博士論文

Beyond protection of invention: Economic analysis on appropriating technology by patent collateralization and licensing

（発明の保護を超えて：特許担保融資とライセンシングに関する経済分析）

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Ph.D. dissertation

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Abstract

This dissertation provides an economic analysis of alternative appropriation strategies for new technologies, with a focus on the role of patents. Aiming at understanding the value of patents and the market of technology, two strategic uses of patents—collateralization and licensing—are examined using rich empirical data from China (an emerging economy) and Japan (a developed country). Patenting strategy of Chinese firms under policy incentives is also covered.

Existing literature on financing innovation focuses on the signaling effect of patenting, but not on the asset property of patents. In a collateral-backed financing deal involving transfer of ownership, liquidity should be as important as the value of collateral, if not more so. Surprisingly, studies on the management of intellectual property have not effectively examined the concept of liquidity for patent assets. A major blank is a discussion of indicators for patent liquidity despite several studies on patent value indicators. This study separates the concept of patent liquidity from patent value and identifies their influences on propensity to lend with patents as collateral. The value of patents is expressed as the maximum discounted revenue a patent can generate while the liquidity is the probability of finding a buyer who agrees to pay for the value. Drawn from existing studies on patent licensing market, particularly studies on generality, several liquidity indicators are proposed from the perspective of technology generality, technology complexity, and technology competition. Controlling the treatment effect of firms' willingness to apply for patent-collateralized loans using PSM method, I find that patents with larger family, broader claim scope, more opposition records and simpler but widely applicable patents are more acceptable as collateral. However, a weak positive significance of IPC based on indicators of generality underlines a cautious interpretation of this widely used indicator. This study also proposes technology competition as an indicator of patent liquidity, but empirical result failed to verify this. A limitation of using patent-generate competition is that we cannot distinguish whether the players in the same field are more likely to be potential buyers, or just substitute technology providers. To further understand these problems, it is important to study licensing activities with dataset containing more specified settings of technology supply and demand, which becomes the motivation to study markets for technology using a novel dataset of licensing activities of Japanese firms.

Contrary to sparse studies of patent collateral, patent licensing is a consistently popular topic in economic and management studies. Interestingly, although the theoretical argument of licensing as a strategy often starts from a discussion of value capture, empirical studies terminate at the value capture stage. One reason is that we still lack comprehensive empirical data regarding the performance outcomes of licensing. The survey data of Japanese firms' licensing activities allowed an empirical analysis of determinants of license revenues with a wide coverage of the competition between technology suppliers, technology buyers, IP protection, and contract structure. Most importantly, this study provided empirical support of a theoretical proposition that multiple contracting helps the small technology venture capture more rent from technology transfer. On the contrary, patent protection does not show a significant contribution to license revenue. The results also provide implications on why patents of a fragmental technology field are not more acceptable as collateral, despite that liquidity shall be improved due to market thickness.

In sum, this study contributes to the literature on technology exploitation strategies other than directly profiting from selling patented products. It underlines the value of patents beyond protection of inventions.

Keywords: patent; license; collateral; innovation; China

JEL codes: O32 O34 G21

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Chapter 1 Introduction

1.1 Patent value beyond protection of invention

Formal intellectual property rights, especially patents, have been widely recognized as pivotal assets for innovative firms to capture rents from their inventions. By disclosing an invention to the public, the inventor is awarded a temporary period of market exclusivity. Patents provide a barrier of imitation and help firms capture rents from commercializing their inventions. However, innovators can appropriate their patents with a number of alternative strategies, including blocking competitors, securing development freedom, building reputations, attracting investors, and most notably, seeking licensing revenues (Blind, Edler, Frietsch, & Schmoch, 2006; Cohen, Nelson, & Walsh, 2000; Somaya, 2012). These benefits are partly derived from market exclusivity, but also come through different mechanisms. For example, patent publications enlarge the disclosure of technologies and attract potential licensees. Active patenting is a strong signal of R&D performance and future growth, motivating investors to provide early stage funding. Thus, patents have value beyond protection of invention, and appropriating strategies may vary among firms.

Differences on appropriating strategies reflect industry conditions and the characteristics of technologies. By surveying US manufacturing firms, Cohen et al. (2000) find that firms in "discrete" product industries, such as chemical industry, are more likely to filing patents for blocking rivals from developing substitute technology, while those in "complex" product industries, such as telecommunication and semiconductor industries, tend to use patent to force rivals into negotiations. Appropriating strategies are also affected by macro policy changes. A different perspective is to separate technologies as "general-purpose technology (GPT)" or "dedicated technology", where GPT is defined as a technology which "can be applied, with low adaptation costs, to different products or industries(Gambardella & Giarratana, 2013a)". GPTs are more suitable to be licensed out as it can help accrue licensing revenues from different sectors without creating direct competitions between the licensor and licensees(Ashish Arora & Fosfuri, 2003; Gambardella & McGahan, 2010).

Appropriation strategies are also influenced by macro policy changes. Theoretically, enhancing patent protections motivates firms to use patent, rather than secrecy, as a strategy to protect innovations, as "inventing around" becomes more difficult. Policies strengthening patents rights include broadening the coverage of patentable technology, e.g. making software algorithms eligible for patenting (Garfinkel, 1996); allowing a wider drafting and/or interpretation of patent claims(Adelman & Francione, 1989; Meurer & Nard, 2005; Sakakibara & Branstetter, 1999); and increasing patent life. Policy changes not only affect the strategies of using patents as a protection for innovation, but also alternative appropriating strategies, such as licensing. Nagaoka (2005) find that stronger intellectual property protection brings more high-royalty licensing contracts in Japan. A widely tested question is whether patent enhancing policy really increased innovations. Lerner(2009) analyses major policy shifts of 60 nations in past 150 years, but did not find a significant positive impact of enhanced patent rights on innovation. Sakakibara and Branstetter(1999) also find no significant increase of R&D investment or innovative output in response to a patent reform in Japan in 1988. A non-traditional patent policy change is patent subsidies initiated by Chinese governments. It is identified as an important factor behind the surge of patent applications(X. Li, 2012), however, its impacts on strategically usage has not been explored with detail.

Several studies that have examined appropriation strategies theoretically and empirically emphasize on patent licensing (including cross licensing) as it has become a widely practiced strategy in the new age of "open innovation" (Chesbrough, Vanhaverbeke, & West, 2006). Patent protection is important in overcoming the market limitation of new technologies: the opportunistic behavior of technology buyers (Gambardella, 2002; Teece, 1988). However, empirical evidence is not consistent on whether the effect is significant, and the appropriation condition, e.g. the competition environments in both sides of licensors and licensees, needs further investigation

(Ashish Arora & Ceccagnoli, 2006; Gambardella, Giuri, & Luzzi, 2007; Kani & Motohashi, 2012).

Patent licensing may provide some revenue for small firms, which can compensate R&D cost, allowing them to be sustained as pure technology providers. Alternatively, the innovators may try to access financing and build their own complementary assets. The value of patents in financing small and medium enterprises (SMEs) is well elaborated by scholars, especially their influence on stock prices (Hirschey & Richardson, 2004) and in obtaining venture capital investment (Conti, Thursby, & Thursby, 2013). However, the practice of using patents as collateral has only recently gained attention in innovation studies (Amable, Chatelain, & Ralf, 2010; Fischer & Rassenfosse, 2011). Contrary to active licensing on a global scale, the use of patents as collateral is still limited and concentrated in a few countries (Japan in the late 1990s and China in the late 2000s). Empirical studies are especially rare in this field.

Current knowledge on markets for technology basically comes from studies on technology licensing, either formal patent licensing or contracted research. However, a rather neglected fact is that a deep study of patent collateral can also deepen our understanding of markets for technology. In patent collateral, the ownership of patent assets is temporarily transferred to a financial institution. The financial institution needs to consider whether the technology can be licensed or sold to a third party if the borrower defaulted. Thus, patents collateral should also be considered from the perspectives of markets for technology.

Aiming at providing new insights on markets for technology, this dissertation provides a novel empirical analysis of alternative technology appropriation strategies focusing on patent collateralization and licensing. Using patent collateral registration data from China and licensing survey data from Japan, this study attempts to identify the value of patents beyond the protection of inventions, the appropriating strategies, and their outcomes.

1.2 Patent collateralization: practices and problems

Practices of using a patent as collateral appeared as early as the 1880s, when Thomas Edison used his patent as collateral to borrow money for starting a business (Baldwin 1995). In the US, there are reports that banks successfully obtained repayment by liquidating collateral patents in 1971 (Bramson, 1981). Since 1995, the Development Bank of Japan (DBJ), a government-owned financial institution, began to accept patents, patent applications, and copyrights as collateral. Since 2007, about 250 IP collateral loans have been assigned (METI, 2007).

However, these practices remain limited due to valuation difficulties and liquidity problems (Harhoff, 2009; Kamiyama, Sheehan, & Martinez, 2006). Generally, the valuation of patents employs an income approach. A market survey is necessary for estimating the potential revenues generated by IP-protected products or services and the IP contribution. Generally, technology experts and patent attorneys are consulted for an assessment of patent scope when using patents as collateral, which is a costly process. In addition, due to market uncertainties and unpredictable technology evolution, the valuation can hardly be objective and precise.

A more severe problem is the illiquidity of patent assets. The technology market is not well developed, and when loan defaults occur, it is very difficult for the banks to sell or license to a third party to defer the cost of a defaulted loan (Harhoff, 2009); thus, banks are unwilling to accept patents as collateral, although financially constrained SMEs have a strong incentive to do so.

A unique case is that of China. Patent-backed debt financing had developed slowly in China until 2006, not only due to the difficulties stated above, but also due to weak intellectual property rights (IPR) enforcement. In the mid-2010s, thanks to stronger IPR enforcement, government promotion of SME financing, and bank reforms, patent-backed debt financing developed very quickly. From January, 2006 to June, 2011, 3,361 patents (including utility models and design patents) have been used in collateral loan assignments, and the debt amount has reached 31.85 billion Yuan (approximately USD 5 billion), with an annual growth rate of 70% (SIPO, 2011).

Another characteristic of patent-based collateral financing in China is the wide involvement of commercial banks. Although policy banks, like the China Development Bank, are providers of patent-based collateral loans for SMEs, they are not as dominant as the DBJ in Japan.

Studying practices of using patents as collateral can provide implication on how patents are valued from both its effectiveness in securing market exclusivity for the borrower and its possible liquidation value for the financial institution, which can provide a new perspective for our understanding of markets for technology.

1.3 Technology exploitation through licensing

Inventors may license their technology owing to varied motivations: building complementary assets for commercializing the technologies on their own is very expensive; some technologies are no longer central to their core business when the firm is shifting to a new domain; or substitutive technologies are available for licensing by competitors (Ashish Arora, Fosfuri, & Gambardella, 2001; Somaya, 2012). The licensors include industry giants like IBM and Qualcomm, a large number of small specialized technology ventures, universities, and "patent trolls" that aggressively use infringement litigation to collect licensing fees (Mock, 2005; Reitzig, Henkel, & Heath, 2007). The global market for technology is estimated at 100 million in 2002, with an annual growth rate of 10.7% (a. Arora & Gambardella, 2010).

Studies on technology licensing are voluminous and contain different focus areas, which can be classified into four categories: incentives to license out and license in (initiation); transaction cost and remedies (market making); licensing structures (contracting); and the outcomes of licensing partnerships (value creation and sharing), although one study may cover several topics together as the topics are mutually related.

The choice of in-house commercialization versus licensing out is well elaborated from both a resource-based view of complementary assets and market conditions (Ashish Arora et al., 2001; Hill, 1992; Teece, 1986a). A technology supplier is more likely to license out when the product market is differentiated and licensing does not disperse its own revenue from production (Ashish Arora & Fosfuri, 2003). On the demand side of the technology market, licensing serves as an alternative to in-house R&D when investment in R&D is too risky or lacks economies of scale, or when the licensee wants to diversify through licensing (Killing & Ontario, 1978; Lowe & Taylor, 1998).

However, due to high transaction costs, the market for technology is far from perfect, and a large number of technologies fail to be licensed out despite the owner's willingness to do so (Gambardella et al., 2007; Kani & Motohashi, 2012). A common problem is that a licensor needs to disclose information to potential licensees; however, after disclosure, these potential licensees may free-ride the technology. Scholars have proposed that patent protection ameliorates the "paradox of disclosure" problem and helps make the market for technology functional (Anton & Yao, 1995; Arrow, 1962; Gans & Stern, 2003).

Licensing is an agreement between two sides of technology transfer. The outcome, such as whether the technology is successfully commercialized, can be affected by the structure and specifications of the contract. A theoretical focus is on the choice between an exclusive and non-exclusive license. Existing industry structures (Arrow, 1962), strength of intellectual property (Anand & Khanna, 2000), substitute threats (Aulakh, Jiang, & Pan, 2009), and technology uncertainties (Somaya, Kim, & Vonortas, 2011) have been identified as determinants of exclusivity.

Theoretical analysis of determinants of licensing propensity and contract structure begins from propositions on how licensing can affect the values created/captured by the licensor/licensee. However, lack of a comprehensive dataset makes it difficult for empirical examinations on whether these propositions are reflected in the outcome of licensing. Therefore, the literature pertaining to the outcomes of licensing partnerships (value creation and sharing) remains limited. Using questionnaire survey data, Jones et al. (2001) found that external technology acquisition negatively impacts firm performance. Recent studies linking technology deals with stock returns found that, although inward and outward licensing generates profits, the magnitude depends on resources and the industry context.

1.4 Research questions

This study addresses the broad question of how firms appropriate their patented technologies beyond preventing infringement, and maintain market monopoly, with focuses on whether patents are effective in securing debt financing from banks and can generate substantial revenues for the firms that license out their technologies, together with other factors.

Patent collateralization is an unexplored topic in academic studies, as the practice is limited and undeveloped in countries in which venture capital functions efficiently, such as the US. China's spurt in patent-collateralized financing generates as much curiosity as encouragement. An essential question needs to be clarified to understand these practices:

What types of patents qualify as collateral?

Current studies on markets for technology using licensing provide some guidance for exploration of this question. Especially literature on demand of technology is inspiring for what types of patents are more easily to be liquidated.

In terms of technology licensing, this study focuses on competition among technology supplier and buyers, its impacts on exclusivity of licensing contracts, which remains unexplored in the existing literature, despite voluminous studies on the pre-contracting stages of licensing. Specifically, this dissertation attempts to answer the following questions through empirical examinations:

Under what conditions does multiple contracting become an optimum strategy for technology transfer?

Does multiple contracting help innovators capture rents in technology licensing?

What is the role of patent protection in the choice of exclusive versus multiple licensing?

Does patent protection help innovators capture rents in technology licensing?

1.5 Thesis structure

The remaining part of this dissertation is organized as follows. Chapter 2 describes the data and methodology along with a brief background and review of literature. In particular, a detailed description of the use of Chinese patent and finance data is provided because bibliometric analysis using the data is still nascent and many clarifications are needed. A study of paten subsidy programs' impacts on patent quality is also provided, both as a demonstration of usage of a new indicator for patent claim scope, and as a description of some backgrounds of patenting activities in China. Chapter 3 addresses patent collateralization using Chinese data. The characteristics of patents used as collateral are studies. Especially, we show that patent used as collateral have broader scope, despite a fact found in Chapter 2 that patent subsidies encourages filing of patents with narrow claims. Chapter 4 presents an empirically examination of licensing activities in Japan, with a focus on competition among technology supplier and buyers, its impacts on exclusivity of licensing contracts, and finally its impacts on licensing revenues. Chapter 5 concludes, providing implications and future research agenda.

Chapter 2 Patent statistics and Chinese patent data

2.1 Patent statistics

Patent data provides a rich source for studying innovation activities of firms as it is available in a large scale and generally well documented(Griliches, 1998; B. H. Hall & Harhoff, 2012; Nagaoka, Motohashi, & Goto, 2010). A patent document contains information on technologies, such as technology classifications and types of technology (product, process or new applications). It also contains legal information, including filing of patent applications, the scope of patent right, granting, renewal, withdraw, and termination of patent right. More importantly, it contains information relating to networks between inventors and firms. For instance, co-applications by multiple entities imply an alliance (Belderbos, Cassiman, Faems, Leten, & Van Looy, 2014; Powell & Giannella, 2010). Co-invented patents can be used to infer the interactions between inventors (Carayol & Roux, 2007). Inter-firm citations of patents provide clues of knowledge spillovers(Y. A. Li, 2014; Nelson, 2009).

One of the major applications of patent information is to measure patent value. Some patent statistics, such as number of forward citations a patent received, indicate high value from theoretic perspectives and the correlations have been verified by empirical studies. The relations between patent value and indicators are generally estimated based on market value of a firm, inventor survey, years a paten has been renewed, or R&D input (A Arora, Ceccagnoli, & Cohen, 2008; Griliches, 1998; Nagaoka et al., 2010). One needs to notice that patent value may have different meanings in different context: 1) the value of the invention and 2) the incremental value of patent protection (B. Hall, 2009; Nagaoka et al., 2010). However, it is difficult to separate the two parts with empirical data (Nagaoka et al., 2010). In this thesis, “patent value” is used to indicate the value of a patented invention as a whole. For the latter meaning, “value of patent protection” is used. Another term, “patent quality” is also widely used in literature with close meaning, but sometimes with more emphasize on the legal strength in surviving a patent opposition and preventing infringement (Hido, Suzuki, Nishiyama, Risa, & Takashi, 2012; Nagata, Shima, N Ono, Kuboyama, & Watanabe, 2008). Widely used patent value indicators include forward citations, claim scope, oppositions, patent families, patent classes, and number of inventors. A review of literature on usage of these indicators is provided for clarification as patent data is used heavily in this dissertation.

2.1.1 Forward citations

Number of forward citations refer to times the patent being cited as a prior art in subsequent patent applications. It is widely used as an indicator of patent value because large number of forward citations reflects technological importance and wider applications (Nagaoka et al., 2010). Citing a patent provide clues that an inventor knows the cited patent, and the new applied invention may have been developed based on technologies protected by the cited patent. The citing side could be potential buyers or licensees of the cited patents. Kani & Motohashi (2012) uses number of forward citations as an indicator of demand for a patented technology.

However, forward citations have its limitations. Firstly, forward citations are only available a few years after publication, limiting its usage in empirical study with newly applied patents. Second, only the US patent system requires applicants to cite all relevant information. European Patent Office (EPO) and Japan Patent Office (JPO) do not have a compulsory requirement for citing, and citations are mainly generated by examiners (Nagaoka et al., 2010). China implements similar patent system as Europe and Japan, but citations created by examiners are not publicly available.

2.1.2 Patent family size

Patent family size, measured as the number of international applications of the same patent, has been used as an indicator of patent value by many researchers (Harhoff, Scherer, & Vopel, 2003; J. O. Lanjouw, Pakes, & Putnam, 1998; Putnam, 1996). It is an informative indicator for value because for each application to a country, application fee and maintenance fee are required. Especially when applying to countries of different languages, translation fee and patent attorney cost is high. If an applicant decides to bear the cost and apply patents for a technology in many countries, it shows that the owner is confident about the economic value of patents. At least, the expected return should be higher than the application cost.

Family size is a timely indicator, because the applicant needs to finish application of the same invention in different countries within a legally constrained time (30 months for PCT application). However, some inventors do not compete in international market, thus have no applications abroad, bringing noise in using family size for comparison of patent value.

2.1.3 Claim scope

Patent claims define the scope of protection, which is generally formed by several constraints. For instance, a claim may define an invented device composed by feature A, B and C. If the patent is granted, any device including the three features enters the scope of the patent right and maybe claimed as infringement. Thus, less restricted claim scope prevents "inventing around" and attributes stronger market power. However, it is difficult to measure claim scope. A proxy used by scholars is number of claims. It is argued that each claims stands for an inventive components, thus an increased number of claims indicates more innovations, and higher value of the entire patents (OECD, 2009). Empirical studies using US patents support this argument (J. Lanjouw & Schankerman, 1997). However, the relationship can be noisy because number of claims can be "inflated" for strategic purposes by certain applicants (OECD, 2009). In China, additional filing fees are required if a patent has more than 10 claims. Those institutional factors need to be included into consideration. Another method for measuring claim scope is context analysis, such as counting words in patent claim. However, this method has not been widely used in empirical studies.

2.1.4 Oppositions

Opposition record is a strong indicator of value, because it is a proof of strong exclusive power which competitors are trying to break. A third party will not take the burden to challenge a patent which has no effect on his business because the opposition process has a cost. Opposition also can be used as a proxy for demand of technology, because the challengers could be hopeful buyers. A common problem is that there are only a small percentage of patents which have opposition records (Nagaoka et al., 2010).

