneity of technology background, all the patent data were selected from the same database. All the patent information this paper used are from PATSTAT database (Patent Statistic Database) and USPTO database (Unite State Patent and Trademark Office). PATSTAT database includes almost all of the patent information of different patent office (For example, European Patent Office (EPO) and Japan Patent Office (JPO)) in the world. The USPTO database included the information of patent charateristics from the year 1976 to 2016.

Multiple indicators is of central interest in the context of measuring innovative performance, and yet, as observed by Hagedoorn (2003), it is an area that is under-researched and under-discussed, so this paper used the different indicators to observe different phenomenon of the evolution of technology development by three research frameworks (Hagedoorn & Cloodt, 2003). The statistical research results was conducted by R language and Statistical Product and Service Solutions (SPSS), and we used the SQL server to filter the patent data from USPTO and PATSTAT database. The analytical methods were conducted individually and were integrated for later using as follows:

IV. Results and Discussion

4.1 Framework 1 - Identification of cross-disciplinary technology

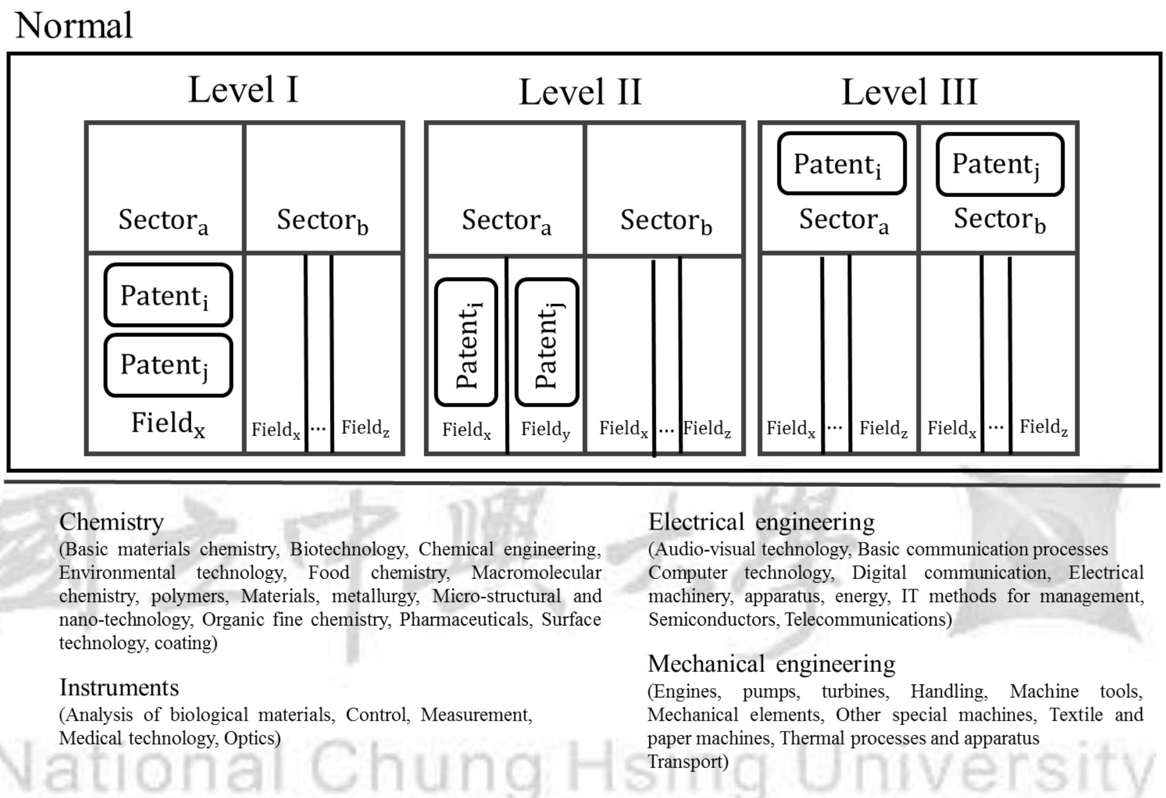

Fig. 2 Definitions of knowledge flow with three types of degree. Patent$_i$ is patent of interest, patent i. Patent$_j$ is prior art cited by patent i.

A picture of the experimental setup of framework 1 is depicted in Fig. 2, and this paper metaphorically depicts what happens in that all kinds of patent citation in Fig. 3 with six types of patent citation. The patent citation will be identify with four levels, which is Normal, Level I, Level II and Level III respectively. "Normal" level is the patent citation without any limitation. Level I is the near patent citation level, which means one patent citing the other patent with the same industrial sector and field. Level II is the external patent citation level, which means the patent citing the other patent with the same industrial sector but different field. Level III is the far patent citation level, which means the patent citing the other patent with the different industrial field. Moreover, a mathematical model was developed for the evaluation of the trend of cross-disciplinary evolution in Table 5. Table 2 and Table 3 illustrate the experimental setup of the negative binomial regression model in Table 5. Table 2 provides the list of four types of regression models that were used in this study, grouped into four technological fields. The dependent variable is ten year time cited count of the patent, and the independent variables are the patent characteristics (i.e. time cited count, assignee count, assignee country count, inventor count, inventor country count, reference count, International Patent Classification (IPC) count, non-patent reference count, foreign reference count, number of technology field and litigation status). Table 3 descriptive the variables used in details of framework 1. Table 4 presents the mean score, median, standard deviation, Min and Max with four regression models, i.e. Normal, Level I, Level II and Level III. The patent data were collected from Unite State Patent and Trademark Office from 1976 to 2013. Because of the Unite State Patent and Trademark Office database provided the data with different patent characteristics.

Table 2 Descriptive of dependent variable, knowledge flows and technological fields.

Name	Description
Dependent variable:	
Ten Year Citations received	Count forward cites within 10 years
Knowledge flows (counts):	
Normal (all patent citation)	Citations made, coded as Normal
Observations (Normal)	1,001,686
Level I (near patent citation)	Citations made, coded as Level I
Observations (Level I)	886,631
Level II (external patent citation)	Citations made, coded as Level II
Observations (Level II)	524,321
Level III (far patent citation)	Citations made, coded as Level III
Observations (Level III)	632,871
Technological fields:	Include 4 sectors and 32 fields
Chemistry section	Include 11 fields
Electrical engineering section	Include 8 fields
Instruments section	Include 5 fields
Mechanical engineering	Include 8 fields

Table 3 Variables used to characterize each patent, i.

Name	Description
Patent characteristics:	
No. of Assignee	Count of patent assignee
No. of Assignee Country	Count of patent assignee country
No. of Inventor	Count of patent inventor
No. of Inventor Country	Count of patent inventor country
No. of Reference	Count of patent reference
No. of IPC	Count of international patent classification
No. of Non-Patent Reference	Count of not patent reference
No. of Foreign Reference	Count of foreign patent reference
No. of Technology Fields	Count of patent technology fields
Patent Litigation	The patent has been litigation
Patent Non-Litigation	The patent has not litigation before

Table 4 Descriptive statistics. (n = 4,667,855 observations), 1976-2013 Source: USPTO, own calculations.

Patent characteristics:	Mean	Median	Std. dev.	Min.	Mix.
Ten Year Citations received	12.85	7	20.83	1	780
No. of Assignee	1.03	1	0.20	1	13
No. of Assignee Country	1.01	1	0.08	1	4
No. of Inventor	2.50	2	1.73	1	41
No. of Inventor Country	1.05	1	0.22	1	6
No. of Reference	13.78	10	15.11	0	166
No. of IPC	4.17	3	4.40	1	166
No. of Non-Patent Reference	3.00	0	9.45	0	198
No. of Foreign Reference	2.46	1	4.23	0	99
No. of Technology Fields	16.72	15	10.72	1	35

Table 5 Estimates of negative binomial regressions. Dependent variable is counts of citations received within 10 years. Second row indicates statistical standard error, 1976-2013 Source: USPTO, own calculations.

