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Short-term loans and Firms' high-quality innovation: Evidence from the access to patent-backed loans in China

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ABSTRACT

When obtaining short-term loans, an innovative firm tends to expand its production scale, thereby reallocating its R&D-related resources away from innovation. By exploiting the unique situation in China that patenting firms for the first time obtained short-term patent-backed loans (PBLs), we find that the PBL access negatively influences firms' propensities of producing high-quality innovation. Consistent with the R&D resource reallocation hypothesis, we find that this negative effect exists only among firms initially having invention patents; it is more pronounced when the PBL covers a larger portion of firm investment and when these firms expand more aggressively. We confirm the scale expansion effect by finding that the PBL access positively influences firms' subsequent size.

1. Introduction

Investment in innovation tends to fall below the optimal level as R&D firms are generally credit constrained (Hall & Lerner, 2010). These firms' financing capacity can be enhanced if banks accept intangible assets (particularly patents) as collateral for loans. While being popular in the U.S. (Hochberg, Serrano, & Ziedonis, 2018; Mann, 2018), such a practice of pledging patents is so far scarce in emerging economies and its potential consequences are yet to be explored. Taking advantage of the recent surge of patent pledge in China, one of the largest emerging economies, this paper is among the first to investigate how the *initial* access to patent-backed loans (hereafter PBLs) influences innovative firms' subsequent investment decisions.

As an innovative firm becomes less financially constrained once getting access to PBLs, it seems reasonable to expect that the firm would invest more in R&D. However, the above argument ignores an important determinant—the loans' term to maturity (i.e., short-term or long-term loans). Theoretically, a firm is subject to refinancing risks when using short-term loans to fund long-term investment while such risks can be largely avoided when using long-term loans (Diamond, 1991; Myers, 1977). It is particularly so for R&D investment as banks are reluctant to renew the loan when firms invest in risky projects. Consequently, firms' propensity to invest in innovation tends to decrease and their propensity to expand the scale tends to increase when only short-term loans are available. However, it does not necessarily imply that R&D expenditures would decrease in value as total available funds have increased.

When running R&D projects, especially those targeting high-quality innovation, firms are faced with additional constraints, such as innovation capacity (e.g., managerial capacity and R&D personnel). When obtaining short-term PBLs, a firm's financial constraints are

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alleviated while its innovation capacity likely remains unchanged, at least in the short run. Scale expansion after obtaining short-term PBLs tends to divert a firm's innovation capacity away from high-quality innovation. Therefore, from the perspective of R&D-related resource reallocation, the output of high-quality innovation would decrease after firms obtain short-term PBLs. Nevertheless, it is ultimately an empirical question how the access to short-term PBLs influences a firm's high-quality innovation.

Though it is interesting to directly explore how the term of debt influences firms' innovation decisions, it is extremely hard to establish such a causal relationship since the term of debt is more or less endogenous to a firm's investment demand. The unique situation in China may help us to circumvent this endogeneity problem. Specifically, it has been documented that in emerging economies (particularly in China), bank loans issued to industrial firms are mostly short-term, with the duration less than a year (e.g., Fan, Titman, & Twite, 2012; Li, Yue, & Zhao, 2009). Our data confirm this regarding PBLs: there is an instant rise in only short-term debt but not long-term debt in the first year of a firm's access to PBLs. Consequently, the term of PBLs can be regarded as exogenous to individual firms other than being chosen according to firms' investment needs.

It was only recently that Chinese firms began to pledge their patents. As shown in Fig. 1, the number of firms that for the first time pledged their patents began to surge in 2008; before that, the number was ignorable. Even as late as in 2016, there were only around 1300 firms that for the first time pledged patents, indicating that the diffusion was still at its early stage. Such a surge was largely driven by governments' promotion policies since 2008 and thus can be regarded as exogenous to firms' investment needs. Consequently, we are less concerned about the timing issue of firms' getting access to PBLs.

We employ a DID (difference-in-differences) approach to investigate how the *initial* access to short-term PBLs influences firms' subsequent investment decisions. Our firm-level data come from the Annual Survey of Industrial Enterprises (ASIE) conducted by China's National Bureau of Statistics (NBS). We restrict our investigation to the period 2009–2013. Since firms with the PBL access are supposed to be substantially different from firms without, we employ a PSM-DID approach. Specifically, we analyze how firms' propensity to produce any high-quality innovation changes surrounding their PBL access by taking those firms without such an access but having similar access likelihood as the control group. To measure a firm's propensity to produce any high-quality innovation, we generate a dummy indicating whether the firm applies for (later being granted) any *invention patents* in a given year or not. We count only invention patents because this type of patents is the most novel compared to the other two types of patents (i.e., utility-model and external-design) granted by the SIPO (State Intellectual Property Office of China). Additionally, we follow the literature (e.g., Balsmeier, Fleming, & Manso, 2017; Briggs, 2015) and generate another high-quality innovation dummy. In this case, among all invention patents in the same one-digit technology class that are filed in the same year, we only count a firm's invention patents that belong to the top 20% of the forward citation distribution.

The parallel pre-trends assumption is essential to the validity of the DID approach, which requires that there is no specific pre-trend in the treatment group compared to the control group. Our diagnostic tests show that this assumption is satisfied. By using a multivariate regression framework, we find a negative and causal effect of the PBL access on the likelihood of a firm producing any high-quality innovation. Specifically, our regression results indicate that the PBL access leads to a 9.2% decrease in the probability of a firm having any invention patents and a 5.6% decrease in the probability of having any invention patents with top citations. It suggests that with the access to short-term PBLs, innovative firms become less likely to produce high-quality innovation.

To further mitigate the concern on reverse causality, we follow the approach of Bertrand & Mullainathan (2003) and examine the dynamics of firms' innovation propensity surrounding the PBL access. We do not find a significant trend in either high-quality

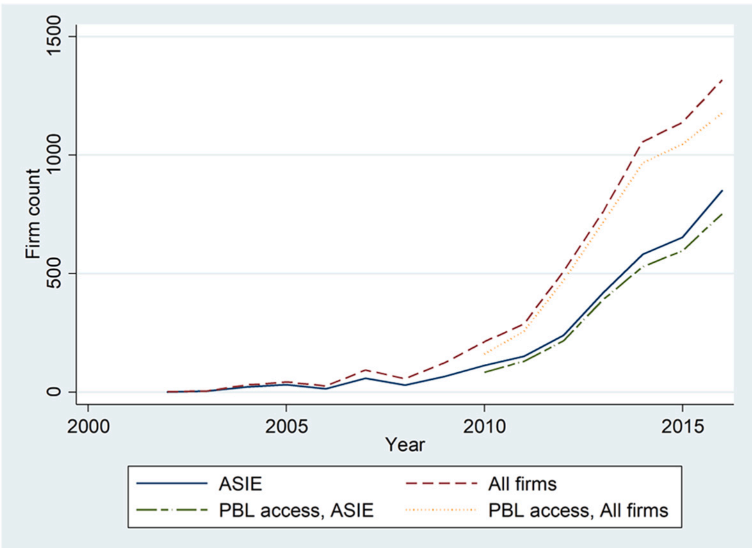

Fig. 1. The diffusion of patent pledge and PBL access, all firms vs ASIE firms.
This figure presents the annual count of patent pledge and the annual count of the PBL access for 2002–2016, respectively. We do so for all firms and ASIE firms separately.

innovation dummy prior to the PBL access but a significant decrease after, indicating that it is the PBL access that caused firms' high-quality innovation propensity to reduce and not vice versa. Additionally, our placebo test suggests that our major result is unlikely driven by pure luck. We also use two dummies of having any low-quality innovation or not (i.e., having any utility-model patents or external-design patents) as the dependent variable and find the PBL access effect insignificant. Last, when the count of high-quality innovation is examined, the PBL access effect is also insignificant, indicating that the PBL access negatively influences firm innovation mainly at the extensive margin and not at the intensive margin.

We then attempt to identify two potential mechanisms through which the PBL access retards firms' high-quality innovation propensity, firm's innovation capacity and their financial constraints. Specifically, we examine how initially having any invention patents and firm size (a commonly used proxy for financial constraints) affect our results, respectively. Consistent with the R&D resource reallocation story, we find that the negative effect only exists among firms initially having innovation patents, which are supposed to have innovation capacity to reallocate in the first place. We also find that the negative effect exists both among small and large firms, suggesting that financial constraints exist in both types of firms. We further find that among firms initially having invention patents, the negative effect is more pronounced when the PBL can cover a larger portion of firm investment and when firms are expanding more aggressively. Our findings also suggest that firms in high-tech industries, faced with severe innovation competition, reallocate R&D resources strategically.

