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Abstract

This paper empirically investigates the effects of patent thickets. One unique feature of our study is to identify two sources of patent thickets: (1) complementarity as measured by the number of the patents to be used jointly with the focal patent in commercialization, and (2) ownership fragmentation as measured by the number of firms whose patents are cited by an examiner for the granting of the focal patent.

There are three major findings. First, there is a significant difference between complex industry sectors and discrete ones regarding complementarity, while the difference regarding fragmentation at the patent level is small. Second, more complementarity is significantly associated with the importance of first mover advantage in research and development (R&D) and (less significantly) with that in commercialization, while fragmentation has little effect on them. Consistent with this finding, complementarity is associated with high patent value. Third, cross licensing motivation significantly accounts for patenting propensity while blocking motivation does not. Complementarity is significantly associated with more patenting for cross licensing, which facilitates both combining the inventions of different firms and preventing the risk of being held up. Furthermore, it does not invite patenting for blocking.

Thus, we do not see significantly negative consequences of patent thickets on R&D, as seen by incumbents. At the same time, it is important to pay focus on policy to avoid granting patents to low quality inventions and to facilitate the mechanism of ex-ante contracting in complex industry sectors where patenting motivations are high.

Keywords: Complementarity, Fragmentation, First mover's advantage, Patenting motivations, Patent thickets, Patenting propensity, Veto rights
JEL classification: O34, O31, O32

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1. Introduction

There is widespread and growing concerns about the patent thicket and its impacts (see recent reports by the UK Intellectual Property Office (2011), Hall et. al (2012), and EPO (2013)). Patent thicket can be defined as a situation where a firm needs to use many complementary patents owned by the other firms in producing its own product. Shapiro (2001) defined the thicket as “a dense web of overlapping intellectual property rights that a company must hack its way through in order to actually commercialize new technology.” Patent thicket may also exist in basic research activity, when the research requires access to many patented research tools (Heller and Eisenberg, 1998).

According to Shapiro (2001), patent thicket results in two problems. The first problem is patent complement problem. When a firm needs to obtain licenses from a number of separate and independent right holders, their royalties may become excessively high due to a double marginalization problem (Cournot problem). While the formation of a patent pool is one solution, it faces a coalition formation problem (Aoki and Nagaoka, 2005). The double marginalization problem reduces the return for each patent holder and underutilization of the patented technologies. It can also invite mutual blocking by manufacturing firms, where each firm tries to prevent its competitor from introducing a new product which uses the other’s patent. The problems are well illustrated by the recent patent battles in mobile phone sector as well as the past battles such as those between Wright Brothers and Glenn Curtis.

The second problem is hold-up problem. Comprehensive ex-ante contracting may be difficult to strike given a large number of patents. This makes a firm becoming more eager to defensively obtain patents to avoid hold-up problem in such sectors as semiconductor sector (Hall and Ziedonis, 2001; Ziedonis, 2004). Holdup opportunities may also create incentives for patenting for the purpose of asserting patents for royalty revenues. Holdup risk reduces the return from investing in commercializing inventions.

Cross-licensing for “solving” these patent thicket problems may have a problem of its own. Such practice reduces the lead time advantage and therefore, the appropriability of R&D (Bessen, 2003). When patentability standard is low, such effect would become stronger since a firm may get a patent to divert the profit away from the pioneer (Hunt, 2006). In such case, a firm uses patents not for appropriating the returns from own R&D but for obtaining return from the other's R&D (that is, free riding).

While much discussed, the empirical bases for these concerns are not well established. While there are a number of recent empirical works with that objective (see the following section for a review), we see the following three problems and our research agenda.

First, most existing studies on patent thicket tend to focus on fragmentation of ownership and do not simultaneously address complementarity. However, since proliferation of patenting and patent ownership fragmentation may be importantly driven by more combinatorial innovation opportunities (product innovation through combining many complementary technologies and more entries in R&D), a direct focus on complementarity is essential. Some studies use the incidence of "triples" and the relative forward citations as measures of complexity of technology or the depth of complementarity. However, these patent-citation-based measures have the fundamental constraint that they do not cover those cases where technologically independent patents have to be combined for a product innovation or for a process innovation. This study introduces a survey-based measure of complementarity.

Secondly, the existing works have not studied the effect of patent thicket on first mover advantage, although there exist some related studies regarding that of the ownership fragmentation on R&D and market value (Noel and Schankerman, 2013), and the timing of initial funding for a startup (Cockburn and MacGarvie, 2009). Since the first mover advantage is perhaps the most important appropriation method in many industries, the negative effect of patent thicket on the first mover advantage can have serious economic consequences. We assess how firms see the importance of the first mover advantage differently depending on the complementarity and the fragmented ownership.

Third, the existing studies have not clarified the mechanism of higher patenting propensity. The past literature (Hall and Zieodonis, 2001) suggests that preventing the risk of being held-up is an important reason for higher patenting propensity in the US semiconductor industry. However, the past literature does not analyze the patenting motivations comprehensively. If higher patenting propensity is brought about by more blocking motivations, the effect could be detrimental. If it is brought about by more licensing motivations, the effect can be more positive. If it is brought about by more "pure defensive patenting" motivations, it is costly but may not be so detrimental as the patenting for blocking. We examine which patenting motivation significantly accounts for higher patenting propensity and how each patenting motivation is associated with complementarity and fragmentation.

The rest of this paper is as follows. Section 2 reviews the existing literatures and Section 3 presents an analytical framework driving our empirical works. In section 4, we describe our data set, in particular our measures of complementarity and fragmentation. Section 5 represents estimation model and section 6 presents estimation results and we conclude in last section.

2. Literature Review

Ziedonis (2004) investigates how the fragmented ownership affects the patenting propensity in the US semiconductor firms. According to her analysis, the more fragmented patent ownership was, the higher a firm's patenting propensity was (see Table 2.1 for a summary of the prior literature). Reitzig (2004) analyzes how the size of the patent bulk (defined as a group of patents coherently protecting an invention) affects patent value in complex and discrete technologies. Depending on whether such bulk consists of substitute patents or complement patents, it is a "fence" or a "thicket", so that this measure does not provide a good measure of complementarity. He has found that the size of such bulk did not affect the value of a patent in complex technologies.

Noel and Schankerman (2013) empirically examine the effects of patent thicket on firms' valuations, firms' patenting propensities and firms' R&D spendings, using CR4 index based on backward citations. They found that greater concentration (less fragmentation) of patent rights among rivals reduced both R&D spending and patenting by the firm but it increasee its market value. Their interpretation is that the former results reflected less need to have an arsenal of patents to resolve disputes when there were fewer players, and the latter results reflected lower transaction costs.

Von Graevenitz et. al(2011a) found out that the fragmentation at technology level measured by HHI index and the complexity measured by the number of triples have significant and positive impact on the number of patent applications in each complex and discrete technology.

Galasso and Schankerman (2010) explores whether the duration of patent dispute (patent infringement case) becomes shorter or longer due to the effect of fragmented patent ownership. According to their results, there was significant evidence that patent dispute surprisingly ended earlier in the fragmented patent ownership situation, while the complementarity led to making the duration of patent dispute longer. The complementarity was measured by the relative level of the forward citations of the patent.

Cockburn and MacGarvie (2009) investigate how the ownership fragmentation influences the initial funding from a VC for the US software venture firms. They found the significant evidence that more fragmentation resulted in delayed initial funding for the US software venture firms. Moreover, they found that firms without patents became less likely to go public if they operated in a market characterized by patent thickets. Entezarkheir (2011) investigates the effect of fragmented ownership on the firm’s value measured by Tobin’s Q and found that the fragmentation diminished the firm’s market value.

Hall et. al (2013) empirically examine whether the complexity measured by the number of triples decelerated the entry timing of UK firms and they found that the complexity hindered the UK firms from entering so that their entries were discouraged.

Table 2.1 Literature review

Studies	Dependent Variable	Complementarity/Complexity	Fragmentation	Measurement Level	Results	Note
Ziedonis (2004)	# of US pat applications	-	Frag(=1-HHI of BCs)	Firm	Frag+	67 US semiconductor firms, 1980-94
Reitzig (2004)	Patent value	the number of (complementary patents) in the group which coherentaly protect one invention	-	Project	Not significant in complex technologoies	612 European patents and related inventions from 5 industries
Cockburn & MacGarvie (2009)	Hazard rate of intial funding	-	HHI of BCs, CR4 of BCs	Firm and Market?	HHI of BCs-	Cumulative stock of pats, the # of cited assignees, US software venture firms
Galasso&Schankerman (2010)	Hazard rate that court dispute ends	Complementarity(=the relative level of the forward citations of the patent)	Frag1(=1-CR4 of BCs), Frag2(=1-HHI of BCs)	Firm, Firm	Complementarity -,Frag1+, Frag2+	US patent infringement cases
Cockburn et al. (2010)	Licensing Cost (Dummy, licensing Cost/Sales)	-	Frag(=1-HHI of BCs)	Tech	Frag+	German Companies
Von Graevenitz et al. (2011a)	Ln(# of pat applications)	Complexity(=# of triples)	Frag(=1-HHI of BCs)	Tech, Tech	Complexity+, Frag+/-	Firms which applying pat app to EPO, 1980-2003
Von Graevenitz et al. (2011b)	Not Available	Complexity(=# of triples)	-	Tech	Not Available	Algorism Description
Entezarkheir (2011)	TobinQ	-	Frag(=1-HHI of BCs)	Firm	Frag-	1975 US publicly traded manufacturing firms, 1979-1996
Hall et. al (2013)	Hazard rate of entry	Complexity(=# of triples)	-	Tech	Negative	UK firms
Noel & Schankerman (2013)	(1)TobinQ, (2)# of US granted pats, (3)Ln(RD)	-	CR4 of BCs	Firm	(1)+, (2)-, (3)-	121 US software firms, 1980-99

Note: BC represents backward citations.

3. Analytical framework and hypotheses

3.1 Complementarity and the value of a patent

We consider a simple model explaining how the value of a patent depends on the scale of complementarity and on the level of ownership fragmentation, which guides our empirical analysis. We assume that the product needs N complementary patents. We assume that these patents become essential ex-post due to the sunk cost of commercializing the product. We denote the quality of patent i by α_i (%) which indicates its proportional effect of such patent on the value of the product. If these patents are owned by a single firm, there is no coordination problem across firms, and the value of the product, V, is given by

$$V(N,0) = \prod q_i\,,\ \ q_i = 1 + \alpha_i, \qquad (1)$$

with α_i>0. We denote a geometric average quality of a patent by $\bar{q}$, with

$$\bar{q} = 1 + \bar{\alpha}. \qquad (2)$$

$$V(N,0) = \prod q_i = \bar{q}^N \qquad (3)$$

When there are separate and independent (M+1) firms owning such patents necessary for the product (M represents the number of the other firms), the value of the product can diminish due to double marginalization problem as well as the other coordination failure. Coordination failure may occur through firms adding marginal patents (almost no technical value (q=1), but essential for the product) to the bundle, if the patentability standard is low. Thus, the value of the product is given by

$$V(N,M) = \theta(M)\bar{q}^N \quad (4)$$

$$\text{with } \theta(M) \leq 1, \partial\theta/\partial M \leq 0, \quad (5)$$

N represents the size of complementarity and M represents the fragmentation of ownership in the above expression.

The marginal value of a patent is given by

$$\partial V(N,M)/\partial N = (ln\bar{q})V(N,M) \quad (6)$$

, which increases with N. That is, the marginal value of a patent increases with more complementarity N. In addition, the average value of each patent is as follows.

$$v = V/N = \theta(M)\bar{q}^N/N \quad (7)$$

For the case of average quality of patents being independent of N, we have the following relationship.

$$\frac{\partial lnv}{\partial N} = \ln\bar{q} - \frac{1}{N} \cong \bar{\alpha} - 1/N. \quad (8)$$

This suggests that unless the average α is close to zero due to low patentability standard, the average patent value also increases with more complementarity N .

If we partially differentiate the average value of a patent in terms of M:

$$\partial v/\partial M = \partial\theta(M)/\partial M(q^N/N) < 0. \quad (9)$$

Thus, as the ownership becomes more fragmented, both the marginal and average value of each patent declines due to more coordination problem among the patent holders, for a given level of N. Such effect is amplified if ownership fragmentation is associated with the addition of low quality patents.

3.2 First mover advantages

We consider R&D incentive for additional complementary patents as well as the incentive for commercializing the patent, focusing on a manufacturing firm which uses the inventions internally generated for its production. As shown in the above section, more complementarity (larger N) is associated with higher marginal or average patent value, due to more synergy. Thus, we expect a stronger motivation for obtaining the first mover advantage in the R&D and for patenting additional complementary patent, since higher patent value strengthens the preemptive motivation in a patent race as shown by a patent race model (Loury, 1979). In addition, the existence of a large number of complementary patents makes the commercialization value of the focal patent larger, which also makes the benefit of obtaining the first mover advantage in commercializing the patent larger.

High complementarity is often accompanied with fragmentation of ownership. The effect of fragmentation (more number of firms, *M*) on R&D competition is ambiguous from a theory. Sharing the technology by more firms makes it more difficult for a firm to differentiate the product, even though the value of the product for the customers increases with more extensive combination. This makes the value of a patent lower, so that the first mover advantage in R&D can be expected to be smaller. A large number of firms also reduce the probability of winning the patent race by each firm. In addition, as discussed by Gilbert and Katz (2011), a firm may wish to count on the other firms to supply complementary patents, once it has one "essential" patent, when the firms distribute the gain based on ex-post Nash bargaining. On the other hand, more competition intensifies patent race, when each firm is rewarded for adding complementary patents. The effect of fragmentation (more number of firms, *M*) on the first mover advantage in commercialization is also ambiguous from a theory, since more competition in product market increases the value of first mover advantage (the difference between the first mover and the others becomes larger) while the chance of having such advantage becomes smaller.

Thus, we have the following hypotheses.

Hypotheses 1 on first mover advantages and patent value

(1) Complementarity increases the value of patent, while fragmentation tends to reduce the value of a patent.
(2) Complementarity can enhance the importance of realizing the first mover advantage (FMA) in R&D, since high complementarity is associated with high value of the complementary patent. It also enhances the importance of realizing the FMA in commercialization.
(3) The effects of fragmentation on the importance of realizing the FMA in R&D and in commercialization are ambiguous. They increase the patent

race and the value of the first mover advantage, but they would also cause value dilution, and more free riding.

3.3 Patenting propensity and patenting motivations

Patenting motivations inform us of the mechanism of higher patenting propensity due to patent thicket. We first inquire which patenting motivation among preventing the risk of being held-up, combining the inventions of different firms and blocking, significantly accounts for the variation of patenting propensity, controlling for a quality of the invention. Unlike past literature, we analyze the patenting motivations explicitly and comprehensively.

If preventing the risk of being held-up is important, we would expect that pure self-defense motivations would significantly account for higher patenting propensity. Patenting of an invention prevents others from suing the firm using its own (perhaps independently discovered) invention, although prior use defense (trade secret not patented but deposited) provides some protection in Japan. If promoting the combination of the inventions of different firms is also important as a patenting reason, we would expect that cross licensing motivation would significantly account for higher patenting propensity, since cross licensing not only serves for reducing the risk of being held up (cross licensing is a mechanism of a mutual forbearance in holding-up) but also for combining the inventions of different firms. There is also another risk that more complementarity and more ownership fragmentation results in actual mutual blocking. In this case, a blocking motivation would drive higher patenting propensity.