Regression Model	Normal	Level I	Level II	Level III
No. of Assignee	-0.1262345***	-0.1217805***	-0.1063721***	-0.1392923***
(Std. Error)	(0.0082607)	(0.0085755)	(0.0102722)	(0.0094888)
No. of Assignee Country	0.1089671***	0.1035240***	0.1047179***	0.1250552***
(Std. Error)	(0.0198814)	(0.0205190)	(0.0240149)	(0.0236205)
No. of Inventor	0.0442374***	0.0451631***	0.0424384***	0.0436226***
(Std. Error)	(0.0008711)	(0.0008926)	(0.0010750)	(0.0010118)
No. of Inventor Country	-0.0302408***	-0.0255640***	-0.0568028***	-0.0058048***
(Std. Error)	(0.0066623)	(0.0068550)	(0.0081264)	(0.0079259)
No. of Reference	0.0181709***	0.0171083***	0.0161669***	0.0139375***
(Std. Error)	(0.0001090)	(0.0001102)	(0.0001349)	(0.0001190)
No. of IPC	0.0134692***	0.0149669***	0.0089305***	0.0207604***
(Std. Error)	(0.0003411)	(0.0003531)	(0.0003934)	(0.0004403)
No. of Non-Patent Reference	0.0053087***	0.0055749***	0.0038629***	0.0093868***
(Std. Error)	(0.0001615)	(0.0001648)	(0.0001795)	(0.0002004)
No. of Foreign Reference	-0.0300336***	-0.0287546***	-0.0275029***	-0.0240610***
(Std. Error)	(0.0003933)	(0.0004016)	(0.0004869)	(0.0004556)
No. of Technology Fields	-0.0236345***	-0.0232416***	-0.0277494***	-0.0248708***
(Std. Error)	(0.0001378)	(0.0001402)	(0.0001838)	(0.0001619)
Patent Litigation	0.7093417***	0.6682017***	0.6788459***	0.6500758***
(Std. Error)	(0.0130345)	(0.0129118)	(0.0150390)	(0.0139798)
Patent Non-Litigation	-1.2040043***	-1.1667831***	-1.1599688***	-1.1439388***
(Std. Error)	(0.1525261)	(0.1699181)	(0.2958029)	(0.2378083)
Constant	2.5574148***	2.6248435***	2.8868732***	2.7841111***
(Std. Error)	(0.0184304)	(0.0190127)	(0.0221552)	(0.0220448)

*** $p < 0.01$: Significance level.
** $p < 0.05$: Significance level.
* $p < 0.1$.

First we want to know whether there have significant different of the patent characteristics in Table 3. Because of the patent characteristics is use as the nature of different intensity of patent citation. In addition, the patent data we collected were toward the negative binomial distribution in framework 1, and the regression method were generated by using negative binomial regression analysis. Negative binomial regression analysis (see Table 5) used to generate the relationship between the value of patents (ten year time cited count of the patent) and patent characteristics (as we mention in data collection). The results in Table 5 shown that all the patent characteristics has significant different. The patent characteristics which can represent the nature of patent citation in framework 1 is assignee count, assignee country count, inventor count, inventor country count and litigation status. Patent characteristics were also used in framework 2 (non-patent reference count, reference count, litigation status and number of technology fields) and framework 3 (IPC count and number of technology fields) to adapt for different needs.

For the sake of a visual picture of the distinction, consider the graphic representation in Figures 3. Fig. 3 provides the six kinds of the nature of different citation to identify the cross-disciplinary technology by using the different intensity of patent citation. The results shows with six dimensions, i.e. internationalization (inventor country count for the patent more than two), patent litigation (litigation status), co-owner (patent citation with the same assignee) and co-inventor (patent citation with the same inventor). The results shown that the patent citing the other patent with the far level of patent citation will have the higher patent value than the near level (see Fig.3), and we identified the cross-disciplinary technology in framework 1 by using different intensity of patent citation is well to illustrate the nature of cross-disciplinary technology.

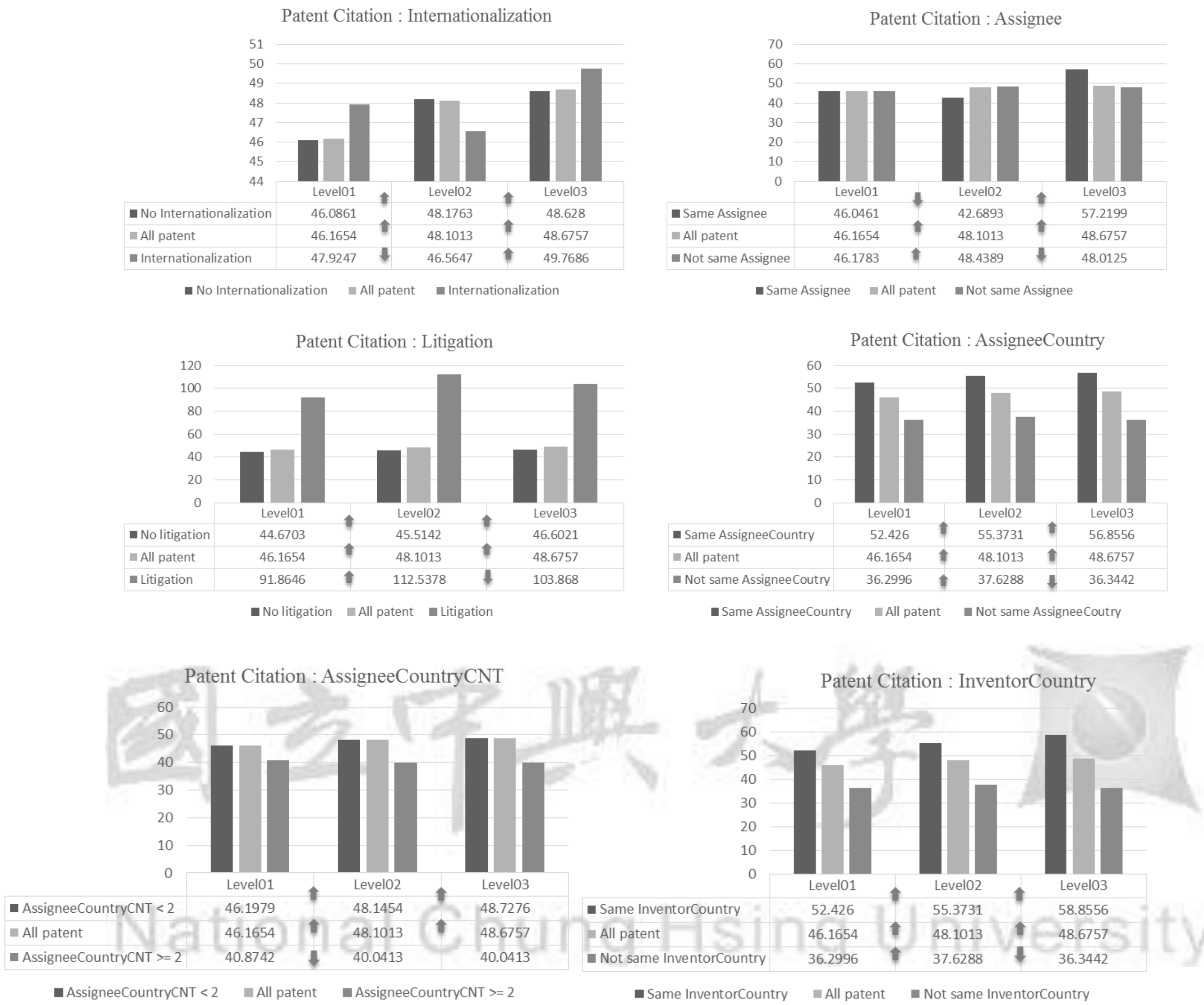

Fig. 3 The average time cited count with different type level and the nature of knowledge flow (the number in the row is time cited count for the patent citation), i.e. internationalization, litigation, co-owner and co-inventor, 1976-2013 Source: PATSTAT, own calculations.

