Preliminary Paper

Fusion Technology and Its Value: Evidence from Korean Patent Data

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Abstract

Innovations are increasingly crossing industry boundaries and fusion technologies have been rapidly developed in the advanced and newly industrialized economies. Given the trend of the increasing importance of fusion technologies in innovations, this paper examines the values of fusion technologies compared to standalone technologies. The paper first hypothesizes fusion technologies are more valuable than standalone technologies. Second, it investigates whether fusion technologies have higher value in the firm which has the more diversified technology base. Previously unrelated technologies are blended and consolidated. Older, current and emerging technologies are fused to create new values. Thus, a firm's diverse technologies may become a new driver of competence-building through technology fusion when technological paradigm changes in the unpredictable manner. To test hypotheses, event-study analysis and survival analysis are used alternatively. Whereas event-study analysis based on abnormal returns

and their determinants is to see market valuation of a technology, survival analysis focuses on the value of technology itself, not income flows accruing from a technology.

In the paper, three distinctive data sets are consolidated for variable constructions. They are patent application data from the Korean Intellectual Property Office, financial data from the Korean Information Service, and scientist-researcher data for the Korea Science and Engineering Foundation. Korean patent data have inventors' identification codes. Then, we can identify a different person of the same name in the data. If an individual patent has inventors from various technological areas, then it can be considered a fusion technology. This paper figures out the number of technological areas involved in a patent application by matching patent data with the scientist-researcher data.

The contribution of the paper is to provide empirical evidence about how valuable fusion technologies are and the relationship between technology fusion and diversification. It will also contribute to the literature on fusion technology and related policies by suggesting three decision criteria about whether a technology is fused one or not using inventors' private information, IPC co-occurrence, and patent citations.

1. Introduction

Technology fusion combines incremental technical improvements from previously separate fields of technologies to create new products. In the early 1990s, Kodama(1992) who coined the term "technology fusion" noticed that innovations were increasingly crossing industry boundaries. He observed that Japan's textile industry spent 70% of its total R&D outside its principal product area and new fiber developed by the textile industry has potential for building materials and medical equipment. Asahi Kasei, a leading textile producer is using its fiber technology to make building materials and a filtration system for kidney dialysis machines. In Korea, Cheil Industries, the former leading textile company which is now classified to a chemical firm and is applying its fiber technology to electronic materials and chemicals. According to Kodama (1992), the market is a driving force to technology. For example, when the customer wants a cheaper, smaller, and more reliable numerical controller for a machine tool, Fanuc created an affordable numerical controller and became a market leader by fusion existing electronic, mechanical, and materials technologies (Kodama, 1992).

Technological diversification of a firm is another source of technology fusion (Choo, 2007). Through recombination of a wider variety of technologies, new fused technologies emerge. Lee (2002) suggests that technologically diversified firms are consciously and constantly mixing and juxtaposing their technologies. Diversity increases the possibility that a previously untried combination will be attempted (Lee 2002). Technology fusion also grows out of R&D collaboration between firms affiliated to different industries or having different technology portfolios.

Fusion technologies come into spotlight from business executives and scientists. It is policy makers and managers of the R&D projects funded by governments that show great interests in technology fusion. Nowadays fusion technologies are becoming the strategic targets of national R&D. It is believed that newly fused technologies create higher value-added rather than traditional technologies. Thus, policy makers try to foster fusion technologies as a conduit for economic high growth. But, in the absence of adequate definition for fusion technologies, policy makers and managers of government R&D projects have a difficulty in selecting fusion technologies which are alleged to be winners in the future.

Despite rising research needs for technology fusion, there exist few studies which address it. With no agreeable definition, policy makers allocate resources depending on the decision of scientists which will be beneficiaries of the R&D funds. Researchers from public research institutes funded by national and local governments often define as fusion technologies particular categories of technologies which are to be fused easily and increasingly such as NT, IT, BT and ET. In addition, the components of a fusion technology and the fused technologies themselves are used interchangeably without distinction. Furthermore, Most of policy makers and managers of government R&D funds have their educational backgrounds in social sciences, or they are generalist even though they are technocrats. Therefore, they are dependent on the scientists which have specialties in specific technological areas. If a scientists argues that his scientific research belongs to fusion technologies, it is not easy to raise persuasive objections. That is, the allocations of scarce resources can be done by microscopic interests at the expense of macroscopic adjustments. From the above perception, this paper tries to provide the criteria for definition of fusion technologies. Another purpose of this paper is to provide evidence that fusion technologies are more valuable than standalone technologies. And then, it will further explore whether fusion technologies have higher value in the firm which has the more diversified technology base. This paper begins with a discussion with the hypotheses and the framework of analyses. In section 3, data and variables are described. Section 4 presents empirical results. Section 5 concludes.

2. Hypothesis and Methodologies

2.1. Hypotheses

Innovations are increasingly crossing industry boundaries and fusion technologies have been rapidly developed in the advanced and newly industrialized economies. Given the trend of the increasing importance of fusion technologies in innovations, this paper examines the values of fusion technologies compared to standalone technologies. The paper first hypothesizes fusion technologies are more valuable than standalone technologies. Second, it investigates the relationship between fusion technologies and a firm's technological diversity. Previously unrelated technologies become blended and consolidated. Older, current and emerging technologies are fused to create new values. Thus, a firm's diverse technologies may become a new driver of competence-building through technology fusion when technological paradigm changes in the unpredictable manner. To test hypotheses, event-study analysis and survival analysis are used alternatively. Whereas event-study analysis based on abnormal returns and their determinants is to see market valuation of a technology, survival analysis focuses on the value of technology itself, not income flows accruing from a technology.

2.2. Survival Analysis

Survival modeling permits us to examine the relationship between survival and one or more predictors. A patent has limited length of life. Furthermore, most of patent are terminated before the statutory life of 20 years (O' Donoghue et al., 1998; Mansfield, 1984; Levin et al., 1987; Schankerman and Pakes 1986). According to Pakes (1986), only 7 percent of French patents and 11 percent of German patents are maintained until the patents expires.