Hypothesis 2 on patenting propensity

If preventing the risk of being held-up is a major consideration, pure self-defense motivation would significantly account for higher patenting propensity. If the combination of the inventions of different firms is also important in addition to preventing the risk of being held-up, cross-licensing motivation would significantly account for higher patenting propensity. On the other hand, if blocking is the primary driver, blocking motivation would significantly account for higher patenting propensity.

We then investigate how these patenting motivations are associated with complementarity and ownership fragmentations. When preventing the risk of being held-up becomes the main concern as complementarity and fragmentation increase, pure self-defense motivation significantly increases with them. If sharing technology becomes additional important objective, the cross-licensing motivation significantly increases with complementarity and fragmentation, and at the same time, the patenting motivation for exclusive exploitation can become weaker in relative sense since a higher value due to high complementarity can enhance the motivation for exclusive exploitation too. If the increase of the opportunity for blocking is important, the blocking motivation increases significantly with complementarity and ownership fragmentations.

Thus, we can develop the following hypothesis for empirical examination.

Hypothesis 3 on patenting motivations

If complementarity and fragmentation increases the risk of being held-up, they would significantly enhance the pure self-defense motivation. If complementarity and fragmentation also increase the opportunities and necessities of the combining the inventions of different firms, they would significantly enhance the cross-licensing motivation. On the other hand, if complementarity and fragmentation increase blocking, they would enhance the blocking motivation.

4. Description of Data

4.1 Data sources

The empirical analysis is based on two data sets: (1) R&D project level data from RIETI inventor survey and (2) Japanese patent data from the IIP patent database. The first data set that we use is “RIETI (The Research Institute of Economy, Trade and Industry in Japan) inventor survey”. This survey collected detailed information from a sample of inventors in Japan and it was conducted during January to June in 2007. The data comes from two sets of inventors: the randomly selected inventors of the basic patent of triadic patents which were granted patents in the US and whose applications were filed at Japan Patent Office and European Patent Office from 1995 to 2001, and those of non-triadic patents filed during the same period. The response rate for this survey is 20.6% (the number of response is 5,278 / the number of posts is 25,642).

The aim of this survey was to collect detailed information on invention process, commercialization process and patenting process from inventors at R&D project level. The questionnaire of this survey covers basic information on inventor's profile as well as applicant's profile, in addition to the objective of R&D project, type of the project, knowledge sources, the other invention inputs and its quality from inventors who actually participated in R&D project. Most importantly for this analysis it asked an inventor to identify the scale of complementary patents, that is, how many patents need to be exploited together for the purpose of commercializing the focal patent.

The second data set that we use is that IIP patent database which was compiled for academic researchers (hereinafter referred to as the IIPPD). The patent database provided by the Institute of Intellectual Property is currently the most comprehensive source of Japanese patent bibliography information and it covers all patent applications filed by the Japanese Patent Office (JPO)[1]. This IIPPD includes the bibliographic information contained in the application to the JPO, such as the patent application number, the application date, the number of claims, the relationship of the cited and citing patents based on examiner citations, the inventor's name, the applicant name, and the applicant address. We manually matched Japanese company names whose samples are limited to listed firms with applicant names in IIPPD[2]. In addition, we use the database of the publication of the patent applications and the other documents (Koho database), which has been developed by Jinko Seimei Kenkyuzyo, a private database firm, in Japan and then we have extracted the inventor citation data from Koho database.

We have assigned an industrial sector for each Japanese applicant, based on the following methodology. First, we have matched the corporate financial data, called "Nikkei NEEDS" (covering listed firms) and "Teikoku Data Bank" (covering non-listed firm) with patent applicant data. A publicly traded (listed) Japanese firm has a primary Japan Standardized Industrial Classification code (SIC code) assigned and we use this SIC code (we use 25 aggregated sectors as used in Survey of Intellectual

[1] For some details, please see Goto and Motohashi (2007).

[2] For name-matching process, please see Onishi et. al (2012).

Property-Related Activities industry code (See Appendix table A.1). Similarly, we use the industry code of Teikoku Data bank for non-listed firms.

4.2 Measuring Complementarity

There are some literatures which attempted to measure the size of complementarity: Galasso and Schankerman (2010), Von Graevenitz et. al (2011a), Von Graevenitz et. al (2011b), and Hall et. al (2013). Galasso and Schankerman (2010) measure complementarity as the ratio between the non-self-citations that the relevant patent has received from those patents in the relevant technology class and the non-self-citations received by all patents in the relevant technology class. This is essentially the relative forward citations. Other studies use the "triple" as a measure of the size of complexity (Von Graevenitz et. al, 2011a; Von Graevenitz et. al 2011b; Hall et. al, 2013)[3]. The triple is defined as the group of 3 firms in which each firm has critical prior art limiting claims on recent patent applications of each of the other two firms, from the perspective of backward XY citation.

As Galasso and Schankerman (2010) state, a direct and ideal measure of complementarity is the number of the actual set of patented inputs used by each firm. Using the survey results, we calculate this measure of the size of complementarity by industrial sectors as the average number of complementary patents jointly used. This measure is based on the data set from RIETI inventor survey, which asked an inventor the number of Japanese patents (including the other firms' patents) is jointly used in the commercial exploitation of the focal patent[4].

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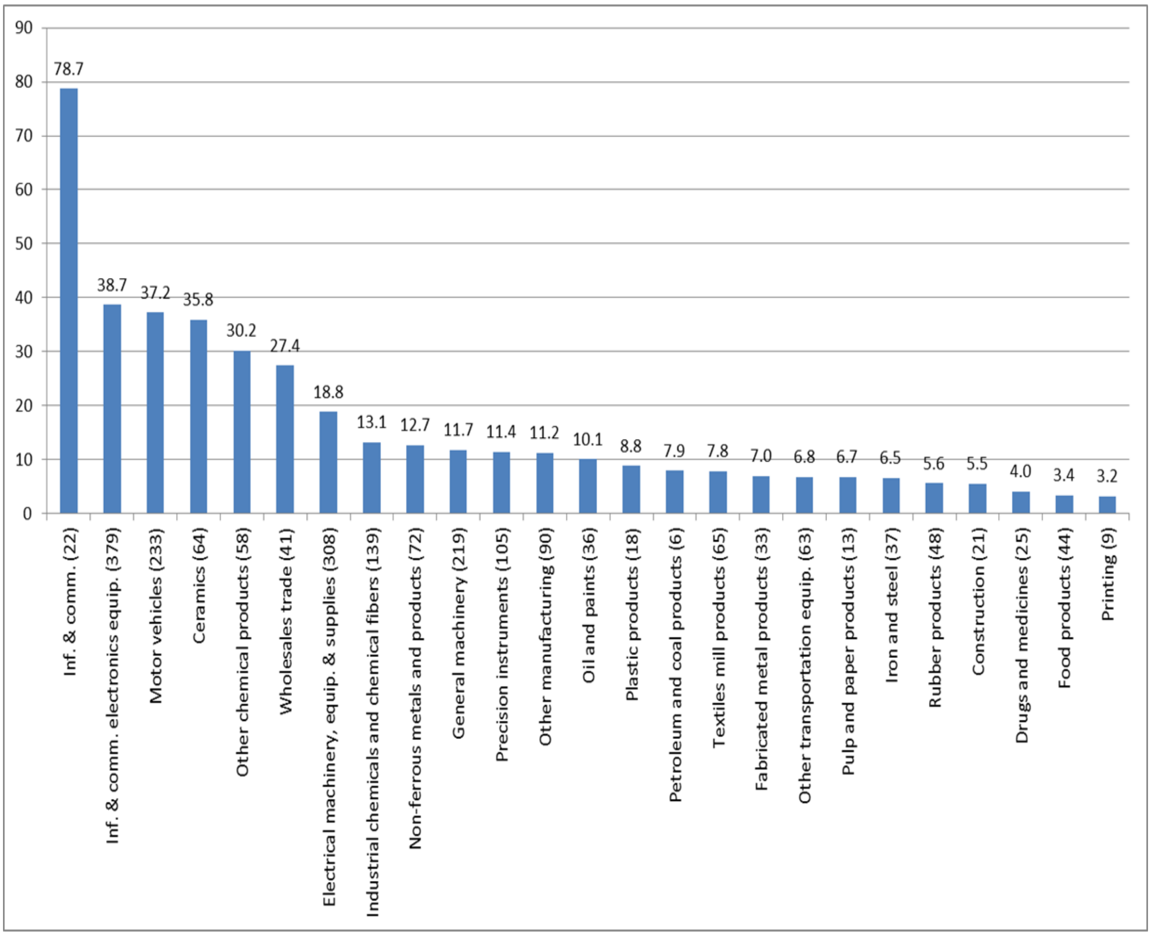
[3] Von Graevenitz et. al (2011a) perceive the concept of the triple as the index of technological complexity in their contexts (Von Graevenitz et. al, 2011b, p.15).

[4] In this survey, we have eight choices for the inventor's answer to the question, "how many domestic patents (including the other firms' patents) are jointly used in the commercial application of the invention?": (1) only a single patent, (2) 2-5 patents, (3) 6-10 patents, (4) 11-50 patents, (5) 51-100 patents, (6) 101-500 patents and (7) 501-1000 patents and (8) more than 1000 patents. We assign each answer choice the mean of figure range such as 1, 3.5, 8, 30.5, 75.5, 300.5, 750.5, and 2000 respectively to calculate the weighted average number of complementary patents necessary for commercializing an invention.

Figure 4.1 The size of complementarity across industrial sectors



Note. The numbers in the bracket indicate the sample size.

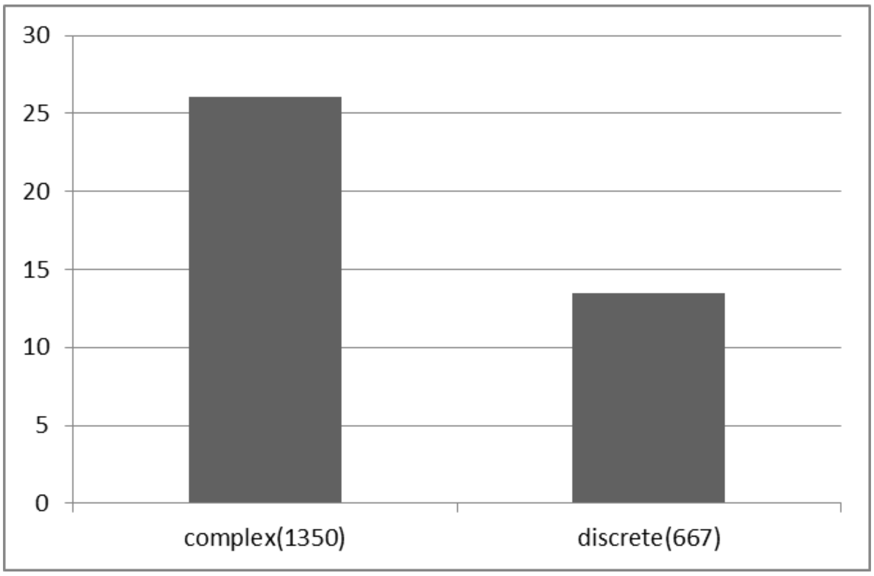
Figure 4.1 illustrates the distribution of complementarity index across industrial sectors[5]. ICT sectors such as information and communication (78 patents), information & communication electronics equipment (39 patents), and motor vehicles have high level complementarity index. Meanwhile, some industries such as drugs and medicines (around 4 patents), and food products (3.4 patents) have low level of complementarity index. These results are consistent with the observations made in existing literatures.

Figure 4.2 depicts the mean value of the size of complementarity between the complex industrial sectors and discrete industrial sectors, which is based on the classification by Cohen et. al (2000). The size of

[5] Those figures in the blanket for each industrial sector indicates the number of sample firms which, in RIETI survey, respond the question about the number of complementary patents necessary for commercializing a product.

complementarity in complex industrial sectors is almost twice higher than that in discrete industrial sectors and we found the statistically significant difference in the size of complementarity between complex and discrete sectors ($t = 3.23$, $p<0.01$) (Figure 4.2).

Figure 4.2 Complementarity index by complex and discrete industrial sectors



Note. The numbers in the bracket indicate the sample size.

4.3 Measuring Fragmentation

The measurement of fragmented ownership in existing literatures is based on backward patent citations. In our study, we use the examiner's backward patent citations since these prior arts are cited during the examination process as the literature potentially negating or restricting the claims of the patent right of the invention. These examiner citations are similar to XY citations in the search report of a European patent. Since we have been able to identify and standardize only the names of the listed Japanese firms, we identify the owners of the cited patents only for these firms. However, the coverage of these firms is very high (more than 80%).

Our measure of fragmentation, the number of cited applicants at patent level, is based on the count of firms who have the patents cited by the examiner with respect to the focal patent (Cockburn and MacGarvie, 2009)[6].

Fragmentation= the number of cited applicants,

The idea for this measure is that a cited patent functions as a veto right which blocks the citing applicant from using her own technology. We also assume that there is no blocking patent when there are no examiner citations. We have constructed this measure from examiner's backward citations data of IIP patent database, matched with the Japanese listed firms[7]. Given that we use pure examiner citations, our index is more similar to the index based on EPO patent database rather than US patent database. Appendix presents some data on the comparison of the fragmentation measures based on examiner citations and inventor citations.

The level of fragmentation at product or process level is very likely to depend both on the level of fragmentation at a patent level as well as on the number of patents to be used together for implementing the product or process, which is equivalent to our measure of complementarity. For an example, if product A needs 10 times more patents than another product B, the ownership of the patents for product A is more likely to be diversified than that for product B, even though the number of firms cited by a patent for product A is the same as that for product B. This point needs to be born in mind in interpreting the coefficients of the fragmentation and complementarity variables in our statistical estimations. That is, if we denote the fragmentation index at a patent level by m, the fragmentation at product level is given by the following.

$$M = \rho m + \mu N \ with \ \rho > 0, \mu > 0 \qquad (10),$$

Thus, the combined effect of the complementarity and fragmentation at product level can be written as

$$AN + BM = (A + B\mu)N + B\rho m \qquad (11).$$

The above equation says that the coefficient of complementarity index N estimated from the right-hand side of equation (11) picks up the effect of the fragmentation unless the effect of the diversification is zero ($B = 0$).

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[6] The number of cited patent applicants is used by Cockburn and MacGarvie (2009). 1- HHI (Herfindahl-Hirschman Index) is used by Ziedonis(2004), Cockburn et. al (2009), Galasso and Schankerman (2010), Extezarkheir (2011), and Cockburn and MacGarvie (2009). 1 - CR4(Concentration Ratio of Top 4 firms in the share of backward citations received) is used by Noel and Schankerman (2013), Galasso and Schankerman (2010), and Cockburn and MacGarvie (2009).

[7] See Goto and Motohashi(2007) about detailed information on IIP patent database. See Appendix 1 about how we calculate the fragmentation in more details.

Figure 4.3 exhibits our fragmentation measure by industrial sectors (the mean value of each fragmentation index at each patent level by industry): the number of firms which have the patents cited by the relevant applicant (fragmentation). In ICT sectors such as information & communication electronic equipment and electrical machinery and equipment and supplies, the level of fragmentation is high (2.5 firms) while it is low in drugs (1.0 firms) and fabricated metal products (1.5 firms). However the variation is smaller compared to that for complementarity index.