We have assumed that with the access to short-term PBLs, financially constrained innovative firms would expand their scale. Consistently, we find a positive effect of the PBL access on firms' subsequent size measured by either total assets or total sales. Such an expansion effect exists among both small and large firms, suggesting that both types are financially constrained. However, the PBL access effect is insignificant when firms' profitability is examined, indicating that the term restriction on PBLs may restrain firms from investing more efficiently. Overall, our findings suggest that R&D resource reallocation and having financial constraints are two underlying mechanisms.

This paper is closely related to the literature on patents as collateral, which is still limited due to the lack of reliable data; it is particularly so in developing countries. Related studies are largely from legal researchers (e.g., Ibrahim, 2010; Mann, 1997). Scholars recently started to study on patents as collateral by exploiting the USPTO Patent Assignment data (e.g., Fischer & Ringler, 2014; Hochberg et al., 2018; Mann, 2018; Mann & Sager, 2007). Among them, Mann (2018) documents that PBLs are an important source to finance R&D in well-established U.S. listed firms. Hochberg et al. (2018) show the importance of similar lending among innovative start-ups.[1] As far as we know, our paper is among the first on this topic in developing countries. Our paper also contributes to the literature by investigating, for the first time, how the initial access to PBLs influences innovative firms' subsequent investment decisions. Different from the literature, our study documents an adverse effect on firm innovation in China where refinancing risks are substantial.

Studies have documented that innovation relies more on equity than debt financing (e.g., Brown, Fazzari, & Petersen, 2009; Brown, Martinsson, & Petersen, 2012, 2013) as innovative firms are credit constrained, lack of collateral being one reason. However, a growing strand of literature has revealed that debt financing acts as an important source of capital not only for non-innovative but also for innovative firms (Kerr & Nanda, 2015). Our study enriches the understanding on the relationship between debt financing and firm innovation: even with access to bank loans, patenting firms' incentive to do high-quality innovation may be retarded when only short-term loans are issued. In this aspect, our study also complements the literature on how debt maturity influences firms' investment strategies, which has been rarely investigated (see Almeida, Campello, Laranjeira, & Weisbenner, 2010 for a notable exception).[2]

This paper also contributes to the literature on how within-firm resource reallocation influences firm innovation.[3] As a firm cannot easily adjust its input, to deal with exogenous shocks, it reallocates within-firm resources from one business unit to another. The important implication of within-firm resource reallocation on firm innovation has not been explicitly discussed until Bloom, Romer, Terry, and Reenen (2013). Bloom et al. (2013) argue that employees (e.g., R&D personnel) may be trapped in a firm as some of their human capital is firm-specific. The negative shock from China's exports reduced the price of goods that a US firm was producing, resulting in a lower opportunity cost for its R&D input. The firm then produced more innovation not because the price of new products was higher but because the opportunity cost of using its R&D input to produce new products dropped. Our paper echoes Bloom et al. (2013) by documenting that R&D input may flow in the opposite direction when its opportunity cost increases. Specifically, the scale expansion trigged by short-term PBLs competes for the use of R&D input in a firm. The firm subsequently does less high-quality innovation because the opportunity cost of using R&D input to do so increases. Our paper highlights the importance of R&D resource reallocation when the relationship between alleviated financial constraints and firm innovation is investigated.

[1] Mann and Sager (2007) investigate the relation between the patenting behavior and the venture capital cycle among startup firms. Fischer and Ringler (2014) investigate which component of patents matters in collateralization decisions. In the same vein, Chava, Nanda, and Xiao (2017) find that borrowers' spreads on bank loans are lower when they hold patents with higher quality; Saidi and Zaldokas (2017) document that a highly-valued patent can be a good substitute to a relationship lender's soft information.

[2] Empirically, there has not been much evidence as variations in firms' debt structure are hardly exogenous. Almeida et al. (2010) exploit the variations in firms' long-term debt maturity right before the 2007 financial crisis for identification. They find that debt maturity matters. Specifically, firms with their long-term debt maturing right after the 2007 crisis reduced capital investment by 2.5% more (on a quarterly basis) than firms with their long-term debt scheduled to mature after 2008.

[3] An important characteristic of a multi-product firm is that individual business units are competing for its scarce internal resources, as argued by Williamson (1975). Bernard, Redding, and Schott (2010) document the importance of within-firm reallocation by finding that in the U.S. manufacturing industry, firms' adding and dropping business lines contributes to one-third of the industry's aggregate growth.

2. Background and hypothesis development

In this section, we first review the development of PBLs in China. Then, we develop our main hypothesis.

2.1. Development of PBLs in China

Enacted as early as in 1995, the Guarantee Law has explicitly stated that intellectual properties (IPs) can be used as valid collateral for loans. However, as the most important part of IPs, patents were rarely pledged for loans for a long time.[4] To have a PBL application approved by a bank, a patenting firm needs to go through a complicated process as follows: 1. the firm submits its PBL application to the bank; 2. involved patents are appraised by a professional appraiser; 3. the bank evaluates submitted documents and the appraisal; 4. with the approval, the firm and the bank sign the loan contract and the patent-pledge contract; 5. the loan contract is implemented and the case is registered at the SIPO.

Because of the complicated process, the financial cost of PBLs is much higher than ordinary loans in the following three aspects. First, a higher interest rate is charged to compensate for extra risks (e.g., 4.75%* (1+ 30% floating) = 6.175%). Second is the patent appraisal fee, about 2%. Third is the PBL guarantee insurance, about 3% (or with the same amount of charge when a guarantee company is involved in). Overall, the financial cost of PBLs is as high as 11.175% given the numbers that we provide above (assuming that the duration of the loan is one year). Clearly, without any subsidy, firms have little incentive to apply for PBLs.

Meanwhile, banks have little incentive to promote PBLs as they are reluctant to accept patents as collateral. First of all, it is difficult to assess the value of patents as it is difficult to evaluate their future net cash flows. Making it even worse, the validity of patent rights is unstable; once alternative technologies are invented, the value of influenced patents may drop sharply. Other risks include infringement lawsuits and ownership challenges (Jacobs, 2011). Last, the patent market is incomplete, making it hard to fully capture the patent value when the firm is default (Teece, 1980). Overall, the reluctance from both sides explained why PBLs were rarely adopted in China before 2008.

Recently, the Central Government began to promote IP-pledge financing (mainly PBLs) as clearly stated in the "Outline of National Intellectual Property Strategy" released in 2008. To compliment the strategy, subsidies such as interest subsidies have been provided by local authorities to encourage small and median enterprises (SMEs) to apply for PBLs, thereby spurring the adoption of PBLs in recent years. It is thus not surprising that the start point of the spur of firms with PBLs was around 2008 as shown in Fig. 1.

The SIPO launched a pilot project of IP-pledge financing in 2008. Since the launch, the SIPO has approved three rounds of total 16 pilot cities/districts to carry out the project.[5] These pilot areas played a substantial role in the surge of patent pledge. According to the official report, in 2010 the number of patent-pledge registrations in these pilot areas reached 207, 57.2% of the national count.[6] It shows that though it was more active in pilot areas, patent pledge also took place nontrivially in other areas across China. Therefore, we do not restrict our analysis to pilot areas.

The information of pledged value, though required to report by the SIPO, is confidential so we do not have the related information. Based on the SIPO's official report, in 2010 the total pledged value was 7.01 billion yuan, 19.5 million yuan on average for each pledge case. The median value lied between 1 and 10 million, and only 15 contracts exceeded 100 million, suggesting that PBLs were mainly distributed to SMEs.

Bank regulations suggest short-term loans when PBLs are issued. As pointed out by the "Guidance on the IP-Pledged Loan Business of Commercial Banks" issued by the China Banking Regulatory Commission, regarding the duration of intellectual property-pledged loans, considering the validity duration of intellectual property rights and the speed of their value depreciation, commercial banks are recommended to issue short-term loans.

To promote PBLs, the key issue is of course to reduce the related financial cost. In practice, local authorities implemented different policies. Because it was at the pilot stage, these policies were not all publicly available. We take Guangzhou, a major city in China, for example to draw a brief picture. At the city level, there was an interest subsidy of 1.5% ($\leq$50 million yuan in principle). The Guangzhou Development Zone, Huangpu District (one district in Guangzhou) has the following additional subsidies: interest subsidy of 3% ($\leq$50 million yuan in principle); patent appraisal fee subsidy of 2% ($\leq$10 million yuan in principle); guarantee fee subsidy of 3% ($\leq$10 million yuan in principle); guarantee insurance subsidy of 3% ($\leq$10 million yuan in principle). Overall, the patent appraisal fee and the guarantee insurance fee were both waived, and the total interest subsidies were 4.5%. In the previous case, the financial cost of PBLs without subsidy was 11.175%. Thanks to the subsidies, it dropped to only 1.175%. This case also reveals another layer of complicacy about local policies: district-level policies, which are even harder to obtain, may substantially differ from city-level.

[4] The first patent pledge happened in 2003. Harbin Taifu Industrial Co., Ltd. pledged two utility-model patents (CN2530391Y and CN2535375Y).

