Ownership Fragmentation, Litigation and Technology Market *

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Abstract

This paper analyzes the relationship between technology ownership and the opposition filing in European Patent Office (EPO). We develop and test a simple two stages game in which the licensing and opposition are jointly determined. Opposition can be used for bargaining an access to a technology. An ex ante negotiation (e.g. licensing) is less attractive under two conditions: when the profit dissipation is over the licensing revenue for the potential licensee or transaction cost is over the opposition cost for the entrant. That is, the opposition frequency should be high when ownership to external technologies are highly concentrated and widely distributed. To empirically test these hypotheses, we use a data set that covers patent opposition during the period 1985-2005, and construct application-based "fragmentation index". Finally, regression results confirm an U-shape relationship between opposition probability and the fragmented patent rights. Besides, conditional on non-zero opposition sample, opposition rate is negatively related to the fragmentation index. This analysis controls for differences in filing, granted rate and technological observed characteristics.

JEL Classification: K41, O34
Keywords: patent, litigation, market structure

*We are grateful to Bruno Van Pottelsberghe, Stefan Bechtold, Michele Cincera, and participants of the internal seminar of iCite and 17th ZEW Summer Workshop for Young Economists ; in Germany for valuable comments and discussion.

1 Introductions and Background

Over the last two decades, worldwide faces to a patent filing exploring, but filing of opposition in EPO keeps stable. As EPO annual report lists, the number of patent filed and granted both get doubled in 2000s while the opposition filing only increases less than 30%. Besides, technology market, such as technology licensing and acquisition, develop rapidly (Arora & Fosfuri 2003[1], Lerner and Merges 1998[29]). Such prior negotiation can be a solution for potential patent disputes. The major subject discussed in this paper is ownership fragmentation to external technology, which can link the analysis between filing an opposition and setting a negotiation.

A mainstream line of research follows a classical litigation framework to study the determinants of opposition in EPO. Proxies for the patent quality, such as family size, forward citation have been confirmed to have positive impact on litigation probability (Lanjouw and Schankerman (2001) [25]; Harhoff et al (2003) [21]). However, recent management scholars discuss the role of patent in market for technology (R.H.Ziedonis, 2004 [40];Arora & Fosfuri 2003[1]). For appropriating the fruits of R&D investment, patent creates profit from a commercial transaction such as licensing, or merge and acquisition. The development of technology market presents a challenge to the patent litigation systems. In this context, we discuss the determinants of opposing a patent not only bases on the patent quality but also ownership structure on external technology market.

Two ownership conditions affect licensing and opposition bargaining: 1) When the technology market is highly concentrated; 2) when the technology market is competitive but the technologies based on a large number of patents typically from numerous different holders. The first condition gives rise to the profit dissipation effect (Arora et al 2001 [2]), whereby licensing will bring a new competitor and make the incumbent firm lost of original market power. This suggests that ex ante bargaining is failing and opposing existed patents are highly possible for entering the market. The second condition can be explained by increasing transaction cost for searching and contracting an ex ante contract. Instead of prior negotiation, opposition is more efficient tool for an access of a technology. Taken together, we expect opposition probability should be high when the technology ownership is highly concentrated and widely fragmented.

We test the main predictions of the model using all the information of patents filed between 1985-2005. The richness of this data set allows us to construct patent application-based proxies for ownership fragmentation for a technology. We find that the fragmentation of ownership rights have an economically and statistically significant effect on the opposition likelihood. We also find conditional on none-zero opposition sample, opposition rate is negatively with the fragmentation index. These findings control for differences in filing, granted rate and technological observed characteristics.

We also assess impacts of ownership fragmentation on opposition propensity for complex and discrete industries. As expected, we observe that discrete industries, especially Drugs, have much higher opposition rate. More specific discrete industries present significant U-shape curves with the market share fragmentation index than the complex industry sample. A key contribution of this paper is to link industrial economics with research on determinants of patent litigation. We construct application-based measures for the fragmentation index at the IPC (International Patent Classification) unit level. New measures capture the patent ownership distribution on the market effectively and describe the causal effect of technology fragmentation on opposition filing

Besides, limited by the data coverage, research on patent enforcement is limited to specific technologies or small sample (Harhoff and Reitzig 2004; Arora et al 2001 [2]); opposition records in EPO provide a possibility for investigations on cross-industry analysis. The most important, this work contributes to complement the relatively underdeveloped empirical research on impact of EPO opposition proceeding.

The reminder of the paper is organized as follows; Section 2 gives on overview on the theoretical caused factors relevant for this paper, linking the available literature on the determinations of opposing drivers. Section 3 contains the empirical setup, starting with the descriptive statistics and followed by the estimation set up and results analysis in section 4. Section 5 summarizes the results and concludes.

2 Theory Development and Hypotheses

2.1 Determinant of Litigation Filing

It is reasonable to analyze patent opposition under the context of litigation events, since in practice, opposition is regarded as a court of "first instance" for European patent (D.Harhoff and Markus Reitzig (2003) [21]; BH.Hall and D.Harhoff,2004 [19]). Priest and Klein (1984) [33] address a standard model on explaining the selection of patent disputes, which states that the parties will go to trial if the return net of legal cost is over the outcome of pre-trail negotiations. Subsequent models allow for different factors effecting litigants' expectations. For example, P'gn (1983)[32] discussed the firms' strategic behavior when the firm owns private information. Lanjouw and Schankerman (2001) [25] developed a model to discuss firms' activity when they regard litigation costs as asymmetric stakes.

Empirical works test these models with three broad categories: a first set of paper report casual empirical evidence, consistent with the private value of patents. The available measures include the number of different jurisdictions patent protection is sought(patent families) (D.Harhoff et al, 1999 [20]) and renewals (JO Lanjouw et al (1998) [24]),the number of patents cited by the following patents (Criscuolo and Verspagen (2008) [10]; D.Harhoff et al. (2003)[22], Lanjouw and Schankerman, 2001[25],2004[26]). The number of claim. (Lanjouw und Schankerman (2003)[25], D.Harhoff und Reitzig (2004)[21]. BH.Hall et al (2001)[18] use the citations information as ingredients to construct two more complex measures, "originality" and "generality" to predict the patent value. van Zeebroeck and van Pottelsbogh de la Potteries (2011)[39] discuss the main methodological issues in measuring and interpreting these indicators. The main conclusion of this strand of the literature is the positive impact of patent value on the probability of being attacked.

A second strand of the literature relates to strategic implications under characteristics of patent applicant. For example, patent portfolio and complementary asset affect firms' decision not only on patenting, enforcing an innovation, but also settling and litigating a patent dispute. Lanjouw and Schankerman (2001) [25] point out that larger, domestic and more established firms were more likely to initiate litigation against smaller companies because they had better information about the activities of their competitors, more resources to defend their intellectual property. These findings persistently come out in , parallel studies, D.Harhoff and BH.Hall (2002) [19], suggesting higher percentage of opposition filing takes place repeatedly between larger players.

