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Patent value and liquidity: evidence from patent-collateralized loans in China

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Patent value and liquidity: evidence from patent-collateralized loans in China

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Abstract

This paper studies how offering patents as collateral influences the decisions of Chinese lenders and determines features that make patents more acceptable as collateral. We develop a lending model incorporating a borrower's likelihood of default, the value of patents offered as collateral, and their liquidity. We show it is essential to consider both the future value and future liquidity of patent collateral, explain why higher-value and more liquid patents are more acceptable collateral, and indicate how patent-collateralization improves high-risk SMEs' chances of receiving loans. We clarify how the complexity of technology influences patent liquidity. An empirical examination employing a novel dataset of patents accepted as collateral in China finds that patents characterized by larger patent family size, broader claim scope, smaller inventor teams, and less supplier-concentrated technological fields are more likely to be accepted as collateral.

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 (Kamiyama et al., 2006; Harhoff, 2009) 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 SIPO, from January 2006 to June 2011, 3,361 patents (including 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 (Kamiyama, 2006; Harhoff, 2009). 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 paper addresses the gap in scholarly knowledge on the basis of studies of patent-collateralized loans in China. It uses a simple decision model to identify determinants of loans involving patent collateral, discusses value and liquidity as features determining patents' acceptability as collateral, and explains how they are incorporated into lending decisions. An empirical study verifies the model and measurement indicators on the basis of patent-collateralized loan assignments in China from 2008 to 2010.

Section 2 introduces the background of patent-collateralized financing in China. In Section 3 we develop our theory and hypothesis on the basis of previous literature. Section 4 is an empirical examination. Section 5 discusses results. Section 6 concludes the paper.

2 Backgrounds

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 et al., 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 the State Intellectual Property Office (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.

2.2 Business models

Figure 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.

(Figure 1 here)

3. Theory development and hypotheses

3.1 Lending decision model

To understand how a firm’s creditworthiness and patents influence lending, we first analyze the expected return of a loan on the basis of general collateral and then incorporate the special characteristics of patent assets. Consider a case in which a bank lends amount A due in year n. The collateral’s value is expected to be V in n years. The expected net return R can be written as equation (1), where p is the probability of loan default, i is the loan’s interest rate, and i_0 is the lender’s cost of capital (i.e., interest rate on deposits).

$$R = (1-p)A(1+i)^n + pV - A(1+i_0)^n,$$

$$0 < p < 1\,, n = 1, 2, 3 \ldots \tag{1}$$

Extra effort is needed to value and liquidate patents pledged as collateral, entailing a fixed cost. The fixed cost of valuation and liquidation C can be incorporated into the return function.

$$R = (1-p)A(1+i)^n + pV - A(1+i_0)^n - C,$$

$$i > i_0, 0 < p < 1\ , n = 1, 2, 3 \ldots \quad (2)$$

SMEs generally find that long-term loans (maturities beyond one year) are more difficult to arrange than short-term loans, and their interest rate is higher because the lender's risk is extended. Loan maturity is irrelevant to this investigation of whether a patent qualifies as collateral, so we separate the decision into two steps. First, the lender decides whether to grant a one-year loan. Next, it extends the maturity and adjusts the interest rate at the borrower's request. We focus on the first step and consider the case *n* = 1. Equation (2) can be simplified as

$$R = (1-p)A(1+i) + pV - A(1+i_0) - C \quad (3)$$

We assume banks base decisions on expected rates of return, with a higher expected rate making them more likely to lend. The expected return rate (*r*) can be written as

$$r = \frac{R}{A} - 1 = (1-p)(1+i) + \frac{pV}{A} - (1+i_0) - \frac{C}{A} - 1 \quad (4)$$

Banks do not know what the market price of patents (*V*) will be after the loan matures, and determine the maximum loan amount according to the assessed value of patents (V_0), which is generally calculated under an income approach. Due to high uncertainties and liquidation difficulties, Chinese banks lend no more than 30% of the assessed value (Sun and Hu, 2009). Thus, we assume A is proportional to (V_0).

$$A = \lambda V_0 \quad (5)$$

We introduce a new variable, liquidity (*L*), to represent the probability of finding a buyer for patents at their assessed value.

$$V = V_0 L. \quad (6)$$

Substituting (5) and (6) into (4), we get the following function (7):

$$r = (1-p)(1+i) + p\lambda L - (1+i_0) - \frac{\lambda C}{V_0} - 1 \quad (7)$$

where i_0, λ, and *C* are independent of individual loan assignments and can be assumed as constants. Thus, *r* becomes a function of the loan's interest rate (*i*), probability of default (*p*), assessed value of patents (*V*), and liquidity (*L*). The lending decision is a function of the expected return rate (*r*).