2.1.5 Patent classes

A patent can be assigned several classification code either in IPC(International patent classification) or US patent codes. Since Lerner (1994) first used number of 4-digit sub IPC classes as an indicator of "patent scope" and found it significantly indicates higher patent value, many scholars have used this indicator in empirical studies (Gambardella et al., 2007; Harhoff et al., 2003; J. Lanjouw & Schankerman, 1997), but the results turns out to be controversy. Lerner (1994) finds that patents assigned more 4-digit IPC classes are more likely to be litigated in biotechnology field. Harhoff et al. (2003) show that number of sub IPC classification is not informative about value. Gambardella et al. (2007) use this variable as an indicator of technology generality and find that number of sub IPC classes correlated with the willingness to license, but has no impacts on whether the offered patent can be licensed.

In my view, number of IPC classes is more suitable as an indicator of application fields rather than exclusive power. Exclusive power should be better explained by claim scope generated directly from claims information rather than number of IPC classes which is for search rather than for defining protection domain.

2.1.6 Number of inventors

Number of inventors is considered as a value indicator from a cost view. The more resources involved, the higher the technical value the invention should be(OECD, 2009). Nagaoka and Owan (2011) found that larger team size of inventors correlates to higher patent quality due to diversities of knowledge.

2.2 Chinese patent data: new indicators, linkage with financial data, and biases

This dissertation includes an economic analysis of patent collateralization using Chinese data. Besides the information of registered patent collateral cases, various patent indicators are needed and it is necessary to match patent data with financial data of Chinese firms. Studies of innovation activities in China exploiting micro patent data are just emerging and quite limited. To the best of my knowledge, there is no study using merged dataset of patents and financial data of Chinese firms with large samples. As a growing economy quickly catching-up in technology development, China has get more and more research interest globally. However, lacking of reliable data creates great difficulties for studying innovation activities in China, making constructing the dataset itself a good contribution to academics. Thus, this section provides a detailed description of Chinese patent data including: its usage and limitation; methods to create indicators; its linkage with financial data; and policy-driven biases. The description is helpful to understand the data used for empirical analysis of patent collateral, but more importantly, it also provide a guide for studies on innovations in China.

2.2.1 Backgrounds

China established its patent law in 1985, and patent applications grew rather modestly until the end of the 1990s. Since 2000, patent applications have surged dramatically. Applications from domestic inventors in particular, surged at an annual rate of 30% from 1999 to 2009 (Figure 2-1).

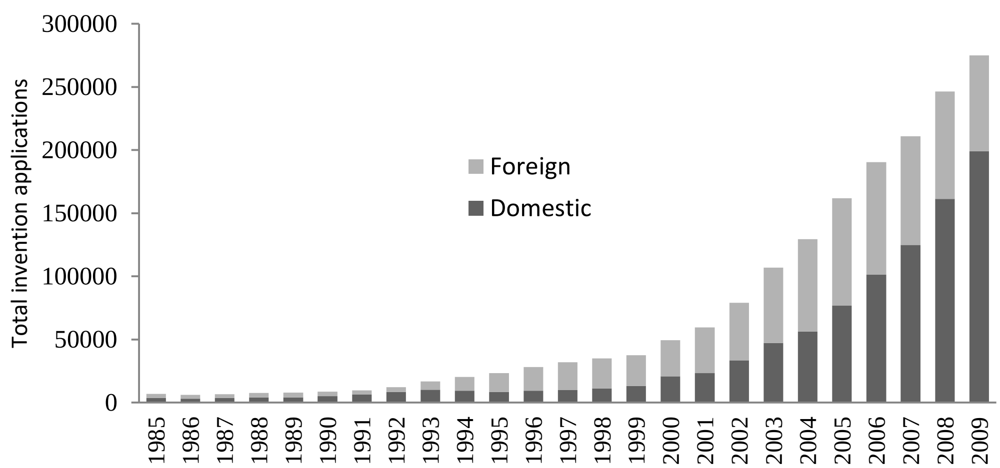

Figure 2-1 Growth of invention patent applications in SIPO (1985~2009)

The surge of patent applications in China has aroused significant research interest in investigating whether the surge is an indicator of the growth of innovative capabilities of Chinese industries and a change from "imitation" to "innovation." Although the rapid increase of Chinese patent applications can be explained by the nation's technology catching up with international players in developed economies, patent quality concerns arise as studies have suggested that such applications are largely supported by local government patent subsidy programs (Li, 2012). Thus, can we rely on patent statistics as an indicator of innovation in China? Several studies have analyzed the determinants of patent application growth, but few have provided empirical evidence on the quality of these patents. It particularly remains unclear whether patent subsidy programs have resulted in the deterioration of the quality of Chinese patent applications.

As patents contain rich and timely information on inventive activities, patent statistics are increasingly used to analyze and measure innovations. While R&D expenditures are widely used as a proxy for innovation input, patent statistics can measure the output. This measure is also more easily obtainable than other proxies for outputs, such as total factor productivity (TFP) (Nagaoka et al., 2010). However, patent statistics are not perfect as innovations are not necessarily patentable or patented, and patent quality varies (Griliches, 1998). The former is generally treated by controlling for industry differences, which largely explains variations in patenting propensity. For instance, patents are more effective in protecting pharmaceutical, chemical, and electronics technology. The latter problem is treated by weighting patents by citations, as frequently cited patents have been proven to have higher technological and economic value (Ashish Arora et al., 2001; Harhoff et al., 2003). However, special care is needed when using patent statistics in China as institutional factors could have distorted patenting behaviors and ultimately patent statistics. One needs to evaluate to what extent Chinese patent statistics have drifted away from the "real" output, which should be highly correlated with R&D expenditures as has been observed in other countries (B. Hall, Griliches, & Hausman, 1986; Pakes & Griliches, 1984).

Using survey data from the National Bureau of Statistics (NBS) of China, Hu and Jefferson (2009) estimate a patent production function for Chinese enterprises, finding significantly low patent-R&D elasticity, and claim foreign direct investment, institution change and other factors behind the patent surge. A recent study shows that patenting propensity has been boosted as much as 160% by patent promotion policies (Li, 2012). These two studies underscore the need to adjust quantitative statistics for patent applications in China. However, it is unclear whether granted patents have also been boosted significantly, which prevents granted patents from being a valid indicator of innovations. Unfortunately, pioneer studies (Hu & Jefferson, 2009; X. Li, 2012) that use industrial survey data cannot answer this question because firms can only provide the number of their applications in the year a survey is conducted; they cannot provide the number of granted patents as that figure can only be known several years later when examination decisions are issued. A more difficult aspect lies in assessing the qualities of patents. Patent quality is generally assessed using detailed patent information, including citation, renewal information, and patent claims. Several studies that use renewal information demonstrate that Chinese-granted patents have lower value than patents by foreign players (Thoma, 2013; Zhang & Chen, 2012). However, using renewal information has its disadvantages in terms of timeliness and thus cannot reflect recent changes in patent quality. Moreover, the two lines of research seem be parallel when dealing with patent quality. Studies based on survey data have illustrated exaggerated growth of patent applications compared to growth of R&D but cannot answer whether the quality of granted patents has been affected. On the contrary, studies using patent information can make horizontal comparisons of patent quality but cannot determine whether this is a new phenomenon that resulted from patent subsidies. The solution should be found in exploiting both data sources. By matching industrial survey data with patent data, a bibliometric analysis of patent statistics can be performed to evaluate the policy impacts on applications, grants, and quality of granted patents. To the best of my knowledge, no such analysis has been performed previously.

2.2.2 Chinese patent data

Patent data in China is available on the SIPO website (http://www.sipo.gov.cn/). It provides formatted data (only with a subscription) covering all patent applications since 1985, when China established its patent system, and provides following information (Motohashi, 2008).

(1) Patent application information of invention patents, utility models, and design patents, including application number, application date, IPC classification, patent number of priority applications, applicants' names and addresses, inventors' names, and the name and address of each patent's attorney. For invention patents and utility models, the title, abstract, and primary independent claim are available; for design patents, the title and a short description are provided. There is a time lag of 18 months between the filing and publication of patent applications.

(2) Examination information of invention patents, including examination request date and issue date of granted patents. Because patent examination generally takes three to four years after filing, a time lag exists in obtaining the result of the final examination decision.

(3) Patent renewal information indicating whether a patent has expired because of unpaid maintenance fees. If the applicant pays past-due maintenance and late fees within six months, the terminated patent rights can be revived and the revival records are also available.

The main drawback of China's patent data is inadequate citation information, a widely used patent quality indicator. Another limitation is that full claim information and patent descriptions are not currently available for automatic processing.

2.2.3 Quantify claim scope

A widely used patent value indicator is the number of forward citations, which reflect a patent's technological importance (Harhoff et al., 2003; Nagaoka et al., 2010). Studies also use citation-weighted patent counts as a more precise indicator of innovation output (Bloom & Van Reenen, 2002; B. H. Hall, Thoma, & Torrisi, 2007). Unfortunately, SIPO does not document this information. An alternative approach is to quantify the breadth of patent claims by counting either the number of claims (J. O. Lanjouw & Schankerman, 2004) or the length of the primary independent claim. Although the number of claims is more widely used in the literature, it has not been well documented[1] in the Chinese context, making it inappropriate for research with large datasets. Malackowski and Barney (2008) propose patent claim length (count of words) as a rough measurement of claim breadth and state the logic as follows.

"While claim breadth cannot be precisely measured mechanically or statistically, counting the average number of words per independent claim in an issued patent can serve as rough proxy if taken from a sufficiently large, statistically relevant sample. That is because each word in a claim introduces a further legal limitation upon its scope."

Meeks and Eldering (2010) also propose that claim length can serve as an initial measurement in determining the scope of claims. Because this method is free of the untimeliness limitation, I apply it to Chinese patent data and create a new indicator of claim scope, defined as **the inverse of logarithm of noun counts in a patent's primary independent claim.** The inverse is taken because a larger number of nouns indicate a narrower claim scope. The measurement is based on Malackowski and Barney (2012), but with modifications. Only the nouns are counted rather than all the words in the claims, because nouns represent more substantial technology factors and are a better proxy of "legal limitation." As the Chinese language does not use spaces to separate words in a sentence, I use the ICTCLAS Chinese lexical analysis program developed by the China Academy of Science to separate and tag nouns. I separate process and usage patents from device patents by text mining of abstracts and control for this in our regressions because the two types of patents have significantly different conventions in claim drafting.

[1] Claims information (except primary claim) is presented as scanned figures files. By reading these files, we can get the number of patents manually, but it is not suitable for analysis of large samples.

2.2.4 Linkage with industrial survey data

Industrial survey data is based on annual investigations by the National Bureau of Statistics of China. The data is also called "Industrial survey data on Large and Medium Size Firms" or "Industrial survey data on manufacturing firms". It has been used in economic studies on several topics: State-owned Enterprise(SOE) privatization and ownership reform (Jefferson, Hu, Guan, & Yu, 2003; Tong, 2009); foreign direct investment (Xu & Sheng, 2012); corporate governance (Cai & Liu, 2009); R&D and firm innovation (Hu & Jefferson, 2009; X. Li, 2012; Motohashi & Yun, 2007); for example. The data covers roughly 150,000 businesses from 1998 to 2002. More businesses were then added, and since 2009, it has covered roughly 380,000 businesses. It includes firm profiles, such as name, ownership, location, established year, and industry, and financial information on assets, revenue, profit, and cash flow. The data covers 31 provinces in Mainland China. Shares of covered businesses in each province are proportional to their shares in China's GDP. Thus, the data does not have a severe regional bias. A major limitation of this data is that information on R&D expenditures is absent for a large number of companies, especially in the years before 2005. Also the R&D expenditure data are noisy, with several types of mistakes for some observations. First, R&D expenditure is set as zero for many observations, but we cannot tell whether that means the firm does not engage in R&D or whether the data are just missing; Second, some observations have R&D expenditures less than 10,000 yuan, which are very likely mistaken inputs because it is unrealistic for a firm to engage in R&D with such a small amount of money. Third, some firms have abnormal figures for R&D expenditures in the year 2005 compared to their values in other years. A possible cleaning method is to drop observations if a particular R&D expenditure grew tenfold or decreased by 90 percent from 2005 to 2006. The industrial survey data and patent data can be matched by firm names, allowing various studies to exploit both R&D and financial performance measures.

2.2.5 Patent subsidies

Patent subsidy programs were launched at the end of the 1990s in response to a strong governmental concern about domestic firms' technological competiveness after China became a WTO member. To strengthen the awareness of intellectual property rights and encourage domestic firms' "endogenous innovation," the central government issued policy guidelines titled "Strengthen Technology Innovation, Develop High-Tech Industries, and Promote Industrialization [of Inventions]". In response to these guidelines, relatively developed regions, such as Shanghai, started promoting patenting activities of local enterprises in 1999. Other provinces followed, and 29 of 30 provinces have launched similar programs by 2007 (X. Li, 2012).

Although the goals are the same, policy design varies across regions, and several governments have made considerable revisions to their policies. Li (2012) describes differences in budget constraints and subsidy amounts between regions. A more subtle difference is the timing and condition of subsidies for invention patents, which are more highly valued and are considered a better indicator of technological capabilities. Subsidy amounts for invention patents are significantly higher than for utility models or design patents.

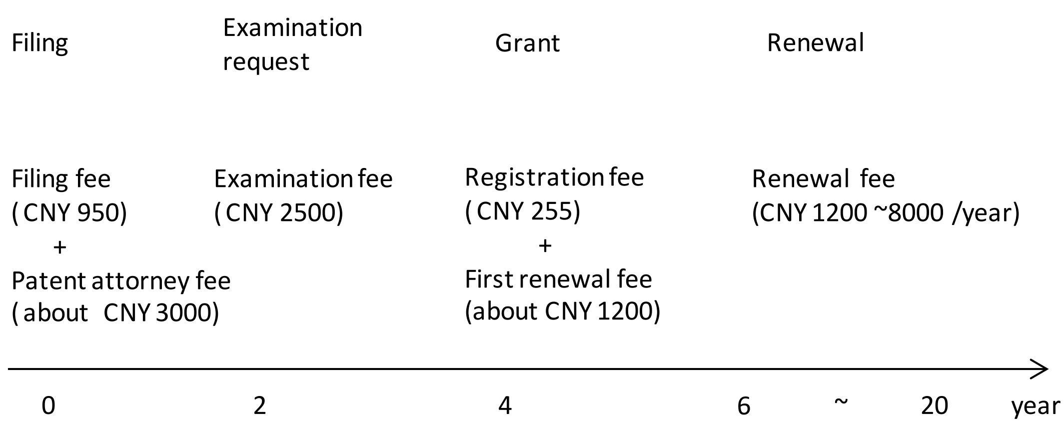

Figure 2-2 Filing and granting procedure for invention patents and relative costs in SIPO

Applying for an invention patent includes three steps: filing, requesting examination, and examination by the patent office (Liang & Xue, 2010; Yang, 2008). The examination request can be submitted within three years after filing. However, an early request is encouraged as applicants must otherwise pay an application maintenance fee each year for two years after filing. Renewal fees are charged to maintain a granted patent's validity. Figure 2-2 illustrates the filing and granting procedure for invention patents and relative costs. Figure 2-2 depicts a typical case, and costs may vary slightly. For example, if a patent has more than 10 claims, the fee includes an additional 150 yuan for each extra claim. However, the examination and registration fees do not change with the number of claims.

Local governments differ in their detailed subsidy conditions. Some governments subsidize only granted patents, intending to promote applications with a good probability of passing the examination. However, such programs may not provide strong incentives for patent filing because three to four years elapse between the filing for and the granting of patents and the examination results are uncertain. Therefore, some governments provide subsidies during the filing and examination stages, allowing the applicants to obtain subsidies immediately after a patent filing or examination request. Applicants are not required to return the subsidies if the applications are rejected by examiners. The amount of the subsidies also differs. Some governments fully subsidize the filing and/or examination fee, whereas others provide subsidies covering only 50%–80% of the fees. Grant-contingent rewards can vary from 500 yuan (Hebei) to 15,000 yuan (Tibet). Some provinces set no firm amount and provide subsidies on a case-by-case basis. Li (2012) first collected information on regional patent subsidy programs and identified the starting year of those programs. On the basis of this information, as summarized in Appendix 1, I checked the policy details in official documents published on local government websites and news reports or by telephone interviews of local officials and categorized the types and amounts of subsidies. A description of the provincial and time distribution of subsidy programs is provided in Appendix 2. By 2008, 80 percent of the provinces in mainland China had initiated filing fee subsidies, while about half of the provinces gave examining fee subsidies and grant-contingent rewards. The subsidy programs have been revised in several provinces, e.g. replacing filing fee subsidies with grant-contingent rewards.

The effect of subsidy programs on the quality of patent applications can be analyzed from two perspectives--patent grant rate (number of granted patents divided by number of total filed applications) and the value of granted patents. An application may not be granted in two cases: 1) the applicant does not request an examination within three years after filing, or 2) the invention does not meet the criteria of patentability, including utility, novelty, and non-obviousness. Therefore, a low patent grant rate may result from a lower rate of examination requests after filing and a higher probability of patent denial by examiners. For simplicity, I define the patent allowance rate as the number of granted patents divided by the number of examined patents. Thus, patent grant rate = examination request rate × patent allowance rate. Correspondingly, for one application, the probability of grant = probability of examination request × probability of allowance.

The effect of filing fee subsidies should be the simplest to determine as they reduce patenting costs from the outset. One may attempt to patent a technology with a lower patentability when subsidies are available. Such applications have a higher probability of being rejected by the examiner, resulting in a decreased rate of patent grants. Moreover, filing fee subsidies may encourage filings of inventions with great market uncertainties. After filing, the applicant may drop the filed applications before requesting examination if it is clear that the economic value of the patent is lower than the subsequent costs for examination and registration. Thus, filing fee subsidies can result in a lower examination request rate and consequently a lower patent grant rate.

The effect of examination fee subsidies can be complex. On one hand, it decreases the total patenting cost and increases the patenting propensity, which may decrease the patent grant rate as more low-quality patent applications may be filed. On the other hand, examination fee subsidies may encourage applicants to request examination for patents that would have been abandoned because of low patentability or low economic value, resulting in a higher examination request rate. The total effect depends on which effect is dominant.

Grant-contingent reward gives patent assignees economic benefits in addition to exclusive rights. Similar to filing fee and examination fee subsidies, it can increase the trend of patent filing, but it will not encourage filing inventions with low patentability as the reward is contingent on patent grants. Therefore, grant-contingent rewards should not affect the patent granting rate. However, grant-contingent rewards can encourage applicants to submit examination requests for inventions with good patentability, but low value. Although applicants may not benefit greatly from the exclusive rights of patents, they can benefit from the subsidy programs. The increased examination request rate results in a higher grant rate. One characteristic of low-value patents is a narrow independent claim because competitors can easily bypass the protected scope and develop similar products. If grant-contingent rewards encourage the filing of low-value patents, we observe narrowed claims.

2.2.6 Empirical evaluation of impacts of patent subsidies

The previous section has provided a theoretic analysis of patent subsidies' possible influence on the behavior of applicants. Empirical studies are needed to check the real outcome. Two empirical tests are performed here. First, patent production function is estimated to get a clear view whether patent growth is a good reflector of R&D activities and to what extent the quantity of patents has been boosted; Secondly, the impact of different subsidy program designs on patent quality is estimated to get policy implications with more details. To investigate whether the policies affect SOEs, privately owned enterprises (POEs) and foreign funded enterprises (FFEs) differently, the sample are divided according to ownerships information identified from the industrial survey data.

(1) Estimation of patent production function

Literature suggests a patent production function in the following form to evaluate the correlation between patents and R&D investment (Griliches, 1998; Hu & Jefferson, 2009; X. Li, 2012; Pakes & Griliches, 1984).

$$log(P_{i,t}) = \alpha log(R\&D_{i,t-1}) + \beta S_{i,t} + \gamma X_{i,t} + Constant$$

$P_{i,t}$ is the number of applications or granted patents applied for by firm i in year t; $R\&D_{i,t-1}$ is the real R&D expenditure in year t-1 ; $S_{i,t}$ stands for patent subsidies firm i received in year t, which is added to reflect the impacts of patent subsidies; $X_{i,t}$ stands for other control variables.