Recently, more paper discuss the heterogeneous adoption of patenting and patent litigation system by relating it to nature of technology. Malerba and Orsenigo (1997) [30] explored innovative activities across industries and technologies, and provides significant intersectional differences in the rate of innovation, the degrees of technological entry and exist, and et al. The distinction between discrete and complex technologies is widely accepted in the literature on patenting (Cohen et al., 2000 [8], Harhoff and Hall (2002) [19]) and selection of patents disputes for litigation (Alberto Galasso &Mark Schankerman 2010 [12]). Technology field, presenting the feature of complexity and cumulativeness, such as electronic, presents increasing proliferation of patent disputes.

3 Theory development and Hypothesis

3.1 Literature Review on Determinants of Opposition Filing

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3.2 Revenue effect and Profit dissipating effect

One weakness of the litigation theory is that treating a patent as an independent item. In fact, management scholars study the patent enforcement from market view, where commercial value of patent always links to other firms' activities on the same technology market. The most discussed transaction activity is licensing, by which firm can profit from R&D investment without production. Recent survey study confirm the widespread licensing among patenting firms in the past decades (Zuniga and guellec, 2008 [41]).

The most frequent condition for licensing out the innovation is when the patent owner has no complementary asset for production. When the patent owner is also the producer, licensing out the technology also brings a new competitor and dissipates the profit. Arora and Fosfuri (2003) [1] highlight two main factors effecting firms' incentive to license out their technology: revenue effect and profit dissipating effect. Revenue effect is defined as the amount of rents in a licensing contract, and profit dissipating effect is given by the loss for the licensor due to the licensing introduce an additional competitor in the technology market. Ownership to the external technology affects both of the factors. The most extreme condition is that only one incumbent in the product market where industry profit are maximized by a monopoly. In stead, when the monopoly licenses the technology to another incumbent, the revenue effect is much lower than the lost loss from the monopoly surplus. As a result, if there are two or more incumbent firm that have proprietary technologies that are substitute for each other, firms are be higher in the absence of a licensing.

Following empirical works also confirm the ownership structure on licensing incentives. For example, Andrea Fosfuri (2006) [11] find that licensing was less common in concentrated chemical products. Gambardella et al. (2007)[13] report that larger firms are less likely to license their technologies.

3.3 Bargaining Game between Patent Licensing and Patent Opposition

In this section, we present a simple two stages game to link the ownership fragmentation, licensing incentive and opposition filings. We can adopt the assumption in Arora and Fosfuri (2003) [1]. Consider a sector where N firm have independently developed technology for the production of a good, and goods on the market are perfectly homogeneous. For simplicity, we also exclude the case of pure technology suppliers without products. The technology product market profits of the incumbent $V(N)$. Based on the conclusion in Arora and Fosfuri (2003) [1]. $V(N)$ decreases as the number of firm N increases, since the licensing creates a new competitor. $Z = V(N) - V(N+1)$ can reflect the profit dissipate effect.

Consider a company plans to enter in a product market, but does not have the technology or has a risk to infringe an incumbent's patent. Adopt the assumption in the litigation game in Galasso and Schankerman (2010) [12], the entrant firm hold a private information of the type of patent p, which represents the probability of patent survive from an opposition, and can be explained by factual issues that is relevant to predict the expected outcome of the opposition, such as the prior art which and challenge the validity to the patent but not found by the patent office. The strength of patent protection also affects the future litigation risk and firm's decision. For simplicity, we exclude the case that the entrant invests in the technology with a risk of future infringement disputes. The entrant company has three options: not enter, enter by buying the technology and invent around the technology and file an opposition to invalid the existed related patent.

Procedural differences between opposition process and US litigation event changes the timeline of the bargaining game between incumbent firm and potential opponent. First of all, In the European Patent Office, there is no settlement and the examiner can pursue an opposition case even if parties involved have achieved some kind of understanding. This feature decides that negotiation contract must take place prior to the filing of opposition and the game will not enter into longer horizon or repeated games. Our discuss license as an ex ante negotiation in a two stages game. Second, we rule out the cost threaten to patent owner. Patent owner doesn't need to payback the fees even the patent has been successfully revoked since opposition in EPO follows the administrative process.

Figure 1 summarizes the timing of the pre-opposition bargaining. At $t = 0$, the entrant makes take-it-or-leave-it negotiation L which is based on the estimation of the likelihood p that the patent will be invalidated. If the incumbent license out the technology, he can earn the royalty rates L for the license but share the profit with a new competitor Z. If the incumbent reject the licensing request, an opposition takes place at $t = 1$ and no longer a chance of negotiation. Opponents need to pay effort c to collect evidence and administrative fees. If the opposition is accepted by the EPO, part or full of the claims will be revoked and patentee will not gain any revenue. Respectively, if the EPO reject the opposition petition, for example, the submitted prior art is not sufficient, patentee still keep the patent rights and opponent needs to pay to get the license.

Applying backward induction, the licensing payment must be no larger than the sum of opponent's expected value of the technology and opposition expenditure.

$$V(N+1) - L \geq (1-p)(V(N+1) - C) - pC$$

Thus, incumbent with patent of type p will accept a licensing contract L only if

$$L \leq pV(N+1) + c \tag{1}$$

Knowing this, the potential licensor's optimization problem is to maximize his expected profit Π by choosing a cut off type p^* , such that incumbent firm above this cut off license out and those below reject it. Formally,

$$Max_p \Pi = \int_p^1 [p * V(N+1) + c - Z]dy + \int_0^p 0dy \tag{2}$$

$$Max_p \Pi = C + pV(N+1) - Z - Cp - p^2 V(N+1) + Zp$$

Set the first derivative equal to zero, solve to find the critical point as:

$$\frac{\partial \pi}{\partial p} = V(N+1) - c - 2pV(N+1) + Z = 0$$

$$p* = \frac{V(N) - c}{2V(N+1)}$$

Entrant makes the licensing contract by maximizing his expected profit by choosing a cut off type p^*, such that incumbent firm above this cut off accept the offer and those below reject it, where

$$E(p) = p* = \frac{V(N) - c}{2V(N+1)} \tag{3}$$

All types of incumbents with $p < p^*$ will not license out the technology, and opposition will be filed. This allows us to summarize a negative impact of the number of firms on the market and the probability to file an opposition, follows $\frac{\partial p*}{\partial x N} < 0$

In other words, when the market is under the monopoly or duopoly conditions, incumbent does not like to offer a license or other kinds ex ante contract, and entrant firms have higher incentive to file an opposition to challenge the blocking technology. Other things being equal, when the technology markets are more competitive, licensing will be more likely. We expect that:

Hypothesis 1a : *opposition rate will decrease with the fragmentation of the external technology markets increases.*

3.4 Ownership Fragmentation and Transaction Cost

However, we do not expect the number of potential technology suppliers monotonically decreases the opposition propensity. Too widespread ownership to external technology also possibly proliferate opposition filings. Recent patent proliferation results in high probability of overlapping rights as well as two widely fragmented ownerships. As the Ziedonis (2004) [40] claims that firms even aggressively file a patent especially when the sector is already fragmented, since patent folio can improve firm's negotiation position rather than exclusion rights. As a result, it is more frequent that one essential technology is held by a group of patents and patent holders. (Hall and Ziedonis (2001) [18]; Bekkers et al, 2002 [3]; Markus Reitzig (2003) [34]).