Maintenance fees must be paid to maintain a patent in force. Failure to pay the current maintenance fee on time may result in expiration of the patent. In the U.S., patent renewal fees are due at 3 ½, 7 ½ and 11 ½ years from the date a patent is granted. In Korea, patent owners can pay renewal fees annually. Considering that every year patent owners decide whether they extend patent protection to the next year, uncertainties in renewal decision of patent owners will decrease in Korea compared to the U.S.. From the fact that none of patent owners pays several years' maintenance fees in advance, we know that patent owners behave to reduce uncertainties on patent renewal decision.

From various parties such as patent lawyers, accountants, licensing executives, business strategists, and economists, attention has been paid to the patent valuation. Different valuation objectives lead to the wide range of valuation methods (Pithethly, 1997). Among the possible valuation approaches, this paper focuses on survival analysis using patent renewal data and event study which investigates the behavior of returns following a patent announcement. This paper aims to examine the value of fusion technologies by borrowing ideas from patent valuation methods.

It has been several decades since scholars recognized the informative values of patent document (Schmookler, 1966; Scherer, 1965). Recently, in U.S., hundreds of thousands patent documents are filed every year. The patent document is a thesaurus which contains valuable information on the innovative activities of economic actors. The concerned parties such as applicants, owners, and inventors disclose their information truly and voluntarily. There are little incentives to distort their information because written document presume whom the right and obligation of patent belong to, officially.

Among the information patent data provide to researchers, are citations and patent classification codes which can be used in constructing technology proximities or knowledge spillover pools (Jaffe and Trajtenberg, 2000; Jaffe, 1986; Choo and Lee, 2008). Recent studies pay attention to the details of a patent document such as inventors which are unexplored till lately (Kim et el., 2006; Kim and Marschke, 2004). Patent documents contain the information about rightful and responsible persons, licenser, and licensee. Some scholars matched voluminous patent data with other sources of data, for example the ProQuest Digital

Dissertation Abstracts database (Kim et el., 2006).

There are several potential methodologies to approximate the value of patent (Pithethly, 1997; Reitzig, 2004)). Surveys are conducted to gather the information not available in the patent files (Giuri el al., 2007). More recently, there was a big survey named PatVal-EU, and based on the survey a series of papers were presented (Giuri et al., 2007; Mariani and Romanelli, 2007; Gambardella et al., 2007).

Patent renewal data provide alternative sources to researchers which study patent valuations. If the renewal decision is made based on the returns generated by the patent right, patent renewal data can be used to estimate private patent values (Schankerman, 1991).

Since information of patent documents is voluminous, much part of the documents is left unexplored till recently. But, due to the rapid development of information and telecommunication technologies, whole of patent document were digitalized and easily excessible. Even information about administrative processes or legal procedures can be obtained in the form of digital files from the official patent office website. Some studies used such details of patent docoments in their analyses (Harhoff and Reitzig, 2004; Zeebroeck, 2007). In the literature patent renewal data are used relatively earlier (Federico, 1958; Pakes and Mark Schankerman, 1984) and attract attention from the academia again(Svensson, 2007; Zeebroeck, 2007; Deng, 2007). Better information on the side of patent owners is reflected in renewal decisions. On the assumption that depreciation rate is same over time and across technology fields, survival length of individual patent can be interpreted as patent value directly.

Patent right is effective within statutory limits of 20 years. Unpayment of maintenance fees terminates patents before expiration. Since voluntary maintenance is needed for a patent to be in force, patent data consist of various status of patents and show the feature of right-censoring which is common form of survival data. Limited length of life which patent has is similar to those of biological organisms or mechanical systems. Death or failure is considered an 'event' in the survival analysis literature. Social phenomena such as insurance cancellation, a firm's exit from an market, and overcoming unemployment can be events. These survival data are characterized by censored observations. Termination or expiration is another example of an event in the survival analysis.

With the survival model we can examine the relationship between survival and one or more predictors, usually termed covariates in the literature (Fox, 2002). This paper uses the Cox proportional hazards model which has been widely used in survival analyses.

The Cox model has the following form.

$$h_i(t) = h_0(t)\exp(\beta_1 x_{i1} + \beta_2 x_{i2} \cdots + \beta_k x_{ik})$$

In log form,

$$\log h_i(t) = \log h_0(t) + \beta_1 x_{i1} + \beta_2 x_{i2} \cdots + \beta_k x_{ik}$$

where X_i s are covariates which affect the hazard function $h(t)$.

The hazard function $h(t)$ assesses the instantaneous risk of a patent being killed in a specific time period Δt, given that it has been renewed until time t (Fox, 2002; Svensson, 2007).

That is,

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr[(t \le T < t + \Delta t) \mid T \ge t]}{\Delta t} = \frac{f(t)}{S(t)}$$

$S(t) = pr(T > t) = 1 - F(t)$

where $S(t)$ implies how a large share of the patents survives beyond a time point *t* (Svensson, 2007).

2.3. Event Study

In finance, an abnormal return is the difference between the expected return of a security and the actual return.

The abnormal return of asset *i* in period *t* is

$AR_{it} = R_{it} - R_{it}^{normal}$

where AR_{it} , *t* = T1, . . . ,T2 are the series of abnormal returns for firm *i* in the event window.

To compute abnormal returns, we first define the normal returns. The normal return is defined as the return that would be expected if the event did not take place (Campbell et. el, 1997). Abnormal returns are sometimes caused by "events" such as mergers, dividend announcements and lawsuits. Public announcement that a patent was granted may contribute to an abnormal return.

With pooled abnormal returns across firms, we can test the impact of the event on stock returns. Under the null hypothesis that the event has no impact on the behavior of

returns, $AR_{it} \sim N(0, \sigma_e^2)$.

We can check whether the average abnormal return for each stock is statistically different from zero with the statistic

$t = \frac{AR_t}{\hat{S}_t}$, where $\hat{S}$ is the abnormal return standard deviation and $AR_t = \frac{\sum_{i=1}^{N} AR_{it}}{N_t}$

In addition to looking at the average abnormal returns for each company, we can use the aggregate abnormal returns by computing cumulative abnormal returns(CAR).