Table 2-1 Summary statistics of patent applications and R&D panel data

Application year	Frequency	Percentage	Cumulative Distribution
1999	336	4.44%	4.44%
2000	399	5.27%	9.71%
2001	466	6.16%	15.86%
2002	565	7.46%	23.33%
2003	491	6.49%	29.81%
2004	791	10.45%	40.26%
2005	934	12.34%	52.60%
2006	1,117	14.75%	67.35%
2007	1,223	16.15%	83.50%
2008	1,249	16.50%	100.00%
Observations: 7, 571			
Number of firms: 1, 419			
	Min	Mean	Max
Observations per firm:	3	5.3	10
Real R&D expenditure(Unit: 1000 yuan)*	18,707	5	5,297,906
Number of applications per year	0	5.6	4,040
Number of grants per year	0	3.6	2,539

The dataset to estimate this function is compiled by merging patent data with industrial survey data which includes the R&D expenditure information. This dataset covers a time span of 10 years from 1998 to 2007, during which R&D data are available for about 20,000 businesses each year, or 10% in the total industrial survey data. After cleaning R&D data noises using the method introduced in Section 2.2.4, I get a dataset with an average of 6,267 observations per year for 10 years, which includes 9, 969 firms. I match the sampled firms in the industrial survey data with the Chinese patent database by their names. As there is a time lag between R&D input and the final output of applications, I use the patent data from 1999 to 2008. 1,420 firms (14.2% of all the sampled firms) have filed at least one invention patent during the ten-year time span. Therefore, I get an unbalanced panel data, which is summarized in Table 2-1.

Though it is possible to add several time lag effects in estimations of relationships between R&D and patent applications, only the one-year lag is consistently significant in different models (Wang & Hagedoorn, 2014). After several experimental estimations, I find that a one-year lag of R&D expenditure is more significant than either contemporaneous or longer lagged values. Also, using more lagged variables will decrease the sample significantly. Therefore, I only include one-year lag R&D expenditures as an explanatory variable. A firm may not apply for any patents in a particular year, resulting in $P_{i,t}$ as zero. To calculate $log(P_{i,t})$, I follow the approach of Pakes and Griliches (1984) to add a small number (1/3) to $P_{i,t}$ for all the observations. Thus, the following dependent variables are composed.

log(Applications): log (number of applications in year t + 1/3);

log(Grants): log (number of patents applied for in year t and granted within 4 years after filing + 1/6).

Patent granting takes 3.87 years on average after filing with the SIPO. The examination process may last longer for some patents because of delays on the sides of both the applicant and examiner. For a recently filed patent, it is unknown whether it will be granted. Thus, I use a time window of four years after filing; 83% of domestic applications have received decisions within that time. Since the chance for an application to be granted is about 50%, I add 1/3 to the number of applications, but 1/6 to the number of grants.

Several category variables are defined to indicate the subsidies received by each firm in year *t*.

FilingSub: category variable; 1 if the filing fee is fully subsidized in the province where the applicant is located, 0.5 if partly, 0 if not.

ExamSub: category variable; 1 if the examination fee is fully subsidized, 0.5 if partly, subsidized 0 if not subsidized.

GrantSub: category variable; 1 if grant-contingent rewards are no less than 2000 yuan, 0.5 if less than 2000 yuan, 0 if no rewards are made.

Since filing fee subsidies and examination fee subsidies are provided instantaneously in many regions, the two variables have a high correlation. To avoid multicollinearity problems, I create another variable, *ApplSub* = *FilingSub* + *ExamSub*, to indicate the subsidies which are not conditioned on grants.

I use *log (total assets)* to control for size effect and included 2-digit NBS industrial code dummies in patent production estimation models.

Table 2-2 reports the estimations of the patent applications production function using OLS and fixed effects linear models.[2] In Model (2) and Model (4), cross-product terms are added to test interaction effects between R&D expenditure and subsidies. To make the results with interaction effects more interpretable, *log(R&D)* is centered to its mean in all the models (Afshartous & Preston, 2011). The results in Model (1) and Model (3) show that *log(R&D)* is positively significant, even when size effects are controlled. Thus, patent growth is at least partly driven by investment in R&D of Chinese firms. *ApplSub* is positively significant, confirming that patent applications

[2] A Hausman specification test supports using a fixed effects model rather than a random effects model, and thus, random effects estimation results are not reported here.

are increased by filing and examination fee subsidies. A more interesting result is that *GrantSub* is also strongly significant, showing that applicants also consider rewards contingent on grants when deciding whether to patent.

Table 2-2 Patent production function estimation: applications

	OLS		Fixed effects	
	(1)	(2)	(3)	(4)
	log(Applications)	*log(Applications)*	*log(Applications)*	*log(Applications)*
log(R&D)	0.159***	0.163***	0.0795***	0.0550***
	(0.00784)	(0.0125)	(0.00959)	(0.0140)
ApplSub	0.0324***	0.0323***	0.0678***	0.0700***
	(0.00789)	(0.00791)	(0.0122)	(0.0122)
GrantSub	0.115***	0.115***	0.225***	0.224***
	(0.0142)	(0.0142)	(0.0209)	(0.0209)
log(R&D) × ApplSub		-0.00199		0.0143
		(0.00933)		(0.0108)
log(R&D) × GrantSub		-0.0109		0.0459**
		(0.0171)		(0.0203)
log(Employee)	0.143***	0.143***	0.186***	0.183***
	(0.0135)	(0.0135)	(0.0363)	(0.0363)
SOE	-0.138***	-0.138***	-0.107***	-0.109***
	(0.0138)	(0.0138)	(0.0222)	(0.0222)
FFE	0.0761***	0.0767***	0.0133	0.0123
	(0.0224)	(0.0224)	(0.0432)	(0.0432)
Constant	-0.682***	-0.683***	-0.826***	-0.819***
	(0.0463)	(0.0463)	(0.116)	(0.116)
Industry dummies	Yes	Yes	Yes	Yes
Observations	7571	7571	7571	7571
Adjusted R2	0.156	0.155		
LogLik	-5163.5	-5163.3	-2784.2	-2779.3

Standard errors in parentheses;
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The cross term of *log(R&D)* and *GrantSub* shows a positive significance only in the fixed effects model (Model (4)). It can be said that rewards contingent on grants will have a stronger impact when a firm invests more in R&D as they are more confident that their applications can pass examination and they can obtain the rewards after the grants. However, this interaction effect is not significant in OLS models, suggesting no significant difference in the effectiveness of grant-contingent subsidies among firms with large or small R&D expenditures.

Table 2-3 reports the estimations results of granted patents. The result is similar to estimations on patent applications. The significant positive effects of subsidies shows that a significant part of those applications stimulated by policy incentives finally also passed examination and resulted in a boosted number of patent grants. Again, the cross-production term of *log (R&D)* and *GrantSub* is positively significant, showing that policy impacts are stronger for firms with more R&D expenditures.

Table 2-3 Patent production function estimation: grants

	OLS		Fixed effects	
	log(Grants)	*log(Grants)*	*log(Grants)*	*log(Grants)*
log(R&D)	0.168***	0.174***	0.0922***	0.0644***
	(0.00917)	(0.0146)	(0.0118)	(0.0173)
ApplSub	0.0365***	0.0366***	0.0800***	0.0829***
	(0.00923)	(0.00925)	(0.0150)	(0.0151)
GrantSub	0.145***	0.145***	0.281***	0.281***
	(0.0166)	(0.0166)	(0.0258)	(0.0258)
log(R&D) × ApplSub		-0.000882		0.0210
		(0.0109)		(0.0134)
log(R&D) × GrantSub		-0.0190		0.0358
		(0.0201)		(0.0250)
log(Employee)	0.150***	0.150***	0.201***	0.198***
	(0.0158)	(0.0158)	(0.0448)	(0.0448)
SOE	-0.153***	-0.153***	-0.126***	-0.128***
	(0.0161)	(0.0161)	(0.0274)	(0.0274)
FFE	0.0725***	0.0733***	0.0283	0.0271
	(0.0262)	(0.0262)	(0.0533)	(0.0533)
Constant	-0.967***	-0.967***	-1.146***	-1.138***
	(0.0541)	(0.0541)	(0.143)	(0.143)
Industry dummies	Yes	Yes	Yes	Yes
Observations	7571	7571	7571	7571
Adjusted R2	0.134	0.134		
LogLik	-6353.0	-6352.6	-4378.1	-4374.8

Standard errors in parentheses;
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

To better understand how patent growth is driven by R&D expenditures and policy incentives, we construct a simulation based on the estimation results. I choose 86 firms from the total 1,419 firms with R&D expenditure data available for ten years, and predict their applications and grants with/without subsidies. Figure 2-3 shows the result of the "average" simulated numbers. Since the numbers of applications/grants are highly skewed, the sample mean does not reflect a "typical" firm's outcome (Hu & Jefferson, 2009). Thus, I first calculate the mean of predicted *log(Applications)* and *log(Grants)* respectively, and plot the number of applications and grants calculated from the mean of logarithms in Figure 2-3.

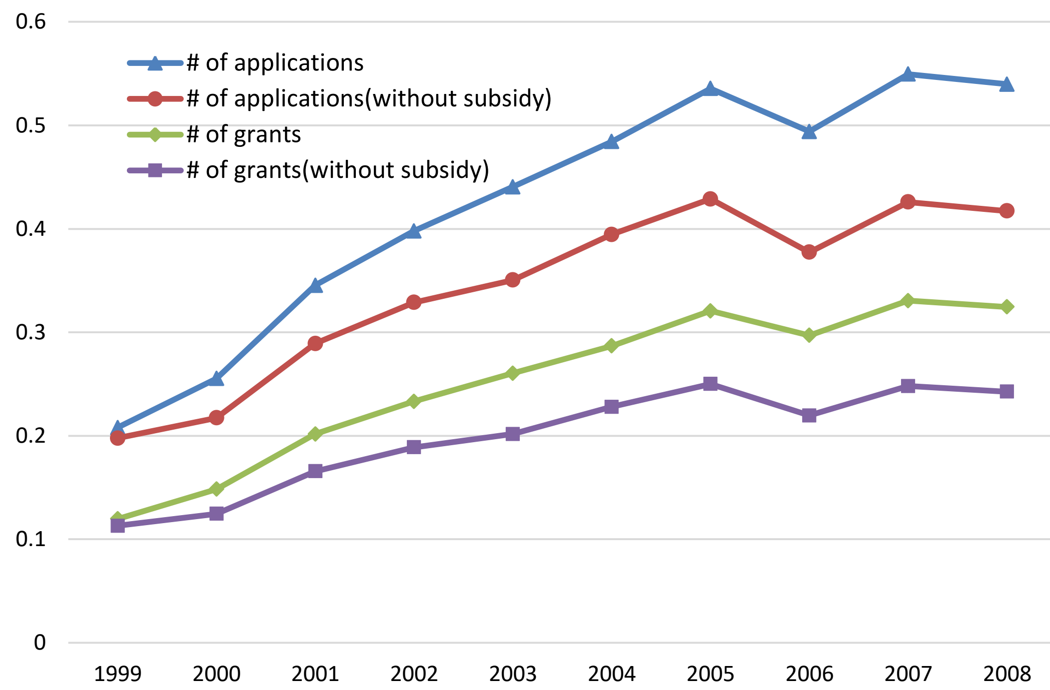

Figure 2-3 Simulation of patent subsidies impacts on patents growth

Figure 2-3 illustrates the contribution of patent subsidies programs in both applications and grants. The gap between predicted numbers with/without subsidies grows as more and more provinces gradually adopted patent subsidy programs. After 2006, the gap becomes stable as nearly all provinces had adopted those kinds of programs. In 2008, the number of patent applications was increased by 23%, while patent grants were increased by 26%. The result is surprising, because one would expect that low-quality patent applications filed under policy incentives may have a higher chance of being rejected in examination and the granted number of patents would not be increased on the same scale as applications. The result is contrary: the grant ratio is higher under subsidies than the simulated number without subsidies. It is necessary to take a more detailed look at how the detailed policy designs affect patenting behavior and quality of granted patents. Nevertheless, even without patent subsidies, we see quick growth in both applications and grants, which is driven by growth in R&D.

Table 2-4 Estimation of ROA using patent statistics

	OLS		Fixed effects	
	ROA	*ROA*	*ROA*	*ROA*
log(R&D)	0.0151***	0.0149***	0.0100***	0.00997***
	(7.56)	(7.49)	(4.98)	(4.96)
log(Applications)	0.00743***		0.00383	
	(2.64)		(1.44)	
log(Grants)		0.00840***		0.00402*
		(3.42)		(1.83)
log(Employee)	-0.0237***	-0.0239***	-0.00176	-0.00156
	(-7.23)	(-7.33)	(-0.23)	(-0.20)
SOE	-0.0260***	-0.0260***	-0.00900**	-0.00905**
	(-8.08)	(-8.07)	(-2.06)	(-2.08)
FFE	0.00697	0.00697	0.0106	0.0107
	(1.23)	(1.24)	(1.18)	(1.19)
Constant	0.106***	0.109***	0.0360	0.0365
	(9.95)	(10.21)	(1.31)	(1.33)
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Observations	4400	4400	4400	4400
Adjusted R2	0.0663	0.0673		
LogLik	4598.4	4600.7	7078.0	7078.8

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

From the input view, I find no significant difference in patent statistics based on applications and grants data as they both are increased by subsidies. Then, we test whether one is better than the other from an output view: are the two types of statistics useful in predicting the performance of businesses? A preliminary estimation of return on asset (*ROA*) using Dataset A is presented in Table 2-4. The explanatory variables include one-year lagged R&D expenditure and logarithms of applications/grants. In OLS models, both lagged *log(Applications)* and *log(Grants)* are significant when *log(R&D)* are controlled. In fixed effects models, only *log(Grants)* is slightly significant. The results suggest that patent statistics have value more than as merely a proxy for investment in R&D, and are especially valuable in making cross-firm comparisons. This can be theoretically explained in two ways: 1) patent counts can partly reflect the R&D efficiency as they provide an indicator of R&D output; 2) formal intellectual property protection can help a firm capture more rents through a market monopoly. A strict test of casualties between financial performance and patenting activities needs more solid theory and model specifications, which is beyond the scope of this paper. However, the result provides preliminary clues indicating that patent statistics are meaningful for measuring "real" innovations from an output view.

(2) Estimation of subsidy policy impacts on patent quality

I take three steps to estimate the effect of patent subsidy programs. First, a probit model is used to estimate the aggregate effects of filing fee subsidies, examination fee subsidies, and grant-contingent rewards on the patent grant rate. An assumption is that before filing, the applicants have considered all available subsidies provided by local governments, including grant-contingent rewards. Second, I test whether grant-contingent rewards affect the claim breadth using ordinary least squares (OLS) estimations. Finally, I use the Heckman two-step model to analyze whether the effect of grant-contingent rewards is reflected in the allowance rate.

The merged dataset of patent data and industrial survey data is used here, but without requiring R&D expenditure information available. Thus, a large sample is available, with 60,244 applications filed from 1998 to 2008 by 12,197 businesses, allowing a detailed test of impacts of different subsidies. Dependent variables are defined as follows.

Granted: dummy variable; equals 1 if an application is granted within four years of filing.

Examined: dummy variable; equals 1 if the applicant files an examination request for a patent application.

ClaimScope: inverse of logarithm of noun counts in a patent's primary independent claim.

Independent variables include *FilingSub*, *ExamSub* and *GrantSub*, which are defined above. The following variables are included as controls.

Non-device: dummy; 1 if the application is for a product or a device, 0 if it is about a method, process, or new usage.

Experience: years between the current application and the applicant's first application.

Literature suggests that experienced applicants may be skilled in assessing the patentability of technologies, drafting strong application documents, and communicating with examiners (Thoma, 2013). Thus, I use *Experience* as a control in our models. The models include technology and year dummies. Technology dummies are generated from the NBER patent classifications based on the IPC, which includes 33 categories. Moreover, I include five regional dummies that indicate whether the applicants are located in Guangdong, Beijing, Shanghai, Jiangsu, or Zhejiang. These top five regions contributed 59% of domestic applications from 1998 to 2008. I use the logarithm of the number of employees to control for firm size effect in estimations as total assets are not available for some observations in this dataset.

Using *Granted* as the dependent variable, I estimate the effects of three kinds of subsidies on the granting probability with probit models. Table 2-5 shows that *FilingSub* is negatively significant whereas *ExamSub* and *GrantSub* are positively significant in the estimations with the entire dataset. The positive significance of *ExamSub* reveals that the effect of examination fee subsidies on increasing the trend for requesting examination is more significant than its effect on encouraging low-quality applications. Grant-contingent rewards have a similar effect on increasing the examination rate. However, the positive significance of *GrantSub* may also result from its effect on increasing the probability of allowance. Table 2-5 reports a negative significance of *ClaimScope*, suggesting that applications with a narrower claim scope are more likely to be granted. In next part, I test whether grant-contingent rewards encourage applicants to file applications with a narrow claims scope to more easily obtain patent grants.

In estimations using sub-datasets, the effects of examination fee subsidies and grant-contingent rewards vary across the categories of applicants. *ExamSub* significantly increased the probability of grants for applications filed by POEs, but decreased it for SOEs and FFEs, suggesting that the effect of examination fee subsidies on increasing the propensity of requesting examination is less significant than its effect on encouraging low-quality applications from SOEs and FFEs. *GrantSub* is positively significant for POEs, but is not significant for SOEs and FFEs, suggesting that grant-contingent rewards may increase the propensity of examination requests for POEs, but not for SOEs and FFEs.

Table 2-5 Probit estimations on determinants of patent grants

Granted	All		SOEs		POEs		FFEs	
FilingSub	-0.303***	(0.0227)	-0.110*	(0.0640)	-0.301***	(0.0254)	-0.422***	(0.154)
ExamSub	0.0848***	(0.0246)	-0.259***	(0.0780)	0.195***	(0.0277)	-0.319***	(0.102)
GrantSub	0.224***	(0.0213)	-0.0189	(0.0662)	0.277***	(0.0238)	0.0554	(0.0950)
ClaimScope	-0.271***	(0.00797)	-0.219***	(0.0238)	-0.276***	(0.00923)	-0.327***	(0.0224)
SOE	0.0775***	(0.0190)						
FFE	0.0550***	(0.0157)						
Non-device	0.0750***	(0.0115)	-0.0420	(0.0356)	0.0903***	(0.0136)	0.0517*	(0.0297)
Experience	0.00807***	(0.00208)	0.00864**	(0.00367)	0.0145***	(0.00299)	-0.0375***	(0.00819)
log(Employee)	0.0132***	(0.00349)	0.00186	(0.0101)	0.0102**	(0.00417)	0.0288***	(0.00974)
Constant	-1.617***	(0.525)	-5.975	(147.9)	-1.548*	(0.912)	-1.273	(0.829)
Year dummies	Yes		Yes		Yes		Yes	
Region dummies	Yes		Yes		Yes		Yes	
Technology dummies	Yes		Yes		Yes		Yes	
Observations	59429		6097		43176		10147	
LogLik	-39379.0		-4019.9		-28525.7		-6539.4	
chi-squared	3336.3		389.1		2522.8		878.5	

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

I estimate whether grant-contingent rewards encourage applicants to file patents with narrower claims using OLS models. The dependent variable is *ClaimScope*. Table 2-6 reports a negative significance of *GrantSub*. The result suggests that grant-contingent rewards encourage more patents with a narrow claim scope, and thus low economic value. In estimations using sub-dataset of different types of enterprises, though *GrantSub* is not significant for SOEs and POEs, the coefficient is negative. *GrantSub* is significantly negative in estimations using applications from FFEs, suggesting that FFEs are also affected by patent subsidy programs.

Table 2-6 OLS estimations of the determinants of patent claim scope

ClaimScope	All		SOEs		POEs		FFEs	
GrantSub	-0.0203*	(0.0104)	-0.0390	(0.0300)	-0.0123	(0.0120)	-0.173***	(0.0354)
SOE	-0.0712***	(0.00989)						
FFE	0.0891***	(0.00816)						
Non-device	-0.0921***	(0.00598)	-0.118***	(0.0194)	-0.104***	(0.00713)	-0.0396***	(0.0136)
Experience	0.000291	(0.00108)	0.00661***	(0.00195)	-0.00217	(0.00157)	0.00890**	(0.00371)
Log(Employee)	0.0162***	(0.00182)	0.000413	(0.00553)	0.0160***	(0.00220)	0.0292***	(0.00444)
Constant	-3.794***	(0.276)	-3.792***	(0.705)	-3.242***	(0.482)	-4.004***	(0.369)
Year dummies	Yes		Yes		Yes		Yes	
Region dummies	Yes		Yes		Yes		Yes	
Technology dummies	Yes		Yes		Yes		Yes	
Observations	59429		6097		43176		10156	
Adj R-squared	0.0747		0.104		0.0783		0.0693	

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Our probit estimation results demonstrate that grant-contingent rewards increase the probability of patent granting. However, it is unclear whether the effect results only from a similar effect to that of examination subsidies on increasing the propensity of examination requests, or whether grant-contingent rewards also increase the probability of patent allowance in the examination process. Results in Table 2-6 demonstrate that grant-contingent rewards encourage the filing of patent applications with a narrow claim scope, which may result from a strategy to increase the probability of allowance.