[5] The first round was in December 2008 with six pilots included: Haidian District (Beijing), Changchun, Nanchang, Xiangtan, Nanhai District (Foshan), Ningxia Hui Autonomous Region. The second round (September 2009) included other six pilots: Chengdu, Guangzhou, Dongguan, Yichang, Wuxi, and Wenzhou. The third round (July 2010) included four: Pudong District (Shanghai), Tianjin, Zhenjiang, and Wuhan. The pilot project seemed to be a success. Subsequently, the SIPO decided to carry out another round of pilot demonstrations of IP-pledge financing and related insurance in 72 regions. The pilot demonstration period was three years since August 2016.

[6] Data come from "The Analysis of China's Patent Pledge Registration and Patent Licensing Contract Record in 2010" released by the SIPO on June 20th, 2011.Website: http://www.sipo.gov.cn/docs/pub/old/tjxx/zltjjb/201509/P020150911515200284498.pdf

2.2. Hypothesis development

Investment in innovation may be below the optimal level as innovative firms are generally credit constrained (Hall & Lerner, 2010), substantial information asymmetry on R&D investment between inside management and outside fund suppliers (Aboody & Lev, 2000) being a major reason. One possible solution to this underinvestment may be collateral pledge, particularly innovative firms using their intelligent property rights such as granted patents as collateral. With collateral pledged, banks would be less concerned about firms' risk taking (Barro, 1976; Stiglitz & Weiss, 1981). Empirical studies have provided evidence that collateral pledging (mainly using real estate as collateral) enhances firms' financing capacity, thereby stimulating their capital investment (Chaney, Sraer, & Thesmar, 2012). However, R&D investment differs substantially from capital investment in several ways: R&D investment is highly risky and its benefits can be enjoyed only in the long run (See Kerr & Nanda, 2015 or Hall & Lerner, 2010 for a review). It makes debt financing not suitable to fund R&D investment in the first place. Though innovative firms, once getting access to PBLs, are supposed to become less financially constrained and thus tend to invest more, these firms may become more inclined to invest in capital than R&D.

The investment preference would be further biased towards capital if PBLs take the form of short-term loans. A major drawback of using short-term debt to finance long-term investment is as follows. As proposed by Diamond (1991) and Myers (1977), short-term debt matures before the cash inflows received from a firm's investment project and thus refinancing is needed; refinancing can be largely avoided by using long-term debt if a firm can strategically match the maturity of long-term debt with the timing of related cash inflows. The refinancing risks (or so called rollover risks) associated with short-term loans can be substantial. As argued by Diamond (1991, 1993) and Sharpe (1991), a firm's continuation value may be underestimated by the bank and thus its loan may fail to be renewed. Additionally, due to changes in market conditions, firms may find it difficult to renew the loan and have to refinance at a much higher interest rate (Froot, Scharfstein, & Stein, 1993).[7] Such refinancing risks are supposed to vary across different types of investment: capital investment will be transformed into tangible assets, which can be used as collateral in the later refinancing, while R&D investment is intangible and involves high information asymmetry, making refinancing less likely to occur. Consequently, it is reasonable to predict that with access to PBLs which are mainly short-term, innovative firms would strongly prefer capital investment to R&D investment.

Though no direct evidence has been provided, the U.S. case seems consistent with the above prediction. It has been documented that through the collateral enhancement channel, real estate appreciation stimulates firms' R&D expenditures and patent output in the U.S. (e.g., Cao, Goh, Jiang, & Yu, 2015; Mao, 2021; Rong & Ni, 2020). Meanwhile, it has also been found that with real estate appreciation, U.S. firms are able to issue debt with longer maturity (Cvijanovic, 2014; Benmelech, Garmaise, & Moskowitz, 2005).[8] More importantly, similar patterns are also found for patent pledge. Mann (2018) documents that PBLs stimulate U.S. firms' innovation; subsequent to patents being pledged, these firms' long-term debt increases substantially while their short-term debt barely changes. Overall, the U.S. case suggests that the availability of long-term debt might be an important mechanism through which collateral enhancement stimulates firm innovation.

In an emerging economy, however, the availability of long-term debt to industrial firms could be a luxury. With an inefficient legal system, short-term debt is more likely to be employed than long-term debt as shortening the loan helps mitigate default risks even when legal regimes are weak (Diamond, 2004; Qian & Strahan, 2007). As documented by Allen, Qian, and Qian (2005), China's legal system is so far under-developed.[9] Perhaps due to the associated legal inefficiency, China has developed a banking system that is cautious about issuing long-term loans to industrial firms. Specifically, the process of approving a long-term loan application is far more complicated than that of a short-term loan application. Consequently, even when it is appropriate to issue long-term loans, to avoid the complicacy, bank agents would simply recommend short-term loans. It has been documented that industrial firms in China heavily rely on short-term debt. Fan et al. (2012) show that the median ratio of long-term debt to total debt in China was about 9%, the lowest among 39 countries in the period 1991–2006.[10]

Even though firms' tendency to invest in innovation tends to decrease when only short-term loans are available, it does not necessarily imply that R&D expenditures would decrease in value as total available funds have increased. However, when running innovation projects, especially those targeting high-quality innovation, firms are faced with additional constraints, such as fixed innovation capacity (e.g., managerial capacity and R&D personnel). Producing more high-quality innovation not only requires easing financial constraints, but also requires that the additional funds result in hiring new managers and R&D personnel or existing ones putting more efforts on innovation. It is reasonable to expect that firms have little incentive to expand innovation capacity upon the receipt of PBLs, which are short-term.

Consider a firm that is faced with both financial constraints and inelastic managerial capacity. When obtaining short-term PBLs, the firm's financial constraints are alleviated while its managerial capacity remains unchanged, at least in the short run. In this case,

[7] As evidence on short-term debt resulting in higher refinancing risks, Harford, Klasa, and Maxwell (2014) find that shortened debt maturity results in firms holding more cash holdings to fight against associated refinancing risks; Almeida et al. (2010) show that during the recent credit crisis, firms with more long-term debt that would be soon due suffered from underinvestment problems.

[8] It may not be the case for small firms. As documented by Custódio, Ferreira, and Laureano (2013), among U.S. industrial firms, those smallest ones had their median long-term debt ratio dropped from 53% in 1976 to only 6% in 2008 perhaps due to increased information asymmetry.

[9] Allen et al. (2005) make the conclusion after carefully comparing China with other countries regarding different aspects such as law enforcement, law agent supply quality, judicial independence, etc.

[10] In Li, Yue, and Zhao (2009), the average long-term debt ratio among scaled industrial firms in China was only 6.4%. In Huang and Rong (2017), the average long-term debt ratio among listed industrial firms in China was about 6.0% and the median was only 2.3%.

expanding production capacity after obtaining short-term PBLs would divert its limited managerial capacity away from innovation activities, thereby resulting in a decline in innovation output. A similar conclusion can be drawn when R&D personnel are fixed. R&D personnel may be required to solve urgent technical problems associated with the expansion and thus have less time to do high-quality innovation, which is not that urgent. Therefore, from the perspective of R&D-related resource reallocation, the output of high-quality innovation tends to decrease after firms obtain short-term PBLs. Nevertheless, it is ultimately an empirical question whether the access to short-term PBLs influences a firm's high-quality innovation positively or negatively. If the effect from R&D-related resource reallocation dominates, one should expect that with the access to short-term PBLs, an innovative firm's tendency of producing high-quality innovation would decrease.

3. Variables and model specification

3.1. Measures of high-quality innovation

Using patent data to measure firms' innovation output has the following advantages. First, patent applications are examined in a consistent and rigorous manner; consequently, patent data systematically capture the progress of innovation. Second, China has signed all major international conventions regarding intellectual property rights (Yang & Clarke, 2005).[11] Last, it has been documented that China is transferring from an economy of imitation to one of innovation (Cai & Tylecote, 2008; Wei, Xie, & Zhang, 2017).

According to China's patent law, three types of patents can be granted: invention, utility model, and external design. These three types differ mainly in the extent of novelty. Invention patents are the most novel. To be granted, an invention patent application must meet three requirements, namely "novelty, inventiveness, and practical applicability." In contrast, granting a utility-model or external-design patent is easier and faster: it is only required that no similar application has been previously granted. Accordingly, the protection period is shorter.

To better reflect a firm's innovation output generated in a given year, we count patents based on the application year instead of the granted year. It is generally concerned that patent counts measure only the quantity but not the quality of innovation. Existing studies use the number of citations that a patent subsequently receives to measure patent quality (e.g., Hall, Jaffe, & Trajtenberg, 2005). Unfortunately, the SIPO Database did not provide publicly available information on patents' backward citations until 2010. Alternatively, we measure patent quality based on patent novelty. Since invention patents are the most novel, we use the number of invention patent applications (later being granted) as the major measure of high-quality innovation output. Specifically, we turn to the SIPO Database and search patents based on applicants' name to calculate the numbers of invention patents (*Patent1*) that a firm applies for (later being granted) in a given year. To measure a firm's propensity of producing high-quality innovation, we define a dummy variable, *Patent1_dum*, which is equal to one if *Patent1* is positive and zero otherwise.