That is,

$$CAR_{(t_1,t_2)} = \sum_{t=t_t}^{t_2} AR_t \ .$$

Following Choi (2007), as a test statistic for CAR this paper uses $t = \frac{CAR_{(t_1,t_2)}}{\hat{S}_{(t_1,t_2)}}$,

where $\hat{S}_t = \sqrt{\left(\sum_{t=t_0}^{t_1-1}(AR_t - AR)^2 / (t_1 - t_0 - 1)\right)}$, $AR = \sum_{t=t_0}^{t_1-1} AR_t / (t_1 - t_0)$,

$$\hat{S}_{(t_1,t_2)} = \hat{S}\sqrt{(t_2 - t_1 + 1)}$$

In Korea, patent owners pay renewal fees yearly except first 3 years to keep the patents in force. Figure 1 shows the existing renewal fee schedule. The annual renewal fees are progressive in the year elapsed. Moreover, the additional fees per claim also increase monotonically. The patent owner chooses the lifespan of the patent, T, to maximize the discounted value of net revenues (Schankerman, 1991).

That is,

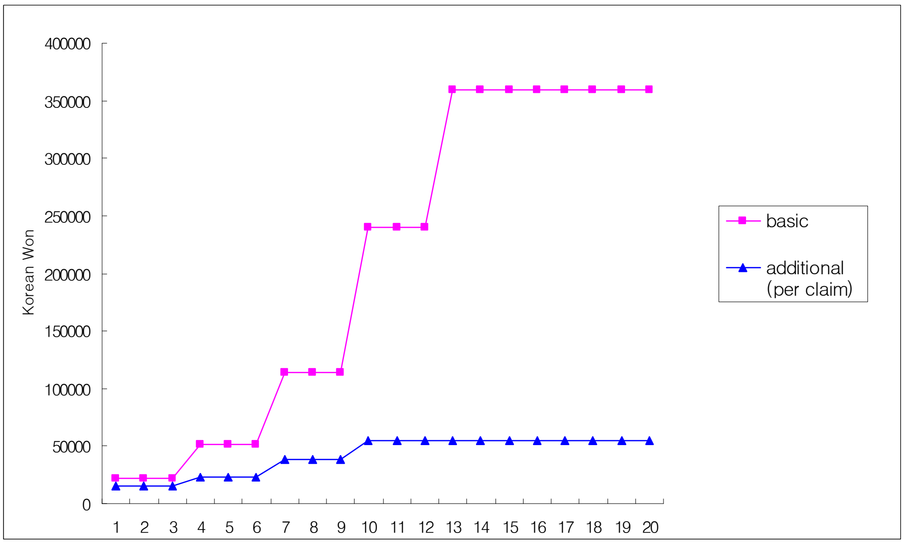
$$\underset{T\in(1,\cdots,M)}{Max} V(T) = \sum_{i=1}^{T} \beta^i (R_{ic} - C_{ic})$$

where β is the discount factor and N is the statutory limit to patent protection, R_{ic} , C_{ic} is the return and renewal fee to holding the patent at time *i*, respectively.

On the assumption that the sequence of net revenues $(R_{ic} - C_{ic})$ is non—increasing in age, the condition for renewal of the patent at age t is that the annual returns to holding the patent cover the renewal fee(Schankerman, 1991).

$R_{ic} > C_{ic}$

Figure 1. Patent renewal fee schedule in Korea



3. Data and variables

3.1. Data Sources

The data used in this paper consist of distinctive data sets from several different sources: (1) patent registration data from the Korean Intellectual Property Office(KIPO); (2) corporate data from the Korean Information Service; (3) information of the scientists and researchers from the Korea Science and Engineering Foundation(KOSEF). (4) US patent data

3.1.1. Patent registration data

The patent data which this paper used were downloaded for the application year 1984-2005 from KIPRIS, a publicly accessible patent database. All items in the patent documents such as applicants, status of applications, international patent class, abstract, inventor, even information on the administrative and legal procedure can be downloaded. But, downloaded data are not easily applicable to a study.

One can only download one file that contains 5,000 applications at a time. About 1,495 text files were downloaded and arranged by variables through the SAS program. Matching applicants in the patent data with company names in the financial data is needed. All applicants and inventors receive their identification numbers. Unfortunately the downloaded files do not include them. But, I had an opportunity to participate in a KIPO's research project as a project manager and could get a part of the numbers enough to match the patent data with other database.

3.1.2 Corporate data

This paper uses patent announcements and some financial information such as R&D investment and sales. These are obtained from the Korean Information Service which is a credit-rating company and provides on-line corporate and financial information. The data covers the announcements of patent acquisition made from 1995 to 2007. But, this preliminary paper only covers announcements from 2002-2006 and for domestic patents.

3.1.3. KOSEF data

The Korea Science and Engineering Foundation is one of the research support institutes. Its annual budget exceeded 1 billion US dollars in 2005. Specialized in basic science research and fundamental R&D, the institute relates itself to researchers affiliated to universities or public research institutes rather than corporates' researchers. To receive project through KOSEF Researchers should register in the institute in advance. Most of the registered researchers have higher academic degrees. Ph.D.s who obtained their degree abroad should register obligatorily to be authorized. For the registered researcher, it is admitted to search scholarly information on other researchers one by one. Repeating the search, the information of 80,979 researchers is identified. Among them fields of studies irrelevant to patent applicants are excluded when matching with inventor data.

3.1.4. U.S. patent data

This paper uses the U.S. patent data constructed by Hall et al.(2001). The data comprise detailed information on almost 3 million U.S. patents granted between January 1963 and December 1999, all citations made to these patents between 1975 and 1999(Hall et al., 2001) The information which used in this paper is generality and originality. In addition, I extracted IPC code with the U.S. patent data obtained from KIPRIS to see whether IPC codes of each individual patent co occur or not.

3.2 Data description

KOSEF data have more information than that available in a researcher's curriculum vitae. We can find researcher's field in detail, for example; security and QoS in wireless sensor networks. But, this paper uses somewhat broad classification. With the information of researchers' subjects we can construct the classification corresponding to 2-digit, 3-digit, and 4-digit industry classification. Furthermore, since researchers reported their subjects where they can play referees' roles, the proximities may be measured.