Figure 4.3 Fragmentation index across industrial sectors (2001-2010)

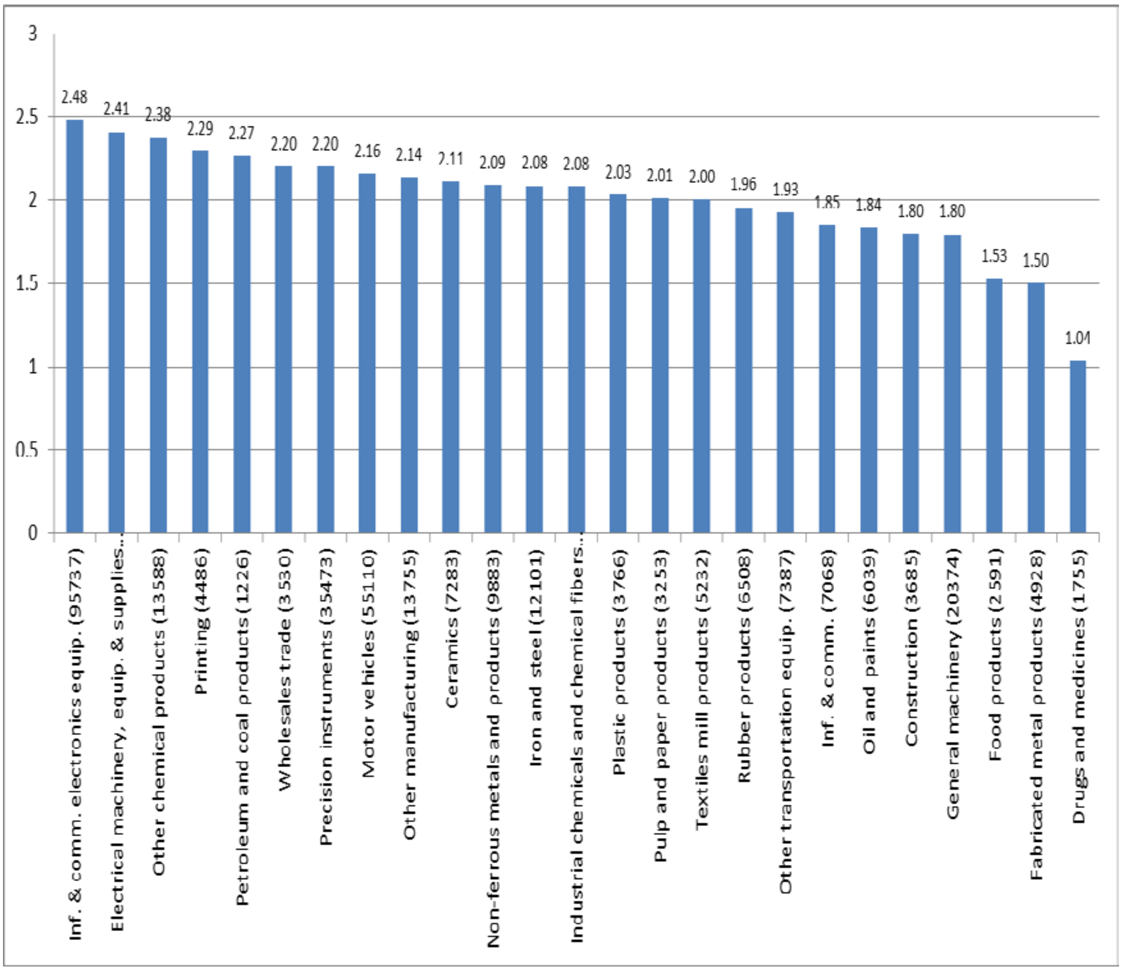
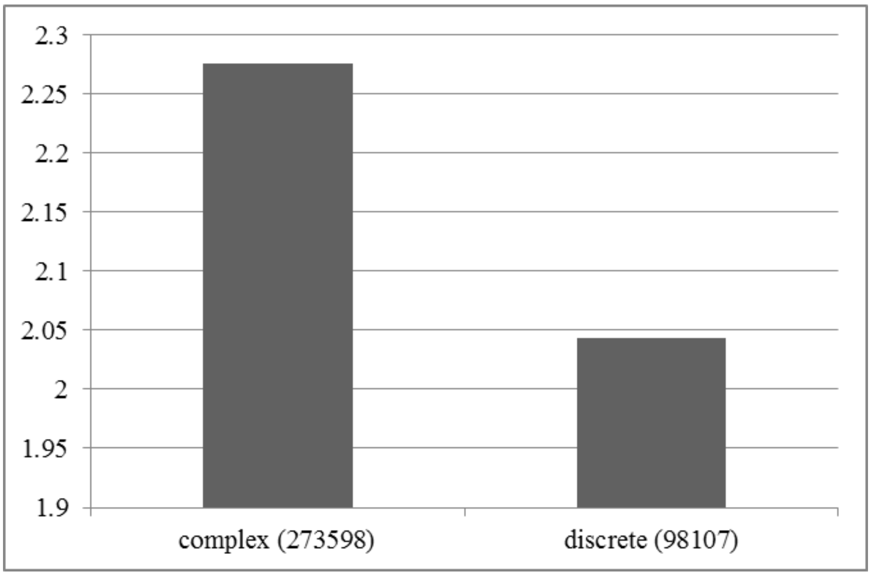


Figure 4.4 and Figure 4.5 represent how the fragmentation indices differ between complex and discrete industrial sectors as well as how they have evolved in the 1990s and 2000s, for complex and discrete industries. The difference of the overall means of the two industries during this period,

although small, is statistically highly significant (t= 35.1), as shown in Figure 4.4. As presented in Figure 4.5, the level of fragmentation in both industries increased in the 1990s and that of complex industrial sectors has been higher than that in discrete industrial sectors and the difference is larger in the 2000s, except for the last year. This relatively stable relative pattern of the fragmentation indices of the two industries is in sharp contrast with the result of EPO patents (displayed in Figure 4.6, Von Graevenitz et. al, 2011a), which show a reversal of the means of the two sectors in the 1990s. Note that our measure of fragmentation is patent level.

Figure 4.4 Fragmentation indices for complex and discrete industrial sectors



Note. The standard deviation is .0034 for complex industrial sectors and .0057 for discrete industrial sectors.

Figure 4.5 Fragmentation between complex and discrete industrial sectors over time

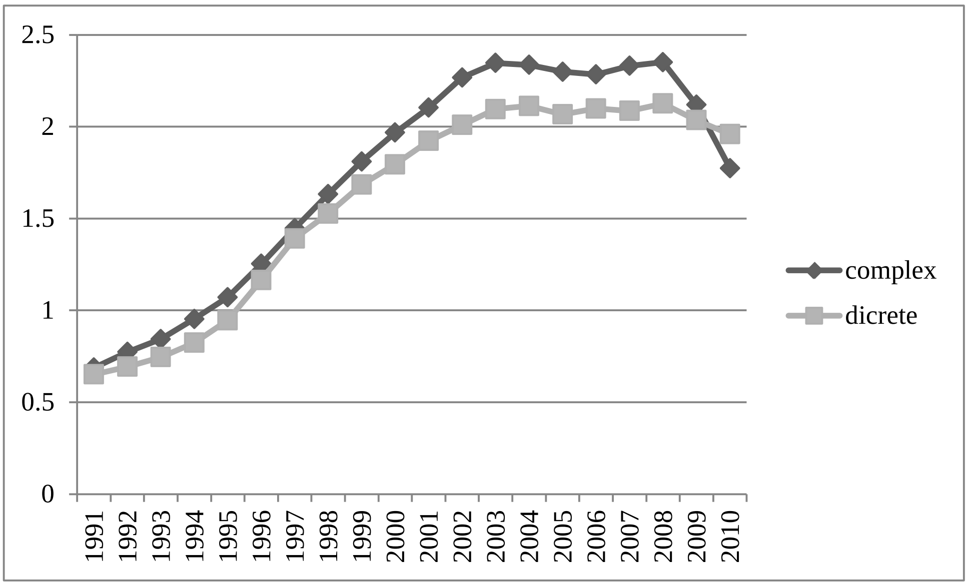
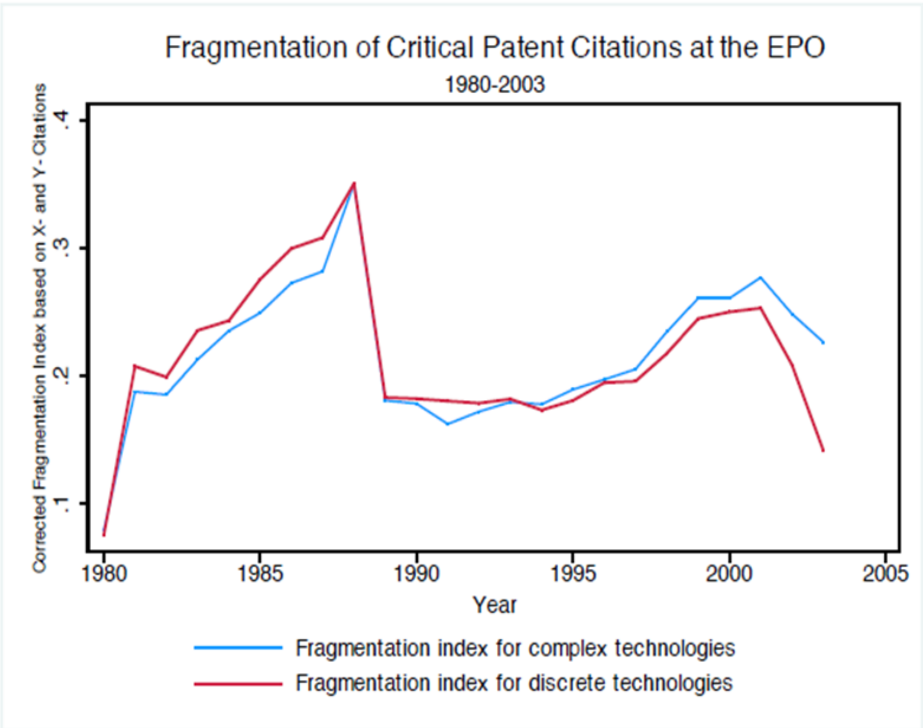


Figure 4.6 Trend of EPO fragmentation between complex and discrete technologies



4.4 Complementarity, fragmentation and Patenting Propensity

We estimate patenting propensity as the number of granted patents from a R&D project relative to the R&D man-month of the underlying R&D project. The RIETI inventor survey provides the number of granted patents which are generated directly from the underlying R&D project. Inventors can choose 6 answer choices: (1)1 patent, (2) 2-5 patents, (3) 6-10 patents, (4) 11-50 patents, (5) 51-100 patents and (6) more than 100 patents. We assign each choice the mean of figure range such as 1, 3.5, 8, 30.5, 75.5, and 200 patents, respectively. We also use a question to capture the R&D effort measured by man-months: (1) less than one man-month, (2) 1-3 man-months, (3) 4-6 man-months, (4) 7-12 man-months, (5) 13-24 man-months, (6) 25-48 man-months, (7) 49-72 man-months, (8) 72-96 man-months, and (9) More than 97 man-months. We assign each choice the mean of figure range such as 1, 3, 5, 9.5, 18.5, 36.5, 60.5, 84.5 and 100 man-months, respectively.

In order to explore whether complementarity is significantly associated with the patenting propensity of a firm across industrial sectors, we calculate the number of granted patents from the project over the R&D effort measured by man-month. Figure 4.7 exhibits the relationship between the patenting propensity and the size of complementarity. As presented in Figure 4.7, there is a positive correlation (0.88) between the patenting propensity and the size of complementarity at sector level. There is also a positive but weaker correlation (0.66) between the patenting propensity and fragmentation of the ownership (Figure 4.8).

Figure 4.7 Patenting propensity (Patents /R&D) and complementarity

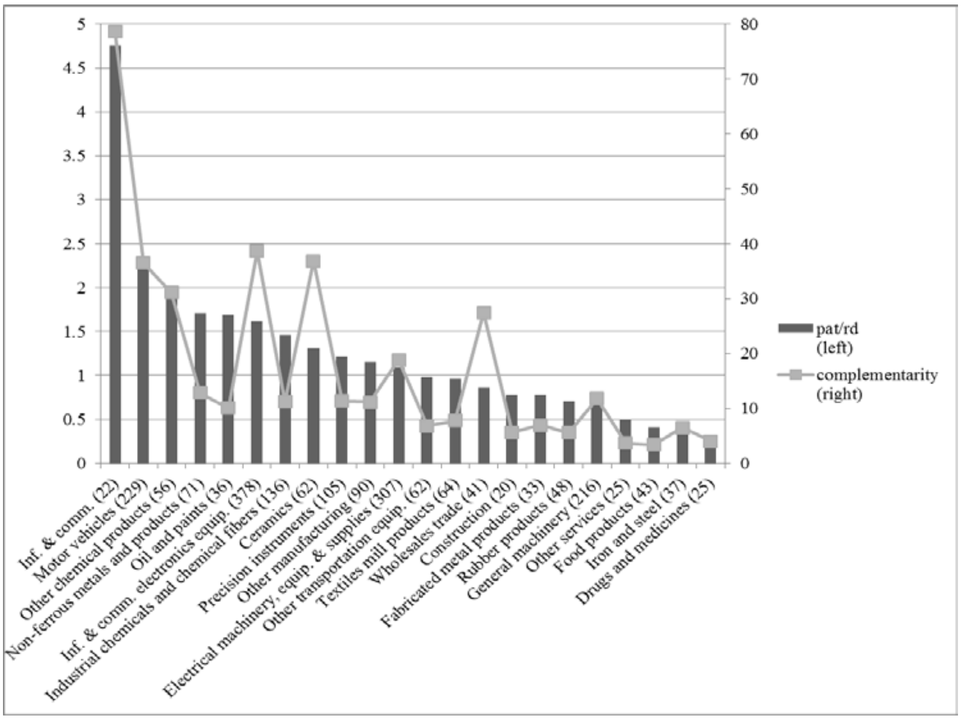
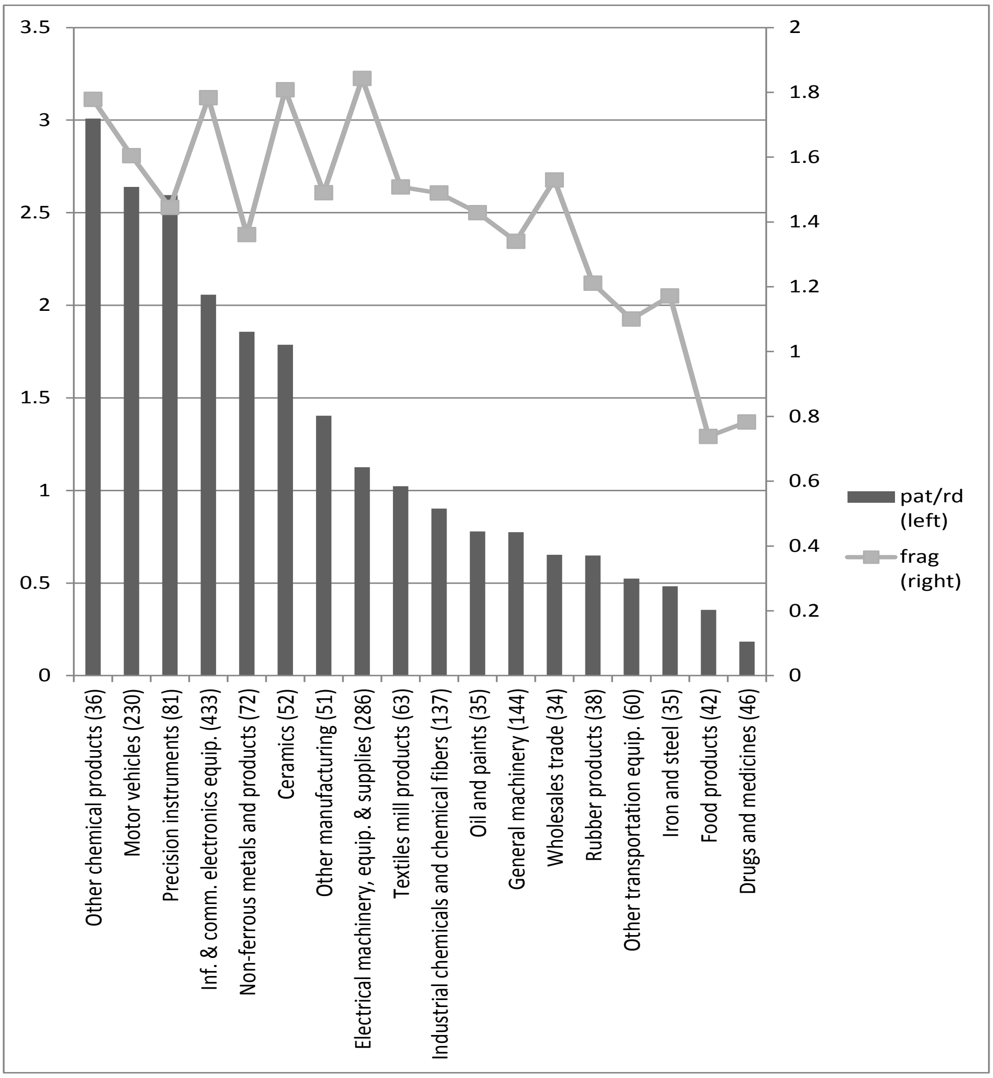
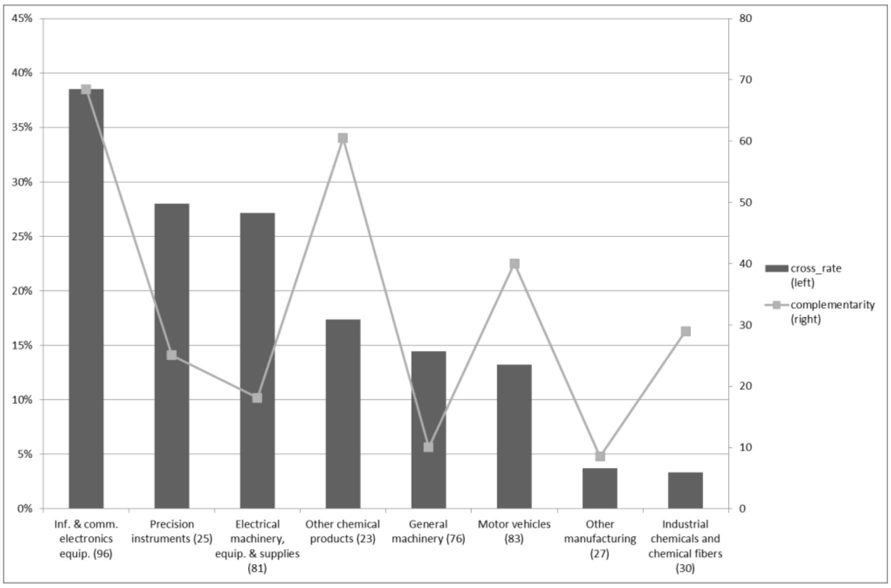