$$\delta(r) = \delta(p, V_0, L, i) = \begin{cases} 1 \text{ if patent– backed loan assigned} \\ 0 \text{ if not} \end{cases},$$

$$\delta'(r) > 0 \quad (8)$$

SMEs understand that their elevated business risk and financing costs justify the higher interest charged by lenders, and banks generally face mandated interest ceilings. Therefore, the loan's interest rate probably is not a source of dispute and can be assumed as a constant. Finally, we obtain lending function (9) and its deviations (10).

$$\delta(r) = \delta(p, V_0, L), \tag{9}$$

$$\frac{\partial\, \delta}{\partial V_0} = \delta'(r)\lambda C \frac{1}{{V_0}^2} > 0,\ \frac{\partial\, \delta}{\partial L} = \delta'(r)p\lambda > 0,\ \frac{\partial\, \delta}{\partial p} = \delta'(r)(\lambda L - 1 - i\,) \tag{10}$$

Function (9) becomes a basic model for analyzing determinants that influence lenders to accept patents as collateral. From the local derivatives, we see that patents with higher value and liquidity are more likely to be accepted as collateral. However, relationship between the borrower's likelihood of defaulting and the lender's likelihood of lending are unclear from this model. If patents can be liquidated easily, banks in principle could earn more revenue if borrowers default. For example, if L = 1 (a buyer will pay price V_0) and $\lambda = 0.3$ (the loan equals 30% of the patent's assessed value), the bank could cover default losses and earn extra returns. In practice, however, patents are expected to have little liquidity.

$$\lambda L - 1 - i < 0 \tag{11}$$

Thus, the derivative on p is negative, and default is not a hoped-for result. However, higher L decreases the absolute value of the deviation, reducing banks' concerns over default. High-risk SMEs have better chances of borrowing if their patents are valuable and liquid.

In this model, the likelihood of default can be assessed using financial data, as illustrated by credit modeling methods in Beaver (1966), Altman (1968), and Altman and Sabato (2007). To predict patents' value and liquidity, information such as patent citations could be useful.

3.2 Patent liquidity indicators

A rich literature discusses patents' values or correlations between their value and information such as patent citations, IPC classifications, inventor teams, and patent family (Lerner, 1994; Lanjouw et al., 1998; Harhoff et al., 2003; Nagaoka et al., 2010). A larger number of patent citations, a larger patent family, and a broader scope of claims are correlated to higher value. If a borrower defaults on a loan collateralized by patents, however, banks seldom have the ability to commercialize the underlying technology. Therefore, whether patents are readily liquid becomes the key question, and measurements of patents' value cannot answer it. Liquidity must be a principal consideration when assessing the acceptability of patents as collateral. Drawing from the literature of asset finance (Mainelli, 2007), we define a patent's liquidity as the probability that it can be converted at an expected value within a specified time. Section 3.1 used this definition and demonstrated how liquidity affects lending decisions. This section clarifies different measures for assessing patents and whether they indicate value, liquidity, or both.

Studies of markets for technology, especially patent licenses, provide insights into analyzing liquidity of technology and patents, including technology generalities, complementary assets, and technology competition (Arora et al., 2001; Gambardella et al., 2007). We view the following factors 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 affect of technology competition on licensing incentives (Arora and 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 Hypotheses

Which is a lender's primary consideration: the firm's credit status or the value of its collateral? If the value of pledged assets exceeds the lender's loss exposure, the borrower's creditworthiness generally becomes less important because the lender is confident of offsetting default loss by liquidating the borrower's collateral. However, its confidence is reduced when patents are the collateral, and only firms with low likelihood of default receive patent-collateralized loans. This leads to our first hypothesis:

Hypothesis 1: Creditors make patent-collateralized loans only to firms with little likelihood of default.

Since there is a concern about low-value patents being offered as collateral and for licensing (Gambardella et al., 2007), we examine whether higher-value patents are more acceptable collateral, which is illustrated 3.1. Following numerous scholars (Putnam, 1996; Lanjouw et al., 1998; Harhoff et al., 2003; Gambardella et al., 2007), we use patent family size, oppositions, and claim scope as proxy variables for value. Citation data for Chinese patents are unavailable and are not featured in our empirical examinations.

Hypothesis 2a: Patents with larger families are more acceptable as collateral.

Hypothesis 2b: Patents challenged by a third party at least once are more acceptable as collateral.

Hypothesis 2c: Patents with larger claim scope are more acceptable as collateral.

This paper primarily examines patents' potential liquidity, which, as noted, is the foremost concern in granting patent-collateralized loans. Per discussion in Section 3.2, we measure liquidity as a function of a patent's generality (number of IPC sub-classifications), complexity (number of inventors), and technology competition (patent shares of top 10 applicants in a four-digit IPC classifications).

Hypothesis 3a: General patents are more acceptable as collateral.

Hypothesis 3b: Simpler patents are more acceptable as collateral.

Hypothesis 3c: Patents applicable to a more competitive field of technology are more acceptable as collateral.