4.2 Framework 2 - Classification of cross-disciplinary technology

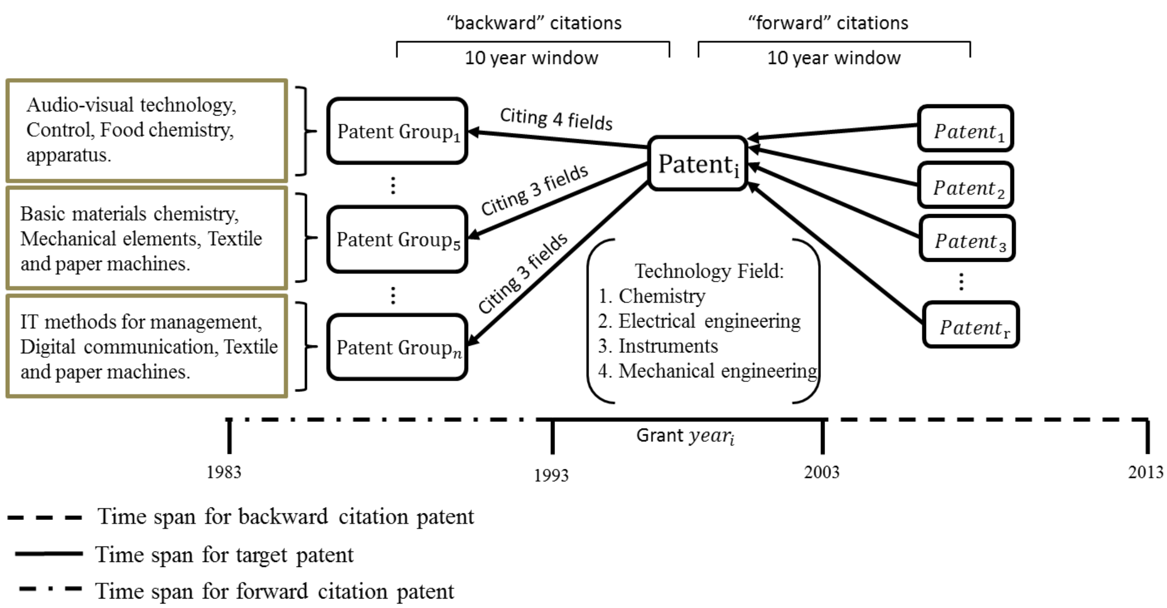

Fig. 4 Schema for patent citations showing backward citations to and from patent of interest with technology field, i. Arrows indicate flows of knowledge.

A picture of the experimental setup of framework 2 is depicted in Fig. 4, and this paper metaphorically depicts what happens in that results in Fig. 5 to Fig. 9. In this part, first we used the different intensities of patent citation to distinguish the cross-disciplinary technology in a different level. Moreover, patent citation is defined by one patent citing a patent group. We use patents granted by the EPO Worldwide Patent Statistical Database (PATSTAT) from 1976 to 2013 in this part. In addition, this part we impose a 10-year-window—on both forward and backward citation pairs—to minimize truncation bias (i.e. the target patent was granted between 1993 and 2003). The number of distinct technology sectors of the patent group will be calculate as the patent characteristics of the patent which citing the patent group. Each patent will be classify with different intensities of patent citation (for example, citing 2 fields, citing 5 fields and citing 9 fields). A regression model was developed for the evaluation of the relationship between the patent characteristics and patent value and test whether the patent characteristics has significant different. Table 7 presents the mean score, standard deviation with five models. We used the multi-factor linear regression analysis to generate the relationship between the value of patents (ten year time cited count of the patent) and patent characteristics because of the data were tendency presented linear distribution.

There have five regression models in this part. Model I means we collect the data without any limitation. Model II means we collect the data only in Chemistry technology field. Model III means we collect the data only in electrical engineering technology field. Model IV means we collect the data only in instrument technology field. Model V means we collect the data only in mechanical engineering technology field. The dependent variable is ten year time cited count of the patent, and the independent variables are the patent characteristics. Some of the significant results in the regression model will be choose to observe the trend of the cross-disciplinary technology evolution. Last, there have some patent indicators will be choose to observe the trend of cross-disciplinary technology evolution (i.e. ratio of litigation patent, average non-patent reference count, average reference count and patent count). The reason why we choose theses patent indicators to observe the trend of the cross-disciplinary technology evolution is that litigation patent, non-patent reference and reference were been prove as a good patent indicator to observe the patent value, and the results in framework 1 that litigation status, reference count and no-patent reference count has significant difference. Table 6 and Table 7 illustrate the experimental setup of the regression model in Table 8. Table 6 provides the list of 5 types of regression models that were used for classifying the data in this study, grouped into nine categories.

Table 6 Descriptive of dependent variable, knowledge flows and regression models.

Name	Description
Dependent variable:	
Ten Year Citations received	Count forward cites within 10 years
Knowledge flows (counts):	
Patent Group$_n$	(A group of patent ; n=1, 2 ,3 …)
Citing 2 fields	Patent Group$_n$ include 2 fields
Citing 3 fields	Patent Group$_n$ include 3 fields
Citing 4 fields	Patent Group$_n$ include 4 fields
Citing 5 fields	Patent Group$_n$ include 5 fields

Citing 6 fields	Patent $Group_n$ include 6 fields
Citing 7 fields	Patent $Group_n$ include 7 fields
Citing 8 fields	Patent $Group_n$ include 8 fields
Citing 9 fields	Patent $Group_n$ include 9 fields
Citing over 10 fields	Patent $Group_n$ include more than 10 fields
Definition of models:	
Model I	Data were collected by All Sector
Observations (Model I)	4,667,855
Model II	Data were collected by Chemistry Sector
Observations (Model II)	908,994
Model III	Data were collected by Electrical Engineering Sector
Observations (Model III)	1,395,560
Model IV	Data were collected by Instruments Sector
Observations (Model IV)	798,888
Model V	Data were collected by Mechanical Engineering Sector
Observations (Model V)	1,239,862

Table 7 Descriptive statistics (n = 4,667,855 observations), 1976-2013 Source: USPTO, own calculations.

	Model I	Model II	Model III	Model IV	Model V
Variable	Mean	Mean	Mean	Mean	Mean
Citing 2 fields	400784.59	55119.15	157001.15	96726.63	64856.00
(Std. dev.)	(228433.54)	(35690.09)	(98085.85)	(57961.18)	(37214.90)
Citing 3 fields	262972.70	38865.41	112300.74	62505.37	35268.30
(Std. dev.)	(155953.10)	(24577.66)	(74748.93)	(37494.00)	(20320.10)
Citing 4 fields	154883.11	23709.70	68021.96	38002.04	18026.52
(Std. dev.)	(95568.79)	(14777.84)	(46924.62)	(23463.36)	(10614.23)
Citing 5 fields	87798.93	14253.70	38291.41	21971.33	9404.81
(Std. dev.)	(58287.17)	(9458.60)	(28072.71)	(14604.40)	(5999.68)
Citing 6 fields	50775.22	8456.19	21015.33	14060.67	5245.22
(Std. dev.)	(35371.16)	(5997.53)	(15768.59)	(10013.25)	(3539.87)

Citing 7 fields	31332.63	5348.30	12426.04	9014.07	3171.74
(Std. dev.)	(23317.54)	(4147.48)	(9478.95)	(7254.26)	(2349.87)
Citing 8 fields	19275.41	3449.74	7377.70	5731.00	1915.07
(Std. dev.)	(14733.46)	(2716.95)	(5878.49)	(4647.15)	(1514.71)
Citing 9 fields	11778.78	2265.37	4317.70	3586.81	1037.48
(Std. dev.)	(8854.16)	(1789.21)	(3400.74)	(2851.76)	(789.39)
Citing over 10 fields	33580.04	5436.63	12442.56	10746.63	2631.74
(Std. dev.)	(27761.75)	(4785.37)	(10590.18)	(9324.27)	(2114.32)

Table 8 The result of estimates of multi-factor linear regression with five models. (n = 4,667,855 observations), 1976-2013 Source: USPTO, own calculations.