There is a self-selection problem with a direct estimation of the probability of patent allowance with examined patent applications (Heckman, 1979): applicants are more likely to select patents with higher grant probability. The allowance rate of examined applications does not provide a good estimation of the allowance rate of applications dropped before examination if those applications have been examined. Bias can be significant because filing and examination fee subsidies can affect the decision about requesting examination. To test whether grant-contingent rewards increase the probability of patent allowance, Heckman two-step selection models are used. I use all applications as observations rather than using only examined patents and control for the selection effect in examination requests. Cross production terms between *GrantSub* and *ClaimScope* are included to test the interaction effects.

Table 2-7 Heckman probit estimations of determinants of patent grants

	All		SOEs		POEs		FFEs	
Granted								
GrantSub	0.103***	0.00288	-0.0672	-0.239	0.150***	0.0812	0.0195	-0.153
ClaimScope	-0.256***	-0.246***	-0.209***	-0.192***	-0.251***	-0.245***	-0.326***	-0.305***
GrantSub × ClaimScope		-0.0302*		-0.0502		-0.0207		-0.0539
SOE	0.0460**	0.0460**						
FFE	0.0209	0.0203						
Non-device	0.0518***	0.0520***	-0.0745**	-0.0744**	0.0662***	0.0663***	0.0343	0.0349
Experience	0.00447**	0.00443**	0.0110***	0.0109***	0.00744**	0.00741**	-0.0443***	-0.0448***
Log(Employee)	0.00289	0.00287	-0.0142	-0.0147	-0.00154	-0.00150	0.0193*	0.0188*
Constant	-0.621	-0.589	-5.279	-5.239	-0.484	-0.459	-1.706***	-0.645
Examined								
FilingSub	-0.662***	-0.662***	-0.180*	-0.180*	-0.728***	-0.728***	-0.440**	-0.396*
ExamSub	0.546***	0.546***	-0.0124	-0.0124	0.651***	0.651***	-0.165	-0.217
SOE	0.215***	0.215***						
FFE	0.239***	0.239***						
Experience	0.0323***	0.0323***	0.0203**	0.0203**	0.0276***	0.0276***	0.0672***	0.0689***
Log(Employee)	0.0467***	0.0467***	0.106***	0.106***	0.0421***	0.0421***	0.0617***	0.0608***
Constant	-0.703	-0.703	3.320	3.327	3.440	3.440	-0.197	-0.531
Constant	-0.394***	-0.395***	-0.246	-0.249	-0.644***	-0.644***	-0.578*	-0.635*
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Technology dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60244	60244	6139	6139	43901	43901	10204	10204
LogLik	-51912.3	-51910.9	-4863.9	-4863.5	-38618.7	-38618.3	-7826.1	-7818.9
chi-squared	2331.2	2333.0	325.8	326.6	1679.0	1680.0	623.4	626.2

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2-7 reports the results. *GrantSub* is positively significant in estimations without cross-production terms between *GrantSub* and *ClaimScope*, suggesting that *GrantSub* generally increases the probability of patent allowance when the selection effect in examination requests is controlled. An institutional perspective is that patent examination results are not affected by any types of subsidy programs because examiners make the decision of approval or rejection. However, the applicant's actions can affect the outcome of examination. First, applicants may make greater efforts in drafting better patent descriptions and responding to Office action (a document of reasons for possible rejection) from examiners if grant-contingent rewards exist. Second, applicants may narrow the breadth of claims to more easily obtain a patent grant. Our results in Table 2-7 suggest greater probability for the second scenario. The cross-production terms show a slightly negative significance, suggesting that grant-contingent rewards may encourage some businesses to strategically narrow patent claim scope to more easily obtain the patent.

In estimations with data subsets, the results vary across different types of applicants. *GrantSub* is positively significant for POEs, suggesting that grant-contingent rewards increase the allowance rate of patent applications from POEs. However, *GrantSub* is not significant for SOEs and FFEs, suggesting that SOEs and FFEs are less interested in rewards contingent on grants.

(3) Robustness check

There is a potential endogeneity problem in this study: whether patent subsidy policy variables are perfectly "exogenous," as the decisions made by a local government may reflect the innovation capabilities of firms, universities, and individuals in that region as well as its budget constraints. To address this problem, I use per capita GDP, lagged patenting intensity (number of patents/GDP), and averaged patent quality indicators (claim scope) as explanatory variables for provincial policy differences. I find a consistent positive significant effect of per capita GDP in launching subsidies at the application stage, suggesting that budget constraints explain part of the provincial variations, as provinces with higher per capita GDP, such as Beijing and Shanghai, are more developed and have higher budgets. However, for subsidies contingent on grants, per capita GDP is not significant, suggesting that it is not simply a budget issue, but rather, more complex considerations are included in policy decisions. We did not find significant effects of lagged patenting intensities or averaged patent quality indicators in policy decisions. Thus, our study does not suffer from serious endogeneity problems.

I made several treatments to the dataset, including adding a small number (1/3 or 1/6) to make *log(Applications)* or *log(Grants)* meaningful. We perform a robust check of this treatment by using negative binomial models with/without fixed effects to estimate the patent production function (Appendices 3 and 4). The results are generally consistent. However, the interaction terms of *log(R&D)* and *ApplSub* or *GrantSub* show a negative significance despite insignificant results in the OLS estimation. The interpretation is that firms with lower R&D expenditure are more likely to be motivated by subsidies. Compared to Li (2012)'s finding of a 60% increase in patent applications driven by patent subsidies using provincial level data, our simulation result is more modest. One possible reason is that firms reporting R&D are generally large firms, and our estimation may have a downward bias. When fixed effects are included, the interaction term between *log(R&D)* and *GrantSub* is still negatively significant. There is an argument that a fixed effects negative binominal model is not a true fixed effects method (Allison & Waterman, 2002). Therefore, the interpretation of the interaction effects in Table 2-2 and Table 2-3 should be made cautiously.

The two datasets have their respective limitations: Dataset A with R&D expenditure data only covers 10% of firms that are covered in the industrial survey and have patent applications; Dataset B does not allow a control for R&D intensity in estimations. I checked the estimation result of patent quality by controlling for R&D intensity (R&D/Sales) using a small dataset of patents applied by firms with R&D data available and report results in Appendix 5. Higher R&D intensity increases the likelihood of patent grants and the breadth of patent claims, and thus indicates higher quality. The estimated coefficients for *GrantSub* and *ApplSub* are consistent with the results in Table 2-5 and Table 2-6. However, *ExamSub* shows a negative significance, demonstrating that its effect in encouraging low-quality filing outweighs an increasing examination request rate. This occurs because firms reporting R&D expenditures generally are larger firms which seldom abandon filed applications before examination (96% applications entered the examination process). The benefits of examination fee subsidies are considered in the decision of whether to file, rather than whether to request an examination.

I also tested the estimation result without excluding patents of the top applicants. The results are generally consistent with what we found by excluding them, except that the interaction term between *GrantSub* and *ClaimScope* becomes insignificant in Heckman's two-stage estimations. The reason could be that those top applicants are less likely to sacrifice claim breadth simply for the sake of grant contingent rewards.

(4) Summary of patent subsidies impacts

The empirical results show that patent count is correlated with R&D input; suggesting patent statistics are informative indicator of innovations in China. However, policy impact is also significant. By simulation, I find an upward bias of patent counts of more than 20%, and more importantly, deteriorated patent quality in narrower claims. This study underline the necessity of adjustments and provide a novel method of using the number of nouns in claims to quantify claim scope, thus overcoming the shortcomings of Chinese patent data that have no citations or lack well-documented patent claim information.

Detailed examination of the impacts of different subsidies provides solid evidence that subsidizing the filing fee generates low-quality applications. More local governments seem to have identified this problem recently as I observe that certain governments, such as Zhejiang and Hunan, have suspended the filing fee and examination fee subsidy and replaced it with grant-contingent rewards. However, the policy shift cannot prevent applicants from strategically filing low value patents, which waste the government budget for promoting innovations. A more complex effect for examination fee subsidies is observed. Although these subsidies have increased the patent grant rate, the increase results from more examination requests for low-quality or low-value patents. That is, the subsidies hindered the filtering effect of examination fees and generated an excessive workload for patent examiners.

The results reveal that applicants strategically file patents with narrow claim scopes to obtain patents more easily after examination. The quality bias between patents filed with/without grant-contingent rewards makes patent counts unreliable. Although adjusting patent statistics using citation data is highly recommended in the literature, it is not practical for Chinese patents where citation data is not available. Patent count weighted by claim scope presents another practical option.

Further research is needed to identify how these subsidy programs have affected R&D activities and intellectual property management, and whether they have achieved the goal of promoting “real” innovation output. Increases in patenting are beneficial to society in that more disclosure of inventions prevents potential duplication of research among players and increases the technology market. However, excessive patents generate complexity in the technology landscape and a “patent thicket” that stifles subsequent innovation. Understanding such social impacts of patenting is important for interpreting patent statistics as an innovation indicator.

Chapter 3 Patent Value and Liquidity: Evidence from Patent-collateralized Loans in China

3.1 Introduction

The prospect of using patents as collateral for loans arises from two facts regarding finances of small- and medium-sized enterprises (SMEs). First, they frequently face financial constraints in commercializing ideas, scaling production, and expanding markets. The gap between demand and supply of debt financing is large because banks avoid high default risks and require sufficient collateral, which SMEs often lack(OECD, 2006). Second, as the global economy becomes more knowledge-driven, intangible intellectual property (IP) becomes innovative SMEs' primary asset, increasing their incentive to use patents as collateral for borrowing.

Patents were used as collateral as early as the 1880s (Baldwin, 1995), but their use remains limited because valuation is difficult (Harhoff, 2009; Kamiyama et al., 2006)and liquidity is a problem (Harhoff, 2009) . In China, weak enforcement of intellectual property rights (IPR) also inhibits patent-backed debt financing, but circumstances have been changing since the 2000s through stronger IPR enforcement, government encouragement of SMEs financing, and bank reform. According to State Intellectual Property Office of China (SIPO), from January 2006 to June 2011, 3,361 patents (including invention patents, utility models and design patents) served as collateral for loans in China, and the amount of debt financed reached 31.85 billion yuan (about US$5 billion) with an annual growth rate of 70%.

China's spurt in patent-collateralized financing arouses as much curiosity as encouragement. How do lenders evaluate borrowers and their patent assets? What types of patents qualify as collateral? Due to incomplete data, research into patent-collateralized lending is limited and often merely introduces practices and problems (Harhoff, 2009; Kamiyama et al., 2006). To the best of our knowledge, Fischer and Rassenfosse(2011) is the only empirical study that addresses decision making by financial institutions involving patents as collateral. Their survey of banks established that holding key patents increased the likelihood of receiving a venture loan, but that patents supplant tangible assets as collateral only when the borrower's financial performance justifies the loan. However, their study is neither based on actual lending data nor does it consider information about the quality of patents; thus, it cannot reveal what features make patents acceptable as collateral.

This study addresses the gap in scholarly knowledge on the basis of studies of patent-collateralized loans in China. It discusses value and liquidity as features determining patents' acceptability as collateral, and clarifies the effectiveness of different patent indicators for measurement of value and liquidity. An empirical study verifies those measurement indicators on the basis of patent-collateralized loan assignments in China from 2008 to 2010.

Section 3.2 introduces the background of patent-collateralized financing in China. In Section 3.3 develop theory and hypothesis on the basis of previous literature. Section 3.4 is an empirical examination. Section 3.5 discusses results. Section 3.6 concludes.

3.2 Backgrounds

3.2.1 Development of patents as collateral in China

Credit constraints are present in China where capital market is not highly developed. Private enterprises had been under particularly severe financial constraints as they are disadvantaged from to get loans from state banks (Poncet, Steingress, & Vandenbussche, 2010). More flexible financing channels are believed to be vital for economy growth.

Enacted in 1995, the Law of Guarantee explicitly states that intellectual property is valid collateral for loans. To acknowledge the temporary transfer of a patent's ownership to third parties—a routine feature of loans collateralized by patents—the law requires that all collateral assignments be registered with SIPO. Despite this legal structure having been constructed earlier, patents remained generally unused as collateral. Moreover, shortage of valuable patent portfolios, poor IPR legal enforcement, and banks' risk aversion account for the slow development. In 2001, China entered the WTO and began to strengthen intellectual property enforcement. Disputes involving infringement of intellectual property grew in number, and a surge of patent applications ensued as Chinese firms began to realize the importance of patents. Patent holders began to seek ways to exploit their patent portfolios, notably in financing, increasing activities involving patents as collateral.

At the same time, the growth of joint-stock banks with private stockholders invigorated competition to China's debt financing market. Many local commercial banks were established in the late 1990s and competition made banks more market-oriented, and some began to differentiate by financing SMEs. They became active in adopting IP as loan collateral.

National and local governments also began to promote IP financing. In 2007, President Hu Jintao announced implementation of the "National Intellectual Property Strategy." A 2008 outline of the policy listed "supporting enterprises to exploit IP value by ownership transferring, licensing, and collateral financing" as central to "construction of an innovative country" (State Council of China, 2008). SMEs pay taxes and create jobs, incentivizing local governments to support their development. They provide consultation, interest subsidiaries, or credit guarantees to help SMEs obtain patent-backed loans.

These forces spurred the practice of using patents as collateral in China, and it has grown quickly.

3.2.2 Business models

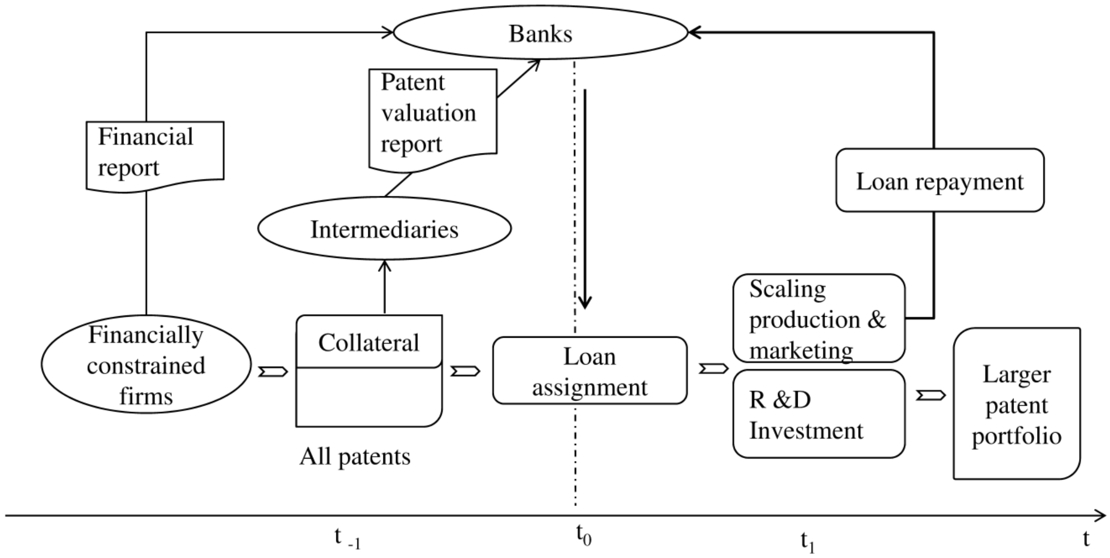

Figure 3-1 Event flow chart of patents-backed loan assignment

Figure 3-1 shows event flows in a typical patent-collateralized financing. A potential borrower with meager tangible assets offers patents as collateral at time t_{-1}. It reports its financial performance, indicates the loan's purpose, and lists the patents it offers as collateral. The bank consults IP, accounting, or legal firms, to assess their value. These intermediaries investigate the patents' technological value, how the technology might be implemented under the lender's ownership, and forecast the market. If the borrower and its patents satisfy the necessary criteria, the lender makes a loan at time t_0. The patents' ownership is transferred to the bank, and the transaction is registered with SIPO. With the loan proceeds, the borrower can invest in production scaling, marketing, and R&D, potentially generating revenues and products. When the borrower repays all principle and interest, its patents are returned. If the borrower defaults, the lender can sell or license the patents to offset its losses.

3.3 Literature review and hypotheses

3.3.1 The role of patents in financing of SMEs

The value of patents in financing SMEs has been well recognized. From 2008 Berkeley patent survey, Graham et al. (2009) find that both the investees and the investors value patents: firms seeking financings appear to patent actively before a funding event and venture capital investors are more likely to fund firms holing patents. In fact, an important reason for start-ups to applying for patents is to secure external financing. The survey also find that not only venture capital investors, but various entrepreneurial investor, including commercial banks and angel investors, use patenting as an inputs in investment decision. However, theoretic explanations on patents' role in financing vary, which can be summarized into three perspectives.

A traditional perspective lays on the intrinsic value of patents embedded in the patented innovations and the exclusive rights. A hypothesis is that innovative firms are more profitable, thus are more likely to give equity investors more return or have better repayment capability for debt investment, though the reality is quite complex and empirical evidences are divided. Early studies show that private rates of return from innovations are very low, despite a high social return(Mansfield, Rapoport, & Romeo, 1977). Teece (1986) points that under weak IP protection profits from innovations may not accrue to the innovators. The effectiveness of patent protection are industrial specific (Schankerman, 1998), and are affected by firm size and types of innovation (Arundel, 2001). In contrast, Geroski *et al.* (1993) find that innovations have a direct positive effect on profitability, and more importantly, innovating firms are relatively insensitive to adverse macroeconomic shocks, which could be a desired property for investors. However, in their data, innovations are identified by experts, not measured from patents. Recent studies investigate the relationship between patent stocks and firm survival, finding that innovations increases survival rate (Buddelmeyer, Jensen, & Webster, 2009; Kazuyuki, 2011). Though R&D expenditure can be used to capture innovation activities of firms, Czarnitzki and Kraft (2010) find that patent stock has a strong and robust effect on profitability for German manufacturing firms, but R&D expenditure does not. Two explanations are given: firstly, patents can reflect the success of R&D projects, thus more directly linked to firm performance; secondly, patent protections prevent imitation and helps capturing rents from innovations.

A widely studied function of patents is its signal effect, which is considered to alleviate the information asymmetry between investors and innovators. Patent filing itself provide valuable information source for the undergoing R&D projects, which is generally difficult to obtain from other sources, especially for non-listed firms with little public information. Some also argue that the signal is costly as filing patents requires efforts of the management and development team, and monetary cost, which makes it more credible(S. Graham & Merges, 2009; Hsu & Ziedonis, 2008). A view is that investors can exploit the expertise of patent examiners in assessing the novelties of a patent from grant decisions. Meanwhile, some argue that "filing a file for patents is an important sign of their managerial sophistication, particularly in codifying inchoate knowledge"(S. Graham & Merges, 2009), thus the signaling does not necessarily need to be effective after patent grants. Empirical studies have verified that both equity and debt investors value the disclosed information from patents. Hsu and Ziedonis (2008) find that doubling in patent application stock can increase funding-round valuation by 24% and signaling value of patents is greater in early-stage funding. Francis *et al.* (2012) find that banks grant lower loan spreads to borrowers with higher innovation capability (measured by both quantities and qualities of patent portfolios).

A rather less emphasized perspective is the liquidation value, the value investors can regain when the firms fails. Although selling or licensing intellectual property can may the loss for investors, due to illiquidity of technology markets, liquidation itself could be very difficult (B. Hall, 2005). Liquidation value of a firm's intellectual property could be extremely low due to several reasons. Firstly, the bankruptcy of the firm itself may have given some clues that its technologies are outdated or are not fit to market needs, making potential buyers unlikely to take the risk to make a second try. Secondly, potential licensees can get a strong bargaining power when technology owners are financially constrained, especially on the edge of bankruptcy. A recent example is the Kodak case. According to a report IEEE Spectrum' report, Kodak was only able to get $94 million from sales of a patent portfolio of experts valued as high as US $4.5 billion, a loss of 95%. A large loss is attributed by a patent invalidated in litigation, which Kodak's chief intellectual property officer claimed could be revived if the firm was not in bankruptcy and had the resources and the financial stability (Harris, 2014).