4. Empirical analysis

4.1 Data description

The main dataset for this paper is SIPO's registrations of patents accepted as collateral. Data include patent numbers, names of pledging entities and lenders, and the period of the pledge. This paper draws on records from 2008 to 2010, which included 401 loans and 723 patents for inventions.

Financial data of Chinese non-listed enterprises (GTA_NLE data) are combined with the name of the patent assignee. They are provided by GTA Information Technology Company Limited and contain time-series financial information of Chinese non-listed enterprises. The dataset spans from 1998 to 2009 and covers 380,000 firms.

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) Pledged patents as a percentage of the borrower's patent portfolio

A firm can offer some or all of its patents as collateral (Figure 1). Of the 346 assignments from 2008 to 2010, on average 2.1 patents are collateralized each loan. The share of the owner's patent portfolio pledged as collateral ranged from 1.3% to 100%.

(2) Age of collateralized patents

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 2 shows that most patents accepted as collateral were two–five years old.

(Figure 2 here)

(3) Field of technology of collateralized patents

Figure 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.

(Figure 3 here)

4.2 Dependent variables and comparison group sampling

The dependent variable, IS_COL, is a dummy indicating whether lenders accepted a patent as collateral. However, registration data contain only successful events and do not record patents that lenders rejected as collateral. We construct a comparison sample of patents not accepted as collateral under appropriate controlling conditions.

This paper regresses against two comparison datasets. Figures 4 illustrate the selection methods. Firstly, for each collateralized patent, a comparison patent from the same technology classification and application year is sampled from all valid Chinese patents not used as collateral. The 723 collateral patents and 722 comparison patents (A comparison patent with the same technology classification and application year does not exist for one collateral patent) formed the first dataset (Dataset A), which totaled 1,445 observations.

To examine how financial standing affects lending, a second dataset is selected from patents whose assignees can be matched in the GTA_NLE database. Besides technology classification and application year, sizes of assignee firms are controlled in sampling. The resulting dataset (Dataset B) includes 238 collateral patents and 223 comparison patents (several patents present no comparison sample). Among the 238 collateral patents, 38 are held by state-owned firms while 37 are held by foreign-owned firms. The other 163 patents are held by private firms.

(Figure 4 here)

The field of technology is controlled because patent indicators must be interpreted separately for different fields. For example, methods of documentation of chemical and mechanic patents differ substantially; however, comparing indicators from merely two fields may be meaningless.

The application year is controlled because age affects a patent's value. In addition, patent law, examination rules, and patent attorneys' documentation styles also differ. To exclude such system-based noise, the application year of patents must be controlled.

Firm size is used to control for the owner's incentive to offer patents as collateral. Large enterprises generally do not need to post collateral because they have financing channels through main banks. Even if collateral is required, they usually have sufficient tangible assets and do not need to offer complex and costly patents as collateral.

4.3 Independent variables

(1) Financial variables

Fixed asset ratio = fixed assets / total assets, indicating liquidity. The fixed asset ratio also serves as a control variable for incentives to seek collateralized loans. A company with adequate fixed assets can offer tangible fixed assets rather than intangible IP assets as collateral. Tangible assets are more easily assessed and acceptable to banks.

DEBT RATIO = debt / equity, indicating leverage.

PROFIT RATIO = net profit / sales, indicating profitability.

(2) Variables for patent value

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

OPPOSITION: Dummy variable stating whether the patent has been challenged in the re-examination committee of SIPO.

CLAIM SCOPE: The opposite 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 opposite of the number of nouns indicates for a broader claim.

PAGES: Number of pages describing the patent. Detailed description helps in supporting a broad patent claim scope. PAGES could indicate patent quality and is used as a control factor in the regression.

(3) Variables for patent liquidity

IPC4S: number of four-digit IPC classes assigned. Following Gambardella et al. (2007), IPC4S is used as a proxy for the generality of technology.

TEAM SIZE: 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.

COMPLEXITY: The product of IPC4S and TEAM SIZE. Technology created by multiple technicians and assigned to many IPC classes probably combines knowledge from several fields and is highly complex.

TOP10 SHARE: shares of top 10 applicants among all applications of the same four-digit IPC classification, indicating for technological competition.

(4) Control variables

OLD FIRM: A dummy variable that equals 1 for companies (the applicants) more than 20 years old and 0 otherwise. Established firms have more and stronger financing channels, lowering their incentive to seek patent-collateralized loans.

YOUNG FIRM: A dummy variable indicating whether companies are more than five years old.

logSALES: the log of total sales, used as a control variable for scale.

STATE OWNED: A dummy variable indicating whether companies are state owned[1].

FOREIGN OWNED: A dummy variable indicating whether companies are owned by investors abroad or investors from Taiwan, Hong Kong and Macau.