	Model I	Model II	Model III	Model IV	Model V
Citing 2 fields	0.642***	0.727***	0.539***	0.734**	0.996***
Citing 3 fields	0.764***	0.205***	0.436***	0.175***	-0.08
Citing 4 fields	-0.572***	0.046	0.185	-0.048	-0.054
Citing 5 fields	0.058	0.025	0.048	0.002	-0.027
Citing 6 fields	0.164***	-0.025	0.05	0.118***	0.008
Citing 7 fields	0.075	0.050**	-0.065	0.061	-0.007
Citing 8 fields	0.064	-0.057	-0.023	-0.007	-0.014
Citing 9 fields	0.013	0.053**	0.009	0.011	-0.044
Citing over 10 fields	0.073***	0.060***	0.069***	0.064***	0.042***
Constant	2625.5	-900.485	7660.785	1959.255	-891.698
R^2	0.999	0.999	0.999	0.998	0.997

*** $p < 0.01$: Significance level.
** $p < 0.05$: Significance level.
* $p < 0.1$.

The results that the patent characteristics were significant in “citing 2 fields”, “citing 3 fields” and “citing over 10 fields” in Table 8, which means these three patent characteristics have explanatory power to illustrate the visual results in Figs. 5, 6, 7, 8 and 9. For the Figs. 5, 6, 7, 8 and 9, we used the patent characteristics form framework 1 (i.e. litigation status, non-patent reference count and patent reference count) as the nature of patent citation, and patent characteristics from framework 2 as the intensity of cross-disciplinary of patent citation to observe the trend of the cross-disciplinary technology evolution, which can classify the cross-disciplinary technology with different degrees to observe the result comprehensively.

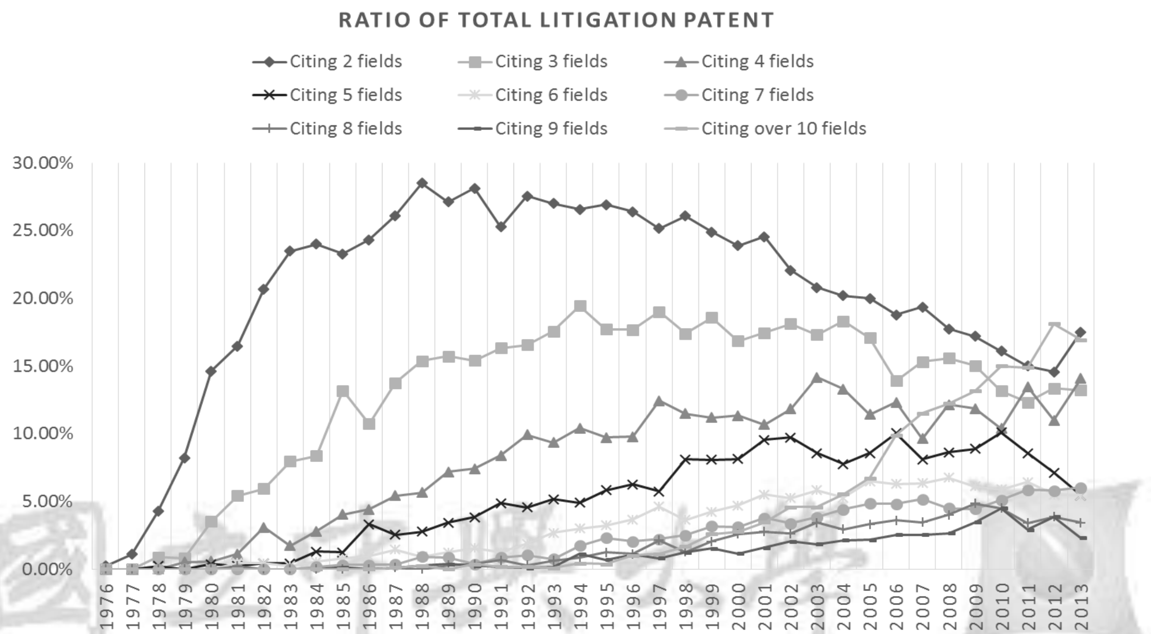

Fig. 5 Ratio of litigation patent count (compare with all litigation patent), 1976-2013

Source: PATSTAT, own calculations.

Fig.5 presents the ratio of total litigation patent with different degree of cross-disciplinary technology. The most important finding from Fig. 5 support the notion that the high cross-disciplinary technology has gradually replaced the low cross-disciplinary technology and become the main valuable patents. Average non-patent reference and reference count of different degree of cross-disciplinary patent and are given in Figure 6 and Figure 7 respectively. The results of Figure 6 shows that high degree of cross-disciplinary patent may have higher count of non-patent referent count than low degree of cross-disciplinary patent. Figure 7 shows that high degree of cross-disciplinary patent indeed have high number of reference than low degree of cross-disciplinary patent.

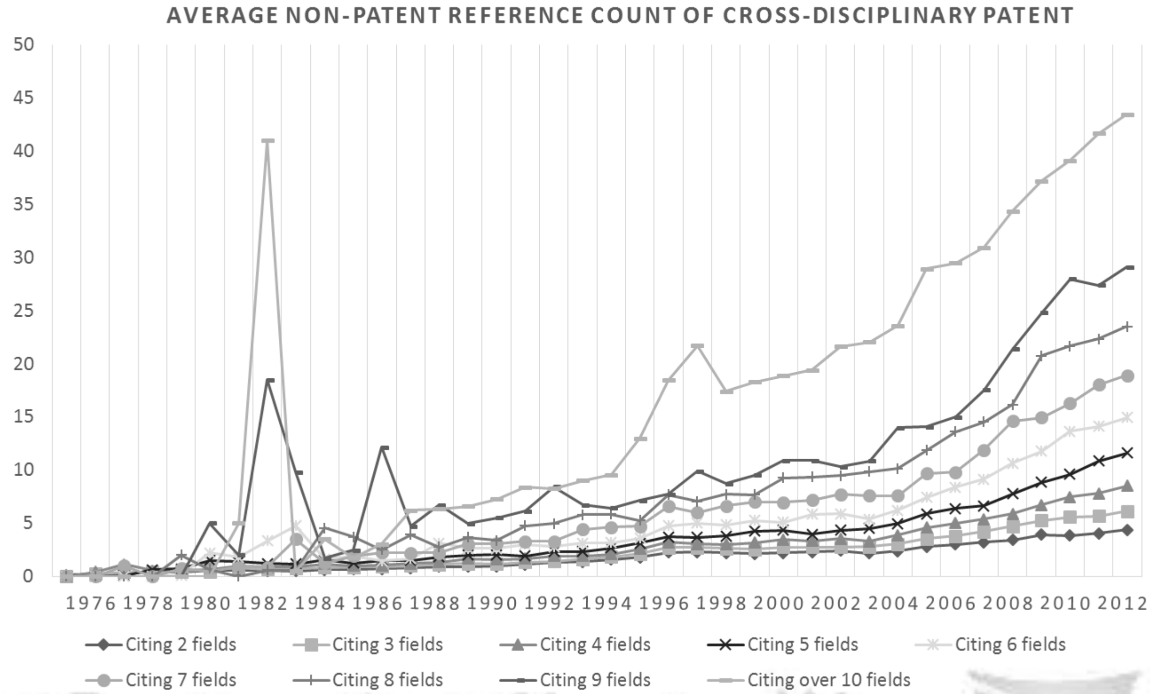

Fig. 6 Average Non-Patent Reference Count of Cross-Disciplinary Patent, 1976-2013

Source: PATSTAT, own calculations.