A number of scholars point at a serious problem that the fragmentation of property rights actually affect incentives to innovate. For example, Shapiro (2001) [37] and Clark and Konrad (2008) [6] use model theory, fragmented property rights can limit firms' willingness to invest in R&D; Empirically, Cho et al 2003 provide survey evidence that firms reported that they had to abandon research projects because of patents held by rivals in biotechnology sector. Thumm(2005) [38] provide an evidence from Swiss firms and Kingston (2001) confirm the damaging affect in the case of complex technologies.

One theoretical explanation for why entrant drops the licensing negotiation relates to the transaction cost. Transaction cost is increasing as the number of potential licensees, especially the indirect costs incurred for searching, contracting and adapting for all the licensed knowledge (Heller and Eisenberg, 1998 [23]; Ziedonis, 2004 [40]). When the ownership fragmentation is too widely, firms have alternative option: opposing the patent directly. Revoking competitor's patents is more efficient way to get access to a technology, also can extend the challenger's market shares. This option is few discussed in the litigation literature with US cases since in US, invalidation proceeding is very expensive, licensing is used as post negotiation tool to settle a litigation suits (Galasso and Schankerman 2010 [12]).

In summary, the presence of multiple sources for a technology titles the balance between the patent licensing and opposition incentive. From the patent owner's perspective, incentive of licensing out is negatively with the gross profits in a self-production. It is less willing to license out the technology than it would be in a competitive market, because licensing creates a significant threat of the monopoly surplus. From opponent's perspective, opposition incentive increases as degree of fragmented ownership to the external technology. Revoking competitor's patents help firm to enter into the market or acquire the market share more efficiently. We formulate the following hypothesis.

Hypothesis 1b : *There exists a U-shaped relationship between the opposition likelihood and fragmentation of a technology market.*

3.5 Complex vs. Discrete Industry

Differences between discrete industry and complex industry are frequently discussed in the literature on patent litigation. Cohen et al (2000) firstly label complex product industries and discrete product industries. Invention as a discrete product can be protected by a limited number of patents while a complex product depends on much more patents.

Patent is an efficient tool for firms, in a discrete industry, to appropriate profit from innovation. For example, BH.Hall et al (2005)[17] test the patent stock and firms' market value, and find that discrete technologies such as Drugs are characterized by a relatively strong product-patent link. Corresponding, studies with US patent litigation data find that discrete product, such as pharmaceuticals industries, particularly likely to generate legal disputes. (Lerner,1995 [28] , Lanjouw and Schankerman, 2001 [25]). Harhoff et al 2004 [21] constructs a comparative control group with European patents and find consistent results with patent opposition rate.

Comparatively, we can expect three reasons may mediate the impact of ownership fragmentation on opposition strategy in a complex industry. Firstly, a complex technology often integrates multiple patents and highly complementary, therefore it is less possible to have a technology monopolist in a complex industry. In fact, cooperative agreements such as patent pools frequently happens at any time, and independently with a litigation threat (Lemley and Shapiro ,2007 [27]). Besides, delay in gaining access to all necessary components of a complex technology will be especially harmful for technologies with a short life cycle. Firms may enter into the market within infringement risk if the licensing is difficult to approach. Also, impact of ownership fragmentation on opposition strategy will be mediated if the potential licensor is pure technology supplier without products, which is frequent in complex industry, such as technology relates to software. Based on the above analysis, we expect that:

Hypothesis 2a : *opposition frequency is high in the discrete product industries.*

Hypothesis 2b : *The effects of fragmentation of technology market on opposition probability are comparatively stronger in discrete product industries.*

4 Description of Data and Patterns

The hypotheses presented in the previous section are tested using patent data granted by European Patent Office. Our sample covers the published patents filed in EPO from 1985 to 2005. A full sample model, selected subsample models, and included control variables; help account for theories of ownership fragmentation on opposition probability.

4.1 Data Source and Construction

A dataset of patent characteristics and opposition events has been built by matching different data sources. The main database used in this paper is based on the PASTAT ("Worldwide Patent Statistical Database" provided by EPO). All of the EPO granted patents with "A" as the kind code that filed between 1985 and 2005 were selected. This data period limits concerns over any sample selection bias, such as examination lag, and enables data on a relatively large range of variables to be gathered.

We extract all patent related information from PASTAT, such as the patent number, filing date, granted date, opposed record, information of the applicants and international patent classifications (IPC) within each IPC class at 4 digits. IPC classes in this paper were extracted from the EPASYS database in January 2006. Data on each patent's legal status and opposition were extrapolated from INPADOC records of the EPO. Patent level data from different sources were linked to EPO granted patents via their application number. Additional data on patent applicants at the PEO were extracted from HAN database of OECD, which cleans and matches of applicant companies' names.

Based on the extracted patent information, we construct a unique dataset. The unit of observation for our study is the event counts within a specific IPC class, and event year. For example, one observations is ID "G09G1986" which is followed by the count of total patent opposition, filing, and grant rate, etc. in "G09G" and 1986.

Patents are classified using the IPC classification, allowing us to analyze differences in patenting activities across different technologies. The categorization used is based on an updated version of the OST-INPI/FhG_ISI technology classification.

In order to consider the specific characteristics of product industries in contrast to fields of technology, we use the distinction between complex and discrete product industries. The definition of complex and discrete product industries follows (Cohen et al, 2000) [7] discrete product industries include chemicals, food, paper and metals, and the group of complex product industries consists of machinery and equipment, electronics, and transportation equipment.

In order to select data of interest to this project, we applied two sorts of filters on patent applicants and IPC classes. First of all, we delete the "small" applicants, whose patent stands less than 5% of the total patents in each class and opposed patent stands less than 5% of the total opposed patents. Further to this, we keep only IPC classes in which at least 30 filings were opposed. After dropping those cases, 10248 observation remains, which constitute our full sample in this paper. The full sample covers 624 IPC over the twenty years.

4.2 Dependent Variables

There exist many ways to count opposition propensities, each carrying its own meaning and limitation. In the baseline model, we discuss the opposition likelihood in a specific IPC class. The dependent variable $Opposition_{it}$ takes the value 1 if at least one opposition has been filed and zero otherwise. We also study the ratio indicator *OR_it* condition on the unit, which has at least one opposition cases. *OR_it* is defined as opposition events divided by total granted patents in the same IPC class i and same year t. As a robust check, we test the propensity indicator *isOpposed_it* , which counts the total opposition filings in IPC class i and year t.

4.3 Independent Variables

A group of literature on patent ownership fragmentation adopt citation-based fragmentation index at the firm level (Ziedonis 2004 [40]; Schankerman and Noel, 2006 [31]; D.Harhoff et al 2014 [9]). This measure describes the fragmentation of prior art and predicts the potential licensor. Instead, the calculation of the fragmentation index in this study is based on all the patent applications in EPO without restriction to certain applicant countries. The calculation of the index is based on IPC classes included in our estimation sample, which can better describe the distribution of the patents ownership on each technology market.