3.3.2 Liquidity of patents as collateral

A rather unexplored topic is what kinds of roles patents plays in collateralized loans. Though holding patents itself provides a signal effect, it cannot explain why the lenders and borrowers take the burden to make an arrangement of collateral. A basic function of collateral is to serve as an offset to default risk, thus the essential value of pledged patents should be close to the concept of "liquidation value". To realize the liquidation value, the pledged patents should be sold or licensed to others, as the financial institutions do not have the option to exploit the intellectual property by themselves. In this view, the liquidation value is close to market value discussed in studies on technology licensing. However, a subtle difference is at the initiation stage of a patent-backed loan, value of patents is assessed under the business environment of the borrower, which is close to the concept of "intrinsic value". It is questionable whether this assessed value can be realized when the borrower defaults, just as the case of Kodak. In fact, Chinese banks lend no more than 30% of the assessed value(Sun & Hu, 2009). The interpretation is deduction is a liquidity penalty. The penalty is needed due to technology, legal and market uncertainty; loss of co-specialized assets; lack of market thickness; and forced compromise in negotiation to reach a quick deal, etc. Drawing from the literature of asset finance (Mainelli, 2007), a patent's liquidity can be defined as the probability that it can be converted at an expected value within a specified time.

The question is how to analyze and measure patent liquidity. Studies on the markets for technology, particularly the concept of technology generalities, complementary assets, and technology competition, provide insights on this topic (Ashish Arora et al., 2001; Gambardella et al., 2007). The following factors can be treated as indications of liquidity.

(1) Generality of technology

Technology applicable to multiple sectors attracts more potential buyers (Gambardella et al., 2007) and can be licensed in differing end markets without intensifying competition among licensees. In addition, royalties can be lower for each license, increasing the potential for successful transactions. This outcome can be called "asset splitting."

(2) Technology complexity

Implementing complex technologies require more complementary assets (e.g., capital and knowledge stock), limiting number of buyers. High patent barriers are another difficulty. Infringement risk is magnified for a final product that incorporates complex technologies protected by multiple patents. Discrete transactions involving one patent could be valueless and difficult.

(3) Technology competition

The licensing literature widely discusses the effect of technology competition on licensing incentives(Ashish Arora & Fosfuri, 2003; Gambardella et al., 2007), and it also could affect liquidity. First, a competitive field of technology has many players, raising the number of potential buyers. Second, technological competition strengthens incentives to buy external patents. If no single player is likely to have a complete patent portfolio, purchasing patents will strengthen their technological capability and power in cross-licensing negotiations. More potential buyers and stronger incentives to purchase patents potentially enhance liquidity of patents in a competitive technology field.

3.3.3 Clarification of patent value and liquidity indicators

As discussed in Chapter 2 of this dissertation, a rich literature discusses patents' values or correlations between their value and information such as patent citations, IPC classifications, inventor teams, and patent family (Harhoff et al., 2003; J. O. Lanjouw et al., 1998; J Lerner, 1994; Nagaoka & Owan, 2011). Those indicators could be interpreted from the perspectives of liquidity.

Forward citations have been widely used as an indicator of patent value because large number of forward citations reflects technological importance and wider applications thus can bring more revenue for the owner. Wider applications mean large number of potential buyers. Especially, owners of the citing patents can be very promising buyers[3]. Thus, more forward citations also indicate higher liquidity. Backward citations refer to the number of references to prior patents generated during the search and examination process. Theory on how backward citations affect patent value is not clear and empirical studies show controversial results. Harhoff *et al.* (2003) presented two possible opposite scenarios of backward citations. A large number of references used by examiners may show many subject matters against the patents, resulting in a small scope and low value. On the other way, some patent lawyers and examiners say that "a patent application seeking to protect an invention with broad scope might induce the examiner to delineate the patent claims by inserting more references to the relevant patents". Thus more backward citations lead to larger patent scope and higher value. Study on surveys of patents inventors' assessment of their own patents seems to support the second scenarios (Harhoff *et al.* 2003). Whether backward citations is an appropriate value indicator is still an open question and need more theory clarifying and examinations. The different possible scenarios on value also affect how to analyze liquidity influence of backward citations. If more backward citations mean a large patent scope, it should correlate to more potential

[3] Kani and Motohashi (2011) used forward citations as an indicator for technology demand in analysis of technology license market in Japan.

buyers and indicate higher liquidity; vice versa. Though patent family size is a good indicator of patent value, it is relatively a weak indicator of liquidity.

A large patent family may be valuable to international buyer or local buyers seeking international market entry, but it is limited to a few patents of significantly high value, such as essential patents for standardization. Opposition record is a strong indicator of value, because it is a proof of strong exclusive power. A third party will not take the burden to challenge a patent which has no effect on his business because the opposition process has a cost. Opposition also can be used as a liquidity indicator, because the challengers could be hopeful buyers. From an income view, larger claim scope indicates higher value; from a technology demand view, larger claim scope secures more potential buyers as there could be more infringers. Thus, larger claim scope also means higher liquidity.

Since Lerner (1994) first uses number of 4-digit sub IPC classifications as an indicator of "patent scope" and found it significantly indicates higher patent value, many scholars have used this indicator in empirical studies, but the results turned out to be controversy (Lanjouw and Schankerman, 1997; Harhoff et al., 2003; Gambardella et al. 2007). In my view, number of IPC classification is more suitable as an indicator of more application fields rather than stronger exclusive power. Exclusive power should be better explained by claim scope generated directly from claims information rather than IPC classification which is for search rather than for defining protection domain. Thus, number of IPC classification is used as a proxy variable for generality and it indicates patent liquidity. Nagaoka and Owan (2011) find that larger team size of inventors correlates to higher patent quality due to diversities of knowledge. However, large team size may mean great complexity especially when the developing the technology requires a diversified knowledge on different fields, which could lead to low liquidity because fewer qualified buyer can be found for the technology. The effectiveness of those patent indicators can be summarized as Table 3-1.

Table 3-1 Summary of patent value and liquidity indicators

Patent indicators	Effect on value		Effect on liquidity	
	Effect	Theory	Effect	Theory
Forward citations	+ +	Greater technology importance	+ +	More potential buyers
Backward citations	+		–	Non-discrete technology require more complementary knowledge and base patents
Family size	+ +	Applicant's confidence in the technology and market forecast	+	More potential buyers from international market
Oppositions	+ +	Strong exclusive power	+ +	Concerned third parties who could be buyers.
Claim scope	+ +	Strong exclusive power	+ +	More potential infringers who could be buyers
Number of IPC classes			+ +	More general technology
Team size	+	Knowledge diversity resulting important technology	–	More complex technology need more complementary assets

Note: Mark "+" states for positive effect; mark "+ +" states for strong positive effects; mark "-" states for negative effect; mark "- -" states for strong negative effects.

3.3.4 Hypotheses

A patent qualified as collateral need to have a substantial liquidation value. As discussed above, liquidation value is affected by the intrinsic value of a patent, but also its liquidity. On basis of the discussions above, patent family size is an appropriate indicator for intrinsic value.

Hypothesis 1: Patents with larger families are more acceptable as collateral.

Theoretically, Patent claim scope and oppositions received have a strong positive effect on both value and liquidity. Thus, the following hypothesis can also be drawn.

Hypothesis 2: Patents with more opposition records are more acceptable as collateral.

Hypothesis 3: Patents with larger claim scope are more acceptable as collateral.

From the perspective of liquidity, generality, complexity and technology competition can also affect whether a patent is more likely to be accepted as collateral.

Hypothesis 4: General patents are more acceptable as collateral.

Hypothesis 5: Simpler patents are more acceptable as collateral.

Hypothesis 6: Patents applicable to a more competitive field of technology are more acceptable as collateral.

3.4 Empirical analysis

3.4.1 Data description

Chinese law requires patents used as collateral being registered with SIPO and the registration being public. The objective is to prevent a patent from being pledged to multiple lenders, which could bring disputes in liquidation of the collateral. The published registration data become the major dataset of our study. Data include patent numbers, names of pledging entities and lenders, and the period of the pledge. Though the rule does not has any explicit punishment for failing to register those transactions, lender, especially financial institutions, has strong incentives to ensure the collateral being registered to protect their interest. Therefore, the registration data covers a large majority of patent-collateralized loans in China, if not exhaustively.

This study draws on records from 2008 to 2010, which included 401 loans and 723 patents for inventions. The lenders' financial information is extracted from GTA-NLE database, which is based on industrial survey data of China, but is better formatted by Information Technology Company Limited. It contains time-series financial information of Chinese non-listed enterprises. The dataset spans from 1998 to 2009 and covers 380,000 firms. Though patent collateral registration data after 2010 is not covered in this study because industrial survey data after 2009 is not publicly available.

Data about claims, IPC classifications, and other information is from the China patent database. Patent family information is from the EPO PATSTAT database. Chinese patent re-examination data are the source for information about contested patents.

(1) Age of collateralized patents

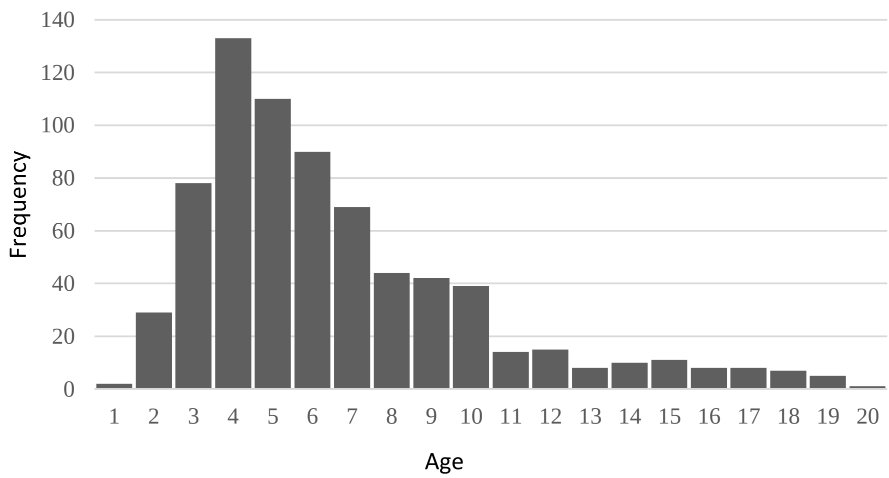

Figure 3-2 Age distribution of patents used as collateral in China (2008–2010)

Patents for inventions enjoy about 20 years of legal protection in most countries, but old patents may not be welcomed in technology markets. Older patents with a brief remaining term of protection present less potential for profit, especially if buyers must acquire complementary assets to implement the technology. Figure 3-2 shows that most patents accepted as collateral were three–five years old.

(2) Field of technology of collateralized patents

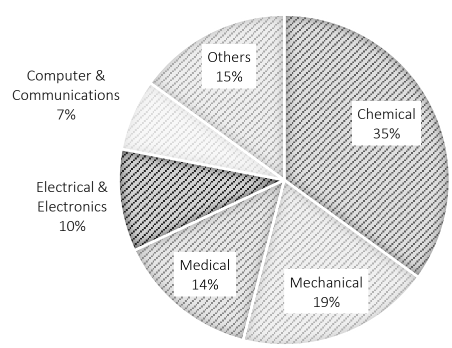

Figure 3-3 Shares of collateral patents in different fields of technology

Figure 3-3 shows the distribution by technology of patents accepted as collateral. Although chemical technology accounts for one-third, the distribution is not strongly concentrated, permitting comprehensive analysis of patents in various fields.

3.4.2 Comparison group sampling

Collateral registration data contain only successful events and do not record patents that lenders rejected as collateral, making a direct comparison between those being accepted and rejected not practicable. Instead, a control sample is needed. However, since a dominant majority of patents are not tried for collateralization because their owners do not need patent-backed loans. The reasons could be they are not financially constrained, or they have enough fixed assets as collateral. Generally, fixed assets are preferable because of the easiness of valuation and liquidation, and banks have expertise in this kind of traditional asset-backed financing. Therefore, the demand of patent-backed loans needs to be controlled in selection of an appropriate control sample. Literature has provided some models for identifying financial constrained firms, with both the demand from firms and supply of business loans from banks being considered. The demand equation is modeled by firm activity, size, substitute financing channels and debt cost. The supply function is modeled by tangible collateral, default risk, banks' cost and age of the borrower (Atanasova & Wilson, 2004; Maddala & Nelson, 1974; Ogawa & Suzuki, 2000; Shikimi, 2011). In China, most of the banks are state-owned and provide better loan terms for state-owned enterprises. Therefore ownership of the borrower also affects the supply of loans. To control all these factors, I use the propensity score matching (PSM) proposed by Rosenbaum and Rubin (1983) to construct a control group of patents. The aim is to select patents that have the same probability of being tested for collateralization, but are rejected by lenders. Therefore, the difference between the control group and patents actually collateralized would reflect the value and liquidity of the patents, rather than their owner's willingness.

The sample is constructed under the following process.

(1) Patents granted before 2010 and financial data of 2007-2009 are matched according to names of the firms, resulting in a dataset of 32, 325 patents including 238 pledged patents.

(2) A probit model is used to estimate the propensity of being pledged.

(3) k -Nearest neighbor matching method is used to select 3 patents as a control for each pledged patent using Stata's psmatch2 command (Abadie, Drukker, Herr, & Imbens, 2004).

The probit estimation model can be specified as follows.

$$Pr(Collateral = 1|X) = F(\beta_0 + \beta_1 Activity + \beta_2 Size + \beta_3 Substitutes + \beta_4 DebtCost + \beta_5 TangibleCollateral + \beta_6 Default\ risk + \beta_7 Interest + \beta_8 Age + \beta_9 SOE) \quad (1)$$

Pr denotes the probability of being pledged as collateral and *F (.)* is a cumulative distribution function. *Activity* is proxied by sales/total assets; *Size* is measured by log(total assets); *Substitutes* is proxied by operating profit ratio because operating profit servers as a substitute for external financing. *DebtCost* is measured by interest expense/total liabilities; *TangibleCollateral* is measured by fixed assets/total assets; *DefaultRisk* is proxied by interest rate coverage ratio; *Interest* states for policy interest on the middle of the year; *Age* states for firms' age and *SOE* takes 1 if the patent-holder is a state-owned firm. Industry dummies are also included as control. The estimation result is reported in Table 3-2.

The result shows that small, young, non-state owned firms with less tangible assets collateral are more likely to use patents as collateral to get loans. However, the relatively smaller default risk and higher operating profit ratio show that those firms perform well. Their seeking of patent-collateralized loans tends to be driven by further expansion, rather than financial distress.

With the matching process, I get a dataset of 916 patents consisted of 238 pledged patents and 678 patents as control group.

Table 3-2 Probit estimation of propensity of using patent as collateral

	Pr (Collateral =1 | X)	
Activity	-0.181***	(-6.00)
Size	-0.201***	(-12.57)
Substitutes	0.411***	(2.77)
DebtCost	0.000917	(1.05)
TangibleCollateral	-0.304*	(-1.94)
DefaultRisk	-0.000445***	(-5.41)
Interest	-0.116***	(-3.12)
SOE	-0.593**	(-2.33)
Age	-0.0152***	(-3.44)
Constant	2.168***	(3.58)
Industry dummies	Yes	
Observations	32325	
LogLik	-1076.4	
chi-squared	659.2	

t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3.4.3 Variables

The dependent variable, *Collateral*, is a dummy; equals 1 if the observation is a pledged patent, 0 otherwise. The following explanatory variables are used.

PatentFamily = number of patent jurisdictions outside China in which a patent grant has been sought.

ClaimScope = the inverse of the number of nouns in the primary claim of patent application file. A greater number of nouns indicate more constraints on the protection domain and a narrower claim scope. Thus, the inverse of the number of nouns indicates for a broader claim.[4]

Oppositions = times a patent has been challenged in the re-examination committee of SIPO.

Generality = number of four-digit IPC classes assigned.

TeamSize = number of inventors, used as a proxy variable for complexity of technology. Technology created by a large group of inventors is likely to be more complex.

[4] I use Chinese Lexical Analysis System (ICTCLAS) provided by Institute of Computing Technology of China for identify nouns in patent claims.

Complexity =1 if the patent is developed by multiple inventors and is assigned to multiple IPC classes, which indicates the technology is a combination of knowledge from several fields and is highly complex. Otherwise, *Complexity* is set as 0.

Competition = 1 – Shares of top 10 applicants in the same technology field defined by four-digit IPC class.

NonDevice : dummy; equals 1 if the patent is a process, method or a new usage; 0 if it is a device or product.

Control variables include *Size* (measured by log (total assets)), industry dummies, and application year dummies.

3.4.4 Empirical results

Table 3-3 Logit estimation on determinants of patent collateral

	(1) *Colllateral*	(2) *Colllateral*	(3) *Colllateral*	(4) *Colllateral*
PatentFamily	0.311***	0.293***	0.290***	0.289***
	(3.72)	(3.49)	(3.42)	(3.44)
ClaimScope	0.00710**	0.00793**	0.00786**	0.00792**
	(2.38)	(2.46)	(2.43)	(2.44)
Oppositions	2.639**	2.676**	2.570**	2.478**
	(2.35)	(2.39)	(2.31)	(2.25)
TeamSize	-0.0218	-0.0179		0.0238
	(-0.67)	(-0.55)		(0.72)
Generality	0.0210	0.0412		0.401***
	(0.21)	(0.40)		(3.04)
Complexity			-0.574***	-1.046***
			(-2.98)	(-4.11)
Competition	-0.699	-0.426	-0.203	-0.405
	(-1.02)	(-0.55)	(-0.26)	(-0.52)
NonDevice	0.0683	0.0115	0.0606	0.0332
	(0.42)	(0.07)	(0.35)	(0.19)
Size	0.149***	0.172***	0.187***	0.188***
	(2.73)	(3.09)	(3.33)	(3.32)
Constant	-1.995**	-1.761*	-1.952*	-2.426**
	(-2.21)	(-1.72)	(-1.90)	(-2.33)
Year dummies	No	Yes	Yes	Yes
Industry dummies	No	Yes	Yes	Yes
Observations	916	916	916	916
LogLik	-501.9	-491.4	-486.9	-482.4
chi-squared	45.76	66.79	75.63	84.67

t statistics in parentheses ; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3-3 reports the estimation results. Model (1) is the basic model. Model (2) includes controls year and industry fixed effects. Model (3) includes Complexity. Model(4) includes all the explanatory variables. *PatentFamily*, *ClaimScope* and *Oppositions* are positively significant in all models, providing strong support of Hypotheses 1, 2 and 3 that patents with larger patent families, broader claim scope, challenged by a third party are more acceptable as collateral. *Generality* show a significant positive effect only when *Complexity* is controlled, which is consistent with Hypotheses 4 and 5 that patents which are simple but can be widely applicable are more likely to be accepted as collateral. However, *TeamSize* is not significant in all the models. An interpretation is that the positive effect of larger team size on patent value is offset by decreased liquidity attributed to higher complexity. When complexity is controlled, the coefficient of TeamSize became positive, though it is not significant. Contrary to Hypothesis 6, *Competition* is not significant and the coefficient is even negative.

3.5 Discussion

3.5.1 Is patent-collateralized loan a "market for lemons"?

A concern on patent-collateralized loan is whether financial institutions have the capability to select the real "gold" from a huge number of patents. The borrowers may just use some patents of low value as collateral and due to information asymmetry; and banks cannot make a clear identification of the quality. Banks require patents pledged patents to be granted inventions survived the examination process in Patent Office. For utility models without a substance examination by Patent Office, Chinese banks require the patent–holders to present a "Report of Utility Model Technical Opinion" issued by SIPO. These approaches can help filtering extremely weak patents, but are far from enough. As shown in Chapter 2, firms can narrow claim scope to get an easier grants. Therefore, there is a strong concern that pledged patents may be consisted by significant number of low value ones, creating the market of "lemons" discussed by Akerlof (1970).

The empirical results show that it is not. From several indicators, I find robust higher value of pledged patents. Firstly, the pledged patents have a larger patent family. There is little theoretical or empirical dispute that larger family size indicates higher value. The result is more persuasive if we consider the fact that those patents are mainly applied by SMEs, which usually lack budgets for extensive patenting, especially abroad. A large patent family shows the owners' confidence in the technology and its market potential. The regression shows that patents accepted as collateral have a larger scope, which could help patent-holders to get monopoly rents from market, and help the lenders to force more potential infringers to sign a licensee agreement if the borrower defaults. If a large claim scope means a high potential for getting licensee revenues, a few opposition records may lead to a realization of licensee revenues. Those challengers who are trying to invalidate the patents, shows a strong interest to enter the market, or more likely, have been using similar technologies which have a risk of infringement. The relatively more oppositions received indicate that collateral patents are of significant value. Thus, patent-collateralized loan is not a "market for lemons", at least currently.