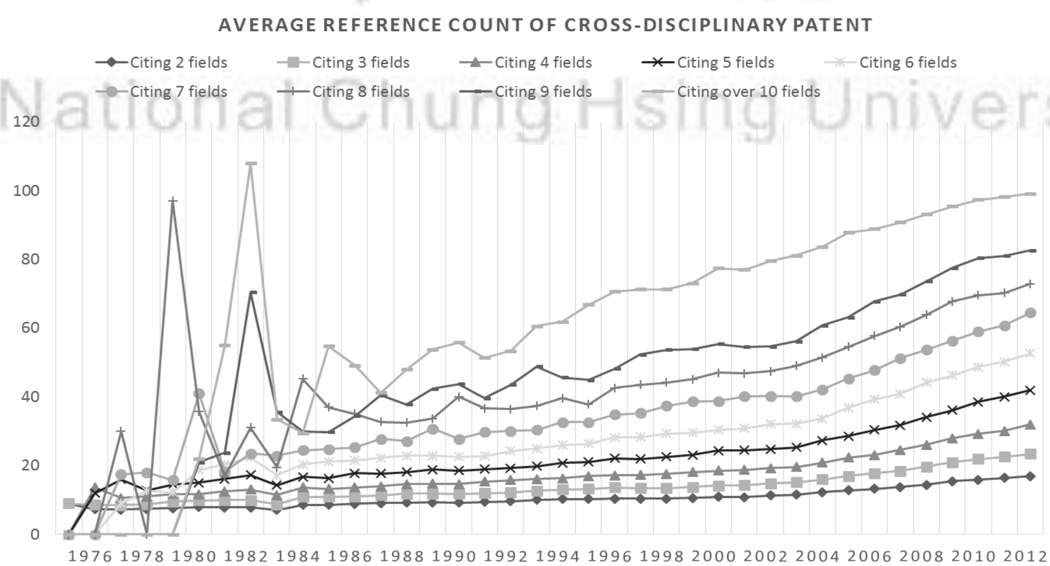

Fig. 7 Average Reference Count of Cross-Disciplinary Patent, 1976-2013

Source: PATSTAT, own calculations.

Fig.8 and Fig.9 used the Stacked Area Chart to demonstrate the yearly number of the different patent application (Fig.8 shown the patent count of cross-disciplinary patent and Fig.9 shown the litigation patent count of the cross-disciplinary patent). The results reflected in Fig.5 indicate that technical indeed continue toward cross-disciplinary development. Fig.9 indicate that technological development has gradually focused on high level of cross-disciplinary. Because it needs a lot of time and money to go through the process of patent litigation, and high level of cross-disciplinary clearly worth.

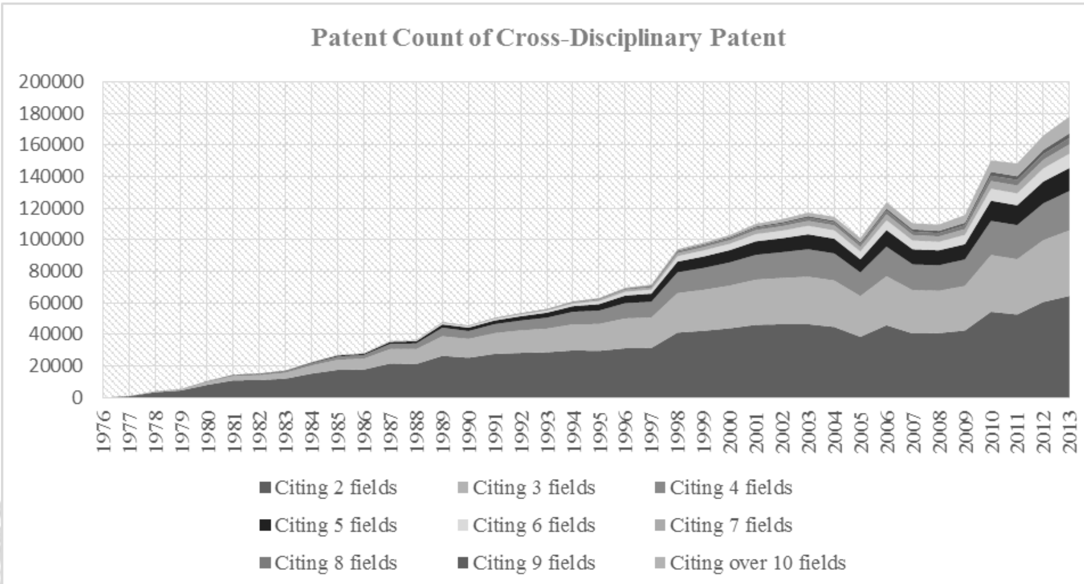

Fig. 8 Litigation patent count of cross-disciplinary patent, 1976-2013 Source: PATSTAT, own calculations.

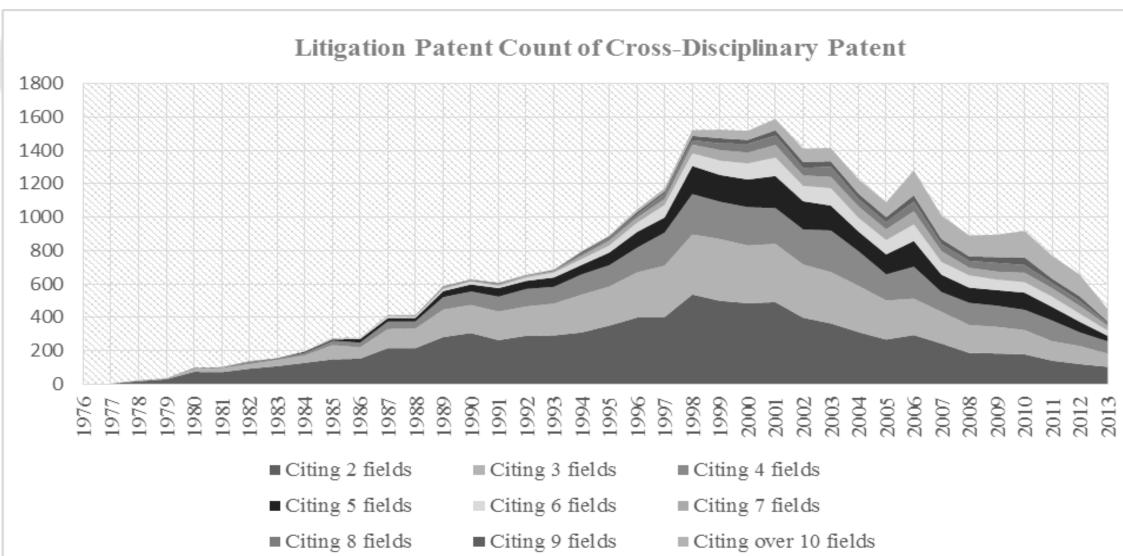

Fig. 9 Cross-disciplinary patent count, 1976-2013 Source: PATSTAT, own calculations.

4.3 Framework 3 - Application of cross-disciplinary technology

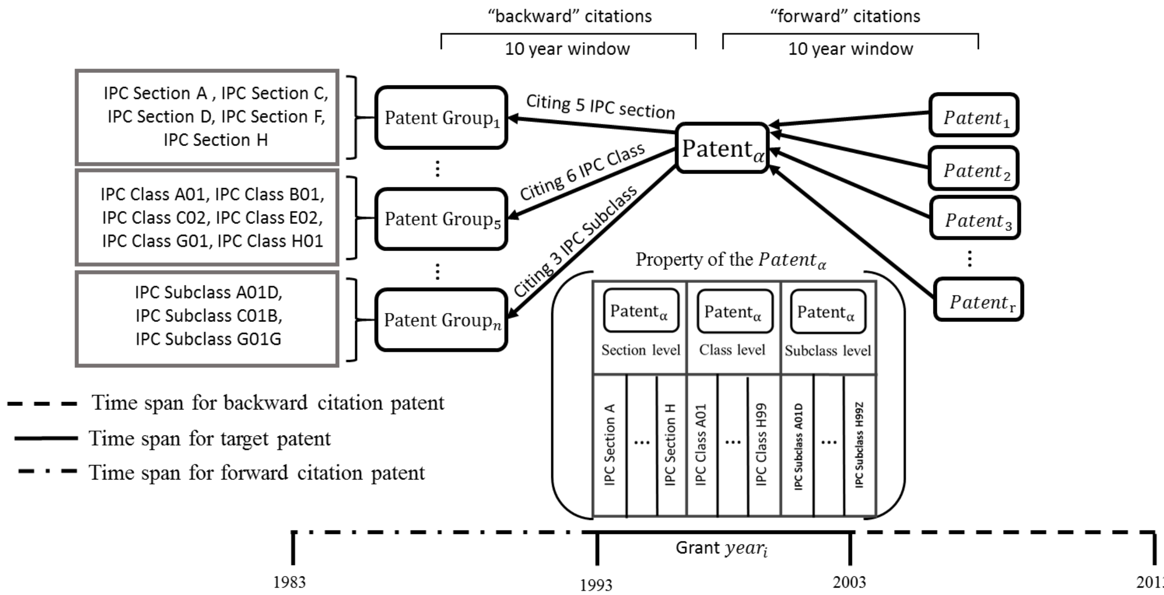

Fig. 10 Schema for patent citations showing backward citations to and from patent of interest with property of the patent. Patent$_\alpha$, Arrows indicate flows of knowledge.