We employ two formula below gives the exact definition of the fragmentation measure:

CR_4 and Herfindahl-Hirschman Index (HHI). The former requires the patent shares of top four companies participating within a patented technology market, while the latter requires information from all participants.

FragmentationCR4 Consider a market where n companies are operating and the share of the patents belong jth firm of the total patents within ith IPC class in year t is s_j . FragmentationCR4 is given by the sum of the patent shares of the largest four firms in the patented technology market.

$$FragmentationCR4_{it} = 1 - \sum_{j=1}^{4} s_j$$

4.4 Descriptive statistics

Table A displays the distribution of opposition cases, broken down by technology sectors and nationality. European patents stand for higher percentage (51%) than patent from other regions across all major technologies. The distribution is similar with the empirical results by Lanjouw and Shankerman (2001) [25]. There are also pronounced differences in opposition counts across technology sectors, holding ownership constant. The most notable percentage is Chemistry (35%) and Mechanical Engineering (35 %).

The index focuses on the activity of the top four firms on the market. Consider the following stylized example: assume that two IPC field, Class A and Class B. Each class receives 100 patents from EPO in 1990. In Class A, only four firms exist on the market and divide the 100 patents. We do not need to identify the distribution among the four firms and we can conclude directly that potential entrants will meet high barrier to enter into Class A. In Class B, one firm controls 40 patents and the rest patents are collectively distributed among other nine firms. Competition among the nine firms increases the probability for collaboration and licensing. We would infer from the above example that Class A is more likely than Class B to engage in opposition with the potential entrants.

As a robustness check, we construct an alternative measure:

FragmentationHHI FragmentationHHI is defined as one minus the sum of the squares of all the patent shares hold by n firms in the market.

$$FragmentationHHI_{it} = 1 - \sum_{n} (s_j)^2$$

The fragmentation is obviously a positive figure. If the market shares are expressed as fractions of the whole market (i.e., $0 < s\_j \leq 1, \forall j$), then we have $0 < FragmentationHHI\_it \leq 1$. If we have a monopoly, where a single company takes all the patents in the market, we have $n = 1$ and $s\_1 = 1 => FragmentationHHI = 0$. But the opposite case, where all the patents in the market is uniformly distributed between the company (perfect competition), we have $FragmentationHHI = 1 - \sum_n (\frac{1}{n})^2 = 1 - \frac{1}{/}n$.

Hence, the higher the value of the $FragmentationHHI$, the higher competition degree on the technology market.

4.5 Control Variables

Filings: Filings_it is measured as the number of patent applications filed at the EPO. It is composed of the patents that were filed directly at the EPO also extends to the patents filed in EPO as second filings. The increased volume of patent filings appeared to a deeper reach into an existing technology, also predict the high risks of patent "thicket". Harhoff et al (2003) [22] finds positive correlation between the EPO oppositions and patent filings. We also expect that in high filing sector, opposition is more likely to occur.

Grant Rate: GR_it is the total granted patent divide the filing amount in the same IPC classification i and time period t. Since granted patent has higher value than patents refused or withdrawn in D.Guellec & Pottelsberghe de la Potterie (2000) [16], an IPC class with high grant rate imply large amount of high quality patent, which has high probability to be involved into opposition. We expect the positive effect of GR_it on opposition.

share_EU/share_US: We identify the nationality of each patent as EU firms, US firms or other by the address of the applicants. Then we calculate the share of patents of Europe applicants ($share\_EU$) and of US applicants ($share\_EU$) over the total patent applications within the same IPC field and same year. Geographical distances between patentees and technology users also affect the incentive to patent, enforce and collaborate. For example, B.P.de la Potterie et al (2012) [36] claims that two countries are more likely to collaborate if they are geographically close to each other. Also, licensor does not operate if licensee is in a distant product or distant geographical market (Arora and Fosfuri, 2003 [1]), F.Caviggioli et al (2013) [5] proves that EPO patents whose priority states are also European countries are more frequently enforced. Non-EU firms file the EPO patents mainly for defendant, not enforce it. In other words, we can expect that overlapping geographical market have high probability of using patents as tools in in negotiating a settlement to patent disputes. We expect that a market with more local companies (high $share\_EU$) has higher probability with patent opposition.

nbIPC4 During an EPO examination process, patents are assigned IPC codes (International Patent Classification) of up to nine digits. Patents can belong to different technological fields and can thus be assigned several IPC codes at the same time. The number of the IPC interprets the breadth of the scope of protection and technical diversity in many previous works.(D.Guellec and BP.van Pottelsberghe 2000 [16]; D.Harhoff & M.Reitzig 2000 [20]; F.Caviggioli et al 2013 [5]). We expect that patents assigned many IPC codes (number of different four-digit IPC codes) have more uncertainty with its validity, more likely to be involved in opposition in the first place.

nbInventors We calculate the average number of patent inventors with patents filed in class i and year t. Number of inventors imply the potential network of the patent. We expect that the market with more inventors is more difficult for the follow-on inventors to negotiate the access to the technology, where has higher risk to be involved in the opposition events.

5 Empirical results

5.1 Features of patent opposition and filings

Figure 2 traces the growth of patent filing since 1985 based in the technological characteristics used in this paper. Overall, EPO are experiencing a constant increase in the number of size of patent applications, especially in complex product industry. The patenting trends are consistent with other research such as Bessen and Hunt (2004) [4], Grindley,P.C, and D.J.Teece. (1997) [15].

Patent opposition trends (Figure 3 and Figure4) are more stable than the growth of filing. There are sharp differences in opposition propensity and opposition rates between discrete product industry and complex product industry. Opposition propensity and opposition rate in discrete technology are both higher than the indicator in complex technology, consistent with literature Harhoff et al (2002) [19]. For example, the aggregate figure of 0.06 means that for every 100 granted patents applied for during the year 1985, they will eventually become the subject of 6 opposition filed cases if they are in the discrete industry while only 1 filed cases if they are in the complex product industry.

Figure5 presents the evolution of patent market fragmentation. Both of the complex and discrete industry present increasing fragmentation trends, which can be regarded as suggestive evidence of an increase in the rate of new innovators entering the industry. The difference of fragmentation index in complex and discrete technology area is negligible.

Table 1 provides additional information on the distribution of fragmentation indicators across the 30 technology areas. It captures a substantial fraction of the variance and shows the significant strategically opposition potential. There are between ten to twenty times as many variances as top5 level, such as control technology and nuclear engineering exhibit significant fluctuate with top5 indicator.

5.2 Descriptive Statistics

The estimation sample bases on total 10248 observations. As shown in Table 2, the median unit (per industry per year) in the sample has 253 patent filings and 0.62 grant rate, with 4.15 opposition a year. The distribution of these variables is highly skewed. We also report the fractional count. The fractional count is the count of the patent activity divided by the registered number of IPC for each patent. Propensity indicator, opposition and Filings get reduced at almost a half., and the rate indicator, opposition rate (OR_Frac) and granted (GR_frac) don't change a lot. On average, there are 2 oppositions, 40% of patents per class have less than 2 opposition, but 10% of those have more than 10 opposition. The pattern consistent with the studies on litigation, only a small number of technologies will be worth litigating over anyway (Grabowski and Vernon, 1994 [14] ; Scherer and Harhoff, 2000 [35].