When matching inventor data with researcher data, I use inventor and researcher's birth information to prevent different persons with the same name from matching together. Majority of the researchers listed in KOSEF databases are those affiliated to universities or public research institutes. Nevertheless, the firstly obtained patent data file includes only firms' inventors. Thus, the number of researchers which has ever had one or more granted patents is just 9,046 and the number of subjects is 1,117. If inventors from universities and research institutes are included, quite a number of researchers will be found.

3. 3. Variables

3.3.1. Co-occurrence

Co-occurrence indicates that some patent applications have multiple IPC codes. Patent documents are classified by at least one classification code. The code which appears first in the patent document is the main or primary classification, and the others are secondary or supplementary classifications. Several empirical suggestions can be made from the multiple classifications. First, the frequencies by which two classification codes co-occur are interpreted as a sign of the strength of knowledge relatedness (Bresch et. al 2003).

Second, the co-occurrence of technology classes can be interpreted from the point of knowledge flow. Verspagen(1997) distinguishes between the main IPC code and the supplementary code. He assumes that the main classification code provides a good proxy of the knowledge-producing sector, while the additional supplementary IPC codes give an indication of technology spillovers to other industrial sectors.

Third, co-occurrence can be an instrument of technological diversification (Choo, 2007). Technological diversity may be an endogenous variable since it can depend on the amount of R&D invested or the feedback of firms' productivity. Co-occurrence of IPC codes is determined by patent examiners and not influenced by firms' productivities. It is reasonable to assume that a patent officer is neutral on factors that are not referred to when the officer grants a patent to the application. The neutrality of the patent officer, with regard to granting only one IPC code or multiple codes, guarantees no correlation between co-occurrence and productivity (Choo, 2007). Forth, IPC Co-Occurrence gives a basis for the analysis of technological combination in the sense that it represents the existence of different technological fields in one invention document (Suzuki el al., 2008). These interpretations are somewhat interrelated. This paper approaches in the viewpoint of third and forth. The paper uses two type of co-occurrences. One(*Cooc*) is the number of co-occurrence, whether a patent has multiple IPC codes or not(*Cooc2*) is another. The count is based on IPC subclasses such as A61Q and B82B. Total number of subclasses is 576. IPC co-occurred maximumly 7 times and at the subclass level 6 times.

3.3.2. Number of inventors.

The paper counts the number of inventors (*no_app*) for each patent. Since the number of different research fields in a patent was constructed from the matched patent data with researcher data, the sample size decreased. Therefore, the paper uses the number of inventors as a alternative proxy for the number of research fields for the whole sample. This paper suggests that the number of researcher from different technology fields is the best measure for technology fusion as long as we can construct the variable. Two types for the variable are used. They are the simple count of different research fields in a patent(*cooc_maj*) and a dummy variable which implies whether more than one research field were involved in the invention(*multi_maj*). The paper made the variable by matching patent data with researcher data. But, sample size shrinks because quite a number of researchers employed in firms did not report their information to the KOSEF. Therefore, the paper added alternatives to the independent variable list as the second and third best.

3.3.3. Originality

We may conjecture that fusion technology cites various fields of patents. Therefore, the paper checks the variables *cooc_maj* and *multi_maj*'s correlations with other constructed variables to see whether the proxies for the fusion technologies are acceptable. But, Korean patent documents did not have the citations till lately. Thus, the paper tests with U.S. patent data.

Trajtenberg et al.(2001) integrated a wide variety of citations-based measures into two distinctive measures. They are generality and originality and defined in the same way as the diversification index.

$$Original_i = 1 - \sum_{k=1}^{N_i} \left(\frac{NCITED_{ik}}{NCITED_i}\right)^2$$

$$General_i = 1 - \sum_{k=1}^{N_i} \left(\frac{NCITING_{ik}}{NCITING_i}\right)^2$$

where *NCITING* denotes the number of patents citing the originating patent, and *NCITED*. denotes the number of patents cited by the originating patent. The larger is *Original* the broader are the technological roots of the underlying research. Therefore, we may infer higher *Original* implies the synthesis of divergent ideas (Trajtenberg el al., 2001).

Both measures may be positively correlated with technology fusion. However, this paper suggests that originality is more related to technology fusion than generality because *Orginal* measures the diversity of underlying technologies.

3.3.4. Other control variables

A patent application will be taken up for examination only if a request for examination is made either by the applicant or by any interested party within 5 years from the filing date of the application. Whether the request for examination is delayed or not may depend on the technological and/or managerial decision of a firm and reflects the value of a patent somehow. Therefore, the paper includes this variable (*Claim_interval*). In literature, the number of claims of a patent is used as a measure of patent quality, alternatively with citations. In addition, patent quality can vary across owners and technology fields. Thus, the paper considers these as controls.

4. Results.

4.1 Summary statistics

Table 1 summarizes variables. The number of observations used in the paper is 718,424 granted patents applied for in the years 1984 ~ 2005.

Table 1. Summary statistics for variables

Variable	Obs	Mean	Std. Dev.	Min	Max
cooc	715,424	0.06	0.27	0	5
cooc2	718,424	0.05	0.23	0	1
no_app	718,424	2.25	1.86	1	34
claim_interval	709,800	0.95	1.71	0	6
# of claim	716,164	8.23	9.65	0	645
event	718,424	0.26	0.44	0	1
live	186,930	10.01	3.70	0	21
foreigner	718,424	0.34	0.47	0	1
domestic firm	718,424	0.52	0.50	0	1
government	718,424	0.00	0.04	0	1
research institute	718,424	0.03	0.17	0	1
university	718,424	0.01	0.12	0	1
individual	718,424	0.10	0.30	0	1
multi_investors	718,424	0.50	0.50	0	1
cooc_maj	27,800	1.22	0.56	1	8
no_maj	27,800	1.27	0.64	1	13
multi_maj	9,067	0.53	0.50	0	1
matching	365,877	0.01	0.11	0	1
matching2	365,877	0.03	0.27	0	8

26% of 718,424 patents were expired or terminated. Average length of patent lives is 10 years from the application date. While an average patent has 8 claims, maximum of the number of claim is 645. Foreign applicants occupy 34% of registered patents applied for 1984~2005. The share of university patents is quite small. It was partly because technology managements of Korean universities take off at 2000s. Before 2000s, professors tended to apply for patents by their names. The greatest number of inventors identified by their research fields in a patent is 13 and the largest number of research fields involved in a patent is 8.