3.5.2 The effectiveness of liquidity indicators

This study tries to distinguish between the value and liquidity of patents because in the context of patents as collateral, both concepts are needed. Financial institutions needs to consider the value of patent assets for the lenders under their ongoing business lines, but also need to consider whether those patent assets can realized their values in transactions, in which the concept of patent liquidity is needed.

The difficult part is how to measure, or find some indicators of liquidity. Some widely indicators, such as oppositions and claim scope, can serve both as value and liquidity indicators. The result shows they are significant in distinguishing patents accepted as collateral. However, empirically the two indicators cannot be used as purely liquidity indicators.

Guided by literature on markets for technology, this study uses generality indicator (number of sub-IPC classes assigned) and complexity (an indicator consisted of number of inventors and number of sub-IPC classes assigned) as liquidity indicators. The interpretation of the two indicators needs a reflection of what sub-IPC classes really tells as empirical studies have yielded controversial results concerning how the number of IPC sub-classifications affects litigation or licensing(Gambardella et al., 2007; J. Lanjouw & Schankerman, 1997; J Lerner, 1994).

I suggest two reasons why a patent could be assigned multiple IPC classifications. First, an applicant might specify several uses for its technology, and an examiner might assign an IPC classification to each one. Thus, general technologies with widely ranging applicability are correlated with more IPC sub-classifications. In this case the IPC is informative about generality. However, there is another reason why some patents have many IPC classifications. If an invention combines characteristics from several technologies, an examiner might assign IPC classes for each characteristic. In this situation, more IPC classes indicate increased complexity rather than more applications. These possible explanations for multiple IPC classifications are confirmed in the "Patent Examination Guide Book" compiled by SIPO to assist patent examiners and attorneys. SIPO explained that assigning an IPC classification for each technological characteristic can facilitate searches for prior art, as a technology characteristic can be found easily by IPC search regardless of its field of application (SIPO, 2010). This could be the reason why different datasets show different results. Lerner's research(J Lerner, 1994) involves patents about biotechnologies. The classification could be mainly from an application view; thus the more IPCs, the wider the scope. However, if other industries are included in the examination, classifications could be attributable to different reasons, making the result vulnerable. Further study to clarify the basis for IPC classifications and more valid indicators for generality are needed.

The estimation result of this study shows that when *Complexity* is controlled, number of sub IPC classes has a positive effect on acceptance of collateral, though not highly significant. Consistent with the theory of complementary assets, the composed indicator of complexity show a significant negative effect on acceptance of collateral.

Another proposed liquidity indicator is technology competition. My hypothesis is that in a fragmental technology field of significant market thickness, patents can be liquidated more easily. However, the result shows a non-significant, but negative effect of *Competition.* An explanation is that competition may also affect the value of patents, as substitute technologies may highly dilute the potential for getting monopoly rents.

3.6 Conclusion

This study has investigated patent-collateralized loans in China. I demonstrated the severable importance of patents' value and liquidity in subsequent transactions as influences on patent-collateralized lending and clarified measures for these two characteristics. Controlling the treatment effect of firms' willingness to apply for patent-collateralized loans using PSM method, I find that patents with larger family, broader claim scope, more opposition records and simpler but widely applicable patents are more acceptable as collateral.

To the best of my knowledge, this is the first empirical study of actual loans collateralized by patents. The empirical findings can at least partly dispel a going concern that patent-collateralized loan may become a "market for lemons" due to information asymmetry between financial institutions and patent holders. The result also shows that complexity and generality indicators are effective in measuring patent liquidity.

The concept framework of this study draws a lot from existing studies on patent licensing market, particularly studies on generality. I find a weak positive significance of IPC based on indicators of generality. However, the interpretation of this indicator needs to be made with caution as the assignment of multiple IPC class can be due to wide application or combination of multiple technologies, which have adverse effect on liquidity.

This study also proposed technology competition as an indicator of patent liquidity, but empirical result failed to verify this. A limitation of using patent-generate competition is that we cannot distinguish whether the players in the same field are more likely to be potential buyers, or just substitute technology providers. To further understand these problems, it is important to study licensing activities with dataset containing more specified settings of technology supply and demand. The next chapter presents a study, focus on the impacts of competitions and the conditions making supplying technology to multiple buyers (multiple) an optimum strategy.

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Chapter 4 Get Pennies from Many or Get a Dollar from One? Multiple contracting in Markets for Technology

4.1 Introduction

The "open innovation" paradigm highlights the importance of accessing external knowledge and the use of external paths to market (Chesbrough et al., 2006). Cooperation between a technology supplier and downstream technology buyers develops co-specialized assets less expensively and commercializes new inventions in a more timely manner (Teece, 1986a). The outcome can be a win – win scenario, as both parties share the rewards. Innovators lacking complementary assets can capture rents from licensing, rather than performing risky in-house exploitation, and down-stream licensees achieve cheaper market-entry opportunities.

However, successful cooperation is a great challenge for both licensors and licensees because the market for technology is imperfect, with high transaction costs raised by low market thickness, uncertainties of technologies, information asymmetries, and opportunistic behaviors by both sides (Arrow, 1962; Gans, Hsu, & Stern, 2008). *Ex-ante* contracting technology suppliers face a risk of potential buyers expropriating the disclosed information without paying. Innovators may be unwilling to license out their technology because it creates potential competitors in the product market and a "rent dispersion" (Ashish Arora & Fosfuri, 2003). A licensor also relies on a licensee's effort in commercializing the technology *ex-post* contracting. On the other hand, a licensee is also exposed to significant transaction hazards. Technology transfer includes the substantial transfer of tacit knowledge, which cannot be well defined in a formal contract. A licensee may need ongoing R&D support from a licensor in overcoming critical problems before production. In addition, a licensee needs to invest in technology-specialized complementary assets with limited alternative use (Hart & Moore, 1988; Somaya et al., 2011).

The literature suggests several remedies to moderate the imperfections of technology markets. Formal intellectual property (IP) protection, especially patent protection, ameliorates the "paradox of disclosure" problem (Anton & Yao, 1995; Arrow, 1962; Gans & Stern, 2003). When patent protection is ineffective, tacit knowledge transfer is combined with other complementary inputs, such as equipment sales (Ashish Arora, 1996). Soyama et al.(2011) argue that the exclusive contract serves as a hostage in licensing alliances and motivates licensees to invest proactively. An effective contracting arrangement makes such inter-firm cooperation realizable and provides benefits for both sides.

Creating a larger cake is in the common interest, but taking a bigger share of the gains becomes a conflicting goal, where bargaining power matters. Bargaining power depends on the capability to generate "good" technologies and market conditions. An attractive technology puts a licensor in a better position and helps capture a substantial share of gains in a licensing agreement, which may completely compensate the ongoing development cost, as in the case of Qualcomm's licensing of CDMA technology (Mock, 2005). However, small technology ventures are generally vulnerable in negotiating with downstream licensees, as they may not have complementary assets for in-house commercialization (Gambardella & McGahan, 2010). They may also have fewer resources for enforcing their IP rights and preventing potential licensees from expropriating their ideas. Also, IP protection itself is not effective in many industries (Gans & Stern, 2003). How can technology suppliers capture high rents from technology markets? A widely discussed strategy is multiple contracting, or supplying technology to more than one buyer. In multiple contracting, the supplier can accrue returns from several market niches and broaden the exploitation of their technology's potential. This, in turn, makes a licensor less reliant on the efforts of each licensee to realize a commercial success and less prone to compromise in negotiation with each licensee. The cost of multiple contracting is a loss of monopoly rents as downstream licensees may face fiercer competition if their products are not well differentiated.

A natural question is under what conditions multiple contracting becomes an optimal strategy in comparison with exclusive contracting with just one licensee. On the basis of Arora & Fosfuri's model of "rent dispersion versus revenue effect," scholars propose that the capability to create general purpose technologies and a fragmented downstream product market with less direct competition lead to multiple contracting (Gambardella & Giarratana, 2013b; Gambardella & McGahan, 2010). Although multiple/single contracting is not strictly equated to nonexclusive/exclusive licensing, as reported by Soyama et al.(2011), the theoretical discussion of exclusivity generally holds when dealing with multiple contracting. This is because multiple contracting usually creates competition between licensees, except for cases where several licensees obtain exclusive rights restricted to their own country. Soyama et al.(2011) suggest that licensees need exclusive rights to compensate for an early-stage investment risk. Aulakh et al.(2009) argue that weak IP protection and substitute threats lead to multiple licensing in international licensing as a licensor cannot effectively extract monopoly rents.

Despite fruitful theoretical studies on the determinants of technology licensing and the importance of multiple contracting, empirical studies have only recently emerged due to lacking comprehensive data. An overlooked fact is that even in the limited empirical papers, there is a subtle mismatch between theoretical and empirical examinations: although the generality of technology and market fragmentation are modeled as the determinants of multiple contracting, they are evaluated only to a binominal outcome of whether licensing occurred (Gambardella & Giarratana, 2013b; Gambardella et al., 2007). Empirical analysis on whether these factors actually yield a large number of license contracts has not been executed. Theoretical analysis also proposes that enlarged exploitation and strengthened bargaining power can help small technology ventures to both create a larger cake and take a larger share (Gambardella & McGahan, 2010), but whether multiple contracting helps innovators to capture rents still remains empirically unexamined.

Using novel survey data on Japanese firms' licensing activities, this study attempts to evaluate the determinants of contract numbers and their effects on the license revenues of technology suppliers. A proposition is that competition among technology suppliers and buyers affects the contract arrangements of multiple/exclusive licensing. An industry competition index is compiled from firms' self-assessments of the number of direct competitors and is applied to both technology suppliers and technology buyers. The result shows that competition among suppliers leads to multiple/nonexclusive contracting, whereas competition among buyers leads to single/exclusive contracts. The effects of patent protection and firm size are also tested. This study provides empirical support for Gambardella & McGahan's argument that multiple contracting helps small innovators capture rents from technology markets.

This chapter is organized as follows. Section 4.2 reports the development of the hypotheses. Section 4.3 describes the data and empirical models. Section 4.4 presents the results and discussions. Section 4.5 summarizes the conclusion of this study.

4.2 Theory and hypotheses

Multiple contracting allows a wider exploitation of a technology's potential use. A good example is the famous Cohen–Boyer rDNA technology. For any single company to exploit their technology at the current scale is impossible, where 2,442 estimated new products have been developed over the duration of the patents (Feldman, Colaianni, & Liu, 2007). Although this is quite a special case and only a small number of technologies have such a large potential to attract hundreds of licensees, relying on one licensee to fully exploit technology is unrealistic. Licensors may also be concerned about the competency of one licensee and suffer the opportunity costs in an exclusive contract (Aulakh et al., 2009). Thus, multiple contracting is preferable as it gives a benefit of "full exploitation."

However, multiple contracting has a cost: the loss of monopoly rents. An exclusive license allows a licensee to monopolize the end product if there is no close substitute, whereas multiple contracting may promote competition among licensees. Arora et al.

(2001) used a "revenue effect" versus "rent-dispersion" model to explain the choices between self-exploitation and license. In their model, a firm would prefer to license only if the license revenue outweighs the rent dispersion resulting from the competition between a licensor and licensees in the product market. This model can still be used in analyzing the choice between exclusive license and multiple (nonexclusive) contracting. Here, the rent-dispersion effects occur among licensees and not between a licensor and licensees. Adding more licensees can increase the exploitation opportunities, resulting in a "revenue effect." If there are several separate applications of technology, then competition among licensees would be weak, increasing the propensity of multiple contracting (Gambardella & McGahan 2010). Empirical evidence shows that propensity to use multiple license increases when technology has a great potential to produce differentiated products (Aulakh et al., 2009).

Thus, a licensor's choice between multiple and exclusive contracting represents a tradeoff between "full exploitation" and the "loss of monopoly rents." Moreover, the contract arrangement is an outcome of negotiation between both sides, and a licensee's optimum strategy could be contrary to that of a licensor. Although both sides have a common interest to limit the "loss of monopoly rents," "full exploitation" is not in a licensee's interests unless a licensor can substantially deduct license fees. The equilibrium between licensors and licensees is dependent on the competition among potential buyers and suppliers of technologies, properties of technologies (e.g., potential for expropriation), and each firm's resources.

4.2.1 Competition among technology buyers

Competition among potential technology buyers in the end-product market could result in substantial "loss of monopoly rents" if multiple licensing is taken, which is against the interest of both the licensor and the licensee. Thus, exclusive licensing is more likely to be reached.

Fierce competition also indicates low degree of product differentiation, and a new exclusively licensed technology could bring competitive advantage for the licensee. Strong incentive of potential licensees to secure technology accessing would give the licensor stronger bargaining power to capture a large share of value created in the cooperative trading.

Hypothesis 1a: The likelihood of using multiple contracting decreases when there is a strong competition among potential technology buyers.

Hypothesis 1b: Licensors capture more rents from technology transfer when there is a strong competition among potential technology buyers.

4.2.2 Competition among technology suppliers

Competition among technology suppliers increases their willingness to license out because a licensor would be less concerned about “rent dispersion” arising from the competition with a licensee in the product market (Kani & Motohashi, 2012). However, whether competition in markets for technology would result in multiple or exclusive contracting is not well elaborated in literature. A rare exception is Aulakh et al.(2009), who propose that substitute threat increases the use of multiple/nonexclusive license. To confront potential substitute technologies, an incumbent would license to multiple, less formidable, licensees and block the entry for others (Eswaran, 1994). An innovator may even license his/her technology broadly to establish an industry-wide design dominance (Hill, 1992). When the competition among potential suppliers is strong, the possibility for a close-substitute technology to exist or emerge is high. Thus, a supplier is more likely to select multiple licensing, licenses quickly and widely, and is ready for compromise.

On the other hand, a licensee derives a stronger bargaining power when there are alternative technology suppliers, in which case they can ask for an exclusive license, or a deduction of license fees. However, exclusive licensing may not be attractive because potential licensees can still access substitute technologies from other suppliers. The exclusive license from one particular supplier does not secure monopoly rents in the product market. Thus, obtaining a nonexclusive, low-royalties license becomes an optimum strategy for a licensee.

Hypothesis 2a: The likelihood of using multiple contracting increases when there is a strong competition among technology suppliers.

Hypothesis 2b: Licensors capture fewer rents from technology transfer when there is a strong competition among technology suppliers.

4.2.3 Patent protection and expropriation risk

Technology transfer can incur substantial transaction costs because of information asymmetry and the opportunistic behaviors of both parties (Ashish Arora et al., 2001; Gambardella, 2002). Patent protection alleviates these problems and plays an important role in influencing technology markets. Prior to any transactions, the innovator needs to disclose information about technology and allow potential buyers to assess its value. A strong patent protection prevents those buyers from taking a free ride on technologies after disclosure. However, technologies based on tacit knowledge may not be suitable for patenting. In this case, the provision of complementary inputs other than patents, such as plant commissioning and equipment sales, can be an efficient strategy for technology transfer (Ashish Arora, 1996).

Although exclusivity is usually discussed with patent licensing, nonpatented technology know-how can also be exclusively provided to one licensee. Exclusive access to superior technology can help a licensee gain a strong competitive advantage and may even monopolize a market. For instance, transferred know-how on process innovations could reduce manufacturing costs and drive out competitors.

The risk of the exclusive licensing of nonpatented technology is the potential for expropriation by outsiders. The leakage of technology information from both a licensor and licensee and reverse engineering can result in the complete loss of monopoly rents. In particular, a licensee is exposed to large risks of *ex-post* contracting despite paying higher license fees associated with an exclusive licensee. Thus, a licensee is only willing to get a cheaper, nonexclusive license when formal IP protection is unavailable. Empirical studies also provide indirect clues that a strong patent protection leads to exclusive contracting (Aulakh et al., 2009) and high royalties (Nagaoka, 2005), although they are executed from a macro view of the legal environment of IP protection, rather than a comparison of patented and nonpatented technologies.

Hypothesis 3a: The likelihood of using multiple contracting increases when technology is not patented.

Hypothesis 3b: Licensors capture fewer rents from technology transfer for nonpatented technologies.

4.2.4 Firm size

Large and small firms have differences in incentives and bargaining power. Small firms may lack complementary resources to implement their (often key) technologies; thus, licensing becomes a critical pathway for commercializing their technologies. Large firms may license their technologies for more complex reasons. For example, technology may not fit the core business of a licensor or it is quite a fundamental technology, where the commercialization opportunities are unclear. Large firms may also license technologies for standardization (Shapiro, 2001). Compared with small ones, large firms are more concerned about the product market competition introduced by licensing, especially for technologies in their core business.

The bargaining power of a licensor determines the share of the total value finally accrued to a licensee. There are concerns that small, specialized firms only have a weak bargaining power in negotiations because they lack the resources to commercialize technology by themselves and must rely on a licensee's complementary assets (Gambardella & McGahan 2010; Gans & Stern 2003). Bargaining power can be strengthened if many potential partners are available and a licensor threatens to cooperate with a third party (Gans &Stern 2003; MacDonald & Ryall 2004). From this viewpoint, a licensor can be tougher in a multiple contracting arrangement than in a negotiation for exclusive licensing. Thus, multiple contracting is especially attractive for small innovators to capture rents in technology markets. A counter-argument is that multiple contracting is costly as a licensor needs to provide technology support and training to a number of licensees, making resource-constrained small firms less likely to select multiple contracting (Jiang, Aulakh, & Pan 2007).

Hypothesis 4a: Small technology suppliers are more likely to use multiple contracting.

Hypothesis 4b: Small technology suppliers capture more rents from multiple contracting.

4.3 Data and variables

4.3.1 Data description

In 2011, the Research Institute of Economy, Trade and Industry (RIETI) of Japan conducted a survey of 18,000 business units of Japanese firms for their new product development activities. 3,705 business units (for simplicity, hereinafter referred as firms) responded to the survey (response rate = 20.6%), and their industrial sectors, number of employees, introduction of new product/process innovation, market condition change, inward and outward technology license revenues(as a share in total sales are identified.

Among the 3,705 responses, 1,390 firms are identified as having introduced new products between 2008 and 2010. For those firms, the industrial classification and market share of their new products, the information sources for developing the product, IP protection, and numbers of competitors providing similar products are identified.

In addition to questions about NPD, the questionnaire also asks several questions about licensing-out/contracted research activities from 2008 to 2010. Among the 3,705 responses, 254 reported having licensing-out/contracted research activities. Figure 4-1 shows the response composition of the two sets of questions.

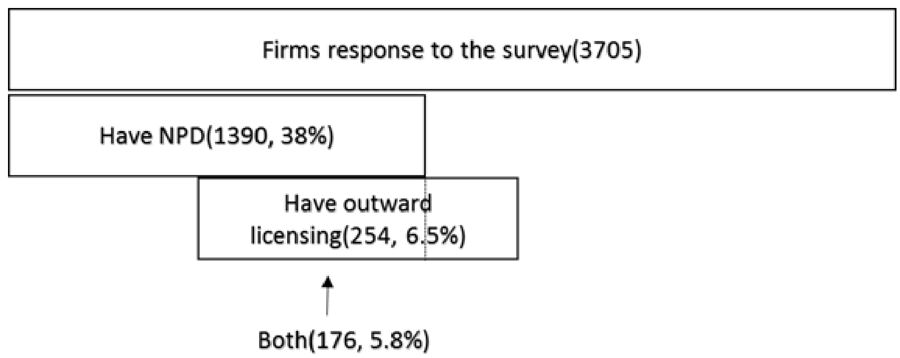


Figure 4-1 Response composition of NPD survey

The questionnaire asks the firms to consider their most important technology ("main technology") licensed out or transferred through technology consulting services, M&A or by forming joint-ventures. Therefore, it should be noted that the unit of observations in this data is one particular technology, instead of firm (or business unit with multiple business firm).

In 2011, the Research Institute of Economy, Trade, and Industry (RIETI) performed a survey of 18,000 business units in Japanese firms regarding their new product development (NPD) (Kani & Motohashi 2013). In addition to questions about NPD, the questionnaire also asked several questions about licensing-out/contracted research activities from 2008 to 2010. Among the 3,705 business units (for simplicity, hereafter referred to as "firms") responded, 254 reported having such activities. Excluding responses with missing data on important questions, 204 firms were extracted as the dataset for this study. The questionnaire asked firms to consider their most important technology ("main technology") that is either licensed out or transferred through technology consulting services, M&A, or managed through joint ventures. Therefore, note that the unit of observation in our data is on particular technologies rather than firms (or business units within a single organization). The data items used in this study are as follows:

- Number of contracts
- Whether technology is initially developed for a special client (i.e., customized)

- Whether technology is patented
- Technology type: product, process, or know-how
- Main technology field of the technology supplier
- Main application fields of technology

The NPD survey also assessed the competitive environment by asking firms that had developed a new product (1,390 of 3,705 responses) to identify how many competitors they face: 0, 1–3, or >3. This question allows us to measure the degree of competition in a specific technology field.