Industry dummies included in the regression on Dataset B are PHARMECTICAL, FOOD, MECHANIC, ELECTRIC, CHEMICAL, ENGINEERING, AUTOMOBILE, and METALLURGY.

4.4 Results

(1) Regression results with patent information

With Dataset A, we use five models for a logit regression. In Model A1, only proxy variables for patent value are used. In Models A2 to A5, liquidity-related variables are used. Since IPC4S and COMPLEXITY are strongly correlated with a coefficient of 0.502 (Appendix 1), they are inserted separately into Models A2 and A3. In Models A4 and A5, TEAM SIZE is used and COMPLEXITY is excluded. Regression results appear in Table 1.

Table 1 Regression results from Dataset A

Coef.(Std. Err.)	Model A1	Model A2	Model A3	Model A4	Model A5
FAMILY SIZE	0.161**	0.176***	0.173**	0.174**	0.170**
	(0.067)	(0.068)	(0.068)	(0.068)	(0.067)
OPPOSITION	0.008	−0.003	−0.040	−0.042	−0.020
	(0.538)	(0.540)	(0.541)	(0.541)	(0.541)
PAGES	0.019**	0.023***	0.025***	0.024***	0.024***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
CLAIM SCOPE	0.003**	0.003*	0.003*	0.003*	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
IPC4S		−0.020			0.006
		(0.071)			(0.076)
TOP10 SHARE		−1.521***	−1.599***	−1.525***	−2.001***
		(0.476)	(0.473)	(0.471)	(0.537)
COMPLEXITY			−0.030**		
			(0.012)		
TEAM SIZE				−0.073***	−0.080***
				(0.023)	(0.023)
R2-a	0.009	0.014	0.017	0.019	0.021

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

FAMILY SIZE and CLAIM SCOPE are positively significant in all models. This result

[1] Following Poncet et al(2010), urban and rural collectively owned enterprises are also pooled together with state owned enterprises.

supports Hypotheses 2a and 2c that patents with larger patent families and broader claim scope are more acceptable as collateral. OPPOSITION is not significant in all the models because only a small percentage of patents have been contested. Only 14 patents in Dataset A were contested, about 1% of its 1,445 observations. Thus, Hypothesis 2b is not verified.

IPC4S shows no significance for liquidity, and Hypothesis 3a is not supported. TEAM SIZE and COMPLEXITY show negative significance, thereby supporting Hypothesis 3b that complex technology is illiquid is less likely to be accepted as collateral. Comparing results of Models A3 and A4 reveals that TEAM SIZE is more significant than COMPLEXITY. TOP10 SHARE, a measurement of technology competition, strongly and negatively correlates with the dependent variable and supports Hypothesis 3c.

(2) Regression results with patent-related variables and firm variables

Drawing from Dataset B, we test how firms' financial performance, patent value, and patent liquidity together affect assignment of collateralized loans. Model B1 includes financial indicators and industry dummies. Models B2–B4 add variables for patent value and liquidity. As in Dataset A, the correlation between IPC4S and COMPLEXITY is high at 0.477 (Appendix 2), so they are added separately. TEAM SIZE replaces COMPLEXITY as a proxy variable in Model B4. Table 2 lists the results.

Table 2 Regression results from Dataset B

Coef. (Std.Err.)	Model B1	Model B2	Model B3	Model B4
FIX ASSET RATIO	-1.089**	-1.158**	-1.191**	-1.252**
	(0.541)	(0.571)	(0.575)	(0.574)
DEBT RATIO	-0.035*	-0.028	-0.030*	-0.034*
	(0.018)	(0.017)	(0.018)	(0.018)
PROFIT RATIO	1.506*	2.347**	2.342**	2.585***
	(0.830)	(0.944)	(0.956)	(0.972)
OLD FIRM	-0.393	-0.376	-0.329	-0.388
	(0.372)	(0.380)	(0.381)	(0.384)
YOUNG FIRM	0.577*	0.435	0.449	0.458
	(0.314)	(0.328)	(0.329)	(0.328)
STATE OWNED	-0.806***	-0.896***	-0.917***	-0.883***
	(0.260)	(0.269)	(0.272)	(0.271)
FOREIGN OWNED	0.370	0.149	0.086	0.073
	(0.265)	(0.276)	(0.279)	(0.280)
logSALES	-0.220***	-0.236***	-0.232***	-0.213***
	(0.063)	(0.066)	(0.066)	(0.065)
FAMILY_SIZE		0.875***	0.842***	0.877***
		(0.297)	(0.287)	(0.286)
OPPOSITION		0.864	0.840	0.698

		(0.884)	(0.880)	(0.879)
PAGES		-0.001	0.007	0.012
		(0.021)	(0.022)	(0.022)
CLAIM_SCOPE		0.007*	0.007*	0.005
		(0.004)	(0.004)	(0.003)
IPC4S		0.065		-0.009
		(0.146)		(0.146)
TOP10_SHARE		2.348**	2.117*	
		(1.091)	(1.082)	
COMPLEXITY			-0.046*	
			(0.028)	
TEAM SIZE				-0.122**
				(0.050)
R2-a	0.124	0.162	0.166	0.164

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

Industry dummies are included in the models, but for simplicity, they are not reported in this table.