Figure 4.8 Patenting propensity (Patents /R&D) and fragmentation



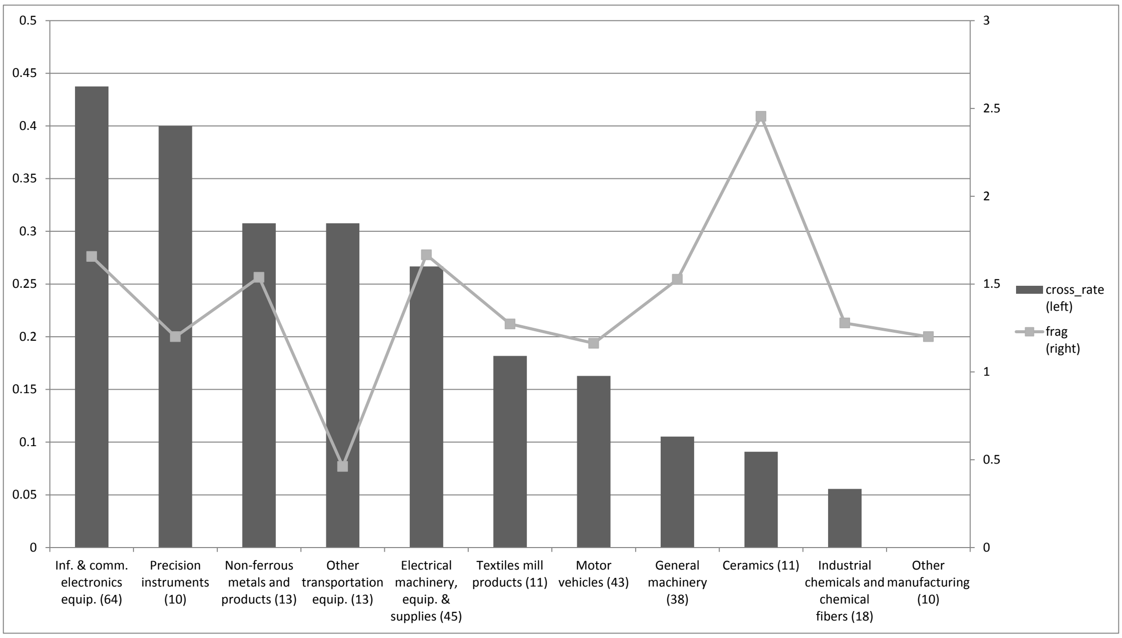
Cross licensing is an important response to complementarity and fragmentation of ownership. Figure 4.9 shows a relationship between the frequency of cross-licensing over the used inventions and the complementarity across industrial sectors. The ICT sectors, such as information and communication electronics equipment, and electrical machinery & equipment, have high levels of cross-licensing frequency, while chemical sector has the low level of cross-licensing. There is a weak but positive correlation (0.5) between the frequency of cross-licensing and the size of complementarity. On the other hand, as presented in Figure 4.10, there is no significant relationship between the frequency of cross-licensing and fragmentation.

Figure 4.9 The frequency of cross-licensing and complementarity



Note: Cross_rate=the frequency of cross-licensing over the used inventions, and the sample industries which are represented in this figure are limited to those industries whose firms are more than 20 firms responding cross licensing in RIETI survey.

Figure 4.10 The frequency of cross-licensing and fragmentation



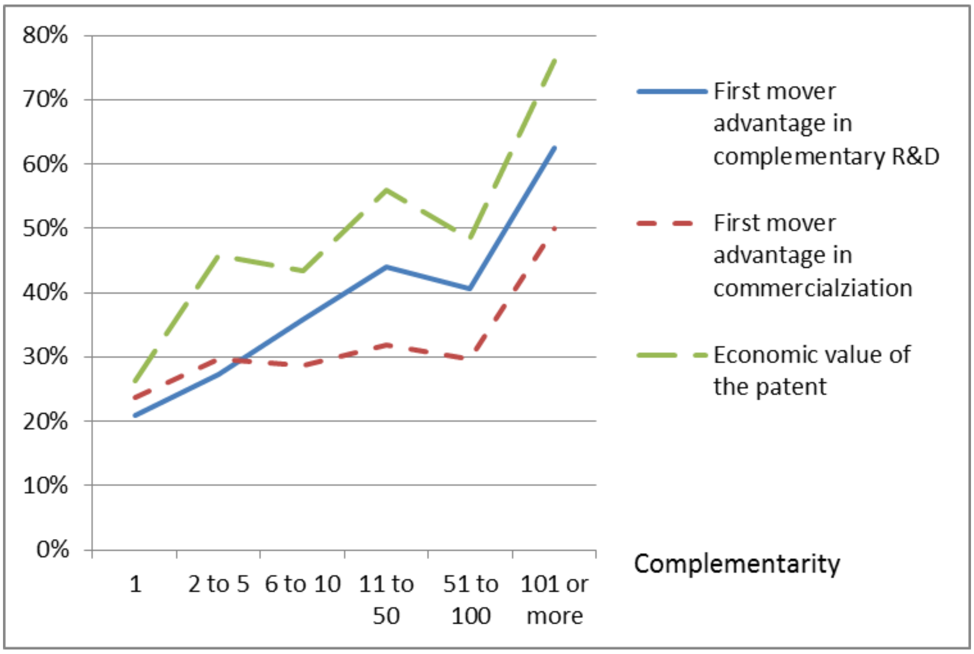
Note: cross_rate=the frequency of cross-licensing over the used inventions

4.5 First mover advantages, patenting motivations, patent value and their relationships with complementarity and fragmentation

We will use two types of first mover advantage (FMA) in commercializing the focal patent in assessing the effects of complementarity and fragmentation. The first type of the FMA is the advantage in undertaking the complementary R&D, as measured by the recognized importance of realizing the first mover advantage in R&D complementary to the focal point (that is, whether it is “very important” for appropriation or not in the scale of Likert scale from 1(“not at all”) to 5 (”very important)). The second type of the FMA is the advantage in the commercialization of the focal patent itself, as measured by the importance realizing the FMA in commercializing the focal point (that is, whether it is “very important” for appropriation or not). As for patent value variable, it is the subjective economic value of the focal patent relative to the inventions in the same field and during the similar period (top 10%, top 25%, top 50 % and bottom 50%) as evaluated by the focal inventor.

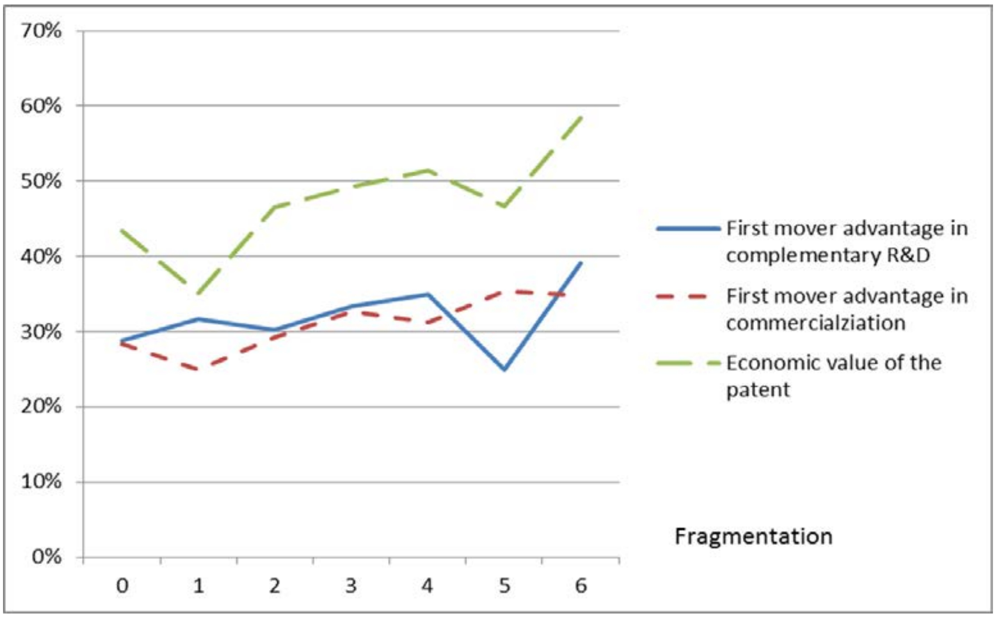
The following Figure 4.11 suggests that the importance of realizing the two types of the FMA become stronger as complementarity rises. The effect is very strong when the focal patent is one of the many complementary patents (complementarity is very high). When the focal patent is a part of a large bundle of the patents (101 or more), more than 60% of the inventors think that realizing the FMA in R&D is very important for appropriation of the value from the R&D while 50% of the inventors think that realizing the FMA in commercialization is very important. The latter effect (the effect on the importance of realizing the FMA in commercialization) is nonlinear, that it, it is significant only when complementarity is very high. The economic value also increases with the size of complementarity. This suggests that increasing number of complementary patents adds the average value of the patents.

Figure 4.11 Complementarity and FMAs/patent value



The following figure suggests that the ownership fragmentation of the backward citations of the focal patent is not significantly associated with the FMAs (Figure 4.12). The economic value tends to rise with more fragmentation. These results are not necessary surprising, since patent with a larger technological scope is likely to cite the patents of more number of firms and simultaneously more valuable and to enhance the FMA.

Figure 4.12 Fragmentation and FMAs/patent value



We use five major reasons for patenting motivations with respect to the focal patent as identified in the survey: (1) exclusive exploitation, (2)blocking, (3) pure self-defense, (4) licensing for revenue, and (5) cross license. All are evaluated as 5 point Likert scale. Pure self-defense is a motivation for patenting only for prevention of the risk that the inventing firm itself is being blocked from using its own invention due to the patenting of an identical or similar technology by the other firms. The firm has no intention of excluding the other firms by that patent. It is likely that such patent does not have a strong exclusionary power ex-ante (due to easy inventing-around) but such patent can still become important ex-post as an insurance once the firm invested in commercializing the technology because of the sunk investment. Thus, the importance of such motivation can be used to measure the importance of hold up risk as perceived by a firm.

Figure 4.13 shows the patent level correlations between complementarity (the size of the bundle of the patent to be used together with the focal patent) and the importance of five patenting motivations of the focal patent: (1) exclusive exploitation, (2) blocking, (3) pure self-defense, (4) licensing for revenue, and (5) cross license. The importance is measured by the frequency of each of 5 patenting reasons being very important for patenting. They show strong correlations between complementarity and the incidence of pure self-defense and two licensing motivations being very important. Two licensing motivations begin to rise when the size of the bundle exceeds 10 and rises continuously. The importance of pure self-defense starts to rise similarly, although we see an initial decline. On the other hand, we see no correlations between the fragmentation index and patenting motivations, as seen in Figure 4.14.