Table 4-1 Tabulations of technology transfer modes

	Technology transfer modes						
	Licensing	Consulting	M&A	JV	Other*	Not answered	Total
Nonpatented	23	28	1	2	22	14	90
Patented	81	9	1	4	9	10	114
Total	104	37	2	6	31	24	209

*Mostly, the supply of technology is already embodied in a product

The questionnaire is designed to cover technology transfer in a broad meaning that is not limited to formal licensing but including technology consulting services and product-embedded technologies that are both patented and nonpatented. Table 4-1 shows the observations tabulated by technology transfer modes for patented/non-patented technologies. For technology transfer by licensing, about three quarters of technologies are patented, whereas a quarter is licensing of nonpatented "know-how." For the rest of the technology transfer methods, "consulting" is most frequently used. In addition, there are substantial numbers of "others," and most of this category is found to correspond to technologies embodied in products (parts), such as OEM supplies, or blueprints for new products. Therefore, the whole sample is divided into two broad categories: formal licensing and nonlicensing by technology transfer mode. The former category is based on IP protection, and licensing contracts of patents or trade secrets while technology to be transferred in the latter is embodied in the products or services. Therefore, in the majority of firms in the latter case, these technologies are not patented. For convenience, this study uses "licensor/licensee" in the same manner as "technology supplier/technology buyer" in nonlicensing technology transfers.

Table 4-2 shows the cross tabulation of patented/nonpatented technologies and customized/noncustomized technologies. Customized technology is developed to meet the demands of a particular customer, whereas noncustomized technology is driven by the initiative of a technology owner. Observing that the share of patented technology is greater for noncustomized cases is natural. However, substantial numbers of firms have patented their technology, even in the case of customized technology.

Table 4-2 Tabulation of patented and customized technologies

	Patented	Nonpatented	Total
Noncustomized	104	66	168 (82%)
Customized	10	26	36 (18%)
Total	114	90	204

Pearson chi2(1) = 14.7608 Pr = 0.000

Table 4-3 tabulates the number of contracts. Among the 204 firms, 77 reported having supplied their "main technology" to only one buyer, whereas 127 firms supplied to more than one buyer. In noncustomized cases, more than half of firms provided their technologies to multiple contractors. In the case of customized technology transfer, observing that the majority is with only one contractor is natural, although a substantial number of firms (11 out of 36) have multiple contracts. They have initially developed a customized technology only for a special client but successfully licensed this technology to others.

Table 4-3 Tabulation of number of contracts

	Number of Contracts				
	1	2~5	6~10	>10	Total
Noncustomized	52	79	20	17	168
Customized	25	7	2	2	36
Total	77	86	22	19	204

The dataset contains technologies applied in 54 industrial sectors. The largest share (10.1%) is taken by software technologies, followed by automobile (9.2%) and pharmaceutical technologies (6.3%). The fragmented distribution of these technologies allows empirical analysis from a general view and comparison with the current literature in each special industry.

The questionnaire also asked firms to indicate their total license revenue (not only for the "main technology") as a percentage of sales. Among the 204 firms, 192 firms provided this information.

4.3.2 Dependent variables

The empirical analysis includes two parts. In the first step, I use an ordered logit model to test the determinants of multiple contracting. The models include an ordinal-dependent variable (*Num*) and a binominal variable (*Multiple*). *Num* indicates the number of contract counterparts generated from the range responses in the questionnaire. The value of *Num* is set by taking the average of the top and bottom boundaries of the ranges. For the last option, with only the bottom boundary (>10), *Num* is set as 20. This treatment shall not bring significant bias in our results as I use ordered logit models where the order, rather than the quantity, is the major stake.

In the second step, I use an ordered logit model to test how license revenue (*Rev*) is affected by the number of contracts (*Num*) or multiple contracting (*Multiple*), together with other factors. *Rev* is the share of license revenue in total sales. It is also an ordinal variable generated from the selected ranges. A similar treatment has been performed in setting values for other category variables.

4.3.3 Independent variables

To test our hypotheses on the competition among technology buyers and suppliers, a measure of the competition is necessary. A common approach is to use an industry/technology concentration index, such as the top-x firms' patent shares in a special field, or the Herfindahl–Hirschman index (Gambardella & Giarratana, 2013b;

Gambardella et al., 2007; Kani & Motohashi, 2012). This study uses a new measure compiled from the self-assessments of players in specific industrial sectors. The NPD survey gets 1,372 firms' assessments of competitor numbers in their respective fields (83 in total). I assign a degree of competition as 0 if a firm does not have a direct competitor; assign 1 if one to three competitors exist; and assign 2 if more than three competitors exist. I take the average of this value for each field to compile an industry/technology field competition index. This index is matched with the main technology field of the technology supplier, providing a measure of supplier competition (*SupplyComp*), and the main application field of technology (the demand side) to get "buyer competition" (*BuyerComp*). The two variables are centered to their means to facilitate the interpretation of interaction effects (Afshartous & Preston, 2011). The other independent variables are listed as follows:

Patented: Dummy =1 if technology is patented

License: Dummy =1 if technology is transferred by formal licensing contracts

Customized: Dummy =1 if technology is initially developed for one buyer

Noncore: Dummy =1 if the technology's application sector is different from the main business sector of a licensor

Product: Dummy =1 if technology is a product, 0 if technology is process or know-how

Process: Dummy =1 if technology is for manufacturing or processing, 0 if technology is a product or know-how

Small: Dummy, =1 if the technology supplier has less than 100 employees

Industrial dummies (*Software*, *Automobile*, *Pharmaceutical* and *Food*) are included as control variables.

4.4 Empirical results

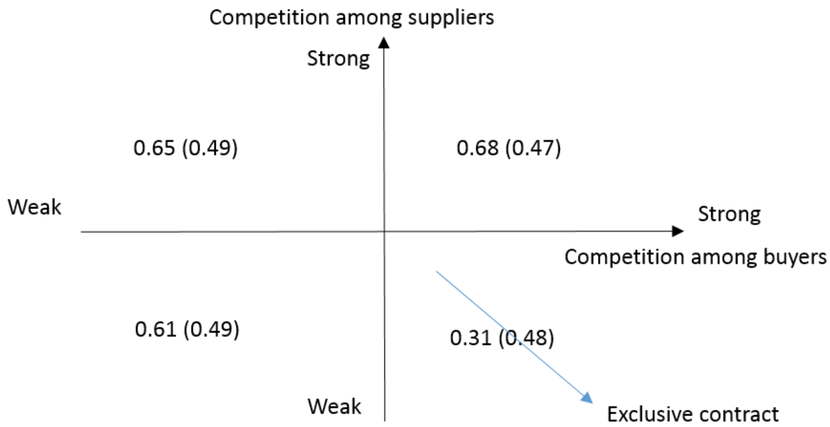
4.4.1 Determinants of multiple contracting

Table 4-4 Estimations on determinants of multiple contracting

	(1)	(2)	(3)	(4)	(5)	(6)
	Num	*Num*	*Num*	*Multiple*	*Multiple*	*Multiple*
BuyerComp	-2.721**	-2.612**	-2.571**	-2.927**	-3.294**	-3.107**
	(-2.53)	(-2.45)	(-2.38)	(-2.18)	(-2.36)	(-2.23)
SupplyComp	3.170***	3.113***	3.034***	3.318**	3.668**	3.509**
	(2.89)	(2.85)	(2.76)	(2.36)	(2.56)	(2.44)
BuyerComp ×(-SupplyComp)		2.503	2.412		7.675*	7.375*
		(0.69)	(0.64)		(1.87)	(1.79)
Patented		-0.658**	-0.886**		-0.650	-0.995**
		(-1.97)	(-2.48)		(-1.54)	(-2.11)
Customized	-2.265***	-2.429***	-2.979***	-2.453***	-2.764***	-3.471***
	(-4.96)	(-5.20)	(-5.27)	(-4.93)	(-5.20)	(-5.07)
Patented × Customized			1.784*			1.888*
			(1.95)			(1.89)
Small	0.571*	0.523*	0.395	0.446	0.421	0.266
	(1.86)	(1.69)	(1.25)	(1.24)	(1.14)	(0.69)
NonCore	-0.330	-0.417	-0.405	-0.310	-0.608	-0.618
	(-1.03)	(-1.19)	(-1.16)	(-0.82)	(-1.45)	(-1.47)
Product	0.885**	0.886**	0.911**	1.048**	1.120**	1.159***
	(2.39)	(2.41)	(2.47)	(2.44)	(2.55)	(2.61)
Process	-0.0183	0.0288	0.0343	-0.0449	0.0429	0.0585
	(-0.03)	(0.05)	(0.06)	(-0.08)	(0.07)	(0.10)
License	-0.502	-0.318	-0.300	-0.396	-0.328	-0.328
	(-1.61)	(-0.96)	(-0.91)	(-1.07)	(-0.80)	(-0.79)
Software	1.595***	1.499***	1.597***	1.406*	1.498*	1.703**
	(2.91)	(2.58)	(2.69)	(1.89)	(1.90)	(2.05)
Automobile	0.0153	0.0670	-0.00761	0.142	-0.000502	-0.0705
	(0.03)	(0.12)	(-0.01)	(0.22)	(-0.00)	(-0.11)
Pharmaceutical	-0.571	-0.728	-0.679	-0.268	-0.659	-0.598
	(-0.94)	(-1.18)	(-1.08)	(-0.38)	(-0.91)	(-0.81)
Food	0.365	0.205	0.189	0.436	0.181	0.140
	(0.55)	(0.30)	(0.27)	(0.48)	(0.19)	(0.14)
Constant				-2.649*	-2.278	-1.815
				(-1.83)	(-1.54)	(-1.22)
cut1	2.359**	1.789	1.575			
	(2.02)	(1.50)	(1.31)			
cut2	4.739***	4.227***	4.049***			
	(3.94)	(3.47)	(3.30)			
cut3	5.798***	5.303***	5.136***			
	(4.73)	(4.28)	(4.12)			
Observations	204	204	204	204	204	204
LogLik	-210.7	-208.4	-206.6	-109.7	-106.5	-104.7
chi-squared	65.50	69.96	73.61	50.94	57.47	61.03

z statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4-4 shows the estimation of determinants of multiple contracting. Models (1), (2) and (3) are ordered logit models, with *Num* as the dependent variable, whereas Models (4), (5) and (6) use logit models with *Multiple* as the dependent variable.



Note: standard deviations in parentheses

Figure 4-2 Competition environment and its effect on multiple contracting

First, *BuyerComp* is negatively significant while *SupplyComp* is positively significant, supporting Hypotheses 1a and 2a, which are that competition among buyers decreases the likelihood of multiple contracting (increases the number of contracts), whereas the competition among technology suppliers results in an opposite effect. To illustrate the relative effects of the two variables, the samples are plotted in a matrix composed of *BuyerComp* and *SupplyComp*, with origin coordinates set as the median of the two variables. Sample mean and standard deviation of *Multiple* are shown in each quadrant (Figure 4-2). The figure illustrates that when the competition among buyers is strong and the competition among technology suppliers is weak, the probability of multiple contracting significantly decreases. The same result can be got from regressions including interaction terms between *BuyerComp* and *SupplyComp* in Model (5) and (6).

The variable *Customized* shows a strong negative significance, which is not surprising as customized technologies are developed to fit the special needs of a client and are generally not provided to others. However, the cross product of *Customized* and *License* is positively significant, which indicates that if the innovator decides to patent a technology initially developed for a special client, then the innovator believes technology to have the potential to be supplied to other users. Patenting technology can help the innovator negotiate with potential buyers.

Patented shows a negative significance in Models (2) and (3), with *Num* as the dependent variable. When the selection effect of patenting customized technology is controlled, it is also negatively significant, as shown in Model (6), with *Multiple* as the dependent variable. The result is consistent with the proposition in Hypothesis 3a that patent protection leads to more exclusive contracting.

The dummy variable *Small* is slightly significant in Model (1) and (2), and the coefficients in the other models are also positive, but the *Z*-value is small in other models and therefore, not sufficiently large to gain a solid support for Hypothesis 4a that small technology suppliers are more likely to use multiple contracting.

4.4.2 Determinants of license revenue

License revenue data for special technologies is not widely available because these are usually a trade secret. The survey on firms' licensing activities is about the "main technology" licensed out, whereas license revenue is coded as the percentage of a licensor's total license revenue to the total sales; thus, it is not a direct measure of the earnings of technology in the sense that other technologies of a licensor may also contribute to the revenue. However, it is still a useful measure of the license revenue of the "main technology" for the reasons as follows:

(1) License revenue distribution is highly skewed, where a small percentage of technologies contribute a large part of license revenue. Thus, for a single licensor in a rather short period (three years), the "main technology" very likely contributes a dominant part in the total license revenue. This is especially true for small firms.

(2) The percentage measurement has a scale-controlling effect that allows comparison among licensors of different sizes. Although several technologies may have been licensed out by different divisions of a large firm in the same time period, dividing license revenue by sales can reflect the contribution of one technology.

Thus, *Rev* is used as the dependent variable in the following ordered logit models to identify the determinants of license revenue. Although license revenue information is available for 192 of the 204 observations, only 101 firms supplied their technology through formal licensing. For the firms supplying their "main technologies" using others methods, such as consulting services, the revenues may not be clarified as license revenue. The regression result is presented in Table 4-5.

Model (1) only uses exogenous variables of *BuyerComp* and *SupplyComp* as main explanatory variables. Models (2) and (3) use *Num* as the explanatory variable, whereas Models (4) and (5) use the binominal variable *Multiple*. Interaction terms are added in Models (3) and (5). Both *Num* and *Multiple* are positively significant when interaction terms with the firm size effect are not included, indicating that supplying technologies to a large number of licensees increases license revenue significantly. The cross term of *Multiple* and *Small* is positively significant in Model (5), which is consistent with Hypothesis 4b that small technology suppliers capture more rents from multiple contracting. A comparison of the models shows that *Multiple* is more significant and its interaction with the firm size effect is better observed. Thus, we can get a preliminary conclusion that the binominal selection of multiple versus exclusive contracting makes a qualitative change in value capture.

SupplyComp shows a consistent negative significance in all models, supporting Hypothesis 2b that licensors capture less rent from technology transfer when there is a strong competition among technology suppliers. The coefficient of *BuyerComp* is positive but not significant. An explanation is that although a licensor can get a stronger bargaining power when technology buyers compete with each other, the total value created in licensing is small because of fierce competition in the product market.

Table 4-5 Estimations on determinants of license revenue

	(1)	(2)	(3)	(4)	(5)
	Rev	*Rev*	*Rev*	*Rev*	*Rev*
Num		0.101**	0.0570		
		(2.04)	(0.76)		
Multiple				1.345***	0.734
				(2.97)	(1.34)
BuyerComp	0.276	0.715	0.856	0.848	1.420
	(0.17)	(0.44)	(0.53)	(0.52)	(0.86)
SupplyComp	-3.190*	-3.413*	-3.441*	-3.877**	-3.965**
	(-1.71)	(-1.79)	(-1.80)	(-1.97)	(-2.02)
Patented		-0.146	-0.125	0.0339	-0.00305
		(-0.28)	(-0.24)	(0.07)	(-0.01)
Small	-0.251	-0.357	-0.642	-0.0764	-1.201
	(-0.56)	(-0.77)	(-1.09)	(-0.17)	(-1.62)
Num × Small			0.0753		
			(0.78)		
Multiple ×Small					1.878*
					(1.92)
Customized	-0.0479	-15.48	-15.63	-15.43	-14.15
	(-0.05)	(-0.02)	(-0.01)	(-0.01)	(-0.02)
Patented ×Customized		16.54	16.63	16.40	14.59
		(0.02)	(0.02)	(0.01)	(0.02)
NonCore	0.409	0.444	0.461	0.458	0.538
	(0.89)	(0.96)	(0.99)	(0.98)	(1.15)
Product	-1.186**	-1.312**	-1.280**	-1.679***	-1.532***
	(-2.23)	(-2.39)	(-2.33)	(-2.89)	(-2.65)
Process	-1.114	-1.359*	-1.360*	-1.491**	-1.406**
	(-1.59)	(-1.90)	(-1.90)	(-2.07)	(-1.98)
Software	1.795*	1.224	1.232	1.259	0.810
	(1.92)	(1.23)	(1.23)	(1.30)	(0.80)
Automobile	1.584**	1.299*	1.456*	1.454**	1.590**
	(2.15)	(1.69)	(1.84)	(1.96)	(2.12)
Pharm	1.691**	1.853**	1.839**	1.941**	1.746**
	(2.29)	(2.47)	(2.45)	(2.52)	(2.26)
Food	21.54	23.67	24.66	23.91	22.45
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
cut1	-2.741	-3.291*	-3.540*	-3.048*	-4.083**
	(-1.60)	(-1.82)	(-1.93)	(-1.68)	(-2.14)
cut2	-0.181	-0.515	-0.738	-0.143	-1.048
	(-0.11)	(-0.29)	(-0.41)	(-0.08)	(-0.57)
cut3	1.483	1.199	0.974	1.637	0.747
	(0.87)	(0.67)	(0.54)	(0.91)	(0.40)
cut4	2.229	1.958	1.727	2.407	1.513
	(1.30)	(1.09)	(0.95)	(1.32)	(0.80)
Observations	101	101	101	101	101
LogLik	-124.0	-118.1	-117.8	-115.6	-113.7
chi-squared	24.16	35.98	36.60	41.03	44.81

Z statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Patented is not significant in all models, indicating patenting itself does not affect licensing revenue. Therefore, a choice between licensing by patent or by know-how makes no difference in licensing revenue; thus, Hypothesis 3b is not supported. An explanation is that technology suppliers optimize their choices of transfer mode for nonpatented technologies. They may profit from providing technology consulting services or by providing technologies embedded in products, since Arora (1996) has putevidence that complementary inputs, such as equipment sales, could substitute the role of patents in knowledge transfer. Table 4-1 shows that nonpatented technologies are more likely to be associated with nonlicensing transfers. Nonpatented know-how may be transferred by licensing only when expropriation risk is low. The result provides clues that the selection is effective, although further examination is required.

4.4.3 Robustness check

One concern is that the multicollinearity problem may exist because the estimations include a few dummies and the sample size is moderate; in some cases, a licensor and licensee are in the same field, making the *SupplyComp* and *BuyerComp* values the same for each observation and resulting in a higher correlation between the two variables. I checked multicollinearity by deleting variables gradually and found that the relations still hold. I used simple linear models and performed a variance inflation factor (VIF) test after regression and obtained a mean VIF of around 1.5 and a maximum of 2.5, which does not indicate a serious multicollinearity problem (O'brien, 2007).

4.5 Conclusion

The "rent-dispersion and revenue effect" model developed by (Ashish Arora & Fosfuri, 2003) lists product market competition as the most important determinants of technology licensing and multiple contracting. Empirical studies have been limited to the former due to a lack of comprehensive data, which requires at least two variables: the number of counterparts in technology transfers and the degree of competition. Another unexplored question is how market conditions (not only competition among licensees in the product market, but also competition among technology suppliers in technology market), together with other factors, including IP protection and complementary assets, affect innovators' rent capture in technology transfer dealings.

The survey data of Japanese firms' licensing activities allow us to make a comprehensive empirical analysis of the questions above. In contrast with existing datasets, with only binominal variable on whether a technology is licensed or not, our survey data provide the number of counterparts and allow us to examine the determinants of multiple contracting. A novel competition index is compiled from self-assessment by players in each industrial sector, which is a closer measurement to the original meaning of product market competition than the existing Herfindahl–Hirschman index-type measurement. This study provides direct empirical support that strong competition among potential buyers decreases the number of contracts and leads to more single (more likely exclusive) licensing. However, there is no significant increase of license revenue if a technology is supplied to a competitive field.

Further, I propose that competition among technology suppliers motivates both the supplier and buyer to select nonexclusive contracting since alternative technology suppliers can create new competitors in the product market even if a licensee gets an exclusive licensee from one supplier. Empirical results show that this factor is even more decisive than the more widely discussed factor of competition among buyers. Competition among technology suppliers not only increases the use of multiple contracting, but also significantly decreases license revenues for a licensor.

This study also finds that nonpatented technologies are less likely to be licensed exclusively due to the lack of instruments available to prevent expropriation. This is not trivial, as existing studies on markets for technology laid particular stress on patented technologies and the value of formal IP protection for technology transfer is generally assessed from a macro view, such as whether a special country has strong IP rights protection. However, for nonpatented knowledge, transferred through a formal licensing contract, the estimations in this study show no evidence that license revenue is decreased.