From the patents just having one research field, patents with more than one inventors are excluded. Thus, 9,067 patents were obtained and used to make the dummy variable *multi_maj*. The variable, *matching* is constructed by adding unmatched patents with only one inventors among the whole sample to the matched sample of 9,067. The variable *matching2* permits the variation of the number of research fields. That is, the variable *matching2* is not a dummy variable.

Table 2. Correlation between variables (large sample)

	# of claim	**# of app.**	**cooc**	**cooc2**	**multi_inv**	**cooc_maj**	**multi_maj**	**matching**
# of application	0.215							
p-value	<.0001							
obs.	716,164							
co_occurrence	0.046	0.058						
p-value	<.0001	<.0001						
obs.	715,424	715,424						
co_occurrence dummy	0.042	0.057	0.947					
p-value	<.0001	<.0001	<.0001					
obs.	716,164	718,424	715,424					
multi_inventors	0.215	0.679	0.050	0.048				
p-value	<.0001	<.0001	<.0001	<.0001				
obs.	716,164	718,424	715,424	718,424				
cooc_major	-0.042	0.359	0.085	0.091	0.165			
p-value	<.0001	<.0001	<.0001	<.0001	<.0001			
obs.	27,236	27,800	27,233	27,800	27,800			
multi_major	0.032	0.741	0.113	0.113	0.991	0.812		
p-value	0.0028	<.0001	<.0001	<.0001	<.0001	<.0001		
obs.	8,883	9,067	8,881	9,067	9,067	9,067		
matching	0.009	0.847	0.035	0.036	0.996	0.812	1.000	
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	
obs.	365,018	365,877	364,496	365,877	365,877	9,067	9,067	
matching2	0.008	0.875	0.038	0.040	0.960	0.972	0.927	0.963
p-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
obs.	365,018	365,877	364,496	365,877	365,877	9,067	9,067	365,877

Table 2 presents the correlation between variables. All correlations are positive and significant. The correlation between *cooc* and *no_app* is 0.058 and 0.085 between *cooc* and *cooc_major*. The correlation between *cooc_major* and *no_app* is 0.359 and much higher than previous ones. Table 3 is for the subsample where the values of *multi_maj* exist. In this case, the correlations between variables are much higher than that of the whole sample. But, the correlation between *no_claim* and *cooc* changes to the negative.

Table 3. Correlation between variables (subsample)

	# of claim	# of app.	cooc	cooc2	multi_inv	cooc_maj	multi_maj
# of app.	0.037						
cooc	-0.033	0.141					
cooc2	-0.035	0.154	0.962				
multi_inv	0.032	0.750	0.111	0.114			
cooc_maj	0.017	0.764	0.144	0.156	0.809		
multi_maj	0.032	0.743	0.113	0.117	0.991	0.814	
matching	0.024	0.792	0.139	0.148	0.921	0.972	0.928

Variables related to fusion technologies of U.S. patent data are described in Table 4. NBER data do not provide multiple IPC codes. The variable *cooc* shown in table 4 is calculated from the data obtained KIPRIS by the author for the year 1990~1999. In U.S. data, IPC codes co-occur 25 times at the maximum. The largest number of co-occurrence of different IPC codes by subclass is 14.

Table 4. Summary statistics of U.S. patents (1990~1999)

variable	obs.	mean	min	max
# of inventors	2,147,767	2.011	1	34.000
general	2,081,698	0.324	0	0.937
original	2,050,363	0.349	0	0.951
gen_orig	1,543,617	0.336	0	0.909
cooc	821,109	1.193	1	14.000

Note: The variable *gen_orig* is the mean of generality and originality

Table 5 reports the correlations between variables related to fusion technologies. As expected, *original* shows higher correlations with *cooc* and *no_inv* than *general*. It implies that technologies citing various fields of technologies are more probable to be fusion technologies than patents cited from many fields.

Table 5. Correlations between variables (U.S. patents)

	no_inv.	general	original	gen_orig
general	0.012			
p-value	<.0001			
obs.	1,610,961			
original	0.042	0.233		
p-value	<.0001	<.0001		
obs.	2,050,362	1,543,617		
gen_orig	0.035	0.789	0.781	
p-value	<.0001	<.0001	<.0001	
obs.	1,543,617	1,543,617	1,543,617	
cooc	0.074	0.063	0.100	0.117
p-value	<.0001	<.0001	<.0001	<.0001
obs.	821,109	430,365	796,051	420,925

Table 6 displays the correlations obtained from mean values by subclass. If aggregated to the classification level of subclass, the correlation between *cooc* and *original* increases to 0.304. It is obvious that taking means of variables increases the correlations between variables. However, in some case it may be appropriate for policymakers to see at aggregate level. Table 1 to 5 are calculated at individual patent level. In the table 1 to 5, a patent is considered as a technology. But, sometimes in the viewpoint of policymakers, data at aggregate level may be more useful.

Table 6. Correlations between variables(using means by subclass)

	cooc	no_inv	general	original
no_inv	0.242			
p-value	<.0001			
general	0.131	0.237		
p-value	0.008	<.0001		
original	0.304	0.102	0.579	
p-value	<.0001	0.0408	<.0001	
gen_orig	0.260	0.176	0.845	0.926
p-value	<.0001	0.0004	<.0001	<.0001

4.2. The results of survival analysis

Figure 2 shows the Kaplan-Meier survival estimates of the patents with multiple research fields(*matching*=1) and the patents with only one research fields(*matching*=0). In figure 3, the values of research fields are used, not taking a dummy variable. Figure 4 and 5 are for IPC co-occurrence. For the figure 5, the two-sample logrank test rejects the null hypothesis at 1% level that the two groups have similar survival distributions. We can conjecture from the Kaplan-Meier estimates that a fusion technology has higher survival rate than stand-alone invention.

Figure 2.