Figure 4.13 Complementarity and patenting motivations

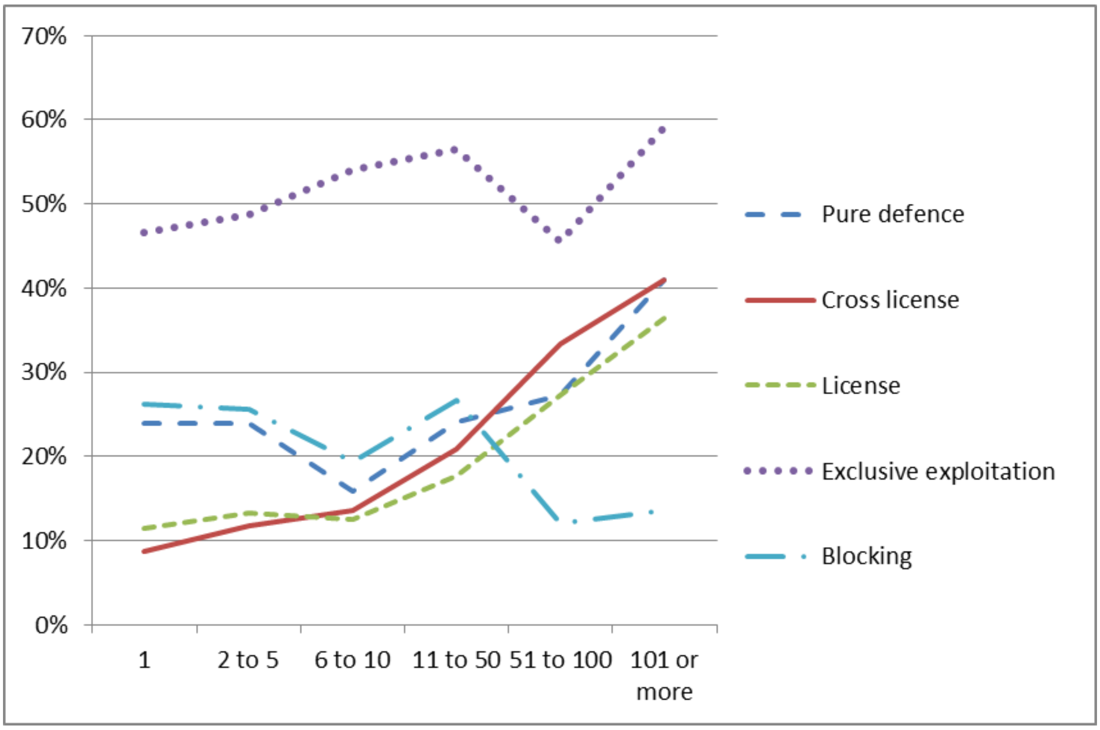
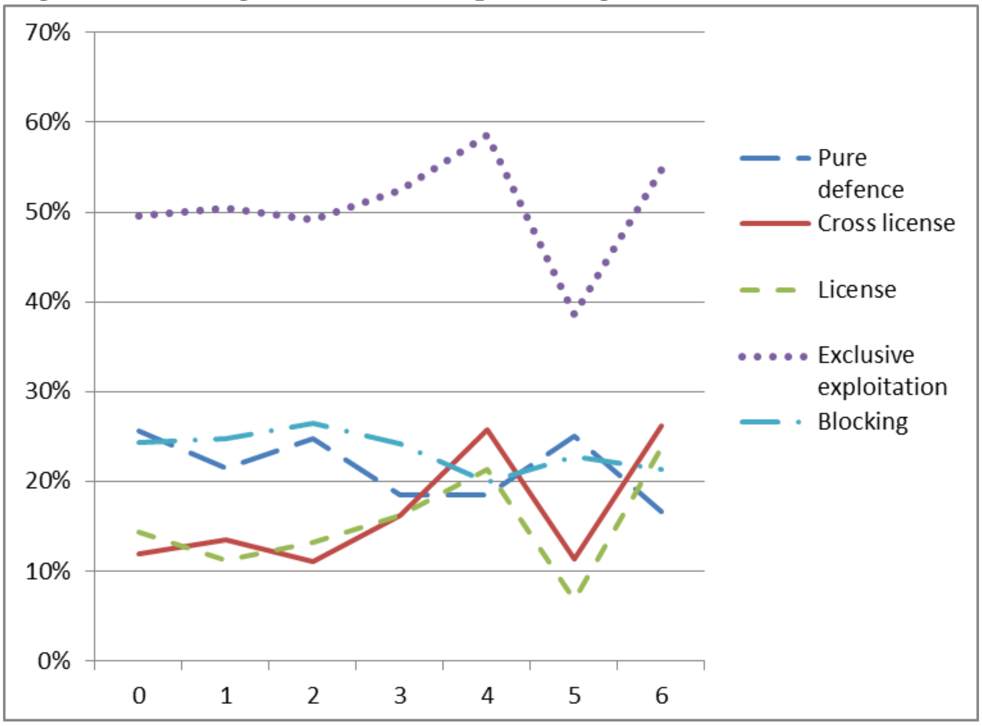


Figure 4.14 Fragmentation and patenting motivations



5. Estimation Models

5.1 First mover advantages and patent value

We estimate the models explaining how often realizing the first mover advantage (FMA) in either R&D and in commercialization is very important for appropriation as well as the perceived economic value of the focal patent. We have three dependent variables: *fmvrd_d*, *fmvmrk_d* and *lnvalued*. The first variable is an indicator variable, showing whether realizing the FMA in R&D complementary to the focal point is very important for its commercial success (1 for Yes and 0 for No), as assessed by the inventor of the focal patent. The second variable is an indicator variable, showing whether realizing the FMA in commercializing the focal point is very important for its commercial success (1 for Yes and 0 for No), as assessed by the inventor of the focal patent. The third variable is the subjective economic value of the focal patent relative to the inventions in the same field and during the similar period. We use the information of the rating of economic value of the invention as the measure of patent value (Top 10%, Top 25%, Top 50%, and Bottom 50%) converted into a value index following a lognormal distribution.

The focal explanatory variables are the measure of complementarity and that of fragmentation. We use the dummies for a complementarity variable in order to accommodate non-linearity of its effect: high complementarity (*bundl_h*) if the size of the bundle of patents is 101 or more (2% of the sample), medium complementarity (*bundl_m*) if it is between 11 to 100 (17% of the sample) and low complementarity if it is 10 or less (82 % of the sample). Similarly we use the dummies for the ownership fragmentation variable: high fragmentation (*fragment_h*) if the number of the firms cited by the focal patent is 5 or more (4 % of the sample), medium fragmentation (*fragment_m*) if it is between 3 and 4 (10% of the sample) and low fragmentation if it is 2 or less (86 % of the sample). In the appendix, we show the results where we use continuous variables measuring complementarity and fragmentation and we find highly similar results (Table A.3). As mentioned earlier, the level of fragmentation at product or process level is very likely to depend both on the level of fragmentation at a patent level as well as on the number of patents to be used together for implementing the product or process (our measure of complementarity), so that the estimated coefficient of our complementarity variable reflects both the effect of complementarity as well as that of fragmentation.

We control for the following additional factors which may cause spurious correlations between these two focal explanatory variables and the importance of FMA and the patent value. The importance of realizing FMA would be high if the invention has a high quality or covers a wide scope, since the profit from its exclusive exploitation increases with its quality and scope. Furthermore, the benefit of combining the focal patent with the other patents would be also larger if its quality is high or it covers a large scope (see section 3.1). Thus, invention quality or its scope can cause a positive correlation between complementarity and the patenting motivation. Similarly, an invention with a large scope can cite the patents with many firms, so that we may also observe a spurious correlation between the ownership fragmentation and the patent value or the FMA. In order to control for this, we introduce the quality and size measure of the focal invention (the number of forward citations and the number of inventors per patent) as well as the total man months for the research project and the PhD degree of the focal inventor.

The importance of realizing the FMA in R&D and commercialization would be high if the invention opens a new research field and is applied in new business area. There will be more opportunities to engage in follow-up research and patenting for such invention, and the gain from the FMA in commercializing such invention will also be large since it is more likely that new complementary assets need to be created. At the same time, the opportunity for combining patents would also be high for such invention since there will be more chances for complementary inventions. Thus, the variation of such R&D nature can also cause a positive correlation between complementarity and the FMA. We control for such frontier-opening nature of the project by the following variables: a dummy indicating whether the underlying research project aims at new product development or new process development rather than its improvement (a dummy *new_prodproc*), by the importance of science literature (*cncpt_sci*, 5 points Likert scale) and that of public research at university or national laboratory (cncpt_res, 5 points Likert scale) as a knowledge source for suggesting the project, the objective of research (whether it is for existing business or for exploring new technology base, rather than for new business) and the stage of research (*basic, development, technology service and the other, rather than applied*).

Competitive conditions can also create spurious correlations. Stronger competition as perceived by a firm can enhance the importance of realizing the FMA and can simultaneously increase the ownership fragmentation and more opportunities for combinatorial innovations. We use 28 industrial sector dummies to control for the variations of these competitive conditions. These dummies also control for the other environmental factors such as demand growth at sector level.

In addition to these basic control variables, we introduce dummies for firm size and for application years. For firm size dummies, we use the employment size categories for each applicant firm: a firm with less than 100 employees, a firm with 100-250 employees, a firm with 250-500 employees, a firm with 501 or more employees. The model for estimation is given by the following equation.

$$\begin{aligned} &First\ mover\ advanteges\ dummies\ or\ Ln(patent\ value) \\ &= \Sigma\beta_{\mathrm{i}}\left(Complementarity_i\ \right) + \Sigma\delta_i(fragmentation\ _i) \\ &+ Effect\ of\ Invention\ quality\ and\ scope \\ &+ Effect\ of\ Frontier\ opening\ + \\ &\quad the\ other\ controls + \varepsilon_i. \qquad (10) \end{aligned}$$

We use OLS for estimations.

5.2 Patenting propensity and patenting motivations

In assessing patenting propensity, we estimate patent production functions. The dependent variable, *lnsize_pat_num*, is a logarithm of the number of patents from the R&D project which generated the focal patent.

Our focal explanatory variables for patent production function are the dummies of the following five patenting motivations as assessed by an inventor in 5 point Likert scale: (1) exclusive exploitation, (2) blocking, (3) pure self-defense, (4) licensing for revenue, and (5)cross licensing.

In order to assess patenting propensity, we need to introduce the R&D inputs comprehensively. We introduce the following key inputs for R&D as explanatory variables: the man months of the R&D project, the quality of the output, type of R&D project (new process or product, knowledge source, and stage of research) as well as the type of business line, which would affect the relative advantage of patenting in appropriation. We control for industry types and the size of firm. Thus, we end up using the same set of explanatory variables as introduced for the model for FMA and patent value.

The estimation model for patenting propensity is given by

$$Ln(Number\ of\ patents) = \Sigma\beta_{\mathrm{i}}\left(Patenting\ motivations_i\ \right) +$$
$$+Effect\ of\ Key\ Inputs\ for\ R\&D + The\ other\ Controls + \varepsilon_i. \qquad (11)$$

We use OLS for estimations.

Finally we also estimate the models explaining the patenting motivations. The five dependent variables are the dummies indicating whether a particular patenting motivation is very important or not (if it is very important, the dummy is set to 1, otherwise 0): *score_defense_d*, *score_crlice_d*, *score_licen_d*, *score_block_d*, *and score_excl_d*, each representing the dummies for the patenting motivations of pure self-defense, cross license, licensing for revenue, blocking and exclusive exploitation.

We use the same set of explanatory variables as for FMA, since almost all significant factors affecting FMA also affect patenting decisions (although, the reverse is not necessarily the case). In particular, the focal explanatory variables are the measure of complementarity and that of fragmentation. One problem we have to address is the endogeneity of the measure of complementarity with respect to cross licensing (as will be later shown, cross licensing affects significantly patenting propensity). When cross licensing is extensive, a firm not only patents more but also can combine its own patents with those of the others which are cross-licensing partners, so that the size of the bundle, which is a measure of our complementarity, is also large. We examine how serious such this endogeneity is by running an estimation, using only the sample of the inventions for which cross licensing did not occur. In the latter sample, there is no endogeneity due to more use of the external patents due to cross licensing.

$$\begin{aligned} &Dummies\ for\ each\ patenting\ motivation \\ &\qquad = \Sigma\beta_i\left(Complementarity_i\ \right) + \Sigma\delta_i(fragmentation\ _i) \\ &\qquad + Effect\ of\ Invention\ quality\ and\ scope \\ &\qquad + Effect\ of\ Frontier\ opening\ + \\ &\qquad\quad the\ other\ controls + \varepsilon_i. \end{aligned} \tag{12}$$

The appendix provides descriptive statistics (Table A.2).

6. Estimation Results

6.1 First mover advantages (FMAs) and patent value

Table 6.1 shows the results on the effects of our measures of complementarity and fragmentation on the first mover advantages (FMAs) and on patent value. Complementarity is significantly associated with R&D FMA both at medium and high level of complementarity. The coefficients are very significant and increase significantly with higher complementarity, even controlling for the quality and the size of the focal invention, the nature of the research (field opening or new business) and others. If complementarity increases to a medium level from a low level, realizing the FMA in complementary R&D becomes very important by 13 % points more. If it increases to a high level from a low level, realizing the FMA in complementary R&D becomes very important by 33 % points more. These results are consistent with our Hypothesis 1.

On the other hand, complementarity is significantly associated with commercialization FMA only at high level of complementarity (and at 10 % level of significance). This is perhaps because, as explained earlier in section 3, when complementarity is high, a firm is more likely to share technologies extensively so that it finds it more difficult to differentiate the product, even though the value of the product for the customers increases with combination. On the other hand, ownership fragmentation significantly affects neither advantage. In particular, it does not reduce significantly FMAs. This does not contradict our Hypothesis 1, since fragmentation has two effects as suggested in the hypothesis: more competitive incentive is, but simultaneously more value dilution is, more free riding and higher cost of coordination are. Appendix Table A.3 presents the results using continuous variables for complementarity and fragmentation, which are very consistent with those presented in Table 6.1.

(Table 6.1)

Consistent with our theoretical expectation, the number of the inventors for the focal patent as well as the importance of the science literature as a knowledge source for the focal invention ha a significantly positive coefficient for FMAs in R&D and in commercialization.

The result for patent value is consistent with those for FMAs. Complementarity is significantly associated with the patent value at 5 % level, even controlling for the quality of the focal patent by its forward citations as well as the size of the inventor man-months among others, according to Model 3a[8]. The size of the coefficient is very large (31% in value). Fragmentation does not reduce the economic value of the patent. These results suggest that fragmentation itself does not have significantly value-reducing effect, perhaps because the negative effect through dilution of the ownership stake is balanced by the positive effect of combination of technologies of diverse firms. That is, our fragmentation measure partially measures the combination of different sources of knowledge. As for control variables, we find significant effects of invention quality and inventor man-months as well as the type of innovation. The importance of these controls is indicated by Model 3b. If we do not control for these variables, the estimated coefficient of the complementary increases significantly to more than 38% points, as shown in Model 3b. The science base is not significantly associated with patent value in Model 3a, unlike FMAs, which may not be surprising since such invention is associated with higher uncertainty in realizing the value.

Table A.4 in the Appendix presents the results separately estimated for complex industry sectors and discrete industry sectors, using continuous variables for complementarity and fragmentation. The complementarity measure is more significant for discrete industry sectors. This might suggest decreasing returns from complementarity and/or the high patenting propensity in complex industry sectors.

6.2 Patenting propensities and patenting motivations

Table 6.2 represents the estimation results on the effects of patenting

[8] This is in sharp contrast with Reiztig (2004) which finds no significant effect, even without controlling for the invention quality and scope. A potential reason is that he did not distinguish complements and substitutes.

motivations on the patenting propensities. The result for Model 5 focuses on the sample from complex industrial sectors and that for Model 6 focuses on the sample from discrete industrial sectors, while that for Model 4 uses the aggregated sample. According to Model 4, only cross licensing motivation among the five major patenting motivations is highly significant in accounting for the level of patenting propensity, controlling for the quality and size of the R&D project among others. If the importance of cross licensing motivation increases from 1 ("not importance at all") to 5 ("very important"), the number of patents increases in total by 37% points (=4×9.3%). Licensing for revenue motivation follows cross licensing motivation in terms of the size of the coefficient (around a half), although it is not significant. Pure self-defense motivation has a much smaller and insignificant coefficient, and exclusive exploitation and blocking motivations have insignificant, and even negative, coefficients.

(Table 6.2)

The results from Model 5 and 6 suggest that these results from the aggregate sample are robust for the subsamples of complex industrial sectors and for that of discrete industrial sectors. In particular, the coefficient of cross licensing motivation is very similar between the two (0.090 for complex industrial sectors and 0.094 for discrete industrial sectors). One difference is that the licensing for revenue motivation has a larger coefficient (0.08), close to that of cross licensing motivation, in complex industrial sectors. This is consistent with the characterization of the complex and discrete industries: technology sharing in the former sectors and more exclusivity in the latter sectors. The blocking motivation is not significant in neither of industries, suggesting that such motivation is no more important in complex industries.