In Non-zero Sample, we omit the observations without any opposition filings. More than half of the observations, however, a unit did not receive an opposition in a given year. As shown in right part of Table 2, omitting zero observations of the units with none opposition would generate a sample that have more patent filings, opposition filings, opposition rate and fragmentation index but no supportive evidence for higher grant rate.

In order to avoid restricting the sample in ways that would favor the dependent variable (opposition) and to retain important information regarding industry with little opposition, we include zero observations of the opposition in the regression. Estimations based on the non-zero sample did not substantively alter the econometric results, and will be discussed more with the regression on opposition rate.

Table 3 display correlations respectively for each of the variables described in the previous section. A review of the correlations between the independent variables indicates that multi- collinearity is generally not a cause for concern. The correlation of 0.61 between $Fragmentationtop4$ and $FragmentationHHI$ confirms the use for robust check.

Table4 describes key variables by selected industries. Average opposition rate (OR) vary greatly by industry. For example, discrete industries, such as Surface technology has more than 140 opposition cases each year, and the opposition rate is around 12%, while complex industries, such as Telecommunications and Information technology have less than 0.2 opposition events each year. Filing statistics also have high variation across industries. Comparatively, more of the discrete industries have higher share of EU patents and one patent cover more IPC codes and number of inventors.

6 Model Specification and Results

6.1 Baseline Specification and Identification Strategy

We primarily check the impact of independent variables on the probability of the opposition event. The dependent variable $Opposition_{it}$ is equal to one for a granted patent that has undergone an opposition procedure and is equal to 0 otherwise. The model estimates the probability that an IPC class is attacked by an opposition event at any point in time, after the opposition cases is filed, it exits the sample, and the subsequent opposition cannot affect the estimation. The basic function is as follow:

$$Opposition_{it} = \alpha + \beta_{OP} X_{it} + \epsilon_{it}$$

$\beta_{OP}$is a vector of parameters to be estimated. We report OLS and Logit regression with heteroscedasticity-fixed standard error.

We also discuss the impact of ownership fragmentation on the opposition rate variables (OR). We report OLS regression with heteroscedasticity-fixed standard error. We also test the model with non-zero sample. The regression function is as follow:

$$OR_{it} = \alpha + \beta_{OR} X_{it} + \epsilon_{it}$$

Table 5 presents the relationship between ownership fragmentation measures and the patent opposition likelihoods. We begin in column (1) by presenting the panel regression approach which controls for characteristics of each IPC class. GR, Filing , number of IPC codes and number of inventor present significant positive impact while the other variables are not. The results consistent with our prior hypothesis that technology areas with active patenting activities, widely scope contain more opposition cases; areas with loose grant standard contains high opposition probability. However, the coefficients of $share_{EU}$ and $share_{US}$ are not statistically significant which can't support our hypothesis on the geographical impact.

In column (2) and (3), we add the fragmentation index in the regression. Column (2) report the results of basic regression on opposition likelihood and Column (3) report the regression on opposition rate and omit the zero values. Including the fragmentation index in Column 2 and Column3 both substantially improves the overall fit of the model and significantly increases its explanatory power relative to the baseline model. This patter suggests that our main explanatory variables play a significant role on top of the controls.

The coefficient of FragmentationCR4 on opposition rate and opposition likelihood shows opposition signs. Higher $FragmentationCR4$ value will positively affect the probability of opposition events, however, based on the result of column (3), we can conclude that the change of the market competition negatively affect the change of the opposition rate. This result is consistent with our Hypothesis 1b.

Hypothesis 1a predicts that the opposition propensity is first increasing and then decreasing in the competition of technology market. To test this hypothesis, we add a square term to the fragmentation index. Column 4 presents the OLS regression on opposition likelihood and Column 6 reports the results by Logit regression. The overall fit of the model significantly increases. The coefficient on $FragmentationCR4$ and $FragmentationCR4$ squared are both significant at the 1% significance level. Support for Hypothesis 1, we obtain a negative coefficient for the basic FragmentationCR4 and a positive coefficient for the square term, suggesting that the relationship between the fragmentation degree and opposition likelihood displays an U-shape.

However, U-shape pattern is not significant with the opposition rate regression. Column 5 reports the regression with opposition rate with the non-zero opposition sample and Column 7 report the results of full sample. Neither result can provide sufficient evidence that market fragmentation makes a U-shape impact on the opposition rates. Only the coefficient, reported in Column 3 confirm the negative impact.

6.2 Separate models by industries

Table 6 reports the regression results based on complex and discrete product industry classification. Both of Sub samples keep the significant U-shape patterns at the 5% level. Also, with the non-zero sample, FragmentationCR4 keep significant negative impact on the opposition rate (No significant evidence to confirm U-shape relationship with opposition rate model).

If we check the impact of ownership fragmentation for each specific industry, show in Table 7, we find that more discrete industries, such as Biotechnology, Materials, Chemical engineering, and Agricultural and food processing strongly support the U-shape hypothesis but fewer complex industry supports this pattern. Therefore, Hypothesis 2b get confirmed. One alternative reason is lack of the samples for concentration market in complex product industry. As the Figure 5 presents, the average of FragmentationCR4 index in complex industries is much higher than that in discrete industries.

6.3 Robustness and Extensions

We perform two tests to confirm robustness of our main finding. First, we use opposition count as the dependent variables. Since the dependent variable is discrete, non-negative, with numerous zero entries, the simplest model form to accommodate count data is the Poisson Regression Model. We report both of the OLS and Poisson regression with fixed effect in Column 1 and Column2 of Table8 and the results confirm the U-shape relationship between FragementationCR4 and opposition count. Second, we use alternative fragmentation index FragmentationHHI. The result is reported in Column 3 and Column 4 in Table 8. The result confirms our primary hypothesis about U-shape relationship between market fragmentation degree and opposition likelihood. Conditional on non-zero sectors, fragmentation degree negative affects the following opposition rate.

7 Conclusion

In this paper, we discuss the impact of ownership fragmentation on opposition probability. We argue that determinant of opposition filing is not merely by evaluating the quality of an individual patent, but also by the external technology market. We combine the license theory to discuss the commercial value of patent involved in a dispute. We argue that competition in the market for technology could increase the ex ante contracting. Indeed, the trade-off between profit dissipation effect and revenue guide licensing decisions, also the incidence of opposition. On the other hand, fragmentation of technology ownership also increase the transaction cost for a licensing contract as well, and then opposition become an efficient tool for entrants to get access to the technology.

We tested this framework using an extensive dataset of European patent. We construct application-based measures for evaluating ownership fragmentation, and test the impact of fragmentation level on the opposition propensity at the sector level. Regression result confirms the U-shape relationship between market fragmentation degree and opposition likelihood. Besides, we have tried to differentiate the impact of market in complex and discrete industry. More discrete industries presents statistically significant on U-shape pattern.