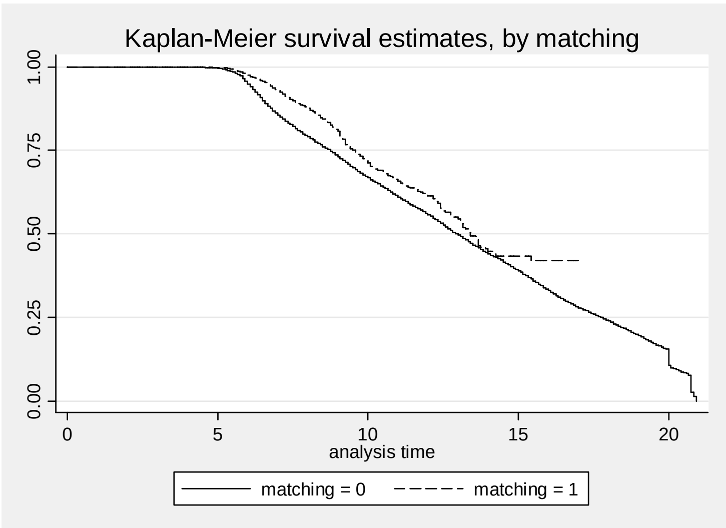


Figure 3.

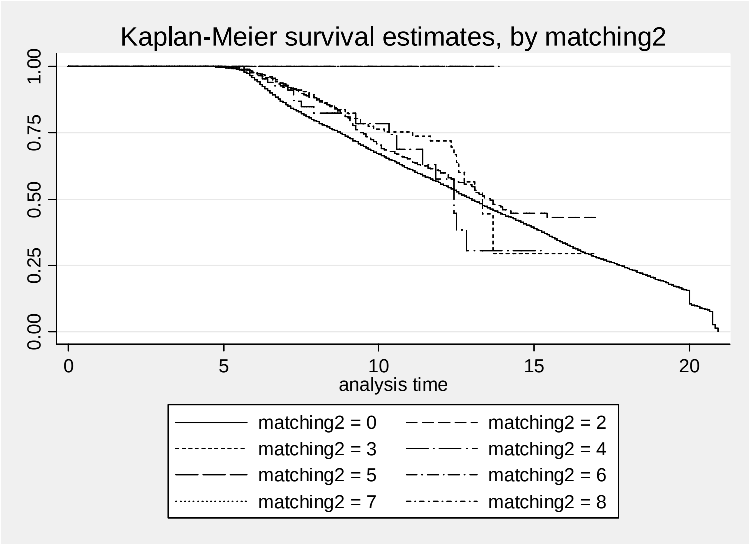


Figure 4.

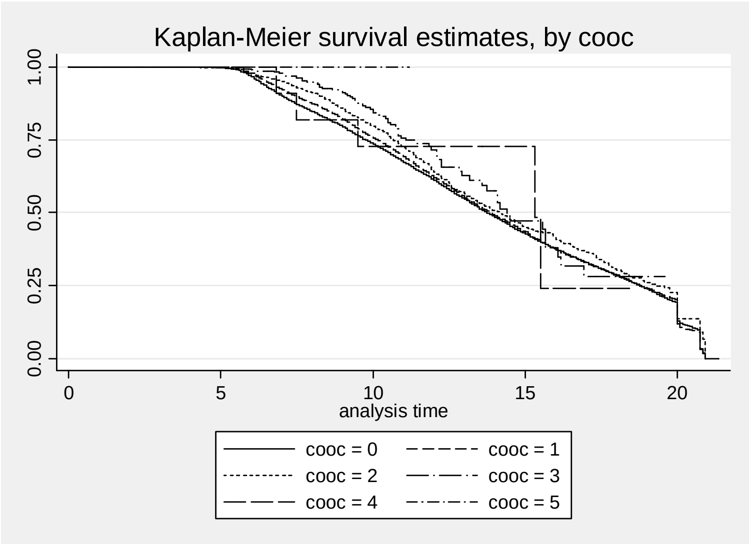
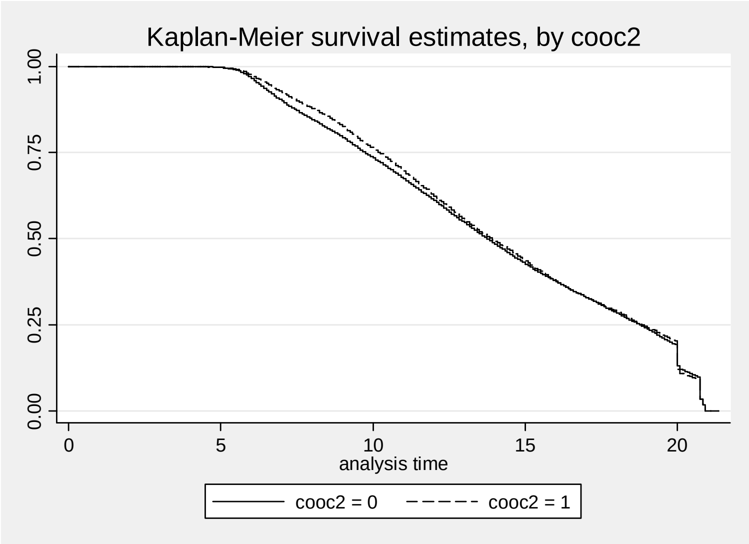
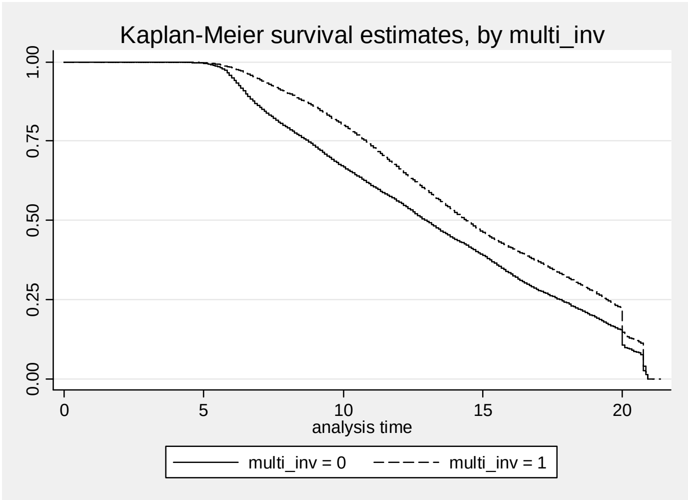


Figure 5.



Note: The variable, *cooc* is a dummy variable which indicates whether IPC codes of a patent co-occur or not.