To be more conservative, we define another measure of high-quality innovation, *HQ_pat*. Following Briggs (2015) and Balsmeier et al. (2017), we define *HQ_pat* as the number of a firm's invention patents that fall into the top 20% of the forward citation distribution among all invention patents filed in the same one-digit technology class and in the same year. The number of forward citations reflects how much a patent is recognized in the future. Therefore, a patent in the top forward-citation rank indicates that it is high-quality innovation. We do not have to address the problem of citation truncation bias as our comparison is within the same year. Accordingly, we define another dummy, *HQ_pat_dum*, which is equal to one if *HQ_pat* is positive and zero otherwise.

3.2. The PBL access dummy

We manually collected the information on firms' initial access to PBLs from patents' legal status. When patents are pledged as collateral, lenders have strong incentives to have it recorded for the purpose of both establishing their lender status and avoiding repeated pledging (Mann, 1997). To obtain information on patent pledge, we first retrieve all patent pledge records from the SIPO Patent Database.[12] The related information is recorded as a string of legal status in the dataset. The keyword "*Zhiya*" (pledge) is used to identify whether a patent's legal status is related to pledge. We retrieve all strings of legal status containing this keyword from the SIPO patent dataset.[13] There are two major types of records, execution and termination; we only keep execution records.[14]

A firm is defined as getting its first access to PBLs in a given year if it is for the first time reported as a pledgor (*Zhiyaren*) in the year

[11] These conventions include the World Intellectual Property Organization (WIPO) (1980), the Paris Convention (1985), the Madrid Agreement (1989), and the Integrated Circuits Treaty (1989).

[12] For data retrieved from the USPTO assignment data set, please refer to Serrano (2010).

[13] Please see Online Appendix for an example of how we retrieve the related information.

[14] Termination records are available only for some PBL contracts. There are two possible reasons why one patent that had been registered as pledged failed to report its termination. First, the entity forgot to terminate even though it was already expired. Second, the related contract was still valid when the data were collected. We are not able to distinguish one from the other. Consequently, we are reluctant to use the termination records to make any implication. For those with termination records, we know how long the related contract lasted. However, this duration is hardly the same as the term of the initial loan contracts. Since a contract may be renewed, the duration should be on average longer than the term.

and the associated pledgee (*Zhiquanren*) is a financial institution.[15] Since the information on pledgees became available only after 2009, we start our investigation on the PBL access at 2010. Accordingly, we generate an access dummy indicating whether a firm has got its first access to PBLs in a given year; it is equal to one if so and zero otherwise.

Patent pledge records, though reported at the patent level, can be aggregated at the contract level based on the registration number. By aggregating at the contract level, we are able to know more about the major characteristics of each patent pledge contract. First, we plot the average patent count of each contract by years in OA Fig. 1. It shows that the average number was increasing over time, indicating that patent pledge contracts on average became more and more valuable. Additionally, we examine the distribution of the number of patents used as collateral in each contract and find that in most of the cases the number was small, suggesting that the related loans were generally distributed to SMEs.

It is also interesting to have some idea about the types of debtors. We notice that the big-four state-owned banks have also been involved in providing PBLs. The distribution of transactions by banks reveals that big-four state-owned banks did not play a dominant role; at least, their proportion was not comparable to their market share. It is consistent with the consensus that small banks are more willing to provide financial services to SMEs (Peek & Rosengren, 1996).

4. Empirical results

4.1. Data sources

Our firm-level data come from the Annual Survey of Industrial Enterprises (ASIE) conducted by China's NBS (National Bureau of Statistics). These are industrial firms, which include all SOEs and those non-SOEs with annual sales revenues over five million yuan (approximately $740,000). The data include firms' basic information, such as main businesses, location, employment, and ownership type. The data also include their basic accounting information. This dataset is becoming one of the most important sources to study Chinese industry.[16] We merge the access year and associated patent pledge information as well as patenting measures with the ASIE data by firm name.

Fig. 1 plots the number of firms that for the first time reported patent pledge over the period 2002–2016. For comparison, we also plot the diffusion among the surveyed industrial firms. As shown, the time trend is comparable to that of the population, suggesting that our sample is to some extent representative.

To clean the data, we delete the following types of observations from the original data. First, there are three major industries in the original: (1) manufacturing, (2) mining, and (3) production and distribution of electricity, gas, and water. Our sample is restricted to manufacturing firms as firms in the other two industries are less innovative. Second, we only include firms with at least one patent of any type; firms that got access to PBLs during the examination years are naturally included. Third, we drop firms which have reported any patent pledge before 2010; even though we do not know whether these records were associated with financial institutions, it was very likely so according to the report from the SIPO and the later data. Fourth, we drop firms which got their PBL access after 2013 as these firms are no longer qualified as control for the study. Fifth, we delete observations that have at least one key variable with an invalid value and delete observations with strange values.[17] Last, to have a balanced panel, we require that a sampled firm existed in 2009 and survived 2013, with all observation years available during the examination period.[18] Through the above procedure, we end up with a sample of 695,460 observations representing 139,092 firms, among which 356 firms had their PBL access between 2010 and 2013.

Panel A of Table 1 reports the summary statistics of firm characteristics for the sampled firms. The definition of each variable is presented in OA Table 1. In the estimations, all financial variables are winsorized at the 1% level in both tails to mitigate the influence of outliers. We report their summary statistics accordingly. As shown, the access to PBLs was scarce; only 0.1% of firm-years have got access to PBLs. The proportion of firms having invention patents was very low at 3.8% and the proportion of firms having invention patents with top citations was even lower at 1.9%. The average leverage rate was 49.3% and the average ROA was 17.3%. On average, 34.3% of firms' total assets were fixed assets. The average firm age was 10.7.

To have some idea about how the PBL access frequency varied across regions among ASIE firms during 2010 and 2013, we present its regional distribution in Fig. 2. It shows that coastal areas tended to have a larger count. Given that the PBL access was apparently not random, we use a propensity score match (PSM) approach to mitigate potential selection bias.

[15] To identify whether a pledge registration is loan-related, we turn to the pledgee's name. We use the following key words to identify whether a pledgee is a financial institution: *Yinhang* (bank), *Xinyong* (credit), *Danbao* (guarantee), *Daikuan* (loan). A patent-pledge registration is not necessarily but very likely related to a loan contract.

[16] The ASIE data in 2010 are not available. To conduct a continuous panel, for related variables, we use the average value of 2009 and 2011 to replace the 2010 value as long as the values in 2009 and 2011 are both available.

[17] The situation includes: (i) total product output less than or equal to zero; (ii) profit greater than total output; (iii) fixed assets less than zero or greater than total assets; (iv) total debts less than zero or greater than total assets; and (v) firm age less than zero.

[18] In our study, the earliest year of a firm's PBL access is 2010; we start our examination at 2009 so that there is at least one year of before-event period for each firm. The detailed sample selection process is presented in OA Table 2.

Table 1
Summary statistics.

Variable	Mean	S.D.	P10	Median	P90
Panel A. Full sample					
Patent1_dum	0.038	0.191	0.000	0.000	0.000
HQ_pat_dum	0.019	0.138	0.000	0.000	0.000
Patent2_dum	0.096	0.294	0.000	0.000	0.000
Patent3_dum	0.031	0.174	0.000	0.000	0.000
Access dummy	0.001	0.031	0.000	0.000	0.000
Leverage	0.493	0.253	0.130	0.502	0.832
ROA	0.173	0.239	0.002	0.078	0.518
Fixed-asset ratio	0.343	0.227	0.074	0.305	0.680
Ln(TA)	10.786	1.360	9.138	10.647	12.615
Age	10.718	7.202	4.000	9.000	18.000
Observations	695,460				
Panel B. Matched sample					
Patent1_dum	0.114	0.318	0.000	0.000	1.000
HQ_pat_dum	0.065	0.246	0.000	0.000	0.000
Patent2_dum	0.227	0.419	0.000	0.000	1.000
Patent3_dum	0.070	0.255	0.000	0.000	0.000
Access dummy	0.068	0.252	0.000	0.000	0.000
Leverage	0.531	0.236	0.193	0.547	0.839
ROA	0.100	0.156	−0.001	0.052	0.251
Fixed-asset ratio	0.257	0.188	0.050	0.217	0.527
Ln(TA)	11.684	1.411	9.911	11.586	13.639
Age	11.486	7.515	5.000	10.000	19.000
Observations	9532				

This table presents the summary statistics for firm characteristics of the sample before and after the match. Variables are defined in OA Table 1.