Regression results generally indicate that DEBT RATIO is lower and PROFIT RATIO is higher for companies that are granted patent-collateralized loans. A lower DEBT RATIO generally portends lower risk, and a higher PROFIT RATIO suggests good repayment capability.

Control variables FIX ASSET RATIO, OLD FIRM, YOUNG FRIM, and logSALES are significant and consistent with the theory that larger, older firms and firms with more fixed assets are less attracted to patent-collateralized loans. Negatively significant STATE OWNED shows that state-owned firms are not active in patent-backed financing, consistent with Poncet et al.(2010) that state-owned firms are not financially constrained.

Among variables for patent values, FAMILY SIZE and CLAIM SCOPE are positively significant. These results coincide with those for Dataset A and show that higher value patents are more likely to be accepted as collateral.

IPC4S, a proxy for patent generality, shows no significant effect on lending, but proxies for technology complexity, COMPLEXY and TEAM SIZE, show negative significance. However, TOP10 SHARE, a proxy for technology competition, is positively significant in Models B2 and B3. That result is attributable to multicollinearity. The correlation coefficient between TOP10 SHARE and PHARMECTICAL is −0.301. TOP10 SHARE also shows relatively strong correlations with other industry dummies and logSALES. These firm variables together sponsor multicollinearity when TOP10 SHARE is included in the regression. If logSALES and industry dummies are excluded, TOP10 SHARE shows no significance. Since scale control variables logSALES and industry dummies are important in comparing financial performance, they are retained, and TOP10 SHARE is excluded in Model B4.

5 Discussion

5.1 Patent value and lending decisions

This research consistently demonstrates that patents with larger patent family size are more likely to be accepted as collateral. There is little theoretical or empirical dispute that larger family size indicates higher value. Besides indicating that patent value significantly influences lending, this result is more persuasive because 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.

Patent scope also affects lending affirmatively. The regression shows that patents accepted as collateral have a larger scope. Also, a well-written, high-quality application better enables patents to withstand opposition. The proxy variable for patent application quality—pages of description—is strongly and positively correlated with the patent-collateralized loan assignment in Dataset A, though it is not significant in Dataset B with fewer observations.

In total, the selected indicators of patent value significantly and positively influence lending, supporting the result deduced from the decision model in Section 3.1.

5.2 Patent liquidity in lending decisions

Results related to patent liquidity variables are complex and need careful explanation. The first finding is that generality of technology (IPC4S) has no explanatory power in lending decisions involving patent collateral. Although in principle a general technology has more potential buyers and should be more attractive in technology markets, this study failed to verify that supposition. That result is not surprising, as several empirical studies have yielded controversial results concerning how the number of IPC sub-classifications affects litigation or licensing (Lerner, 1994; Lanjouw and Schankerman, 1997; Gambardella et al., 2007).

We 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 classifications for each characteristic. In this situation, multiple IPC classifications can indicate a narrower scope because the patent has more special technological characteristics 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 why different datasets show different results. Lerner's (1994) research 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.

This paper also examined how technology complexity affects liquidity of patents and whether it is reflected in lending. Two measures are used: the number of inventors on the team (TEAM SIZE) and the product of team size and the number of IPC sub-classifications (COMPLEXITY). Both variables are negatively significant, confirming that complex technologies created by larger teams of inventors are less liquid and less likely to be accepted as collateral. The finding is interesting because empirical studies (e.g., Nagaoka et al., 2011; Gupeng and Xiangdong, 2012) found that large teams create more important and valuable technologies. A negative correlation between team size and loan assignment shows that the positive effect on value is less significant than the negative effect on liquidity. A surprising result is that TEAM SIZE is more significant than COMPLEXITY. As discussed in Section 3.3, although larger TEAM SIZE indicates higher complexity, it may correlate to higher patent value, which may reduce its significance in the final result. However, the result shows that the negative effect on liquidity is much stronger. Noise in IPC classifications may produce the lesser significance of COMPLEXITY. If IPCs are classified according to applications rather than composition of technology, they are irrelevant to technology complexity.

The variable for technology competition (TOP10 SHARE) is strongly significant and negatively correlated to lending in Dataset A. This is consistent with the hypothesis that less concentrated fields of technology have more buyers and suppliers, facilitating an active market for technology and liquidity for patents. One point deserves mention: although TOP10 SHARE or other proxy variables for technology competition are obtainable for each patent, they are more meaningful as characteristics of a field of technology or an industry than of individual patents. A patent in a field of technology without dominant players has more opportunities for transactions, but successful transactions can be determined by a patent's technological value and liquidation considerations, such as complementary assets. Although TOP10 SHARE is positively significant in Dataset B, it mostly results from multicollinearity between TOP10 SHARE and industry dummies, as discussed in Section 4.4.