There are two useful directions for further research. The First is to investigate how bargaining outcomes affect the further litigation risk. To do this would require a more comprehensive dataset that collecting opposition cases and equivalent patents involved in a litigation suit. Survey evidence on the actual timing and structure of negotiations between downstream users and upstream patent holders would be extremely useful. The second direction is to examine more fully how firm characteristics, including the size and liquidity position of disputants, affect the strategy of opposing or settling.

Table 1: the statistics of $FragmentationCR4$ among different industries.

OST30	N	Mean	sd	Min	Max
Electrical machinery	504	0.95	0.09	0.38	1.00
Audio-visual technology	189	0.96	0.08	0.22	1.00
Telecommunications	357	0.94	0.10	0.17	1.00
Information technology	189	0.92	0.13	0.17	1.00
Semiconductors	21	1.00	0.00	1.00	1.00
Optics	210	0.96	0.06	0.60	1.00
control technology	651	0.93	0.12	0.00	1.00
Medical technology	189	0.98	0.02	0.90	1.00
Nuclear engineering	147	0.85	0.22	0.00	0.98
Organic fine chemistry	126	0.94	0.12	0.43	1.00
Macromolecular chemistry, polymers	147	0.99	0.01	0.94	1.00
Pharmaceuticals, cosmetics	420	0.89	0.14	0.00	1.00
Biotechnology	231	0.95	0.07	0.50	1.00
Agriculture, food chemistry	336	0.94	0.09	0.33	1.00
Chemical and petrol industry	105	0.99	0.01	0.95	1.00
Surface technology, coating	42	1.00	0.01	0.98	1.00
Materials, metallurgy	273	0.89	0.14	0.14	1.00
Chemical engineering	357	0.94	0.06	0.56	1.00
Materials processing, textiles	420	0.90	0.17	0.00	1.00
Handling, printing	231	0.93	0.06	0.41	0.99
Agricultural and food processing	777	0.89	0.12	0.25	1.00
Environmental technology	126	0.94	0.04	0.76	0.99
Machine tools	504	0.92	0.09	0.30	1.00
Engines, pumps	462	0.92	0.09	0.25	1.00
Thermal processes and apparatus	399	0.92	0.08	0.40	0.99
Mechanical elements	378	0.91	0.13	0.00	1.00
Transport	651	0.91	0.13	0.00	1.00
Space technology, weapons	252	0.78	0.19	0.00	0.98
Consumer goods and equipment	987	0.89	0.13	0.20	0.99
Civil engineering, building, mining	504	0.95	0.05	0.63	0.99
Total	10248	0.92	0.12	0.00	1.00

*Notes:The slope ones are discrete industries, Standardized beta coefficients * p¡0.05, ** p¡0.01, *** p¡0.001*

Table 2: Descriptive Statistics

	Full Sample, n = 10248				Non-zero Sample: n = 4069			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
$Opposition$	4.15	15.40	0.00	379.00	10.45	23.06	1.00	379.00
$Opposition_{frac}$	2.10	8.26	0.00	185.51	5.28	12.46	0.08	185.51
OR	0.02	0.05	0.00	0.50	0.06	0.06	0.00	0.50
OR_{frac}	0.02	0.05	0.00	0.53	0.05	0.06	0.00	0.53
$Filings$	253.23	532.36	1.00	11442.00	409.51	697.04	4.00	11442.00
$Filings_{frac}$	159.73	329.52	0.25	5680.76	249.55	416.87	1.31	5617.06
GR	0.62	0.14	0.04	1.00	0.62	0.14	0.08	1.00
GR_{frac}	0.61	0.15	0.03	1.00	0.61	0.14	0.05	1.00
HHI	0.89	0.13	0.00	1.00	0.94	0.07	0.00	1.00
$CR4$	0.92	0.12	0.00	1.00	0.96	0.06	0.09	1.00
$share_{EU15}$	0.48	0.16	0.00	1.00	0.45	0.13	0.00	0.92
$share_{US}$	0.25	0.13	0.00	1.00	0.28	0.12	0.00	0.80
$nbIPC4$	2.08	0.47	1.00	5.21	2.21	0.48	1.21	4.41
$nbInventor$	2.23	0.56	0.92	8.43	2.49	0.58	1.18	8.43

Table 3: Correlation matrix

	$Filings$	GR	HHI	$CR4$	$share_{EU15}$	$share_{US}$	$nbIPC4$	$nbInventor$
$Filings$	1							
GR	-0.2168	1						
HHI	0.2517	-0.0633	1					
$CR4$	0.2655	-0.1244	0.6109	1				
$share_{EU15}$	-0.2248	0.1709	-0.1281	-0.0707	1			
$share_{US}$	0.2061	-0.1147	0.1399	0.0406	-0.6249	1		
$nbIPC4$	-0.0121	-0.2269	0.0985	-0.0936	-0.1846	0.185	1	
$nbInventor$	0.3092	-0.1581	0.2563	0.1401	-0.4497	0.3456	0.4003	1

Table 4: Descriptive Statistics by OST30, the slop ones are discrete industries.