4.2. Matching process

A typical approach to estimate the effect of the PBL access on firm patenting is to run an OLS regression. However, this approach is subject to endogeneity problems. Particularly, unobserved factors may influence both firms' financing decisions and their subsequent patenting behavior. Unfortunately, we do not have proper instruments to deal with this type of endogeneity. Alternatively, our identification strategy is to explore a quasi-natural experiment based on a matching approach, as proposed by Heckman, Ichimura, & Todd (1997).

The treatment group is defined as those 356 firms that had their initial PBL access during the period 2010–2013. If all other firms are included in the control group, one would be concerned that firms in the control group may have different propensities of getting access to PBLs from those in the treatment group, which may lead to estimation bias. For this reason, we pick up the control firm for a treated firm based on the closest propensity score to the treated firm regarding the likelihood of firms' access to PBLs.

Following Seru (2014), we estimate the likelihood of firms' access to PBLs year by year from 2010 to 2013. Since having at least one granted patent is a necessary condition to obtain PBLs, we restrict the estimation to the sampled firms with at least one patent that has been granted before the examination year. To avoid the situation that a candidate firm is chosen more than once, for the likelihood estimation of a given year, only firms that get access in the year and candidate firms that have not been chosen as control in the previous years are included.[19] Our likelihood estimation is based on a probit specification as follows.

$$Prob\left(Access_{i,t}=1\right)=\lambda_0+X^0_{i,t-1}\lambda_1+\varepsilon_{i,t}, t=2010,2011,2012,2013 \quad (1)$$

where subscripts i and t represent firm and year, respectively. $Access_{i,t}$ is the access dummy indicating whether firm i gets access to PBLs in year t; it equals one if so, and zero otherwise. $X^0_{i,\,t-1}$ is a vector of firm characteristics in year t-1, including leverage, fixed-asset ratio, ROA, log of total assets, firm age, change in *Patent1_dum*, and one-year lagged change in *Patent1_dum*. As *Patent1_dum* is our major dependent variable, we include its annual change to ensure that the parallel pre-trends assumption holds.[20] We forward *Patent1_dum* by one year to count for the possible lagged effect from the PBL access, so the change in *Patent1_dum* is its difference between year t and t-1. Another concern is that some time-trend pattern of patenting changes may be correlated with both the PBL access and subsequent patenting; for example, an upper trend implies a boom of patenting, which may result in the PBL access. We thus further include a one-year lag of the change in *Patent1_dum*.

The candidate firms whose predicted access probability is the top five closest to that of the treated firm are chosen as its control

[19] We do so to ensure that the sample is exactly the same between the univariate DID analysis and the multivariate regression. As a robustness check, we also do the match by allowing for repeated draws. Our major results remain unchanged.
[20] Lemmon and Roberts (2010) state that the parallel trends assumption does not require the level of *Patent1* to be the same for both the control and the treatment group before the access but does require similar trends in *Patent1* before the access.

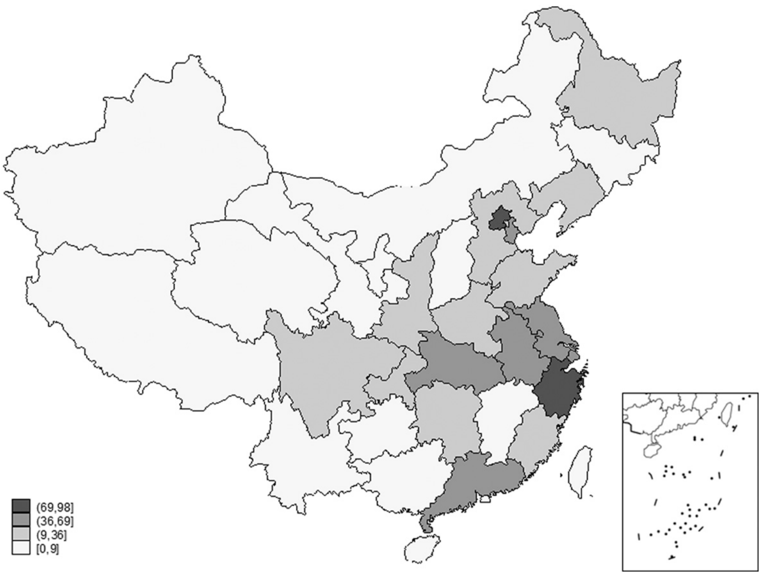

Fig. 2. The distribution of PBL access for 2010–2013, ASIE firms.
This figure presents the regional distribution of the PBL access count among ASIE firms between 2010 and 2013.

firms.[21] Meanwhile, one may be concerned that matched control firms, though with the closest propensity scores, may be far apart and thus not comparable to the treated. We thus further require the absolute distance between the propensity scores of the treated firm and its control not to exceed 0.0001; that is, we set the caliper at 0.0001. After the match procedure, we end up with 356 one-to-five pairs of matched firms.[22] To make the periods before and after the event more balanced, we only include observations between year *t*-3 and *t* + 2 (*t* represents the access year). Specifically, for firms with PBL access in 2010, the observation in 2013 is dropped; for those with PBL access at 2013, the observation in 2009 is dropped; control firms are treated similarly based on the matching year.[23]

Panel B of Table 1 shows the summary statistics of firm characteristics for the matched sample. The summary statistics of firm characteristics are similar to the full sample, except that these firms were more innovative.

4.3. Balance tests

The validity of the DID estimate critically relies on the parallel pre-trends assumption. To satisfy this assumption, we have included the change of *Patent1_dum* and its one-year lag in the matching process. We now present two pieces of evidence to further support this assumption. First, panel A of Table 2 presents the accuracy of the matching process. As shown, the distributions of estimated access probabilities between the treated firms and the control firms are very close.

We then compare firm characteristics between the treatment and the control group in the year right before the event in panel B of Table 2. For each variable, the difference between these two groups is statistically insignificant. Overall, our diagnostic tests indicate that the propensity score matching process has successfully removed observed differences in pre-event characteristics between the treatment and the control group. We are thus more confident that the changes in *Patent1_dum* after the event, if any, are due to the PBL access.[24]

4.4. Debt change surrounding the PBL access

To have some idea on the debt dynamics surrounding the PBL access, panel A of Table 3 shows the difference in the leverage ratio (total debt over total assets) for the treatment and the control group over a four-year window surrounding the event year (i.e., year *t*-3 to year *t*). The coefficient on the interaction term remains positive and significant at least at the 5% level no matter one-year lagged control variables are included or not (columns 2 and 1). We then rerun the regressions by using the short-term debt ratio (short-term debt over total assets) and the long-term debt ratio (long-term debt over total assets) as the dependent variable, respectively. Column 4

[21] The purpose of using 1:5 matching is to enhance estimation efficiency. Since we have a huge pool of candidate firms, the matching precision is easily satisfied.

[22] Note that the number of control firms is not exactly 356*5. Though in most of the cases it is an exact 1 to 5 draw during the matching process (psmatch2) provided by the Stata, it falls short in a few. Consequently, we lose 4 firms in the control group.

[23] We also rerun the regressions without this restriction and our major results persist (not reported).

[24] Even with a careful match, it is still impossible to ensure that firm innovation would follow a similar trend afterwards in the absence of the treatment. In this aspect, caution should be exercised when interpreting the results.

Table 2
Estimated propensity score distribution and balance test.

Panel A. Estimated propensity score distribution								
	Obs.	Mean	S.D.	Min.	P10	P50	P90	Max.
Treatment	356	0.002	0.001	0.000	0.000	0.001	0.004	0.009
Control	1776	0.002	0.001	0.000	0.000	0.001	0.004	0.009
Difference	356	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel B. Balance test								
	Treatment group		Control group	Difference	*t*-test		*P*-value	
Change in Patent1_dum$_{t-1}$	0.020		−0.015	0.036	1.408		0.159	
Change in Patent1_dum$_t$	0.022		0.000	0.022	0.853		0.393	
Leverage $_{t-1}$	0.535		0.537	−0.002	−0.150		0.881	
ROA $_{t-1}$	0.094		0.094	0.001	0.112		0.911	
Fixed-asset ratio $_{t-1}$	0.240		0.240	0.000	0.039		0.969	
Ln(TA$_{t-1}$)	11.739		11.679	0.060	0.745		0.456	
Age$_{t-1}$	11.439		11.289	0.150	0.349		0.727	

In this table, panel A compares the estimated propensity score distributions between the treatment and the control groups. Panel B presents the balance test results for the pairs of treatment and control firms.