5.3 Influence of firms' financial performance on lending decisions

The decision model in Section 3.1 shows that firms' likelihood of default affects their likelihood of obtaining a patent-collateralized loan. Lenders assess default from a firm's financial status. Using profit ratio as a measure of profitability and the debt-to-equity ratio as a measure of leverage, we found both ratios showing significance in most models. Firms receiving loans have higher profit ratios, even after controlling for industry differences. This evidence supports the assertion that banks only lend to companies presenting low likelihoods of default, even though their loans are collateralized by patents. The leverage ratio correlates negatively with loan assignments, although less significantly than profit ratio in several regression models. This finding also shows that lenders select relatively safer borrowers with low leverage.

Fixed asset ratios and firm age are used to control for the incentive to use patents as collateral. Empirical results confirmed that firms with more fixed assets as well as older firms are less likely to use patents as collateral. We also found that patents applied by state-owned enterprises are unlikely to be used as collateral, which mainly because those enterprises have better financing channels with state-owned banks.

6 Conclusion

This paper has investigated patent-collateralized lending in China. Using data for patents accepted as loan collateral, we showed that lending decisions are based on the borrower's likelihood of default, patent values, and patent liquidity. We 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. We argued that indicators of high-value patents might indicate poor liquidity; thus their effect on transactions could be complex and require careful examination by lenders.

To our knowledge, this is the first empirical study of actual loans collateralized by patents. Our findings confirmed that lenders make patent-collateralized loans only to lower-risk firms; a patent's assessed value is a secondary consideration, even if it surpasses the amount of the loan. We find that patents used as collateral have larger patent families and broader claim scope, suggesting higher value. More important, we found that complex patents created by larger inventor teams are less likely to be accepted as collateral, whereas patents in competitive technological fields are more acceptable. Our empirical study also found that the number of IPC sub-classifications is not explanatory as an indicator of patents' liquidity.

Further studies are needed to overcome this study's limitations. Data selection is one limitation. Only patents accepted as collateral are published in China; thus, this paper had to randomly select a comparison group of patents. A more solid result can be obtained with more private data about firms that sought unsuccessfully to use patents as collateral. The sampling noise can be removed. Another limitation is that the effect of citation is unexamined due to data limitations.

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Appendix 1

Correlations between variables in Dataset A

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FAMILY SIZE	(1)	1.000							
OPPOSITION	(2)	−0.011	1.000						
PAGES	(3)	0.117	−0.030	1.000					
CLAIM SCOPE	(4)	0.057	0.039	−0.154	1.000				
IPC4S	(5)	−0.001	0.003	0.082	0.042	1.000			
TOP10 SHARE	(6)	0.069	−0.014	0.157	−0.082	−0.124	1.000		
COMPLEXITY	(7)	−0.004	−0.028	0.087	−0.042	0.502	−0.060	1.000	
TEAM SIZE	(8)	−0.001	−0.025	0.050	−0.058	0.007	0.000	0.785	1.000