This study also provides empirical evidence that multiple contracting makes a qualitative change in value capture, especially for small innovators who lack the option to conduct in-house exploitation of their inventions.

The study contributes to the literature on technology markets by providing a comprehensive empirical analysis of several theoretical propositions concerning technology exploitation through multiple contracting and, more importantly, the determinants of value captured by licensors.

This study several limitations. First, the survey data cannot strictly distinguish whether a single contract entails exclusive licensing or just a licensor's willingness to license to others, but is unable to find a second licensee. It is just from the statistical view that multiple contracting generally is nonexclusive and single contracting is highly corrected by an exclusive license. Therefore, although the theoretical discussion still holds, our estimations contain noise. Second, the sample size is moderate, preventing us from testing more interaction effects, which can be explored in future studies. Third, this study takes a two-step approach: investigating the determinants of multiple contracting first and analyze whether multiple contracting affect license revenue. However, there is an alternative explanation there are some potential factors which determines both multiple/exclusive license and license revenue, such as characteristics of technologies, creating a potential endogeneity problem. Due to data limitations, I have not made an in-depth analysis. Further studies are needed.

Chapter 5 Conclusion, Implications and Future Research

5.1 Conclusion

This dissertation provided an economic analysis of alternative appropriation strategies for new technologies, with a focus on the role of patents. Aiming at understanding the value of patents and the market of technology, two strategic uses of patents—collateralization and licensing—are examined using rich empirical data from China (an emerging economy) and Japan (a developed country). Patenting strategy of Chinese firms under policy incentives is also covered.

Profiting from innovations would be difficult without prevention of imitation (Teece, 1986b) and intellectual property right, especially patent protection, is considered the basic tool for securing rents from their innovations. However, several surveys have revealed that protection of invention does not top the ranking of motivation for patenting(Cohen et al., 2000; S. J. H. Graham et al., 2009). Firms have been exploiting the value of patents via a variety of strategies, which can be classified in different ways: defensive vs. offensive; practicing vs. non-practicing; protection vs. financial, etc. Academics have carried fruitful studies on those strategies and provide much implication on our standing of patent value. A traditional perspective lays on the intrinsic value of patents embedded in the patented innovations and the exclusive rights. However, due to disclosure effect of patents, the signaling function of patents in financing is also well recognized. A relatively new perspective is the transaction value of patents, usually studied on licensing activities of firms. This dissertation aimed to expand this line of research and provide new insights.

Patents collateralization and licensing are two topics which are not accompanied with each other so often. One reason is that financing based on patent collateral is a phenomenon largely unexplored in innovation studies. In the sparse studies, patent collateral is discussed under the context of signaling effects. However, the two strategies have strong internal links: the value realizable in transactions. The value of pledged patents can be realized only by sales or licensing when the borrower defaults.

Intuitively, those patents pledged as collateral should have similar characteristics with patents that are licensed out. However, there is a subtle difference: the pledged patents are currently exploited by their owners, who are often the inventors and are not readily available in markets for technology. Meanwhile, if liquidation is needed, the transaction needs to be quick, as financial institutions that got the pledged patents, do not have the option to use the technologies by themselves. In contrast, the patents offered for licensing may not fit the business of their owners and the owners can be more patient for reaching a deal. Thus, liquidity requirements are different.

Existing literature on financing innovation focuses on the signaling effect of patenting, but not on the asset property of patents. In a collateral-backed financing deal involving transfer of ownership, liquidity should be as important as the value of collateral, if not more so. Surprisingly, studies on the management of intellectual property have not effectively examined the concept of liquidity for patent assets. A major blank is a discussion of indicators for patent liquidity despite several studies on patent value indicators. This study separates the concept of patent liquidity from patent value and identifies their influences on propensity to lend with patents as collateral. The value of patents is expressed as the maximum discounted revenue a patent can generate while the liquidity is the probability of finding a buyer who agrees to pay for the value. Drawn from existing studies on patent licensing market, particularly studies on generality, several liquidity indicators are proposed from the perspective of technology generality, technology complexity, and technology competition. Controlling the treatment effect of firms' willingness to apply for patent-collateralized loans using PSM method, I find that patents with larger family, broader claim scope, more opposition records and simpler but widely applicable patents are more acceptable as collateral. However, a weak positive significance of IPC based on indicators of generality underlines a cautious interpretation of this widely used indicator. This study also proposed technology competition as an indicator of patent liquidity, but empirical result failed to verify this. A limitation of using patent-generate competition is that we cannot distinguish whether the players in the same field are more likely to be potential buyers, or just substitute technology providers. To further understand these problems, it is important to study licensing activities with dataset containing more specified settings of technology supply and demand, which becomes the motivation to study markets for technology using a novel dataset of licensing activities of Japanese firms.

Contrary to sparse studies of patent collateral, patent licensing is a consistently popular topic in economic and management studies. Interestingly, although the theoretical argument of licensing as a strategy often starts from a discussion of value capture, empirical studies terminate at the value capture stage. One reason is that we still lack comprehensive empirical data regarding the performance outcomes of licensing. The survey data of Japanese firms' licensing activities allowed an empirical analysis of determinants of license revenues with a wide coverage of the competition between technology suppliers, technology buyers, IP protection, and contract structure. Most importantly, this study provided empirical support of a theoretical proposition that multiple contracting helps the small technology venture capture more rent from technology transfer. On the contrary, patent protection does not show a significant contribution to license revenue. The results also provide implications on why patents of a fragmental technology field are not more acceptable as collateral, despite that liquidity shall be improved due to market thickness.

This study relied heavily on patent statistics and is built on the findings of pioneering works. Meanwhile, it also contributes to future studies with patent data, especially with unexplored data from emerging economies, like China. The first contribution is a novel indicator of patent scope by text-mining patent claims, which makes evaluation of patent quality possible even when citation data are not available. The empirical analysis of patent collateral and the impact of patent subsidies used this indicator and proved its effectiveness. More importantly, I found that grant-contingent patent subsidies encouraged a strategic behavior of limiting patent claims to get easier grants, resulting in more patents with lower quality and lower economic value. With the same measurement of claim scope, patents used as collateral have shown a broader claim scope, dispelling a concern that patents collateral may become a market for "lemons".

The second contribution is a comprehensive evaluation of patent statistics as an innovation indicator in China, focusing on the impacts of patent subsidies by local governments.

In sum, this study contributes to the literature on technology exploitation strategies other than directly profiting from selling patented products. It underlines the value of patents beyond protection of inventions.

5.2 Implications

A combination of the empirical results shows interesting impacts of several policies. Current innovation policies have emphasized the role of intellectual property, and governments have encouraged small innovators to protect their inventions by patenting. However, the value of patents can only be captured with appropriate strategies. Patent subsidy programs may motivate firms to strategically file narrow patents, which are not as effective in protecting inventions and securing financing; as our results show, patents with a narrow claim scope are not well-qualified as collateral. Another negative impact of patent subsidy programs is that the boosted applications may increase the workload of patent examiners. Especially, subsidies of examination fee have hindered patent applicants to make serious judgment of values of their patents before requiring a substance examination, which create unnecessary social cost. The increased workload of examiners may decrease the precision of examination, and weaken the patent grants' function as a signal of quality. The empirical results of this dissertation, together with the theory of GPTs in the literature, highlight the importance of multiple contracting in the sustainable growth of small technological specialized firms. Innovation policy may place greater emphasis on supporting small firms to generate GPTs while government can provide platforms for interactions with different industrial sectors and help innovators find more applications for their technologies.

The surge of patenting in China at least partly reflects the growing innovative capabilities and a more serious recognition of values of intellectual properties. However, the more challenging task is to exploit intellectual assets, which may be decisive for firms' shift to the high end of global value chains. Patents-backed financing is one of such a try. This study has attempted to clarify from a scholastic view what kinds of characteristic make a patent more likely to be acceptable as collateral and made a preliminary conclusion that those patents accepted as collateral are not "lemons". The findings also find some indicators which can serve as guide in selecting patents with both high value and liquidity as collateral. However, patents in general are illiquid assets. With more and more patents being used as financing, it is challenging for financial institutions can maintain an effective evaluation of pledged patents. More monitoring and continuing study of this practice are needed, especially on cases that the borrower defaulted and the patents need to be liquidated. The improvement of the liquidity of patents may rely largely on the development of technology market. A cooperation of financial institutions and intermediaries for the IP market, such as non-practicing entities, defensive patent aggregators, online IP platforms discussed by Hagiu and Yoffie (2011), may facilitate the liquidation of patents.

For academics, this study mainly contributes in the form of an empirical examination of several theoretical propositions. Most prominently, empirical support is found for the proposition that multiple contracting helps innovators capture rents from licensing. It also provides an implication that some generally used statistics from patent information may show different results when used in different contexts, namely, whether transactions of technology and patent rights take place. The author hopes that the concept of viewing patents from both value and liquidity aspects would be helpful in technology market studies.

5.3 Limitations and Future Research

This study relies on empirical data with noises, which is far from perfect for analyzing complex management issues; thus, the data limitations have affected the scope and precision of the results, and interpretations should be made with caution.

In the study of patent collateral, a comparison group of patents is used as selected with PSM method, although more solid results can be obtained by comparison with data from firms that unsuccessfully sought to use patents as collateral; unfortunately, these data are not currently available. In the study of licensing activities in Japan, the strict distinction between single and exclusive licensing is not permitted in the dataset, which brings noise to the results. The theories of the determinants of multiple contracting/single licenses are explained in text and a concise mathematic model is needed.

Future studies could improve the results by using a better formatted dataset. Besides, an interesting research direction is to study the effect of debt financing on firm performance. Did the SMEs receiving patent-backed loans in recent years efficiently use that financing to create more innovations? How about the total social value of promoting such new ways for financing SMEs? Amable et al. (2010) have developed an endogenous growth model showing the leverage effect on innovation growth of using patents as collateral. Further research could empirically examine this issue and provide innovation policy implications.

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Appendixes

Appendix 1 Summary of patent subsidy programs

Province	Start year	Filing fee subsidies	Examination fee subsidies	Grant contingent rewards
Beijing	2000	Fully	Partly	No
Tianjin	2000	Fully	No	No
Hebei	2005	Partly	No	Low
Shanxi	2003	Fully	Fully	No
Inner Mongolia	2002	Fully	Fully	No
Liaoning	2006	Fully	No	High
Jilin	2004	Partly	Partly	Low
Heilongjiang	2001	Fully	No	Low
Shanghai	1999	Fully	Fully	High
Jiangsu	2000	Fully	Fully	No
Zhejiang	2001 - 2005	No	Fully	No
Anhui	2003	No	No	High
Fujian	2002 - 2005	Fully	Fully	No
Jiangxi	2002	Partly	Partly	No
Shandong	2003	Partly	Partly	High
Henan	2002	Partly	Partly	Low
Hubei	2007	No	No	Low
Hunan	2004 - 2006	Partly	Partly	No
Guangdong	2000	Partly	Partly	No
Guangxi	2001	Fully	Partly	High
Chongqing	2000	Fully	No	Low
Sichuan	2001	Partly	Partly	No
Guizhou	2002	Fully	Partly	No
Yunnan	2003	Partly	Partly	Low
Tibet	2004	Fully	Fully	High
Shaanxi	2003	Fully	No	High
Qinghai	2006	Fully	Partly	No
Xinjiang	2002	Partly	No	High
Hainan	2001	Partly	No	No

Data source: the authors' collection from official documents published on local government websites and news reports or telephone interviews of local officials.

Filing and examination fee subsidy as “Fully” if the amount is equal to the fees charged by SIPO, and “Partly” if the amount is unclear or less than the fee charged. Grant-contingent reward is classified as “High” if the amount is no less than 2000 yuan, and “Low” if unclear or less than 2000 yuan.

Appendix 2. Number of provinces administered subsidy programs

Year	Filing fee subsidy #	(Percentage)	Examination fee subsidy #	(Percentage)	Grant-contingent rewards #	(Percentage)
1998	0	(0.0%)	0	(0.0%)	0	(0.0%)
1999	1	(3.2%)	1	(3.2%)	1	(3.2%)
2000	6	(19.4%)	4	(12.9%)	2	(6.5%)
2001	10	(32.3%)	7	(22.6%)	4	(12.9%)
2002	16	(51.6%)	12	(38.7%)	6	(19.4%)
2003	20	(64.5%)	15	(48.4%)	10	(32.3%)
2004	23	(74.2%)	17	(54.8%)	12	(38.7%)
2005	24	(77.4%)	17	(54.8%)	13	(41.9%)
2006	26	(83.9%)	17	(54.8%)	16	(51.6%)
2007	25	(80.6%)	16	(51.6%)	17	(54.8%)
2008	25	(80.6%)	16	(51.6%)	18	(58.1%)

The percentage is calculated by dividing number of provinces administered subsidy programs by 31, which is the total number of provinces of mainland China since Chongqing became a municipality in 1997.

Appendix 3. Negative binominal estimation of patent production function: applications

	Negative binominal model		Negative binominal model with fixed effects	
	Applications	*Applications*	*Applications*	*Applications*
log(R&D)	0.711^{***}	0.986^{***}	0.376^{***}	0.475^{***}
	(0.0327)	(0.0614)	(0.0390)	(0.0648)
ApplSub	0.193^{***}	0.903^{***}	0.301^{***}	0.511^{***}
	(0.0442)	(0.177)	(0.0501)	(0.179)
GrantSub	0.329^{***}	1.673^{***}	0.980^{***}	1.447^{***}
	(0.0732)	(0.286)	(0.0798)	(0.291)
log(R&D) × ApplSub		-0.197^{***}		-0.0575
		(0.0489)		(0.0466)
log(R&D) × GrantSub		-0.371^{***}		-0.125^{*}
		(0.0767)		(0.0741)
Size	1.159^{***}	1.152^{***}	0.364^{***}	0.352^{***}
	(0.0626)	(0.0623)	(0.0847)	(0.0850)
SOE	-1.000^{***}	-1.003^{***}	-0.667^{***}	-0.663^{***}
	(0.0739)	(0.0737)	(0.0890)	(0.0891)
FFE	0.120	0.197^{*}	0.158	0.161
	(0.105)	(0.106)	(0.116)	(0.116)
Constant	-6.299^{***}	-7.304^{***}	-3.550^{***}	-3.876^{***}
	(0.204)	(0.276)	(0.291)	(0.339)
lnalpha				
Constant	1.467^{***}	1.458^{***}		
	(0.0277)	(0.0277)		
Industry dummies	Yes	Yes	Yes	Yes
Observations	7571	7571	7090	7090
LogLik	-10215.3	-10196.2	-5639.1	-5636.8
chi-squared	3173.2	3211.3	501.1	494.8

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

ApplSub: subsidies of filing fee or examination fee; GrantSub: reward contingent on patent grants.

Appendix 4. Negative binominal estimation of patent production function: grants

	Negative binominal model		Negative binominal model with fixed effects	
	Grants	*Grants*	*Grants*	*Grants*
log(R&D)	0.679***	0.897***	0.365***	0.440***
	(0.0335)	(0.0616)	(0.0408)	(0.0681)
ApplSub	0.206***	0.743***	0.321***	0.421**
	(0.0439)	(0.175)	(0.0537)	(0.188)
GrantSub	0.437***	1.541***	0.993***	1.520***
	(0.0732)	(0.281)	(0.0846)	(0.305)
log(R&D) × *ApplSub*		-0.148***		-0.0283
		(0.0478)		(0.0490)
log(R&D) × *GrantSub*		-0.304***		-0.141*
		(0.0751)		(0.0779)
Size	1.093***	1.090***	0.416***	0.404***
	(0.0617)	(0.0616)	(0.0893)	(0.0896)
SOE	-0.890***	-0.892***	-0.682***	-0.679***
	(0.0739)	(0.0739)	(0.0937)	(0.0938)
FFE	0.0941	0.179*	0.240*	0.245**
	(0.106)	(0.109)	(0.125)	(0.125)
Constant	-6.236***	-7.038***	-3.825***	-4.064***
	(0.202)	(0.275)	(0.308)	(0.358)
lnalpha				
Constant	1.444***	1.439***		
	(0.0298)	(0.0298)		
Industry dummies	Yes	Yes	Yes	Yes
Observations	7571	7571	6904	6904
LogLik	-9357.8	-9345.6	-5110.0	-5108.1
chi-squared	2796.7	2821.1	466.5	461.7

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
ApplSub: subsidies of filing fee or examination fee;
GrantSub: reward contingent on patent grants.

Appendix 5 Estimations of determinants of patent grants and claim breadth controlling R&D intensity

	Probit estimation		OLS estimation	
	Granted		*ClaimScope*	
R&D/Sales	0.570**	(0.286)	0.329**	(0.139)
FilingSub	-0.275***	(0.0548)		
ExamSub	-0.150***	(0.0582)		
GrantSub	0.179***	(0.0516)	-0.0399*	(0.0239)
ClaimScope	-0.253***	(0.0168)		
SOE	0.0975***	(0.0378)	-0.102***	(0.0186)
FFE	0.00797	(0.0321)	0.116***	(0.0158)
NonDevice	0.000159	(0.0244)	-0.104***	(0.0121)
Experience	-0.00218	(0.00359)	0.00142	(0.00177)
log(Employee)	0.0123	(0.0103)	0.0271***	(0.00510)
Constant	-5.521	(138.5)	-3.996***	(0.641)
Year dummies	Yes		Yes	
Region dummies	Yes		Yes	
Technology dummies	Yes		Yes	
Observations	14553		14555	
Adjusted R2			0.0939	
LogLik	-9408.9			
chi-squared	1337.2			

Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

ClaimScope: breadth of claims; Granted: dummy variable; equals 1 if an application is granted within four years of filing; FilingSub: subsidies of filing fee; ExamSub: subsidies of examination fee; GrantSub: reward contingent on patent grants; Non-device: dummy indicating whether a patent is a non-device (process or usage) patent.

Appendix 6 Correlations between variables in Dataset A of Chapter 2

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Applications)	(1)	1.000							
log(Grants)	(2)	0.963	1.000						
log(R&D)	(3)	0.325	0.301	1.000					
ApplSub	(4)	0.067	0.063	0.063	1.000				
GrantSub	(5)	0.102	0.111	0.035	-0.027	1.000			
log(Employee)	(6)	0.178	0.164	0.435	-0.095	-0.056	1.000		
SOE	(7)	-0.119	-0.113	0.009	-0.103	-0.123	0.300	1.000	
FFE	(8)	0.105	0.093	0.089	0.088	0.030	0.028	-0.164	1.000

Appendix 7 Correlations between variables in Dataset B of Chapter 2

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Granted	(1)	1.000										
Examined	(2)	0.241	1.000									
GrantSub	(3)	0.037	0.046	1.000								
FilingSub	(4)	-0.088	-0.068	-0.045	1.000							
ExamSub	(5)	-0.073	0.007	-0.136	0.534	1.000						
ClaimScope	(6)	-0.136	-0.060	-0.052	0.001	0.034	1.000					
Non-device	(7)	0.043	0.069	0.018	-0.033	-0.030	-0.037	1.000				
SOE	(8)	0.046	0.022	0.019	-0.050	-0.112	-0.034	0.029	1.000			
FFE	(9)	-0.024	0.044	0.035	-0.019	0.132	0.027	0.017	-0.159	1.000		
log(Employee)	(10)	0.006	0.063	-0.070	-0.114	-0.087	-0.005	0.040	0.196	0.220	1.000	
Experience	(11)	0.026	0.070	-0.051	-0.022	-0.042	-0.001	0.066	0.220	0.005	0.397	1.000

List of Abbreviations

CDMA	Code Division Multiple Access
DBJ	Development Bank of Japan
FFE	Foreign Funded Enterprise
GPT	General Purpose Technology
ICTCLAS	Institute of Computing Technology, Chinese Lexical Analysis System
IP	Intellectual Property
IPC	International Patent Classification
IPR	Intellectual Property Rights
JPO	Japan Patent Office
NBER	the National Bureau of Economic Research
NBS	National Bureau of Statistics of China
NPD	New Product Development
OECD	Organization for Economic Co-operation and Development
OEM	Original Equipment Manufacturer
PCT	Patent Cooperation Treaty
POE	Privately Owned Enterprise
RIETI	the Research Institute of Economy, Trade and Industry
SIPO	State Intellectual Property Office of China
SME	Small- and Medium-sized Enterprise

SOE	State Owned Enterprise
TFP	Total Factor Productivity
VIF	Variance Inflation Factor

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