Table 3
The instant effect of PBL access on capital structure.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Total debt		ST debt		LT debt	
Panel A. Debt ratios						
Post*Treatment	0.026**	0.027***	0.031***	0.031***	−0.0001	−0.00004
	(2.56)	(2.65)	(2.71)	(2.75)	(−0.02)	(−0.01)
Post	−0.017**	−0.017**	−0.012	−0.012	−0.0001	−0.0001
	(−2.34)	(−2.36)	(−1.37)	(−1.37)	(−0.04)	(−0.03)
L.ROA		−0.068		−0.083*		0.013
		(−1.57)		(−1.85)		(0.75)
L.Fixed-asset ratio		0.021		0.022		−0.008
		(0.59)		(0.61)		(−0.49)
L.Ln(TA)		−0.013		−0.005		0.000
		(−1.38)		(−0.56)		(0.05)
Age		−0.017		−0.022		0.006
		(−0.79)		(−1.01)		(0.94)
Observations	5634	5634	5634	5634	5634	5634
Adjusted R^2	0.822	0.822	0.775	0.776	0.656	0.655
Panel B. Log of debt amount						
Post* Treatment	0.195***	0.167***	0.241***	0.209***	0.106	0.079
	(4.86)	(4.19)	(5.61)	(4.88)	(0.60)	(0.45)
Post	−0.111***	−0.107***	−0.125***	−0.119***	−0.211	−0.214
	(−3.81)	(−3.63)	(−3.08)	(−2.93)	(−1.58)	(−1.60)
L.ROA		0.158		0.122		0.906
		(0.91)		(0.58)		(1.23)
L.Fixed-asset ratio		0.082		0.204		−0.218
		(0.52)		(1.11)		(−0.39)
L.Ln(TA)		0.326***		0.345***		0.383**
		(7.64)		(7.37)		(2.26)
Age		−0.023		−0.054		0.133
		(−0.30)		(−0.68)		(0.78)
Observations	5634	5634	5511	5511	1984	1984
Adjusted R^2	0.933	0.937	0.895	0.900	0.805	0.808
Firm dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes

This table estimates the effects of the PBL access on debt ratios during the period year *t*-3 to event year *t* by using the matched sample. The variables are defined in OA Table 1. In panel A, the dependent variable is the leverage ratio, short-term debt ratio, and long-term debt ratio, respectively. In panel B, it is the log of the related debt amount. For all regressions, standard errors are clustered at the firm level. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

indicates that the PBL access leads to an instant increase in a firm's short-term debt ratio by 3.1 percentage points. In contrast, such an effect is ignorable when the long-term debt ratio is examined.

Additionally, to check the robustness of the debt measure, we rerun the regressions of panel A by using the log of the debt amount (in million dollars) as the dependent variable in panel B. As shown, the interaction coefficient remains positive and significant at the 1% level when short-term debt is examined. Column 4 indicates that the PBL access results in a firm's short-term debt instantly increasing by 20.9%. We thus confirm that the PBL access is associated with a substantial increase in short-term debt but not in long-term debt.

So far, we have confirmed that PBLs are mainly short-term loans. However, whether PBLs can be renewed after the first year is also an important factor affecting firms' innovation decisions. In an extreme case, when a short-term loan can be renewed unconditionally and at a low financing cost, it can be regarded as long-term. To have some idea on the likelihood of PBLs being renewing in the coming year, in panel A of Fig. 3 we present the average short-term debt ratio for the treated and the control firms, from three years before firms' PBL access to three years after. For comparison, each ratio is normalized by its value in the year right before the access. As shown, on average the short-term debt ratio increased in the access year and then dropped back near to its initial level in the next year, indicating that short-term loans obtained by firms through patent pledge needed to be repaid in the second year and the chance of renewing was low. In contrast, we do not see such a pattern when the long-term debt ratio is examined as shown in panel B. One possible explanation is that PBL-related subsidies were likely temporary and the renewal procedure of PBLs may not have been well designed as this type of loans was still at its early stage. Additionally, as the PBL was short-term, after the first year the financing cost would come back to the regular level, higher than that of ordinary loans. High financing costs would have prohibited firms from renewing their PBLs.

Our examination period falls in the period that China's economy was facing continuous downward pressure. We do find some evidence in Fig. 3 that firms' financial condition was worsening during this period as the average short-term debt ratio was downward sloping for both treated firms and control firms. In this aspect, we tend to think that we have controlled for the effect of the downward pressure by including the control group.[25]

4.5. Baseline estimations

We examine how the PBL access affects firms' high-quality innovation propensities. With the presence of many dummies, the regression process is hard to converge when using the probit or logit specification. Following Bertrand, Luttmer, & Mullainathan (2000), we perform the test by estimating the following linear probability (LP) model.

$$Prob\left(Patent_{i,t+1}=1\right)=\beta_1 Post_{i,t}{}^{*}Treatment_i+\beta_2 Post_{i,t}+X_{i,t}\theta+Year\_dum+Firm\_dum+\mu_{i,t+1}, \quad (2)$$

where the dependent variable, $Patent_{i,t+1}$ is one of two high-quality innovation dummies of firm i in year $t+1$. $Post_{i,t}$ indicates whether the firm-year is after the event or not; it equals one if so and zero otherwise. $Treatment_i$ is a dummy indicating whether firm i is treated or control; it is equal to one if the firm is treated, and zero if it is control. We include year dummies to account for macro shocks to firms' patenting activities. We also include firm dummies to capture the patenting heterogeneity across firms. Following the literature, $X_{i,t}$ represents a vector of firm characteristics that may affect a firm's innovation propensity, including leverage, ROA, fixed-asset ratio, log of total assets, and firm age. For all specifications, standard errors are adjusted for clustering at the firm level. The coefficient on $Post_{i,t}{}^{*}Treatment_i$, β_1 captures the access effect on firm innovation. If the PBL access negatively influences firms' high-quality innovation propensities, β_1 should be significantly negative.

Table 4 presents the estimation results of eq. (2). First, we use *Patent1_dum* as the dependent variable. Column 1 only includes *Post*Treatment* and *Post* as independent variables while column 2 includes all control variables. In both cases, the coefficient on the interaction term remains negative and significant at the 1% level, and its magnitude is almost unchanged. Column 2 indicates that the PBL access leads to a 9.2% decrease in the probability of a firm having any invention patents. Regarding control variables, all coefficients are statistically insignificant. It is not surprising as we have controlled for firm fixed effects.

We then repeat the regressions of columns 1 and 2 by using *HQ_pat_dum* as the second high-quality innovation propensity measure in columns 3 and 4, respectively. Consistently, the interaction coefficient remains significantly negative.[26] Column 4 indicates that the PBL access leads to a 5.6% decrease in the probability of a firm having any invention patents with top citations. Overall, our estimation results support our main hypothesis of R&D resource reallocation.[27]

To check the robustness of our measures of high-quality innovation propensities, we generate two additional high-quality innovation dummies, *HQ_pat15_dum* and *HQ_pat25_dum*. *HQ_pat15_dum* (*HQ_pat25_dum*) is defined as whether in a given year the firm applies for any patent (later being granted) with citations at the top 15% (25%) among all patents in the same classification that are filed in the same year. We then use these two dummies as the dependent variable and rerun the baseline regressions, respectively. As shown in Appendix Table 1, the coefficients on the interaction term remain negative and significant at least at the 5% level, indicating

[25] It is likely that a firm's tendency to use PBLs to alleviate operating difficulties was higher during this period. Since we have no treated before the downward period, it is impossible for us to identify whether such a PBL access effect on high-quality innovation varied substantially before and after the global financial crisis.

[26] We also use invention-patent application counts as the dependent variable and find its effect insignificant (not reported). It indicates that the PBL access does not result in fewer invention-patent applications but fewer granted ones. One possible explanation is that the firm may be under pressure from local authorities to submit sufficient patent applications; some cases tend to be weak and thus less likely to be granted.

[27] We reach similar results when using 1:1 matching as shown in OA Table 3. Additionally, we reach similar results when using the full sample as shown in OA Table 4. Last, we use different matching methods and find similar results. Specifically, we use the radius matching with the caliper of 0.00000005 and the Kernel matching method with the bandwidth of 0.00000006, respectively. As shown in OA Table 5, upon changing the matching method, the coefficient on the interaction term remains negative and significant at the 1% level, indicating that our major results are robust to different matching methods.