The estimated coefficients of the control variables are consistent with our theoretical expectation. The project with higher quality focal patent, a larger project (with more man-months), a project for new product or process and for new business generates significantly more patents. In addition, a large firm patents more.

The results suggest that the main driver for the variation of patenting propensity across projects is cross-licensing motivation in both complex and discrete industrial sectors. On the other hand, the pure self-defense motivation and the blocking motivation are not significant. They imply that higher patenting propensity from a project does not on average indicate a more blocking motivation nor only the importance of preventing the risk of being held up. Instead, they indicate the combination of the motivation of preventing the risk of being held up and the motivation of combining the inventions across firms, both of which can be achieved through cross licensing.

Table 6.3 shows the results for patenting motivations. Consistent with the results of Table 6.2, complementarity is highly significantly associated with cross licensing (statistically significant at 1% for high level of complementarity and at 5% for medium level) and licensing for revenue motivations (statistical significance at 5%). If the complementarity is very high (the focal patent is embodied in the bundle of patents with 101 or more patents), the probability that cross licensing is very important motivation increases by 29% points, relative to the case with low complementarity (Model 8). Similarly, the probability that a licensing for revenue motivation is very important increases by 24% points, if the complementarity increases from a low level to a high level (Model 10).

The probability that pure self-defense motivation is very important also increases by 20% with the increase of complementarity from a low level to a high level, although it is significant only at 10% level (Model 7). On the other hand, the blocking and the exclusive exploitation motivations are not significantly associated with complementarity (the blocking motivation has a negative coefficient, Model 11). The fragmentation variable is not significantly associated with any patenting motivation.

(Table 6.3)

Model 9 using only the sample of the patents not used for cross licensing suggests that cross licensing is still highly associated with complementarity at medium level. Removing the sample where the cross license is actually made significantly reduces the endogeneity of the size of the bundle (the measure of the complementarity in this paper) with respect to the cross licensing of the focal patent, although it also reduces the variation of the bundle (the incidence of high complementarity is only 1.45% in the subsample of no actual cross license but it is 12.5% in the subsample of actual cross license). A smaller coefficient of high complementarity dummy could be explained by the latter result. The fact that the coefficient of the complementarity dummy at medium level remains essentially the same indicates that complementarity does promote cross licensing motivation.

The above results are consistent with the conclusions from Table 6.2. Complementarity does not significantly drive more patenting for blocking. It does not invite patenting for pure self-defense. It invites patenting for seizing the economic opportunities of a combination of the inventions of different firms as well as of preventing the risk of being held up. Table A.5 in the appendix shows the results for patenting motivations using continuous variables for complementarity and fragmentation, which are highly consistent with the results in Table 6.3. There are no significant differences of the results for complex industry sectors and discrete industry sectors with respect to the estimations for patenting motivations (not reported).

7. Conclusions

In this paper, we have empirically investigated the effects of patent thicket where a firm needs to use many complementary patents owned by the other firms in producing its own product. Significant concerns exist for patent thicket as indicated by recent reports by the UK Patent Office and by the EPO. One unique feature of our study is to identify two sources of patent thickets: (1) complementarity as measured by the number of the patents to be jointly used in commercialization of the focal patent and (2) fragmentation as measured by the number of firms whose patents are cited by an examiner in examining the granted focal patent. Introducing a measure of complementarity is important, given that patent thicket may largely reflect more opportunities for combinatorial innovations. Based on the extensive data set from RIETI inventor survey and from patent bibliographic data, we have analyzed how these sources affect the first mover advantages (FMAs), which is the main competitive incentive for R&D, and the patent value. We have also investigated how the prevention of the risk of being held up, accessing the technologies of the other firms and blocking motivations are more or less important as patenting motivations in the industrial sectors where patent thicket is important.

There are three major findings. First, there is a significant difference between complex industrial sectors and discrete industrial sectors regarding complementarity, while the difference regarding fragmentation at patent level is relatively small.

Secondly, more complementarity is significantly associated with the importance of FMA in R&D and (less significantly) in commercialization, while more fragmentation is not. Consistent with this, more complementarity (that is, a focal patent has more complementary patents) is significantly associated with higher patent value, even controlling for the quality and the scope of the focal patent by its forward citations among others. Fragmentation does not reduce the economic importance of the patent.

Thirdly, cross licensing motivation significantly accounts for the variation of patenting propensity in both complex and discrete industrial sectors. Licensing for revenue also significantly accounts for patenting propensities in complex industrial sectors. On the other hand, a blocking motivation and a pure self-defense motivation are not significant drivers for higher patenting propensities. Cross licensing motivations for patenting as well as licensing for revenue motivation is significantly associated with complementarity, while blocking motivation for patenting is not. Thus, complementarity does not significantly invite more patenting for blocking. It does not invite only patenting for pure self-defense either. Rather, it invites patenting for seizing the economic opportunities of a combination of the inventions of different firms as well as of preventing the risk of being held up through cross licensing.

Thus, complementarity is the main driver for patent thicket phenomena and we do not see significantly negative patent thicket effects on R&D as seen by incumbents. Complementarity is actually associated with a stronger incentive for acquiring first mover advantage in R&D. Higher patenting propensity is significantly driven by cross licensing motivation and not by such motivations as blocking or simply minimizing the risk of being held up. We do not observe significantly negative effect of fragmentation either.

However, at the same time, patenting motivations are high where complementarity is important. Granting a patent to a low quality invention would not strengthen the synergy effect of complementarity and causes more fragmentation and the erosion of pioneering patents as well as more risk of holdups. Thus, it would be important that policy focus would be paid to avoiding the patents grants to low quality inventions and to facilitating the mechanism of ex-ante contracting in complex industry sectors.

There are a number of future research issues. We have found that the main driver is complementarity but this may be partly due to a highly imperfect nature of our fragmentation measure. Further study would be important to improve fragmentation measures. Our results show that the fragmentation as measured by the number of firms cited in the focal patent does not reduce its economic value. It would be important to deepen our understanding of its causes. It could represent partly a positive effect of combining technologies of diverse firms.

Table 6.1 FMAs and patent value

		First mover advantage in R&D	First mover advantage in commercialization	Value of the focal patent	Value of the focal patent
		(Model 1)	(Model 2)	(Model 3A)	(Model 3B)
	VARIABLES	fmvrd_d	fmvmrk_d	lnvalued	lnvalued
Complementarity (base: low)	bundl_m	0.127***	0.0261	0.0564	0.155**
	(medium)	(0.0400)	(0.0386)	(0.0764)	(0.0750)
	bundl_h	0.329***	0.189*	0.312**	0.383***
	(high)	(0.101)	(0.101)	(0.131)	(0.135)
Fragmention (base: low)	fragment_m	0.00584	0.0168	0.0748	0.0940
	(medium)	(0.0296)	(0.0297)	(0.0596)	(0.0573)
	fragment_h	-0.0153	0.0762	0.0463	0.0887
	(high)	(0.0537)	(0.0541)	(0.0937)	(0.0887)
Quality and size of the focal invention	ln1fwcit_inv	0.0111	0.0190	0.0651**	
		(0.0152)	(0.0154)	(0.0290)	
	lninventors	0.0399*	0.0614***	0.0736	
		(0.0238)	(0.0233)	(0.0454)	
Inventor inputs	lnmonth2	0.0163	0.0212*	0.0508**	
		(0.0113)	(0.0110)	(0.0226)	
phd	phd	0.0827	0.0695	0.0261	
		(0.0627)	(0.0614)	(0.109)	
Innovation type(base:improvement)	new_prodproc	0.0549*	0.0108	0.154**	
		(0.0297)	(0.0310)	(0.0609)	
Knowledge sources	cncpt_sci	0.0420***	0.0207**	0.0294	
		(0.00880)	(0.00872)	(0.0182)	
	cncpt_res	-0.0197*	-0.00583	-0.00104	
		(0.0102)	(0.0102)	(0.0185)	
Research objective (base: new business)	_Iobjective_2	-0.0225	-0.00191	-0.0503	
	(existing business)	(0.0374)	(0.0367)	(0.0687)	
	_Iobjective_3	-0.00721	-0.0950	0.284	
	(new techology base)	(0.0894)	(0.0872)	(0.185)	
	_Iobjective_4	0.107	-0.0556	-0.0877	
	(other)	(0.181)	(0.154)	(0.294)	
Research stage (base: applied)	basic	0.0818*	-0.00301	0.0988	
		(0.0436)	(0.0429)	(0.0801)	
	dev	0.0218	0.0453	0.0702	
		(0.0321)	(0.0329)	(0.0624)	
	service	-0.0247	0.0663	-0.00707	
		(0.0409)	(0.0472)	(0.0884)	
	oth_stage	-0.127	0.0454	0.109	
		(0.0929)	(0.131)	(0.229)	
Sample	_Itriadic_1	0.0242	-0.0434	0.0567	0.143*
	(triadic)	(0.0374)	(0.0393)	(0.0762)	(0.0731)
Size of the applicant (base: large)	_Iorg_2 (medium)	-0.0781	0.0736	0.159	0.0896
		(0.0579)	(0.0644)	(0.131)	(0.119)
	_Iorg_3(Small)	0.00315	-0.00855	0.0762	0.149
		(0.0709)	(0.0740)	(0.147)	(0.132)
	_Iorg_4 (very small)	-0.0953	-0.0969	0.186	0.218
		(0.0674)	(0.0696)	(0.162)	(0.145)
	Observations	1,172	1,173	939	1,011
	R-squared	0.114	0.074	0.125	0.073
	Adjusted R-squared	0.0697	0.0273	0.0693	0.0325
	RMSE	0.443	0.446	0.773	0.788
	Log Likelihood	-678.8	-689.3	-1061	-1171

Note. *** p<0.01, ** p<0.05, * p<0.10, Robust standard errors in parentheses. The coefficients for application year dummies and industry dummies are not reported.

Table 6.2 Patenting propensity

		(Model 4)	(Model 5)	(Model 6)
	VARIABLES	lnsize_pat_num	lnsize_pat_num	lnsize_pat_num
		Total	Complex	Discrete
Patenting motivations (Likert Scale)	score_crlice	0.0926***	0.0894**	0.0938*
		(0.0294)	(0.0375)	(0.0538)
	score_defence	0.0146	0.0270	−0.0114
		(0.0291)	(0.0393)	(0.0506)
	score_licen	0.0462	0.0811**	0.0215
		(0.0286)	(0.0365)	(0.0519)
	score_excl	−0.00121	−0.0247	0.0364
		(0.0292)	(0.0368)	(0.0606)
	score_block	−0.0296	−0.0462	−0.00438
		(0.0304)	(0.0410)	(0.0524)
Quality and size of the focal invention	ln1fwcit_inv	0.116***	0.115***	0.115***
		(0.0264)	(0.0358)	(0.0427)
	lninventors	−0.102**	−0.0815	−0.141
		(0.0428)	(0.0521)	(0.0878)
Inventor inputs	lnmonth2	0.217***	0.239***	0.173***
		(0.0206)	(0.0264)	(0.0365)
phd	phd	0.0351	0.114	−0.0302
		(0.0909)	(0.149)	(0.116)
Innovation type	new_prodproc	0.198***	0.219***	0.143
		(0.0523)	(0.0671)	(0.0960)
Knowledge sources	cncpt_sci	0.0611***	0.0730***	0.0365
		(0.0163)	(0.0208)	(0.0289)
	cncpt_res	0.0104	−0.00895	0.0408
		(0.0169)	(0.0229)	(0.0272)
Research objective (base: new business)	_Iobjective_2	−0.286***	−0.263***	−0.346***
	(existing business)	(0.0671)	(0.0860)	(0.122)
	_Iobjective_3	−0.0510	−0.0426	−0.0382
	(new techology base	(0.130)	(0.164)	(0.255)
	_Iobjective_4	0.319	0.841	0.000892
	(other)	(0.347)	(0.540)	(0.466)
Research stage (base: applied)	basic	0.135*	0.142	0.166
		(0.0697)	(0.101)	(0.108)
	dev	0.105*	0.0976	0.125
		(0.0567)	(0.0771)	(0.0936)
	service	0.0155	−0.00530	−0.0202
		(0.0800)	(0.110)	(0.131)
	oth_stage	0.242	0.0767	0.878***
		(0.188)	(0.229)	(0.287)
Sample	_Itriadic_1	−0.00670	−0.0665	0.0806
		(0.0645)	(0.0811)	(0.116)
Size of the applicant (base: large)	_Iorg_2 (medium)	−0.285***	−0.334**	−0.291**
		(0.102)	(0.161)	(0.139)
	_Iorg_3(Small)	−0.257**	−0.244	−0.209
		(0.127)	(0.181)	(0.215)
	_Iorg_4 (very small)	−0.284**	−0.192	−0.253
		(0.130)	(0.146)	(0.315)
	Observations	1,709	1,086	496
	R-squared	0.225	0.243	0.231
	Adjusted R-squared	0.198	0.216	0.156
	RMSE	0.952	0.980	0.893
	Log Likelihood	−2312	−1500	−623.9

Note. *** p<0.01, ** p<0.05, * p<0.10, Robust standard errors in parentheses. The coefficients for application year dummies and industry dummies are not reported.