Figure 6



Note: The variable, *multi_inv* indicates whether the number of inventors involved in a patent is more than one or not.

Table 7 displays the Cox regression with no controls to get just sketchy knowledge for the concerned variables. All alternative variables for technology fusion except *multi_maj* decrease the hazard rate significantly. Next, the paper adds control variables to the Cox regression. The results are shown in table 8. In the full models, the variables for fusion technologies are negative and highly significant except *matching*. In the table 8, the variables *tech 2~6* are dummy variables for technological fields. The classification used here followed the one elaborated in collaboration with the Observatoire des Sciences and des Techniques (OST, Paris), Institut National de la Propriete Industrielle (INPI, Paris), and Fraunhofer Gesellschaft-ISI (Karlsruhe)(OECD, 1994). They regrouped IPC codes into 30 different technology fields and then aggregate to 6 broader fields. This paper uses the 6 broader fields. The baseline technology field in table 8 is the electrical-electronic technologies. All other technology fields show significant positiveness. This means the hazard rate is lowest in technology field 1. Another category is the types of applicants. The baseline type is foreign applicants. Foreigners' patents have much longer life than other types except the patents owned by the government.

Table 7. Regressions without other controls

		Coef.	z	P>z	# of subjects	# of failures	LR chi2
model1	# of app.	-0.09	-64.14	0.00	718,147	186,930	4,700(0.00)
model2	multi_inventors	-0.40	-86.11	0.00	718,147	186,930	7,418(0.00)
model3	multi_maj	0.11	1.90	0.06	9,066	1,176	3.6(0.06)
model4	matching	-0.28	-6.61	0.00	365,723	98,881	48.1(0.00)
model5	matching2	-0.13	-6.74	0.00	365,723	98,881	50.8(0.00)
model6	cooc	-0.06	-6.53	0.00	718,147	186,643	43.7(0.00)
model7	cooc2	-0.05	-5.41	0.00	718,147	186,930	29.8(0.00)

Table 8. Regression with controls

	model1	model2	model3	model4	model5	model6	model7
# of app.	-0.06						
	-38.99***						
multi_inv.		-0.27					
		-51.23***					
multi_maj			-0.18				
			-2.41**				
matching				-0.38			
				-8.44			
matching2					-0.17		
					-8.60***		
cooc						-0.04	
						-4.69***	
cooc2							-0.05
							-5.31***
# of claim	-0.01	-0.01	-0.02	-0.01	-0.01	-0.01	-0.01
	-22.25***	-22.58***	-3.44***	-18.67***	-18.66***	-27.18***	-27.24***
claim_interval	-0.17	-0.17	-0.26	-0.21	-0.21	-0.17	-0.17
	-121.31***	-120.07***	-9.39***	-84.84***	-84.85***	-116.18***	-119.94***
tech2	0.20	0.20	0.25	0.28	0.28	0.19	0.19
	22.07***	22.17***	2.54**	22.07***	22.07***	21.08***	21.10***
tech3	0.35	0.35	0.22	0.32	0.33	0.29	0.29
	44.50***	45.73***	2.50**	21.71***	21.76***	37.55***	37.43***
tech4	0.39	0.40	0.50	0.39	0.39	0.37	0.37
	50.58***	51.17***	5.34***	34.78***	34.78***	48.02***	48.13***
tech5	0.63	0.62	0.63	0.72	0.72	0.63	0.63
	95.66***	93.82***	5.89***	87.15***	87.15***	96.48***	96.52***
tech6	0.42	0.41	0.11	0.44	0.44	0.43	0.43
	42.60***	41.01***	0.49	36.66***	36.66***	43.47***	43.58***
domestic firm	0.07	0.05	-2.49	0.07	0.07	0.12	0.12
dummy	12.26***	8.26***	-4.92***	7.72***	7.72***	19.12***	19.71***
owned by	-2.32	-2.34	-45.12	-1.31	-1.31	-2.40	-2.39
government	-12.07***	-12.14***	.	-2.93***	-2.93***	-12.46***	-12.44***
university	0.07	0.07	-1.60	0.30	0.31	0.01	0.01
dummy	3.95***	4.05***	-3.13***	7.12***	7.17***	0.31	0.58
research institute	0.16	0.18	-2.44	0.22	0.23	0.14	0.14
dummy	3.63***	4.01***	-4.67***	2.73***	2.80***	3.05***	3.14***
individual dummy	0.50	0.47	-2.49	0.42	0.42	0.56	0.56
	54.47***	50.76***	-4.64***	34.10***	34.10***	61.35***	61.93***
# of subjects	709,132	709,132	8,832	361,960	361,960	708,421	709,132
# of failures	181,019	181,019	1,174	96,169	96,169	180,758	181,019
LR chi2	42,942(0.00)	43,923(0.00)	296(0.00)	24,323(0.00)	24,328(0.00)	41,255(0.00)	41,317(0.00)

4.3. The results of the event study analysis

Table 9 reports the results of an event study analysis. The analysis includes 574 announcement of patents granted from 214 listed firms. The paper used market-adjusted return model.

That is,

$$AR_{it} = R_{it} - R_{it}^{normal}$$

where R_{it}^{normal} is market returns.

As an estimation window, the paper used 30 days estimation window (that is, from the 60^{th} trading day to 31^{st} trading day before the announcement date). The overlapping announcements within estimation and event window are excluded

Table 9 shows that there are announcement effects shortly before and after the announcement. This is more clarified by table 10. When narrowing and moving the event window, there exist announcement effects for the windows (-5, +5), (-5, 11) and (-2, +1). Table 11 represents cross-section analyses with CARs as dependent variables. The table shows the effect of the variable *cooc* on the CARs. In all specifications, the coefficients are positive. For event windows (-5, -1) and (-2, +1), the variables are significant at 5% level. For event windows (-30, +20) and (-5, +5), the variables are marginally significant. Therefore, we can conclude that announcements of fusion technologies have positive effects on the abnormal returns.