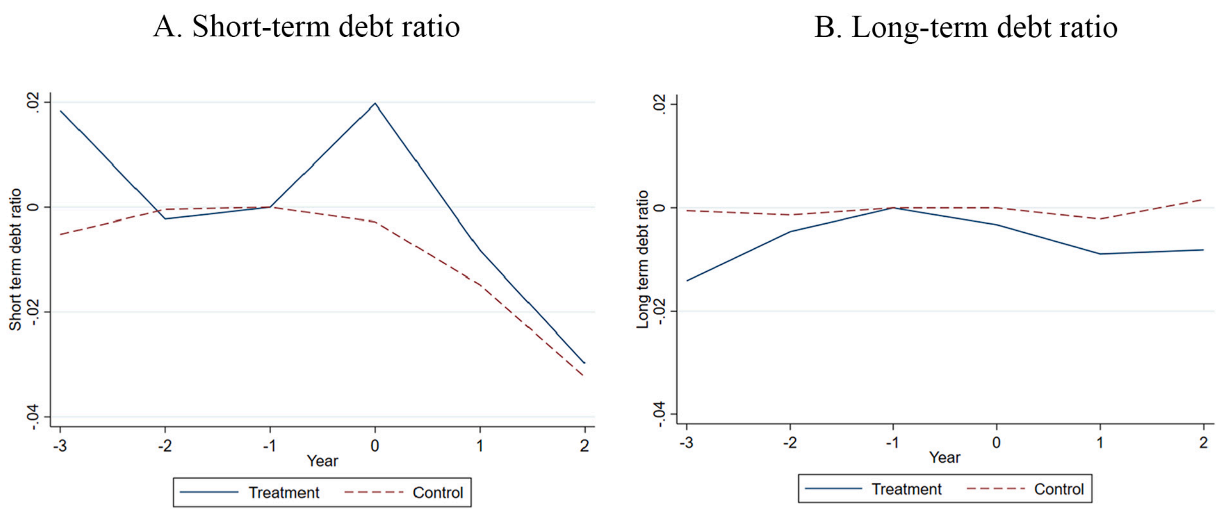

Fig. 3. Leverage ratio dynamics around the PBL access.
This figure shows the average short-term debt and long-term debt ratio for the treated and the control firms, from three years before firms' PBL access to three years after. For a given firm, year 0 is the year when the firm gets access to PBLs. For comparison, each value is normalized by the value at year −1. The sample is comprised of 356 treated firms and 1776 control firms matched based on the procedure described in Table 1.

Table 4
The effect of PBL access on high-quality innovation propensity.

	(1)	(2)	(3)	(4)
Dependent variable	Patent1_dum		HQ_pat_dum	
Post* Treatment	−0.092***	−0.092***	−0.057***	−0.056***
	(−3.66)	(−3.65)	(−3.07)	(−2.98)
Post	0.011	0.010	0.019**	0.018*
	(0.94)	(0.91)	(2.04)	(1.93)
Leverage		−0.027		0.002
		(−1.06)		(0.09)
ROA		−0.004		0.029
		(−0.16)		(1.21)
Fixed-asset ratio		0.022		0.006
		(0.66)		(0.25)
Ln(TA)		0.007		−0.007
		(0.77)		(−1.19)
Age		−0.028		0.023
		(−0.82)		(1.11)
Firm dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observations	9532	9532	9532	9532
Adjusted R^2	0.377	0.377	0.306	0.306

This table estimates the effect of the PBL access on firms' high-quality innovation propensity by using the matched sample. The variables are defined in OA Table 1. The dependent variables are *Patent1_dum* and *HQ_pat_dum*, respectively. For all regressions, standard errors are clustered at the firm level. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

that our major results are robust to defining high-quality innovation using different thresholds.[28]

To address the concern that our major result may be driven by chance, we run simulations that randomize the assignment of treatment firms in our sample. For each simulation, we randomly draw 356 treatment firms from the pool of all sample firms and treat the rest as control firms. We than rerun the regressions of Table 4 based on the randomized sample. We repeat the simulation 500 times. Table 5 summarizes the distributions of the coefficient on the interaction term and its *t*-statistic by reporting their mean, standard deviation, 10th percentile, median, and 90th percentile. The estimated coefficients are close to zero and much smaller than

[28] We also rerun the baseline regressions by using 10% as the threshold to define high-quality innovation. The coefficient on the interaction term, though negative, is only marginally significant. Additionally, we find that the adverse effect exists among treated firms initially having invention patents, indicating that initial innovation capacity still matters. However, this effect turns positive and significant at the 10% level among treated firms initially without invention patents, suggesting alleviating financial constraints may stimulate firms with low innovation capacity to generate innovation with really high quality. Last, we find that the adverse effect still exists among large firms.

those reported in Table 4. In addition, the distributions of the *t*-statistics show that none of them is statistically significant. Therefore, it is unlikely that our major results are driven by pure luck.

It takes time for a patent application to be granted, especially for an invention patent application. The grant lag is about 2 to 4 years for an invention patent while it is within a year for the other two types (He, Tong, Zhang, & He, 2018). As a result, there may exist a truncation bias on the patent count as an invention patent application in the later year is more likely still at the examination stage and not yet granted. To address this truncation bias, we redefine the high-quality innovation dummy (*Patent1_3y_dum*) by only counting a firm's invention patent applications in a given year that are later granted within three years (*Patent1_3y*). For example, for the latest examination year 2014, we count granting till 2017. Accordingly, we rerun the regressions. As shown in Appendix Table 2, the interaction coefficient remains significantly negative no matter whether we include control variables or not and its magnitude only changes mildly. Therefore, our results are unlikely driven by such a truncation bias.

For robustness checks, we also define two low-quality innovation dummies, having any utility-model patent (*Patent2_dum*) and having any external-design patent (*Patent3_dum*) that a firm applies for (later being granted) in a given year. We then repeat the regressions by using *Patent2_dum* and *Patent3_dum* as the dependent variable, respectively. As shown in Appendix Table 3, the interaction coefficient is insignificant when these two low-quality innovation dummies are examined. The insignificance indicates that only high-quality innovation is severely influenced by the PBL access. It is consistent with our argument that high-quality innovation is not urgent and thus more likely to be negatively influenced by R&D resource reallocation. It also helps to rule out the possibility that firms may have switched from producing invention patents to utility-model patents; otherwise, we should have found the interaction coefficient to be significantly positive when *Patent2_dum* is examined. Overall, our estimation results show that the PBL access is negatively associated with firms' high-quality innovation propensities, but it is not the case for low-quality innovation.

One may be concerned that some contemporaneous industry and regional policies may have influenced both the PBL access and firms' innovation incentives in opposite directions. To alleviate this concern, in Appendix Table 4 we repeat our baseline regressions by including city-year dummies and industry-year dummies, respectively. We first use *Patent1_dum* as the dependent variable. In columns 1 and 2 we include industry-year dummies while in columns 3 and 4 we include city-year dummies. In both cases, the coefficient on the interaction term remains negative and significant at the 1% level. We then repeat the regressions of columns 1 to 4 by using *HQ_pat_dum* as the dependent variable in columns 5 to 8. Again, the coefficient on the interaction term remains significantly negative. Therefore, we conclude that it is unlikely that the negative relationship between a firm's PBL access and the likelihood of having high-quality innovation is driven by common unobservables such as changes in industry and regional policies.

Last, to check whether the PBL access effect on high-quality innovation exists at the intensive margin, we rerun the baseline regressions using the count of high-quality innovation (i.e., *Patent1* and *HQ_pat*) as the dependent variable. Cohn, Liu, & Wardlaw (2022) emphasize that using the log of patent counts plus one as the dependent variable is not acceptable and likely leads to estimation bias. Since we have a large number of observations with zero patent counts, it is very likely subject to this issue. Following Cohn et al. (2022), we estimate a fixed-effects Poisson model. As shown in Appendix Table 6, the coefficient on the interaction term, though negative, persists insignificant no matter which measure is used as the dependent variable. It indicates that the PBL access negatively influences firms' high-quality innovation mainly at the extensive margin but not at the intensive margin. It seems reasonable as we expect that our major results come from financially constrained firms' reaction to the PBL access and it is hard for these constrained firms to generate invention patents in a time-persistent manner.

4.6. Dynamics of having any high-quality innovation surrounding the PBL access

To mitigate the reverse causality concern, we examine the dynamics of high-quality innovation propensities surrounding the PBL access. If reverse causality drives our major results (e.g., firms get access to PBLs to meet their investment needs), a change in high-quality innovation propensity should be evident even before the access year. To rule out this possibility, we follow Bertrand & Mullainathan's (2003) approach and generate six event dummies, *Before3*, *Before2*, *Before1*, *Current*, *After1,* and *After2*, which denote relative years around the PBL access year. We then rerun the regressions of Table 4 by replacing the access dummy with these six dummies except for *Before1*. Because of the exclusion, the observations in the year before the PBL access are thus treated as the reference group.

The estimation results are presented in Fig. 4.[29] When either *Patent1_dum* or *HQ_pat_dum* is used as the dependent variable, the coefficients on *Before3* and *Before2* are statistically insignificant, suggesting that there is no substantial change in high-quality innovation before the PBL access. Thus, the timing of the PBL access seems exogenous to firms' investment needs. For *Patent1_dum*, the coefficient on *Current* is negative and becomes significant at the 5% level, so are the coefficients on *After1* and *After2*. For *HQ_pat_dum*, though the coefficient on *Current* is insignificant, the negative coefficients on *After1* and *After2* are significant at the 10% and 1% level, respectively. In both cases, the magnitude of these coefficients tends to increase over time after the PBL access. These results thus suggest that the likelihood of having any high-quality innovation decreases after the PBL access. Overall, the above analysis suggests that the PBL access negatively influences firms' high-quality innovation propensity and not vice versa.