A picture of the experimental setup of framework 3 is depicted in Fig. 10, and this paper metaphorically depicts what happens in that results in Fig. 11 to Fig. 13. In this framework, we considerate the IPC classification to represent the intensities of patent citation base on the structure of framework 2. Because of the paper in Nemet (2012) provide extensive discussions of the applications of IPC classification to observe the technology trend (Nemet & Johnson, 2012). This study used this kinds of new classify method to improve the robustness of the results of framework 2. To address this issue, the framework 3 contained between 6 and 16 pairs of variables with three IPC classification, i.e. IPC section, IPC class and IPC subclass.

First, this study also used the different intensities of patent citation to distinguish the cross-disciplinary technology in a different level in framework 3. Moreover, patent citation is defined by one patent citing a patent group. The number of distinct technology IPC sectors, IPC class and IPC subclass of the patent group will be calculate as the patent characteristics of the patent which citing the patent group. Each patent will be classify with different intensities of patent citation (i.e. citing 2 IPC section, citing 3 IPC section, …, citing 6 IPC section, citing 2 IPC class, citing 3 IPC class, …, citing 11 IPC class, citing 2 IPC subclass, citing 3 IPC subclass, …, citing 16 IPC subclass).

Second, the multi-factor linear regression analysis were used to generate the relationship between the value of patents (ten year time cited count of the patent) and patent characteristics (see Table 10). There have three regression models in this part. Model (1) means we defined the intensities of patent citation with IPC section level. Model (2) means we defined the intensities of patent citation with IPC class level. Model (3) means we defined the intensities of patent citation with IPC subclass level. The dependent variable is ten year time cited count of the patent, and the independent variables are the patent characteristics. Some of the significant results in the regression model will be choose to observe the trend of the cross-disciplinary technology evolution.

Last, we defined "own classification" as the number of the distinct technology IPC section, IPC class and IPC subclass for the patent, which citing the patent group. "Intensities of Patent Citation" as the different patent characteristics for the patent, which citing the patent group. This study compared the patent value between "own classification" and "Intensities of Patent Citation" with the same IPC level to observe the trend of cross-disciplinary technology evolution by observing the average time cited count in framework 3. The reason why this paper compare the two indicators is that we want to know the patent value of self-multi-technology and cross-disciplinary technology with different intensity. Table 9 provides the list of 3 types of regression models that were used for classifying the data in this study, grouped into 3 categories, i.e. citing with IPC section, citing with IPC class and citing with IPC subclass. The definition of IPC show in appendix.

Table 9 Descriptive of dependent variable and knowledge flows.

Name	Description
Dependent variable:	
Ten Year Citations received	Count forward cites within 10 years
Knowledge flows (counts):	
(Patent Group_n)	(A group of patent ; n=1, 2 ,3 …)
Citing α Section	Patent Group_n include α section ; α = 1, 2, 3 …
Citing β Class	Patent Group_n include β class ; β = 1, 2, 3 …
Citing γ Subclass	Patent Group_n include γ subclass ; γ = 1, 2, 3 …

Table 10 The result of estimates of multi-factor liner regression with three classifications. (n = 4,667,855 observations), 1976-2013

Source: USPTO, own calculations.

IPC Section	Model (1)	`IPC Class	Model (2)	IPC Subclass	Model (3)
Citing 1 Section	0.339***	Citing 1 Class	0.164***	Citing 1 Subclass	0.244***
(Std. Error)	(0.000)	(Std. Error)	(0.000)	(Std. Error)	(0.000)
Citing 2 Section	0.391***	Citing 2 Class	0.196***	Citing 2 Subclass	0.251***
(Std. Error)	(0.000)	(Std. Error)	(0.000)	(Std. Error)	(0.000)
Citing 3 Section	0.181***	Citing 3 Class	0.178***	Citing 3 Subclass	0.185***
(Std. Error)	(0.000)	(Std. Error)	(0.000)	(Std. Error)	(0.000)
Citing 4 Section	0.081***	Citing 4 Class	0.144***	Citing 4 Subclass	0.123***
(Std. Error)	(0.000)	(Std. Error)	(0.000)	(Std. Error)	(0.000)
Citing 5 Section	0.034***	Citing 5 Class	0.109***	Citing 5 Subclass	0.079***
(Std. Error)	(0.000)	(Std. Error)	(0.000)	(Std. Error)	(0.000)
Citing 6 Section	0.012***	Citing 6 Class	0.081***	Citing 6 Subclass	0.050***
(Std. Error)	(0.000)	(Std. Error)	(0.000)	(Std. Error)	(0.000)
Constant	$1.746 \cdot 10^{-8}$	Citing 7 Class	0.058***	Citing 7 Subclass	0.033***
(Std. Error)	(0.009)	(Std. Error)	(0.000)	(Std. Error)	(0.000)
R^2	0.999	Citing 8 Class	0.043***	Citing 8 Subclass	0.022***
		(Std. Error)	(0.000)	(Std. Error)	(0.000)

(Continued)

IPC Section	Model (1)	`IPC Class	Model (2)	IPC Subclass	Model (3)
		Citing 9 Class	0.032***	Citing 9 Subclass	0.015***
		(Std. Error)	(0.000)	(Std. Error)	(0.000)
		Citing 10 Class	0.024***	Citing 10 Subclass	0.011***
		(Std. Error)	(0.000)	(Std. Error)	(0.000)
		Citing 11 Class	0.019***	Citing 11 Subclass	0.008***
		(Std. Error)	(0.000)	(Std. Error)	(0.000)
		Constant	$2.765 \cdot 10^{-8}$	Citing 12 Subclass	0.006***
		(Std. Error)	(0.000)	(Std. Error)	(0.000)
		R^2	0.999	Citing 13 Subclass	0.005***
				(Std. Error)	(0.000)
				Citing 14 Subclass	0.004***
				(Std. Error)	(0.000)
				Citing 15 Subclass	0.003***
				(Std. Error)	(0.000)
				Citing 16 Subclass	0.002***
				(Std. Error)	(0.000)
				Constant	$5.442 \cdot 10^{-8}$
				(Std. Error)	(0.000)
				R^2	0.999

All patent characteristics are significant different in Table 10, which means we can use the patent characteristics in framework 3 as different intensity of patent citation. After we get the result from Table 10, we used the patent characteristics and patent own classification to compare the difference in the different intensity of cross-disciplinary. To observed the trend of the cross-disciplinary technology evolution with two dimensions, i.e. self-multi-technology (own classification) and citation relationship (intensity of patent citation).