Appendix 2

Correlations between variables in Dataset B

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
FIX ASSET RATIO	(1)	1.000											
DEBT RATIO	(2)	0.001	1.000										
PROFIT RATIO	(3)	-0.212	-0.034	1.000									
OLD FIRM	(4)	-0.006	0.016	-0.100	1.000								
YOUNG FIRM	(5)	0.238	0.063	-0.080	-0.142	1.000							
STATE OWNED	(6)	0.056	-0.002	0.025	0.171	-0.065	1.000						
FOREIGN OWNED	(7)	0.161	0.039	-0.087	-0.147	0.128	-0.327	1.000					
logSALES	(8)	0.076	-0.004	0.012	0.226	-0.204	0.080	0.155	1.000				
PHARMECTICAL	(9)	0.037	0.054	0.145	0.133	-0.125	0.014	-0.048	-0.013	1.000			
FOOD	(10)	0.058	-0.004	-0.008	-0.039	0.114	0.024	0.022	-0.007	-0.049	1.000		
MECHANIC	(11)	-0.094	-0.161	-0.084	-0.018	0.057	-0.029	-0.007	-0.119	-0.173	-0.047	1.000	
ELECTRIC	(12)	0.024	0.000	-0.041	-0.065	-0.010	0.014	0.144	0.106	-0.161	-0.044	-0.155	1.000
CHEMICAL	(13)	0.062	0.008	0.065	0.041	0.062	0.005	-0.081	-0.030	-0.277	-0.075	-0.267	-0.248
ENGINEERING	(14)	-0.132	0.096	-0.071	-0.029	-0.049	-0.030	0.073	-0.014	-0.083	-0.023	-0.080	-0.074
AUTOMOBILE	(15	0.000	0.140	-0.017	-0.036	0.075	-0.011	-0.012	0.072	-0.044	-0.012	-0.043	-0.040
METALLURGY	(16)	0.002	0.004	-0.031	0.072	0.037	0.010	-0.044	-0.007	-0.088	-0.024	-0.085	-0.079
FAMILY SIZE	(17)	0.118	-0.018	-0.243	-0.042	0.157	-0.070	0.198	-0.048	-0.047	0.004	0.041	0.162
OPPOSITION	(18)	-0.015	0.004	-0.016	-0.042	-0.002	0.012	0.092	-0.047	0.046	-0.014	0.000	0.006
PAGES	(19)	-0.157	-0.042	-0.014	-0.079	-0.044	-0.073	0.004	-0.025	0.027	-0.083	0.005	0.139
CLAIM SCOPE	(20)	0.069	-0.009	0.012	0.047	0.001	0.020	0.066	0.061	0.111	0.022	-0.143	0.001
IPC4S	(21)	-0.032	0.032	-0.073	0.043	-0.046	-0.027	-0.038	-0.040	0.027	-0.034	-0.088	0.008
TOP10 SHARE	(22)	-0.097	-0.042	-0.056	-0.074	-0.037	0.039	0.089	0.152	-0.301	-0.085	-0.001	0.194
COMPLEXITY	(23)	-0.009	-0.019	0.035	0.107	-0.005	0.061	-0.177	0.006	0.084	-0.005	-0.129	-0.048
TEAM SIZE	(24)	-0.022	-0.049	0.123	0.084	-0.014	0.051	-0.180	0.017	0.166	0.004	-0.133	-0.072

To be continued

Continued

		(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
CHEMICAL	(13)	1.000											
ENGINEERING	(14)	-0.128	1.000										
AUTOMOBILE	(15	-0.068	-0.021	1.000									
METALLURGY	(16)	-0.136	-0.041	-0.022	1.000								
FAMILY SIZE	(17)	-0.093	-0.008	-0.023	-0.045	1.000							
OPPOSITION	(18)	-0.081	-0.024	-0.013	-0.026	-0.027	1.000						
PAGES	(19)	-0.125	0.009	-0.027	-0.028	0.108	-0.006	1.000					
CLAIM SCOPE	(20)	0.093	-0.081	0.008	-0.002	0.026	0.027	-0.263	1.000				
IPC4S	(21)	0.113	-0.099	-0.050	-0.008	-0.009	0.027	0.013	0.054	1.000			
TOP10 SHARE	(22)	-0.106	0.248	0.110	-0.033	0.088	-0.068	0.119	-0.205	-0.142	1.000		
COMPLEXITY	(23)	0.210	-0.092	-0.027	0.032	-0.043	-0.054	0.169	-0.047	0.477	-0.136	1.000	
TEAM SIZE	(24)	0.154	-0.068	-0.029	0.064	-0.029	-0.062	0.210	-0.055	-0.068	-0.117	0.761	1.000