		opposition		OR		Filings		GR		top4		$share_{EU}$		nbIPC		nbInventor	
OST30	sample	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	sd		mean	sd	mean	sd
1	0.61%	0.35	0.92	0.03	0.06	322.27	685.27	0.61	0.20	0.79	0.24	0.41	0.19	2.37	0.54	2.64	0.63
2	4.92%	1.19	2.15	0.01	0.01	298.78	288.25	0.61	0.14	0.95	0.09	0.46	0.15	1.93	0.37	2.29	0.42
3	1.84%	0.65	1.63	0.00	0.01	562.09	845.45	0.58	0.17	0.96	0.08	0.36	0.13	1.80	0.30	2.15	0.41
4	3.48%	0.03	0.18	0.00	0.00	451.09	911.53	0.57	0.15	0.94	0.10	0.39	0.11	1.99	0.39	2.18	0.35
5	1.84%	0.24	0.63	0.00	0.01	677.89	1234.32	0.52	0.19	0.92	0.13	0.31	0.15	1.90	0.38	2.33	0.38
6	0.20%	9.90	5.59	0.01	0.01	2387.33	1033.60	0.50	0.15	1.00	0.00	0.26	0.04	1.68	0.16	2.70	0.20
7	2.05%	1.50	2.21	0.01	0.01	410.80	438.27	0.56	0.17	0.96	0.06	0.28	0.11	1.79	0.30	2.59	0.46
8	6.35%	1.07	5.36	0.00	0.01	278.37	513.84	0.58	0.16	0.93	0.12	0.43	0.13	2.05	0.35	2.18	0.37
9	1.84%	5.64	9.06	0.02	0.02	620.50	706.24	0.57	0.12	0.98	0.02	0.39	0.11	1.80	0.31	2.18	0.41
10	1.43%	0.45	1.05	0.01	0.02	67.08	43.06	0.61	0.17	0.85	0.22	0.45	0.14	2.03	0.37	2.49	0.44
11	1.23%	19.44	22.10	0.04	0.03	959.89	1069.55	0.60	0.15	0.94	0.12	0.38	0.10	2.38	0.61	3.53	0.60
12	1.43%	43.14	22.79	0.09	0.02	799.52	452.90	0.64	0.11	0.99	0.01	0.37	0.05	2.46	0.31	2.98	0.28
13	4.10%	9.22	16.54	0.09	0.09	171.35	227.96	0.60	0.18	0.89	0.14	0.44	0.14	2.49	0.51	2.80	0.52
14	2.25%	11.12	17.38	0.07	0.05	229.65	300.38	0.61	0.15	0.95	0.07	0.40	0.11	2.32	0.44	2.66	0.39
15	3.28%	11.60	12.06	0.10	0.06	191.56	190.21	0.64	0.14	0.94	0.09	0.43	0.11	2.36	0.41	2.75	0.35
16	1.02%	38.86	30.14	0.08	0.03	1183.13	1114.12	0.50	0.14	0.99	0.01	0.32	0.05	2.48	0.37	3.28	0.45
17	0.41%	143.29	104.75	0.12	0.04	2806.74	3146.07	0.58	0.13	1.00	0.01	0.45	0.09	2.44	0.36	2.91	0.34
18	2.66%	9.45	12.49	0.14	0.09	116.79	166.99	0.59	0.14	0.89	0.14	0.45	0.12	2.68	0.53	2.74	0.52
19	3.48%	5.27	12.03	0.02	0.03	261.39	416.75	0.61	0.13	0.94	0.06	0.50	0.10	2.21	0.40	2.23	0.43
20	4.10%	1.60	4.05	0.01	0.01	261.89	343.84	0.67	0.12	0.90	0.17	0.49	0.19	1.81	0.31	2.00	0.46
21	2.25%	0.92	1.50	0.02	0.04	104.08	84.10	0.63	0.11	0.93	0.06	0.62	0.13	1.85	0.52	1.86	0.33
22	7.58%	3.09	7.16	0.03	0.04	137.98	250.56	0.64	0.14	0.89	0.12	0.49	0.15	2.16	0.50	2.24	0.58
23	1.23%	1.65	2.18	0.02	0.03	160.02	173.27	0.59	0.14	0.94	0.04	0.50	0.10	2.57	0.40	2.34	0.37
24	4.92%	0.88	1.59	0.01	0.02	122.92	123.24	0.65	0.10	0.92	0.09	0.52	0.12	2.15	0.39	2.06	0.42
25	4.51%	0.26	0.85	0.00	0.01	142.08	166.59	0.67	0.14	0.92	0.09	0.46	0.11	2.06	0.33	2.19	0.43
26	3.89%	0.79	1.65	0.01	0.03	98.76	85.72	0.61	0.14	0.92	0.08	0.55	0.14	2.31	0.44	2.17	0.44
27	3.69%	0.79	1.67	0.00	0.01	221.82	221.90	0.67	0.12	0.91	0.13	0.56	0.10	2.13	0.42	1.97	0.35
28	6.35%	0.22	0.61	0.00	0.00	156.43	211.18	0.68	0.11	0.91	0.13	0.62	0.14	1.88	0.30	1.98	0.41
29	2.46%	0.15	0.69	0.01	0.03	40.16	34.74	0.64	0.16	0.78	0.19	0.58	0.18	1.95	0.45	2.10	0.42
30	9.63%	0.51	1.12	0.01	0.02	94.06	84.17	0.58	0.13	0.89	0.13	0.49	0.15	1.91	0.47	1.91	0.53
Total	10248	4.15	15.40	0.02	0.05	253.23	532.36	0.62	0.14	0.92	0.12	0.48	0.16	2.08	0.47	2.23	0.56

Table 5: regression estimates-opposition likelihood and opposition rate

	Baseline	1	2	3	4	5	6
GR	0.046***	0.051***	-0.095***	0.055***	-0.101***	0.691***	-0.011
$Filings$	0.043***	0.045***	-0.074***	0.045***	-0.078***	0.697***	-0.021
$share_{EU15}$	-0.004	-0.003	0.096***	0.002	0.095***	0.015	0.033**
$share_{US}$	0.008	0.011	0.053**	0.012	0.056**	0.154	0.025*
$nbIPC4$	0.031*	0.027*	-0.047*	0.024	-0.043*	0.320*	-0.021
$nbInventor$	0.064***	0.056***	0.013	0.044***	0.029	0.394**	0.01
$FragmentationCR4$		0.063***	-0.254***	-0.165***	0.075	-1.803**	0.026
$FragmentationCR4^2$				0.268***	-0.378***	3.078***	-0.037
N	10248	10248	4069	10248	4069	6258	10248
r2	0.008	0.011	0.075	0.014	0.079		0.002

Table 6: regression estimates-opposition likelihood and opposition rate

	1	2	3	4
$FragmentationCR4$	-0.276***	-0.369***	-0.281***	-0.317***
$FragmentationCR4^2$	0.395***		0.542***	
$grantRate$	0.054***	-0.034	0.089***	-0.079***
$isFiling$	0.087***	-0.157***	0.040*	-0.076**
$share_{EU15}$	-0.011	0.153***	0.019	0.097***
$share_{US}$	0.008	0.063*	0.056**	0.097***
$nbIPC4$	0.033*	0.232***	0.063**	-0.014
$nbInventor$	0.046***	0.099***	0.133***	0.038

Table 7: regression estimates-opposition likelihood and opposition rate

	$FragmentationCR4$	$FragmentationCR4^2$	$FragmentationCR4$
Electrical machinery	-1.061**	1.228**	0.054
Audio-visual technology	-1.048*	1.295**	0.216**
Telecommunications	-0.178	0.21	0.014
Information technology	-0.516	0.809	0.053
Semiconductors	not enough observations		
Optics	-1.158	1.26	0.078
control technology	-0.133	0.238	0.452***
Medical technology	-6.591	7.101	-0.05
Nuclear engineering	0.136	-0.206	0.807***
Organic fine chemistry	-0.01	0.84	0.091
Macromolecular chemistry, polymers	not enough observations		
Pharmaceuticals, cosmetics	-0.113	0.569*	0.401***
Biotechnology	-1.387*	2.011**	0.562***
Agriculture, food chemistry	0.619	-0.059	0.563***
Chemical and petrol industry	not enough observations		
Surface technology, coating	not enough observations		
Materials, metallurgy	-0.964**	1.533***	0.239**
Chemical engineering	-1.815*	2.166**	0.133
Materials processing, textiles	-0.29	0.456*	-0.077
Handling, printing	-0.815	0.784	0.091
Agricultural and food processing	-0.974***	1.243***	0.156***
Environmental technology	-1.335	1.818	0.425***
Machine tools	-0.53	0.696	0.109
Engines, pumps	-0.394	0.457	0.022
Thermal processes and apparatus	-0.13	0.216	0.047
Mechanical elements	-0.121	0.21	0.07
Transport	-0.11	0.225	0.065
Space technology, weapons	-0.458*	0.507*	0.009
Consumer goods and equipment	-0.562	0.687	0.093
Civil engineering, building, mining	-0.208	0.318	0.091