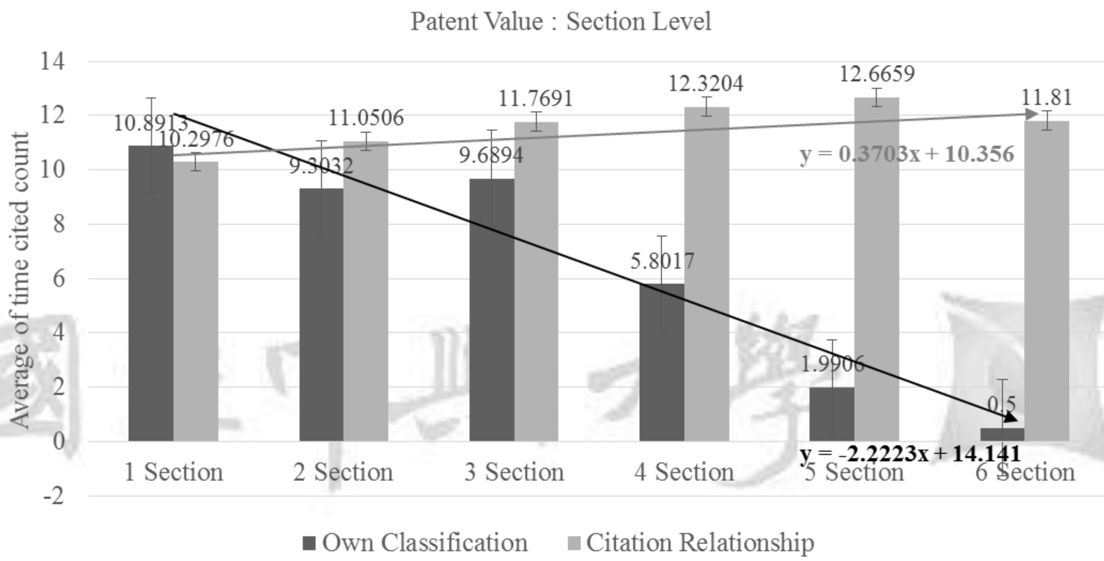

Fig. 11 The average time cited count with IPC section level, 1976-2013

Source: PATSTAT, own calculations.

In general, as observed in Fig. 11, the average time cited count of self-multi-technology (own classification) has decreasing from low degree self-multi-technology to high degree of self-multi-technology. But the average time cited count of cross-disciplinary technology has increasing from low degree of cross-disciplinary technology to high degree of cross-disciplinary technology.

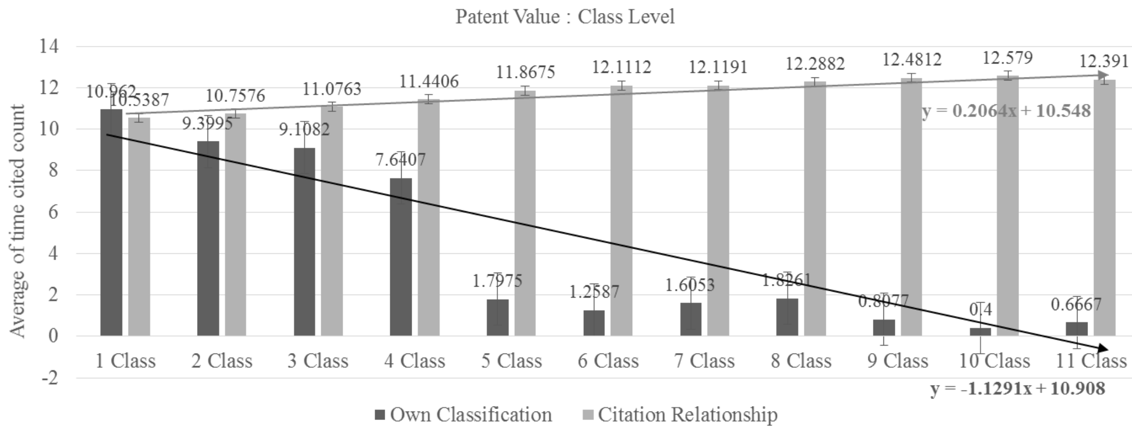

Fig. 12 The average time cited count with IPC class level, 1976-2013 Source: PATSTAT, own calculations.

Figs. 12 and 13 illusteate the average time cited count of self-multi-technology and cross-disciplinary technology by IPC class lavel and IPC subclass level with different degrees. Figs. 12 and 13 shows the same results that the average time cited count of self-multi-technology has decreasing from low degree self-multi-technology to high degree of self-multi-technology, and the average time cited count of cross-disciplinary technology has increasing from low degree of cross-disciplinary technology to high degree of cross-disciplinary technology.

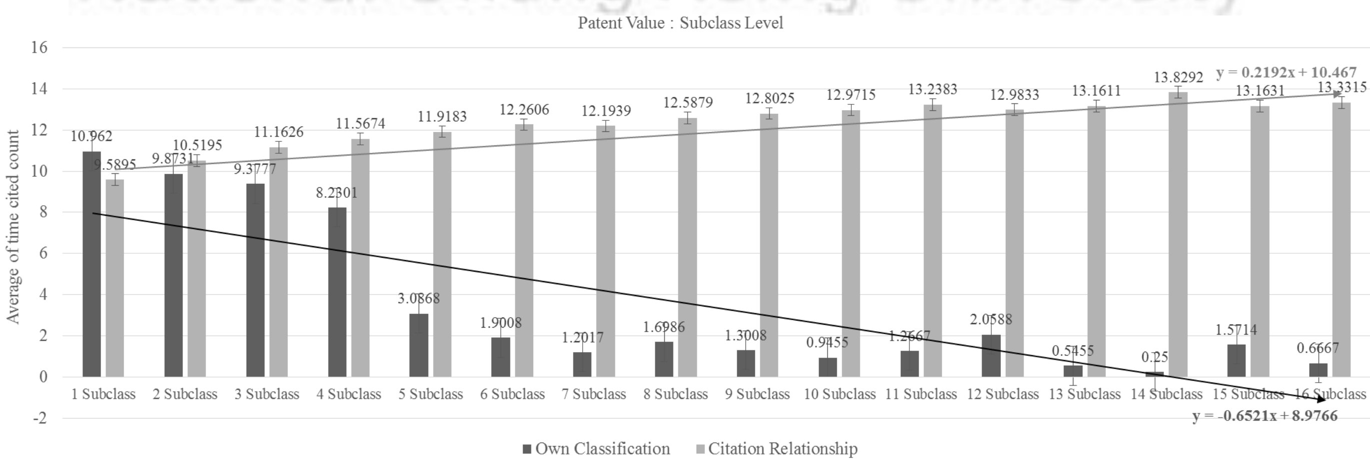

Fig. 13 The average time cited count with IPC subclass level, 1976-2013

Source: PATSTAT, own calculations.

4.4 Discussion of the results

There have several research findings as follows:

A. Table 5 shown the patent characteristics have significant differences in regression models, which means the patent characteristics can observe the patent value (time cited count of the patent). In framework 1, this paper considerate the nature of the patent citation (i.e. internationalization, litigation status, co-owner and co-inventor) to observe the patent value with different intensities. But there have some good patent characteristics can estimate the patent value like non-patent reference count, patent reference count and patent count. The non-patent reference count have been shown that can observe the relationship between industries and university, and the patent reference can estimate the patent value. So we used this two patent characteristics to observe the trend of cross-disciplinary technology in framework 2.

B. Fig. 3 shown that the patent citing the other patent with the far level of patent citation will have the higher patent value than the near level. Moreover, the results shown that this paper identify the cross-disciplinary technology by using different intensity of patent citation is well to illustrate the nature of cross-disciplinary technology.

C. Litigation patent has been considerate as a high value of technology in many thesis. Fig.5 shown the ratio of litigation patent in high intensity of cross-disciplinary technology has gradually replaced the low intensity of cross-disciplinary technology. Moreover, the results of Fig.5 shown that high intensity of cross-disciplinary technology become the main valuable patents.

D. There have some studies has shown that the patent indicator non-patent reference as the high influencing factor can estimate the intensity of the relationship of industry-university cooperation. Fig.6 shown that the higher the intensity of the cross-disciplinary technology has the higher probability to generate an industry-university cooperation.