Table 9. Abnormal returns(AR) and cumulated abnormal returns(CAR)

date	AR	AR_t	CAR	CAR_t
-30	-0.0012	-0.79	-0.0012	-0.79
-29	-0.0015	-1.00	-0.0027	-1.21
-28	-0.0010	-0.69	-0.0037	-1.39
-27	-0.0007	-0.44	-0.0044	-1.42
-26	0.0011	0.69	-0.0033	-0.91
-25	-0.0005	-0.30	-0.0038	-1
-24	-0.0002	-0.12	-0.0039	-0.98
-23	-0.0043	-3.11***	-0.0082	-1.96*
-22	-0.0018	-1.31	-0.0100	-2.30**
-21	-0.0004	-0.31	-0.0104	-2.33**
-20	-0.0004	-0.24	-0.0105	-2.29**
-19	0.0021	1.38	-0.0082	-1.77*
-18	-0.0006	-0.41	-0.0087	-1.77*
-17	0.0010	0.65	-0.0076	-1.47
-16	-0.0005	-0.31	-0.0077	-1.46
-15	0.0002	0.13	-0.0075	-1.35
-14	0.0013	0.91	-0.0058	-1.04
-13	0.0018	1.30	-0.0038	-0.67
-12	-0.0017	-1.23	-0.0056	-0.94
-11	-0.0025	-1.81*	-0.0079	-1.31
-10	-0.0001	-0.07	-0.0078	-1.24
-9	-0.0015	-1.05	-0.0093	-1.45
-8	-0.0011	-0.77	-0.0106	-1.62
-7	0.0014	1.02	-0.0091	-1.37
-6	0.0001	0.08	-0.0088	-1.31
-5	-0.0004	-0.29	-0.0091	-1.34
-4	0.0015	1.06	-0.0077	-1.11
-3	0.0004	0.27	-0.0070	-0.99
-2	0.0035	2.31**	-0.0037	-0.52
-1	0.0044	3.10***	0.0011	0.15
0	0.0028	1.87*	0.0044	0.61
1	-0.0033	-2.43**	0.0009	0.12
2	-0.0006	-0.44	-0.0001	-0.01
3	-0.0014	-0.93	-0.0007	-0.09
4	0.0008	0.53	0.0003	0.03
5	0.0012	0.86	0.0020	0.24
6	0.0000	-0.02	0.0019	0.22
7	0.0017	1.15	0.0035	0.41
8	0.0026	1.74*	0.0052	0.6
9	0.0017	1.12	0.0070	0.8
10	0.0009	0.61	0.0080	0.89
11	-0.0007	-0.42	0.0074	0.82
12	-0.0026	-1.81*	0.0052	0.57
13	0.0018	1.21	0.0075	0.8
14	0.0031	2.24**	0.0110	1.15
15	0.0003	0.24	0.0115	1.17
16	-0.0024	-1.62	0.0091	0.92
17	-0.0016	-1.05	0.0068	0.68
18	-0.0015	-1.06	0.0059	0.59
19	0.0019	1.30	0.0078	0.77
20	0.0008	0.58	0.0086	0.85

Note: All CARs are accumulated from 30 days before announcement date.

Table 10. CARs by various event windows

	CAR	t-value
(-30, +20)	0.0086	0.85
(-30, -1)	0.0011	0.15
(-5, +5)	0.0099	2.18**
(-5, -1)	0.0096	3.18***
(-2, +1)	0.0075	2.56**
(-1, +1)	0.0039	1.56
(0, +1)	-0.0005	-0.22
(0, +5)	-0.0002	-0.05

Table 11. Cross-section analysis with CARs

	CAR(-30, +20)		CAR(-5, +5)		CAR(-5, -1)		CAR(-2, +1)	
variable	Coef.	t-value	Coef.	t-value	Coef.	t-value	Coef.	t-value
cons.	-0.122	-4.06***	-0.024	-1.89*	-0.010	-1.23	-0.013	-1.56
cooc	0.117	1.71*	0.057	1.86*	0.042	2.08**	0.048	2.42**
rnd_inten	0.001	0.96	0.001	1.35	0.001	2.89***	0.001	2.06**
y02	0.151	3.46***	0.034	1.74*	0.027	2.16**	0.015	1.26
y03	0.105	2.74***	0.018	1.04	0.024	2.23**	0.017	1.58
y04	0.128	3.60***	0.033	2.12**	0.017	1.67*	0.017	1.76*
y05	0.094	2.92***	0.034	2.41**	0.017	1.84*	0.019	2.15**
tech2	0.064	2.13**	0.011	0.78	-0.006	-0.68	0.003	0.33
tech3	0.042	1.41	-0.004	-0.27	-0.006	-0.66	0.002	0.22
tech4	0.038	0.97	0.009	0.52	0.000	0.00	0.015	1.29
tech5	0.074	1.94*	0.018	1.06	0.007	0.65	-0.003	-0.30
tech6	0.043	1.00	0.008	0.42	0.003	0.25	-0.003	-0.25
Adj R-sq.	0.025		0.004		0.014		0.008	

Note: Dependent variables are CARs obtained by each event window.

5. Concluding remarks and suggestions for further work

This preliminary paper suggests that fusion technologies have higher value than stand-alone technologies. It also investigates the high possibilities of three alternative proxies of fusion technologies. In the paper, distinctive data sets are consolidated for variable constructions. The paper identifies a different person of the same name in the different source of data. Above all, the problem afflicting the researchers which try to relate inventors' characteristics to innovation was cleaned up in the paper. The paper also suggests the new idea that if an individual patent has inventors from various technological areas, then it can be considered a fusion technology. This paper figures out the number of technological areas involved in a patent application by matching patent data with the scientist-researcher data.

The paper tries to make a contribution by providing empirical evidence about how valuable fusion technologies are and the relationship between technology fusion and diversification. But, the latter was not conducted yet due to voluminous data and time constraint. IPC co-occurrence can be interpreted as an instrument variable of technological diversification (Choo, 2007) and also as a proxy measure of fusion technologies. In addition, whether fusion technologies have higher value in the firm which has the more diversified technology base should be examined.

This paper also tries to contribute to the literature on technology fusion and related policies by suggesting some decision criteria about whether a technology is fused one or not. Candidates for the criteria are co-occurrence of inventors' research fields, IPC co-occurrence, and patent citations. For the policy implications, the fields of technologies needs to be aggregated. The examinations mentioned above will improve the paper.

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