Table 6.3 Patenting motivations

		(Model 7)	(Model 8)	(Model 9)	(Model 10)	(Model 11)	(Model 12)
		score_defense_d	score_crlice_d	score_crlice_d	score_licen_d	score_block_d	score_excl_d
	VARIABLES			(no actual cross license)			
Complementarity (base: low)	bundl_m (medium)	0.0500	0.110***	0.102**	0.0465	0.0106	0.0162
		(0.0377)	(0.0341)	(0.0405)	(0.0318)	(0.0376)	(0.0425)
	bundl_h (high)	0.203*	0.293***	0.113	0.235**	−0.0583	0.0550
		(0.106)	(0.107)	(0.133)	(0.105)	(0.0840)	(0.120)
Fragmention (base: low)	fragment_m (medium)	−0.0386	0.00558	0.0423	0.0229	0.00536	0.0117
		(0.0296)	(0.0242)	(0.0284)	(0.0244)	(0.0301)	(0.0344)
	fragment_h (high)	−0.0583	0.0497	0.0602	0.0241	−0.00482	−0.0514
		(0.0500)	(0.0459)	(0.0533)	(0.0421)	(0.0516)	(0.0570)
Quality and size of the focal invention	ln1fwcit_inv	0.0257*	0.00638	0.0104	0.0210	0.0148	0.0288*
		(0.0147)	(0.0126)	(0.0144)	(0.0136)	(0.0149)	(0.0167)
	lninventors	−0.0318	−0.0179	−0.0150	0.00466	−0.0343	−0.0135
		(0.0236)	(0.0204)	(0.0234)	(0.0201)	(0.0240)	(0.0267)
Inventor inputs	lnmonth2	−0.0156	0.00575	0.00227	0.00793	0.0129	0.0394***
		(0.0112)	(0.00910)	(0.0107)	(0.00958)	(0.0115)	(0.0126)
phd	phd	−0.0604	0.0277	0.00103	0.0918	0.0115	−0.00497
		(0.0538)	(0.0500)	(0.0510)	(0.0562)	(0.0599)	(0.0652)
Innovation type	new_prodproc	0.0204	−0.0110	−0.00661	−0.000426	0.0202	0.0579
		(0.0311)	(0.0247)	(0.0282)	(0.0238)	(0.0314)	(0.0366)
Knowledge sources	cncpt_sci	0.0191**	0.0232***	0.0297***	0.00821	−0.00243	0.0420***
		(0.00881)	(0.00751)	(0.00872)	(0.00717)	(0.00937)	(0.00993)
	cncpt_res	−0.00963	−0.00992	−0.0158	−0.000562	−0.00524	−0.0588***
		(0.0101)	(0.00828)	(0.00976)	(0.00857)	(0.0102)	(0.0107)
Research objective (base: new business)	_Iobjective_2 (existing business)	0.0793**	−0.00185	0.00485	−0.0239	0.0453	0.0118
		(0.0329)	(0.0304)	(0.0354)	(0.0307)	(0.0349)	(0.0407)
	_Iobjective_3 (new techology bas	−0.0260	−0.00878	−0.0297	0.0612	0.0877	0.0325
		(0.0834)	(0.0685)	(0.0705)	(0.0886)	(0.0881)	(0.0947)
	_Iobjective_4 (other)	−0.00396	0.121	0.544**	0.0565	0.0280	−0.135
		(0.187)	(0.193)	(0.267)	(0.201)	(0.189)	(0.247)
Research stage (base: applied)	basic	−0.0651*	−0.0296	−0.0311	0.0578	−0.0516	0.0567
		(0.0385)	(0.0331)	(0.0353)	(0.0383)	(0.0409)	(0.0445)
	dev	−0.0149	−0.0258	−0.0469	−0.00462	−0.00331	−0.0211
		(0.0336)	(0.0289)	(0.0334)	(0.0288)	(0.0339)	(0.0374)
	service	−6.93e−05	0.0257	0.0625	0.0268	0.0244	0.0377
		(0.0475)	(0.0357)	(0.0439)	(0.0364)	(0.0495)	(0.0506)
	oth_stage	0.0494	−0.0582	−0.0258	0.00560	0.0112	−0.00410
		(0.115)	(0.0708)	(0.0826)	(0.0898)	(0.126)	(0.123)
Sample	_Itriadic_1 (triadic)	0.0172	0.0368	0.0324	0.0192	−0.0313	0.0589
		(0.0392)	(0.0289)	(0.0324)	(0.0286)	(0.0415)	(0.0451)
Size of the applicant (base: large)	_Iorg_2 (medium)	0.0552	−0.0478	−0.0244	−0.00708	−0.0322	−0.152**
		(0.0656)	(0.0360)	(0.0495)	(0.0475)	(0.0621)	(0.0675)
	_Iorg_3(Small)	0.129	−0.0600	−0.0303	−0.0946**	0.200**	0.141
		(0.0930)	(0.0430)	(0.0547)	(0.0431)	(0.0940)	(0.0923)
	_Iorg_4 (very small)	0.0433	0.00646	−0.0371	0.0117	−0.0367	−0.0560
		(0.0816)	(0.0610)	(0.0582)	(0.0633)	(0.0705)	(0.0950)
	Observations	1,053	1,048	732	1,048	1,052	1,053
	R−squared	0.061	0.097	0.107	0.084	0.063	0.116
	Adjusted R−squared	0.00893	0.0470	0.0360	0.0333	0.0109	0.0674
	RMSE	0.418	0.338	0.316	0.338	0.426	0.483
	Log Likelihood	−547.9	−322.1	−167.7	−320.5	−565.8	−699.2

Note. *** p<0.01, ** p<0.05, * p<0.10, Robust standard errors in parentheses. The coefficients for application year dummies and industry dummies are not reported.

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Appendix

1. Calculation of fragmentation index in Japan

In order to construct the index of fragmentation, we calculate the number of firms which have the patents cited by an examiner (excluding the self-citations). We consider a hypothetical situation that a firm is blocked by the rival firms with the patents of which are cited by the examiner. In such case, the backward citation linkage shows the relationship between a veto right holder and the patentee.

In estimating the fragmentation index, our measurement of fragmentation is subject to four conditions: (1) non self-citation data (excluding self-citation data), (2) a granted patent's (which has completed patent examination and issued) citation data, (3) examiner's citation and (4) non co-applicants (sole applicants) as citing patents (but no cited patents). The reason why we limit our sample to non-self-citation is that self-citation never functions as veto rights[9]. Secondly, our sample is limited to the patent citations for granted patents. This makes us to avoid the truncation problem. Third, examiner's citation is usually recognized as the citation which is blocking the other firm from obtaining the relevant patent while inventor's citation represents knowledge flow from previous patent documents. Lastly, the reason why our sample is limited to the sample with the citing applicants as sole applicants is that the definition of self-citation becomes very complicated in case of citing co-applicants.

In an example as displayed in Figure A.1, we identify 4 veto right holders which have the patent cited by an examiner (applicant C, D, E, F), 1 self-citation (JP2010AAAAAA-JP2009BBBBBB), 2 non self-citations (JP2010AAAAAA-JP2007CCCCCC; JP2010AAAAAA-JP1998DDDDDD) from Case A. Applicant B does not block applicant A, since the patent held by applicant B is co-owned by applicant A.

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[9] We classify all backward citations into two categories: (1) self-citation and (2) non self-citation. Self-citation is usually defined as a citation where the citing and the cited patent documents share at least one applicant. Non self-citation is defined as a citation where the citing and the cited patent documents never share one applicant.

Figure A.1

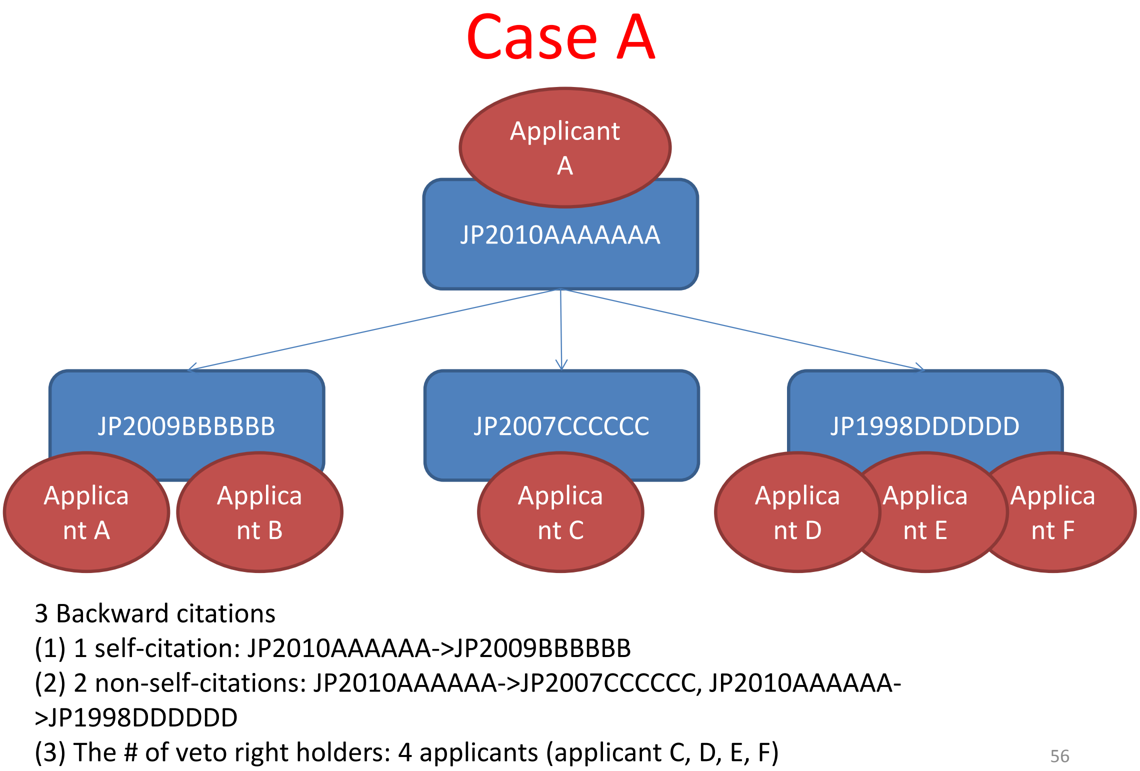
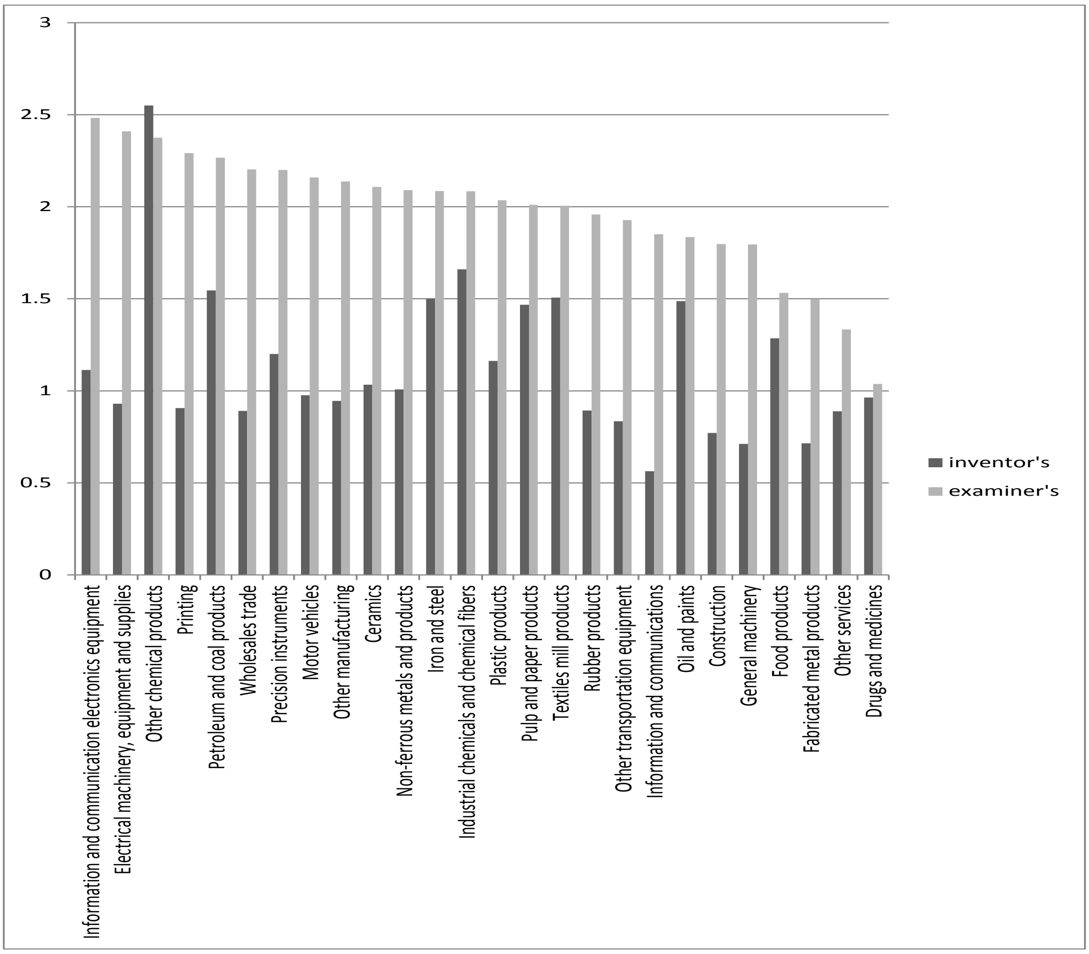


Figure A.2 provides a comparison between fragmentation index based on between examiners' citations and that based on inventors' citations by sectors. It shows a large difference in the patterns, so that the correlation between the two measures is very weak. It indicates the driver of knowledge flow is quite different from that of blocking relationship.

Figure A.2

Comparison fragmentation index based on examiners' citations and that based on inventors' citations by sectors (2001-2010)



2. Definition of Complex and Discrete industrial sectors

Cohen et. al (2000) classify sectors into three categories: complex industrial sectors, discrete industrial sectors and other sectors. According to Cohen et. al (2000), discrete industrial sectors are defined as the ones whether a new, product or process is comprised of a relatively small number of patentable elements. In addition, they define complex industrial sectors as the ones where a new product or process is comprised of numerous separately patentable elements. In this study, we classified 28 sectors defined by the SIC code into three categories, following Cohen et al. (2000) and Von Graevenitz et al. (2011a). Table A.1 shows discrete/complex/other industrial sectors for 25 industries out of 28 sectors.

Table A.1 Complex/discrete/other sectors

indold_id	sectors	type	indold_id	sectors	type
3	Construction	complex	16	Iron and steel	discrete
4	Food products	discrete	17	Non-ferrous metals and products	discrete
5	Textiles mill products	discrete	18	Fabricated metal products	discrete
6	Pulp and paper products	discrete	19	General machinery	complex
7	Printing	discrete	20	Electrical machinery, equipment and supplies	complex
8	Industrial chemicals and chemical fibers	discrete	21	Information and communication electronics equipment	complex
9	Oil and paints	discrete	22	Motor vehicles	complex
10	Drugs and medicines	discrete	23	Other transportation equipment	complex
11	Other chemical products	discrete	24	Precision instruments	complex
12	Petroleum and coal products	discrete	25	Other manufacturing	others
13	Plastic products	discrete	27	Information and communications	complex
14	Rubber products	discrete	28	Wholesales trade	others
15	Ceramics	discrete			

Table A.2 Descriptive Statistics (1) for Table 6.1 to Table 6.3

	Total					Complex		Discrete	
Variable	Obs	Mean	Std. Dev	Min	Max	Obs	Mean	Obs	Mean
fmvrd_d	1172	0.30	0.46	0	1	745	0.28	333	0.35
fmvmrk_d	1171	0.29	0.45	0	1	744	0.25	333	0.34
lnvalued	936	0.42	0.80	−0.80	1.75	582	0.39	283	0.51
bundl_m	1172	0.17	0.37	0	1	745	0.18	333	0.14
bundl_h	1172	0.02	0.14	0	1	745	0.02	333	0.01
fragment_m	1172	0.34	0.48	0	1	745	0.34	333	0.37
fragment_h	1172	0.08	0.27	0	1	745	0.08	333	0.08
lnbundl_size	1171	1.49	1.18	0	7.14	744	1.56	333	1.37
ln1fragment_f	1172	0.73	0.66	0	2.485	745	0.74	333	0.76
ln1fwcit_inv	1172	1.00	0.97	0	5.62	745	0.93	333	1.20
lninventors	1172	0.78	0.60	0	3.045	745	0.74	333	0.91
lnmonth2	1172	2.47	1.32	0.405	4.963	745	2.42	333	2.64
lnsize_pat_num	1148	1.51	1.04	0	4.324	726	1.51	328	1.58
score_defense_d	1050	0.02	0.13	0	1.00	662	0.02	304	0.02
score_crlice_d	1045	0.14	0.35	0	1.00	661	0.16	304	0.12
score_licen_d	1045	0.14	0.34	0.00	1.00	661	0.13	304	0.15
score_excl_d	1050	0.50	0.50	0	1	663	0.46	304	0.57
score_block_d	1049	0.24	0.43	0	1	662	0.22	303	0.26
phd	1172	0.06	0.24	0	1	745	0.04	333	0.13
new_prodproc	1172	0.71	0.45	0	1	745	0.70	333	0.73
cncpt_sci	1172	2.77	1.79	0	5	745	2.63	333	3.19
cncpt_res	1172	1.41	1.53	0	5	745	1.26	333	1.77
objective	1172	1.85	0.47	1	4	745	1.85	333	1.81
basic	1172	0.15	0.35	0	1	745	0.11	333	0.24
applied	1172	0.36	0.48	0	1	745	0.31	333	0.49
dev	1172	0.76	0.43	0	1	745	0.79	333	0.68
service	1172	0.10	0.30	0	1	745	0.09	333	0.13
oth_stage	1172	0.01	0.11	0	1	745	0.01	333	0.01
triadic	1172	0.85	0.35	0	1	745	0.84	333	0.86
large	1172	0.89	0.32	0	1	745	0.90	333	0.86
MediumFirm	1172	0.03	0.17	0	1	745	0.03	333	0.03
SmallFirm	1172	0.03	0.17	0	1	745	0.03	333	0.03
verysmall	1172	0.03	0.17	0	1	745	0.03	333	0.03
applyear	1172	1997.9	1.8361	1995	2002	745	1997.8	333	1998.01