E. Fig.7 shown that the high intensity of cross-disciplinary technology indeed have high number of reference than low intensity of cross-disciplinary technology, which means the high intensity of cross-disciplinary technology have the higher patent value than the low intensity of cross-disciplinary technology.

F. We can clearly to see that technical indeed continue toward the high intensity of cross-disciplinary technology development in Fig.8. In addition, technological development has gradually focused on high level of cross-disciplinary in Fig.9.

G. Figs. 11, 12 and 13 shown the higher intensity of cross-disciplinary technology will the higher patent value, and the results of framework 3 shown that the higher intensity of cross-disciplinary has a positive effect to a technology, but the higher intensity of self-multi-technology has a negative effect to a technology.

What factors have led to the overwhelming popularity of the cross-disciplinary? Probably the major reason for its success is the fact that such techniques are more valuable. The second reason for cross-disciplinary popularity is the fact that over time transitive, more and more industries tried to cooperate with other field's industries. One explanation for this is that technological diversification has become a trend no matter for different perspective to observe. Through the results we can systematic understanding the trend of evolution of technology and technology development is continuing towards diversity. Moreover, cross-disciplinary technology will become the mainstream trend. This paper already mention above through the past studies in literature review. There have three answer for answering the research questions as follows:

1) Whether the combination of different technologies is the trend of industrial development? The answer is yes, Fig. 3 shown that the value of internationalization, co-owner and co-inventor technology is higher than non-internationalization, non-co-owner and non-co-inventor technology. It also illustrate that the patent citing the other patent with the far level of patent citation will have the higher patent value than the near level. Fig.5 shown that high intensity of cross-disciplinary technology become the main valuable patents, and technical indeed continue toward the high intensity of cross-disciplinary technology development in Fig.8. 2) Whether the cross-disciplinary technology is more valuable technology? The answer is yes, Fig.5 demonstrate the ratio of litigation patent count of cross-disciplinary technology, and the high intensity of cross-disciplinary technology has become the main valuable patents. Figs. 11, 12 and 13 shown the higher intensity of cross-disciplinary technology will the higher patent value, and Fig.7 shown that the high intensity of cross-disciplinary technology indeed have high

number of reference than low intensity of cross-disciplinary technology.

3) Whether industry decides to develop a cross-disciplinary technology is good or not? The answer is yes, cross-disciplinary technology can indeed improve the value of the product, and may deepen the relationship between industries. Technical indeed continue toward the high intensity of cross-disciplinary technology development in Fig.8, and technological development has gradually focused on high level of cross-disciplinary in Fig.9. According to the above results, we can clearly to understand that the industries decide to development a cross-disciplinary technology will have high probability to get the new technology with high patent value.

V. Conclusion

The results of Fig. 2 clearly support the notion that multi-dimension technology, for example, internationalization patent and co-owner patent has an advantage over non-multi-dimension technology. These findings lead us to believe that different kinds of patent characteristics should be used in order to observe the trend of technology evolution in different views. Fig. 6 and 7 illustrate that technical indeed continue toward cross-disciplinary development. The degree of cross-disciplinary has a positive effect to a technology, but the degree of self-multi-technology has a negative effect to a technology. Three of these findings are worth summarizing: 1) Technical indeed continue toward cross-disciplinary development, 2) Technological development should focused on high level of cross-disciplinary, 3) The results indicated that integrating different technology into a new technology was beneficial to create the higher value of a new technology. Data were collected primarily by means of raw data from PATSTAT database, which have been used in several empirical studies such as Frietsch (2014). Research method is use data analysis, and the result were examined. These findings in this paper lead us to believe that continued research and development of cross-cutting technology should be used in order to accelerate industrial upgrading. The results of this study clearly support the notion that industries can enhance the competitiveness by developing the cross-disciplinary technology. The present study enhance the previous studies' findings by providing a much more detailed examination of the trend of cross-disciplinary evolution. Theoretical models of the structure of invention such as (Arthur, 2007; Kesidou & Demirel, 2012), need to be confirmed and modified through empirical evidence. The three studies and this paper can complement each other well, for each emphasizes a different aspect of the evolution of technological development. Discussion of these element of economic and political environment is beyond the scope of this paper. It is not within the scope of this paper to provide an extended discussion of the ongoing debates. Even though this body of research has the undeniable merit of offering valuable insights into the cross-disciplinary technology evolution, it has some limitations such as economy environment. This method of investigation is not without problems. "Citing 11 fields", "citing 12 fields" … "citing 35 fields" needs to be distinguish as research objects in the future in framework 2. The study does suggest that the detailed study of how cross-disciplinary acts are performed over time is a promising line of inquiry. Future research is obviously required, but this is an exciting first step.

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Appendix

IPC Section
(A~H)
Section – 1^{st} level

IPC Class
(A01~H99)
Class – 2^{nd} level

IPC Subclass
(A01B~H99Z)
Subclass – 3^{rd} level

IPC Section
A - HUMAN NECESSITIES
B - PERFORMING OPERATIONS; TRANSPORTING
C - CHEMISTRY; METALLURGY
D - TEXTILES; PAPER
E - FIXED CONSTRUCTIONS
F - MECHANICAL ENGINEERING; LIGHTING; HEATING; WEAPONS; BLASTING
G - PHYSICS
H - ELECTRICITY

IPC Class (Example)
A01 - AGRICULTURE; FORESTRY; ANIMAL HUSBANDRY; HUNTING; TRAPPING; FISHING
A21 - SUBJECT MATTER NOT OTHERWISE PROVIDED FOR IN THIS SECTION
B01 - PHYSICAL OR CHEMICAL PROCESSES OR APPARATUS IN GENERAL
B02 - CRUSHING, PULVERISING, OR DISINTEGRATING; PREPARATORY TREATMENT OF GRAIN FOR MILLING
C01 - INORGANIC CHEMISTRY
C02 - TREATMENT OF WATER, WASTE WATER, SEWAGE, OR SLUDGE
D01 - NATURAL OR MAN-MADE THREADS OR FIBRES; SPINNING
D02 - YARNS; MECHANICAL FINISHING OF YARNS OR ROPES; WARPING OR BEAMING
E01 - CONSTRUCTION OF ROADS, RAILWAYS, OR BRIDGES
E02 - HYDRAULIC ENGINEERING; FOUNDATIONS; SOIL-SHIFTING
F01 - MACHINES OR ENGINES IN GENERAL; ENGINE PLANTS IN GENERAL; STEAM ENGINES
F02 - COMBUSTION ENGINES; HOT-GAS OR COMBUSTION-PRODUCT ENGINE PLANTS
G01 - MEASURING; TESTING
G02 – OPTICS
H01 - BASIC ELECTRIC ELEMENTS
H02 - GENERATION, CONVERSION, OR DISTRIBUTION OF ELECTRIC POWER

IPC Subclass (Example)
A01D - HARVESTING; MOWING
A21B - BAKERS' OVENS; MACHINES OR EQUIPMENT FOR BAKING
B01B - BOILING; BOILING APPARATUS
B02C - CRUSHING, PULVERISING, OR DISINTEGRATING IN GENERAL; MILLING GRAIN
C01B - NON-METALLIC ELEMENTS; COMPOUNDS THEREOF
C02F - TREATMENT OF WATER, WASTE WATER, SEWAGE, OR SLUDGE
D01H - SPINNING OR TWISTING
D02H - WARPING, BEAMING, OR LEASING
E01B - PERMANENT WAY; PERMANENT-WAY TOOLS; MACHINES FOR MAKING RAILWAYS OF ALL KINDS
E02C - SHIP-LIFTING DEVICES OR MECHANISMS
F01L - CYCLICALLY OPERATING VALVES FOR MACHINES OR ENGINES
F02D - CONTROLLING COMBUSTION ENGINES
G01G – WEIGHING
G02B – OPTICAL ELEMENTS, SYSTEMS, OR APPARATUS
H01C - RESISTORS
H02H - EMERGENCY PROTECTIVE CIRCUIT ARRANGEMENTS