Table 8: regression estimates-opposition likelihood and opposition rate

	1	2	3	4
$top4$	0.009	-0.074***		
$top42$	-0.003	0.110***		
$grantRate$	0.052***	0.009***	0.049***	-0.080***
$isFiling$	0.285***	0.003***	0.043***	-0.056**
$share_{EU15}$	0.029***	0.009***	-0.003	0.086***
$share_{US}$	0.023***	0.006***	0.009	0.050*
$nbIPC4$	0.027***	0.005***	0.024	-0.056**
$nbInventor$	0.027***	0.014***	0.058***	-0.034
hhi			-0.069*	-0.131***
$hhi2$			0.127***	
N	10248	8001	10248	4069
r2	0.177		0.01	0.036

Figure 1: Bargaining in Opposition Game

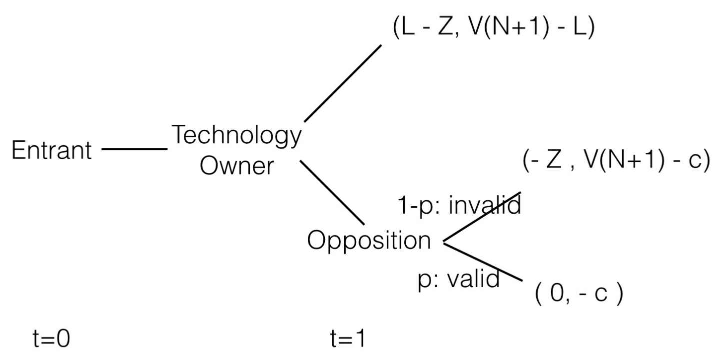
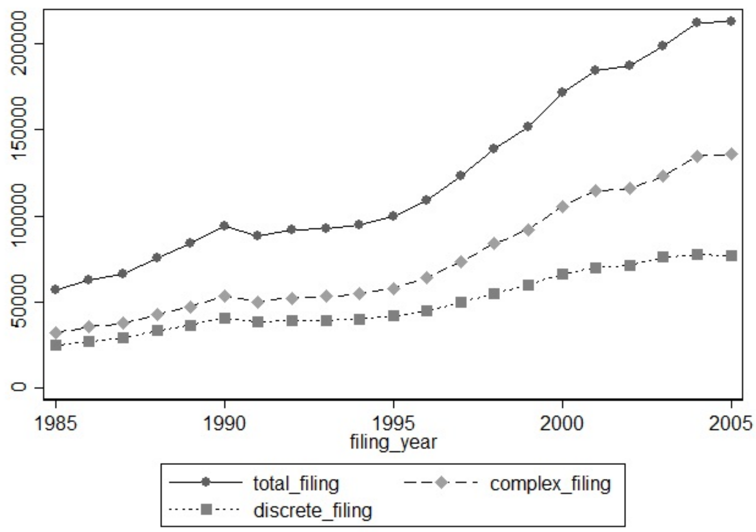


Figure 2: trends of observations with patent filings



Notes: annual number of patent applications filed at the EPO by filing year. Black line with coin indicates total patent applications. Line with diamonds indicates the patent application in complex technology areas. Line with squares indicates the patent applications in discrete technology areas.

Figure 3: Trends of patent opposition, with subsample of industries

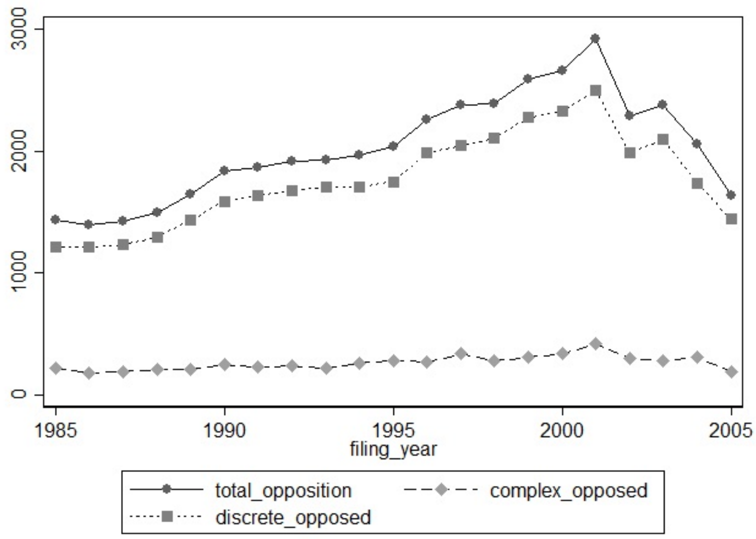


Figure 4: Trends of patent opposition rate

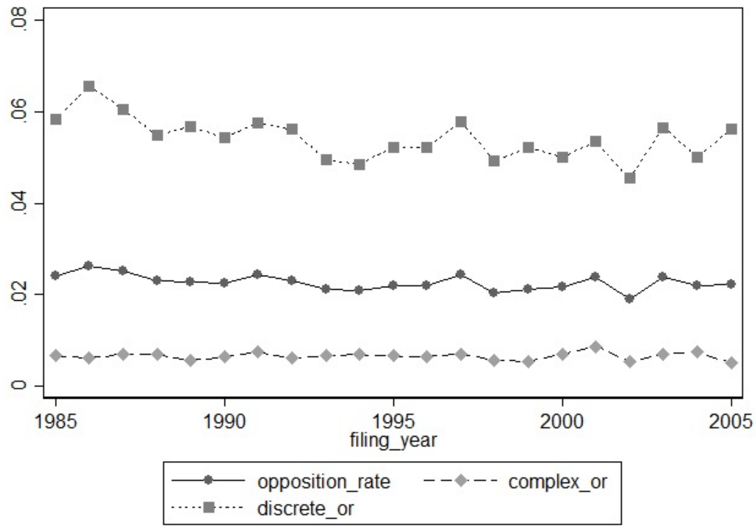
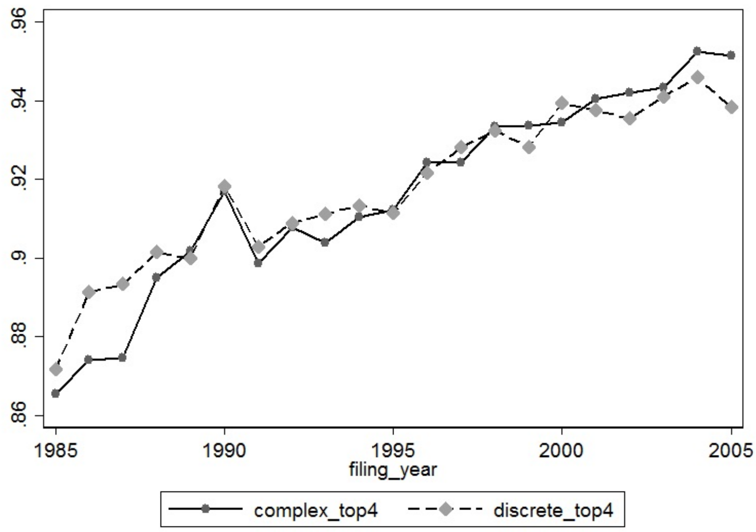


Figure 5: Evolution of ownership fragmentation, with subsample of industries



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