Table A.3. FMAs and patent value (using continuous variables for complementarity and fragmentation)

		(A_Model 1)	(A_Model 2)	(A_Model 3)	(A_Model 4)
	VARIABLES	fmvrd_d	fmvmrk_d	lnvalued	lnvalued
		Total	Total	Total	Total
Complementrity	lnbundl_size	0.0614***	0.0239*	0.0546**	0.0853***
		(0.0123)	(0.0122)	(0.0231)	(0.0219)
Fragmentation	ln1fragment1_f	0.00681	0.0198	0.0302	0.0505
		(0.0210)	(0.0214)	(0.0424)	(0.0405)
Quality and size of the focal invention	ln1fwcit_inv	0.0100	0.0179	0.0653**	
		(0.0152)	(0.0154)	(0.0287)	
	lninventors	0.0415*	0.0630***	0.0781*	
		(0.0237)	(0.0233)	(0.0453)	
Inventor inputs	lnmonth2	0.0116	0.0187*	0.0453**	
		(0.0114)	(0.0112)	(0.0229)	
phd	phd	0.0839	0.0648	0.0126	
		(0.0619)	(0.0609)	(0.107)	
Innovation type(base:improvement)	new_prodproc	0.0522*	0.00902	0.151**	
		(0.0296)	(0.0309)	(0.0610)	
Knowledge sources	cncpt_sci	0.0411***	0.0207**	0.0296	
		(0.00882)	(0.00876)	(0.0180)	
	cncpt_res	−0.0218**	−0.00649	−0.00366	
		(0.0101)	(0.0101)	(0.0184)	
Research objective (base: new business)	_Iobjective_2	−0.0189	−0.00133	−0.0433	
	(existing business)	(0.0372)	(0.0365)	(0.0685)	
	_Iobjective_3	−0.0105	−0.0943	0.281	
	(new techology base)	(0.0905)	(0.0887)	(0.183)	
	_Iobjective_4	0.114	−0.0575	−0.0875	
	(other)	(0.177)	(0.151)	(0.279)	
Research stage (base: applied)	basic	0.0888**	−0.000484	0.0996	
		(0.0432)	(0.0428)	(0.0797)	
	dev	0.0163	0.0428	0.0622	
		(0.0317)	(0.0327)	(0.0621)	
	service	−0.0208	0.0652	−0.00576	
		(0.0405)	(0.0470)	(0.0874)	
	oth_stage	−0.155*	0.0338	0.0727	
		(0.0925)	(0.128)	(0.228)	
Sample	_Itriadic_1	0.0196	−0.0447	0.0483	0.131*
	(triadic)	(0.0371)	(0.0391)	(0.0764)	(0.0732)
Size of the applicant (base: large)	_Iorg_2 (medium)	−0.0647	0.0779	0.169	0.105
		(0.0586)	(0.0647)	(0.131)	(0.118)
	_Iorg_3(Small)	0.0228	0.00126	0.0955	0.181
		(0.0705)	(0.0738)	(0.146)	(0.133)
	_Iorg_4 (very small)	−0.0697	−0.0838	0.213	0.262*
		(0.0676)	(0.0686)	(0.161)	(0.145)
	Observations	1,171	1,172	939	1,011
	R-squared	0.118	0.072	0.125	0.076
	Adjusted R-squared	0.0749	0.0276	0.0719	0.0380
	RMSE	0.442	0.447	0.771	0.785
	Log Likelihood	−676.2	−689.9	−1060	−1169

Note. *** p<0.01, ** p<0.05, * p<0.10, Robust standard errors in parentheses. The coefficients for application year dummies and industry dummies not reported.

Table A.4. FMAs and patent value (Complex vs. Discrete sectors, using continuous variables for complementarity and fragmentation)

		(A_Model 5)	(A_Model 6)	(A_Model 7)	(A_Model 8)	(A_Model 9)	(A_Model 10)	(A_Model 11)	(A_Model 12)
	VARIABLES	fmvrd_d		fmvmrk_d		lnvalued		lnvalued	
		Complex	Discrete	Complex	Discrete	Complex	Discrete	Complex	Discrete
Complementrity	lnbundl_size	0.0413***	0.131***	−0.000588	0.0888***	0.0383	0.0954**	0.0722**	0.122***
		(0.0146)	(0.0234)	(0.0139)	(0.0253)	(0.0289)	(0.0438)	(0.0279)	(0.0386)
Fragmentation	ln1fragment1_f	0.0102	0.0397	0.0388	−0.00742	0.00619	0.0803	0.0361	0.0572
		(0.0256)	(0.0452)	(0.0264)	(0.0436)	(0.0543)	(0.0776)	(0.0518)	(0.0714)
Quality and size of the focal invention	ln1fwcit_inv	0.0220	0.00401	0.0180	0.0103	0.0607	0.0583		
		(0.0193)	(0.0259)	(0.0199)	(0.0255)	(0.0379)	(0.0459)		
	lninventors	0.0258	0.0975*	0.0592**	0.0860*	0.0894*	0.0274		
		(0.0277)	(0.0509)	(0.0274)	(0.0517)	(0.0542)	(0.0976)		
Inventor inputs	lnmonth2	0.0186	0.00958	0.0165	0.0252	0.0491*	0.0309		
		(0.0141)	(0.0227)	(0.0138)	(0.0221)	(0.0284)	(0.0451)		
phd	phd	0.0661	0.0678	−0.0447	0.122	−0.00434	−0.0162		
		(0.0931)	(0.0861)	(0.0849)	(0.0923)	(0.175)	(0.138)		
Innovation type(base:improvement)	new_prodproc	0.0270	0.115*	−0.00480	0.0544	0.217***	0.0713		
		(0.0366)	(0.0604)	(0.0377)	(0.0621)	(0.0757)	(0.126)		
Knowledge sources	cncpt_sci	0.0578***	−0.00969	0.0303***	0.0171	0.0353*	0.0124		
		(0.0103)	(0.0196)	(0.0102)	(0.0192)	(0.0214)	(0.0389)		
	cncpt_res	−0.0340***	0.00219	−0.0105	−0.00171	0.0258	−0.0244		
		(0.0124)	(0.0193)	(0.0125)	(0.0193)	(0.0230)	(0.0357)		
Research objective (base: new business)	_Iobjective_2(existing business)	−0.00218	−0.0632	−0.0107	−0.0150	−0.0331	−0.0536		
		(0.0444)	(0.0761)	(0.0441)	(0.0709)	(0.0853)	(0.144)		
	_Iobjective_3(new techology base)	0.0818	−0.317*	0.0486	−0.423***	0.360	0.0630		
		(0.107)	(0.169)	(0.115)	(0.102)	(0.238)	(0.341)		
	_Iobjective_4(other)	0.142	−0.169	−0.213**	−0.191	−0.256	−0.0723		
		(0.249)	(0.171)	(0.0850)	(0.146)	(0.361)	(0.378)		
Research stage (base: applied)	basic	0.0498	0.124*	−0.0105	0.0214	0.144	0.0454		
		(0.0578)	(0.0739)	(0.0587)	(0.0703)	(0.109)	(0.136)		
	dev	0.0337	−0.00658	0.0631	0.0323	0.0557	0.0720		
		(0.0395)	(0.0587)	(0.0422)	(0.0601)	(0.0795)	(0.110)		
	service	0.00557	−0.0862	0.0996	0.00834	−0.0101	−0.0535		
		(0.0507)	(0.0695)	(0.0610)	(0.0831)	(0.130)	(0.144)		
	oth_stage	−0.196**	0.248	0.000299	−0.0455	−0.108	0.217		
		(0.0993)	(0.155)	(0.145)	(0.391)	(0.255)	(0.488)		
Sample	_Itriadic_1 (triadic)	0.0550	−0.121	−0.0199	−0.154**	0.0226	0.133	0.124	0.152
		(0.0441)	(0.0749)	(0.0456)	(0.0780)	(0.0911)	(0.153)	(0.0882)	(0.136)
Size of the applicant (base: large)	_Iorg_2 (medium)	−0.0949	−0.0983	0.0245	−0.0248	0.216	0.296	0.0844	0.269
		(0.0733)	(0.104)	(0.0917)	(0.103)	(0.164)	(0.206)	(0.166)	(0.176)
	_Iorg_3(Small)	0.0370	−0.00397	0.0988	−0.124	0.253	−0.225	0.302**	−0.212
		(0.0985)	(0.121)	(0.103)	(0.109)	(0.170)	(0.301)	(0.145)	(0.242)
	_Iorg_4 (very small)	−0.0174	0.0235	−0.0352	−0.0316	−0.0389	0.757***	0.129	0.505**
		(0.0851)	(0.129)	(0.0916)	(0.148)	(0.199)	(0.219)	(0.188)	(0.218)
	Observations	744	333	745	333	583	285	620	311
	R-squared	0.129	0.213	0.053	0.169	0.117	0.224	0.040	0.178
	Adjusted R-squared	0.0882	0.102	0.00877	0.0523	0.0635	0.0932	0.00982	0.0992
	RMSE	0.430	0.451	0.435	0.463	0.760	0.772	0.784	0.766
	Log Likelihood	−410.5	−185.0	−419.6	−193.4	−649.5	−308.1	−718.6	−343.7

Note. *** p<0.01, ** p<0.05, * p<0.10, Robust standard errors in parentheses. The coefficients for application year dummies and industry dummies not reported.

Table A.5. Patenting motivations (using continuous variables for complementarity and fragmentation)

		(A_Model 13)	(A_Model 14)	(A_Model 15)	(A_Model 16)	(A_Model 17)	(A_Model 18)
		score_defense_d	score_crlice_d	score_defense_d	score_licen_d	score_block_d	score_excl_d
				(no actual cross license)			
	VARIABLES	Total	Total	Total	Total	Total	Total
Complementarity	lnbundl_size	0.0194	0.0469***	0.0240*	0.0299***	-0.00829	0.0118
		(0.0124)	(0.0111)	(0.0145)	(0.0108)	(0.0118)	(0.0144)
Fragmention	ln1fragment1_f	-0.0407*	0.0230	-0.0426*	0.0125	0.00608	-0.000460
		(0.0212)	(0.0179)	(0.0248)	(0.0177)	(0.0209)	(0.0241)
Quality and size of the focal invention	ln1fwcit_inv	0.0259*	0.00393	0.0294*	0.0198	0.0155	0.0285*
		(0.0148)	(0.0127)	(0.0178)	(0.0136)	(0.0150)	(0.0166)
	lninventors	-0.0312	-0.0168	-0.0202	0.00601	-0.0349	-0.0127
		(0.0236)	(0.0203)	(0.0276)	(0.0201)	(0.0241)	(0.0267)
Inventor inputs	lnmonth2	-0.0152	0.00295	0.00489	0.00549	0.0142	0.0379***
		(0.0112)	(0.00935)	(0.0131)	(0.00979)	(0.0115)	(0.0128)
phd	phd	-0.0556	0.0281	-0.0950	0.0902	0.0154	-0.00434
		(0.0535)	(0.0507)	(0.0603)	(0.0569)	(0.0600)	(0.0651)
Innovation type(base:improv	new_prodproc	0.0210	-0.0150	0.0101	-0.00194	0.0216	0.0591
		(0.0312)	(0.0246)	(0.0365)	(0.0238)	(0.0314)	(0.0365)
Knowledge sources	cncpt_sci	0.0196**	0.0229***	0.0196*	0.00830	-0.00264	0.0414***
		(0.00885)	(0.00752)	(0.0100)	(0.00719)	(0.00937)	(0.00993)
	cncpt_res	-0.0108	-0.0117	-0.0117	-0.00161	-0.00526	-0.0592***
		(0.0101)	(0.00823)	(0.0113)	(0.00854)	(0.0101)	(0.0107)
Research objective (base: new business)	_Iobjective_2	0.0765**	-0.00355	0.0469	-0.0242	0.0435	0.0149
	(existing business)	(0.0327)	(0.0303)	(0.0389)	(0.0303)	(0.0349)	(0.0407)
	_Iobjective_3	-0.0324	-0.0117	-0.0927	0.0616	0.0938	0.0454
	(new techology ba	(0.0866)	(0.0730)	(0.0924)	(0.0908)	(0.0907)	(0.0956)
	_Iobjective_4	-0.00428	0.134	0.425	0.0601	0.0252	-0.130
	(other)	(0.193)	(0.199)	(0.302)	(0.201)	(0.185)	(0.247)
Research stage (base: applied)	basic	-0.0646*	-0.0226	-0.0792*	0.0595	-0.0520	0.0561
		(0.0385)	(0.0333)	(0.0414)	(0.0384)	(0.0405)	(0.0445)
	dev	-0.0169	-0.0293	-0.0418	-0.00803	-0.00196	-0.0216
		(0.0335)	(0.0287)	(0.0402)	(0.0287)	(0.0338)	(0.0374)
	service	-0.000360	0.0275	0.0129	0.0277	0.0246	0.0399
		(0.0476)	(0.0359)	(0.0550)	(0.0368)	(0.0496)	(0.0506)
	oth_stage	0.0502	-0.0779	0.111	-0.00333	0.0142	-0.00645
		(0.117)	(0.0693)	(0.146)	(0.0893)	(0.127)	(0.123)
Sample	_Itriadic_1	0.0169	0.0358	-0.0211	0.0164	-0.0305	0.0571
	(triadic)	(0.0392)	(0.0290)	(0.0449)	(0.0286)	(0.0413)	(0.0449)
Size of the applicant (base: large)	_Iorg_2 (medium)	0.0520	-0.0385	0.0236	-0.00241	-0.0340	-0.148**
		(0.0667)	(0.0359)	(0.0847)	(0.0475)	(0.0626)	(0.0682)
	_Iorg_3(Small)	0.125	-0.0421	0.163	-0.0847*	0.195**	0.144
		(0.0923)	(0.0436)	(0.105)	(0.0436)	(0.0950)	(0.0922)
	_Iorg_4 (very small)	0.0498	0.0319	-0.00679	0.0257	-0.0418	-0.0541
		(0.0813)	(0.0611)	(0.0886)	(0.0650)	(0.0698)	(0.0957)
	Observations	1,052	1,047	736	1,047	1,051	1,052
	R-squared	0.059	0.096	0.079	0.082	0.063	0.115
	Adjusted R-square	0.00886	0.0474	0.00904	0.0330	0.0128	0.0681
	RMSE	0.419	0.338	0.402	0.338	0.426	0.483
	Log Likelihood	-548.8	-323.0	-346.6	-321.7	-565.6	-699.2

Note. *** p<0.01, ** p<0.05, * p<0.10, Robust standard errors in parentheses. The coefficients for application year dummies and industry dummies not reported.