Figures

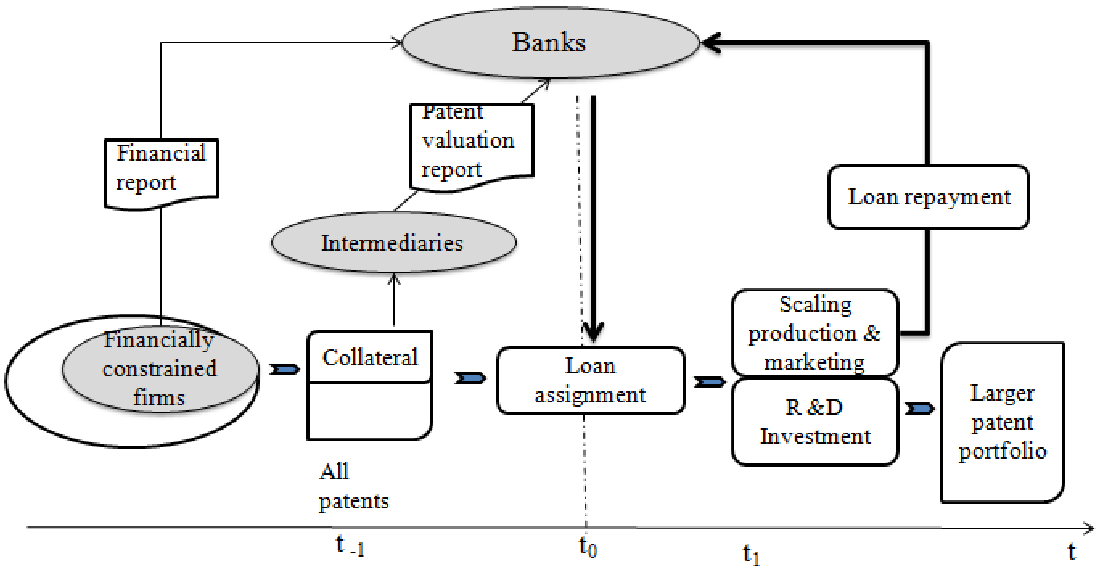


Figure 1 Event flow chart of patents-backed loan assignment

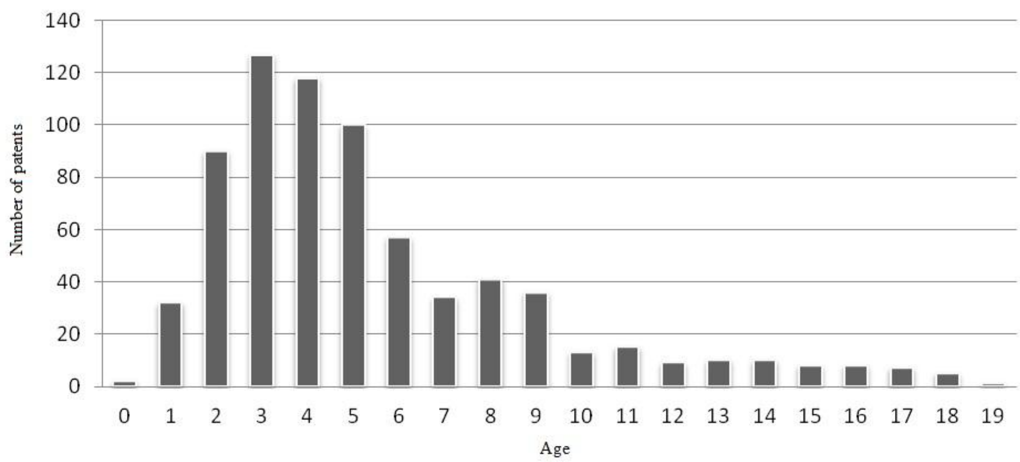


Figure 2 Age distribution of patents used as collateral in China (2008–2010)

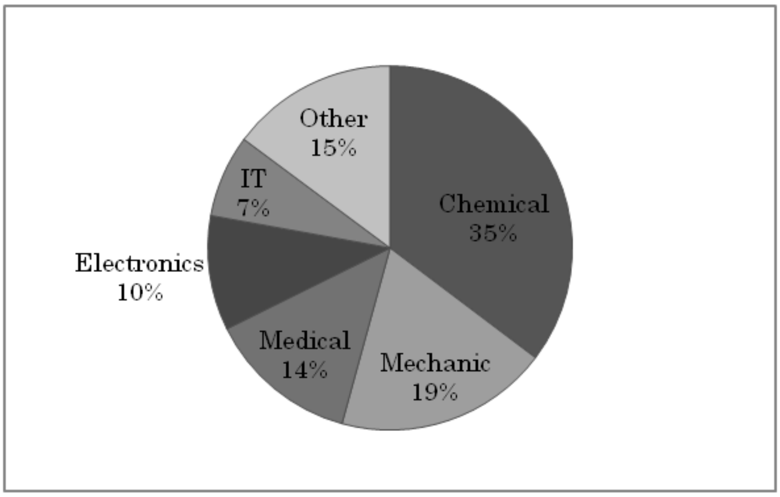
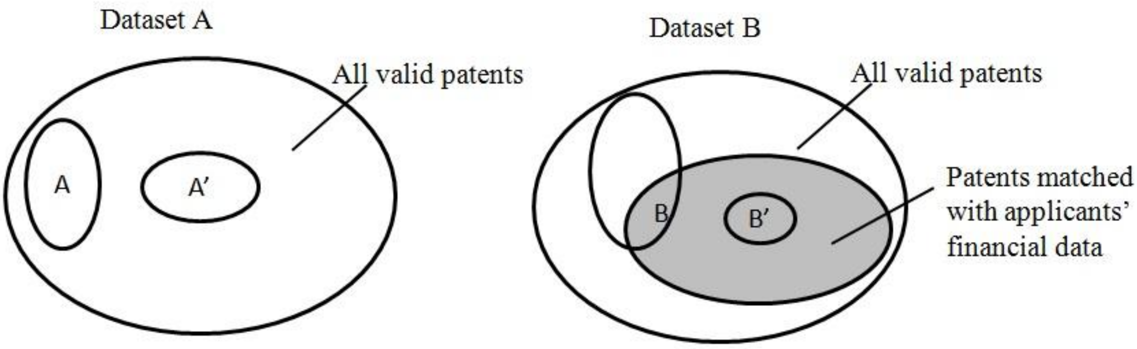


Figure 3 Shares of collateral patents in different fields of technology



A: all the collateral patents; A': a random selected comparison group; B: collateral patents matched with applicants' financial data; B': a random selected comparison group in all the patents matched with financial data.

Figure 4 Comparison group sampling