When *Patent1_dum* is examined, the negative coefficient on *Current* is already significant at the 5% level. To be consistent with the dynamics, in our baseline regressions we use the specification of one-year lag. High-quality innovation may take longer than one year

[29] The detailed estimation results are presented in OA Table 6. One may be concerned that the satisfactory results are due to that we have already matched the sample. To address this issue, we also rerun the regressions by using the full sample instead of the matched sample. As shown in OA Table 7, our major results remain unchanged.

Table 5
Placebo tests for regressions (randomized samples).

Variables	Observations	Mean	S.D.	P10	Median	P90
Regression of Patent1_dum:						
Coefficient	500	0.001	0.015	−0.018	0.001	0.018
T-statistic	500	0.045	0.866	−1.070	0.063	1.103
Regression of HQ_pat_dum:						
Coefficient	500	−0.000	0.011	−0.014	0.000	0.014
T-statistic	500	0.006	0.852	−1.027	0.014	1.158

This table presents placebo test results for regressions. The results come from 500 simulation tests by using randomized samples. In each simulation, we draw a random sample of treatment firm-years from the matched sample firms year by year, and then treat the rest firm-years as the control group. We then perform the regressions of Tables 4 based on the randomized sample. We repeat the simulation process by 500 times and summarize the distributions of the coefficients and t-statistics for the variable of interest, *Post*Treatment*.

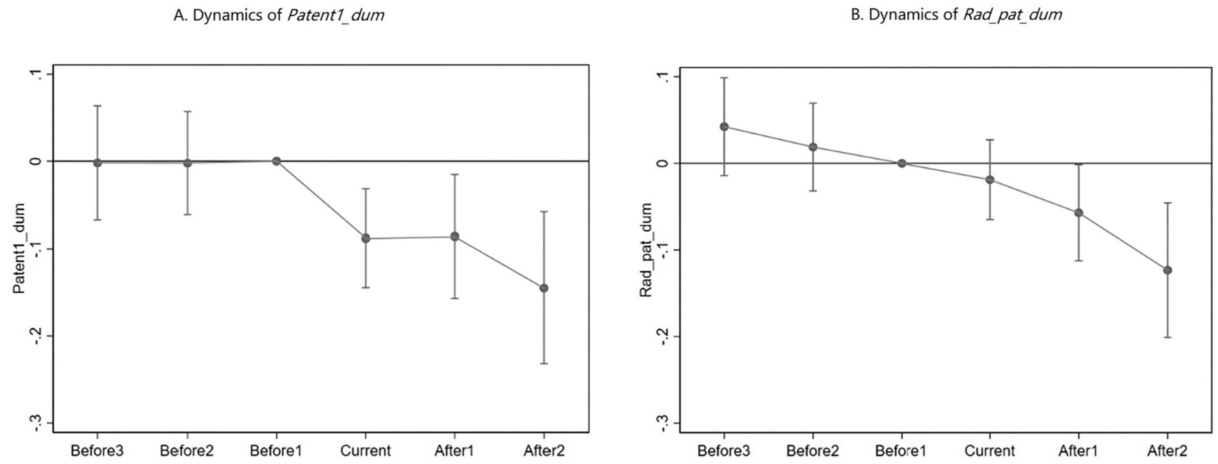

Fig. 4. Innovation dynamics around the PBL access year.
This figure shows the dynamics of high-quality innovation propensities from three years before firms' PBL access to two years after. For a given firm, *Current* represents the year when the firm gets access to PBLs. Reported coefficients are relative to the default group of the year right before the PBL access (*Before1*). The vertical bar around each point represents the 95% confidence intervals. In panel A, we use *Patent1_dum* as the dependent variable. In panel B, we use *HQ_pat_dum* as the dependent variable.

to materialize. Consistent with this view, when *HQ_pat_dum* is examined, the coefficient on *Current* is insignificant, indicating that the negative PBL-access effect takes longer to materialize when high-quality innovation is more strictly defined.

One potential concern is that by lagging the PBL access by only one year, our major results may be driven by that one year after the PBL access, firms may lose innovation in the short run because of funding long-term R&D. We thus rerun the baseline regressions with the PBL access dummy lagged by two years. As shown in Appendix Table 5, the coefficient on *Post*Treatment* remains negative and significant at the 1% level, suggesting that our major results are robust to specifications with different lags.

4.7. Underlying mechanisms

Having established a causal and negative relationship between the PBL access and firms' high-quality innovation propensities, we further explore the underlying mechanisms through which the PBL access retards firms' high-quality patenting. We hypothesize that the PBL access retards firms' invention patenting through two mechanisms, firms' innovation capacity and their financial constraints.

The hypothesis of R&D resource reallocation implies that a firm's initial innovation capacity should play an important role. If a firm has no such capacity in the first place, the reallocation would not happen. We regard firms that have used invention patents as collateral as initially having innovation capacity. In panel A of Table 6, we rerun the baseline regressions by replacing the interaction term with its interaction with two invention-patent dummies, a having-invention-patents dummy and a having-no-invention-patent dummy. A treated firm is defined as initially having invention patents if it used at least one invention patent as collateral to obtain the PBL; otherwise, it is defined as initially having no invention patent. Two dummies are defined accordingly. No matter which measure is used as the dependent variable, the coefficient on *Post*Treatment*Having invention patents* is significantly negative, and its magnitude is much larger than that on *Post*Treatment*Having no invention patent*, which is statistically insignificant. We thus conclude that the negative effect only exists among firms initially having innovation patents.

Financial constraints also play a role in the R&D resource reallocation story. Even when getting access to PBLs, a firm without financial constraints should have no incentive to change its original investment strategy as its investment is already at the optimal

Table 6
Heterogenous effects of PBL access on high-quality innovation propensity.

	(1)	(2)	(3)	(4)
Dependent variable	Patent1_dum		HQ_pat_dum	
Panel A. Initial innovation capacity				
Post*Treatment	−0.049	−0.050	0.025	0.027
*Having no invention patent	(−1.22)	(−1.24)	(1.01)	(1.05)
Post*Treatment	−0.116***	−0.116***	−0.104***	−0.103***
*Having invention patents	(−3.70)	(−3.68)	(−4.27)	(−4.20)
Observations	9532	9532	9532	9532
Adjusted R^2	0.377	0.377	0.309	0.309
Panel B. Firm size				
Post*Treatment	−0.087**	−0.087**	−0.084***	−0.082***
*Large size	(−2.42)	(−2.42)	(−2.94)	(−2.88)
Post*Treatment	−0.096***	−0.096***	−0.030	−0.029
*Small size	(−2.85)	(−2.84)	(−1.31)	(−1.26)
Observations	9532	9532	9532	9532
Adjusted R^2	0.377	0.377	0.307	0.307
Panel C. Investment coverage				
Post*Treatment	−0.063	−0.064	−0.093**	−0.092**
*Low coverage	(−1.44)	(−1.47)	(−2.39)	(−2.39)
Post*Treatment	−0.172***	−0.174***	−0.114***	−0.113***
*High coverage	(−3.94)	(−3.93)	(−3.78)	(−3.73)
Observations	6094	6094	6094	6094
Adjusted R^2	0.395	0.395	0.302	0.302
Panel D. Scale expansion				
Post*Treatment	−0.107**	−0.107**	−0.070**	−0.070**
*Low expansion	(−2.47)	(−2.47)	(−2.15)	(−2.16)
Post*Treatment	−0.131***	−0.133***	−0.138***	−0.137***
*High expansion	(−2.92)	(−2.94)	(−3.78)	(−3.77)
Observations	6094	6094	6094	6094
Adjusted R^2	0.394	0.394	0.302	0.302
Panel E. Industry type				
Post*Treatment	−0.098***	−0.099***	−0.119***	−0.118***
*Non-high-tech	(−2.72)	(−2.73)	(−4.34)	(−4.32)
Post*Treatment	−0.172***	−0.173***	−0.064	−0.064
*High-tech	(−2.79)	(−2.80)	(−1.25)	(−1.24)
Observations	6094	6094	6094	6094
Adjusted R^2	0.394	0.394	0.302	0.302
Control variables		Yes		Yes
Firm dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes

This table estimates heterogenous effects of the PBL access on firms' high-quality innovation propensity by using the matched sample. The dependent variables are *Patent1_dum* and *HQ_pat_dum*, respectively. In panels C to E, we restrict our sample to treated firms initially having some invention patents along with their matched control firms. For all regressions, standard errors are clustered at the firm level. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

level. In this aspect, one should expect the access effect to be pronounced among firms with financial constraints but not among those without (e.g., Almeida & Campello, 2007; Rampini & Viswanathan, 2013). Generally, small-sized firms are expected to be more financially constrained and it is a common practice to use firm size to proxy the extent of a firm's financial constraints (e.g., Almeida, Campello, & Weisbach, 2004; Li, 2011). Meanwhile, small-sized firms are less likely to initially have innovation capacity and thus their innovation is less likely to be influenced by the PBL access. It is thus ultimately an empirical question whether the adverse effect is more pronounced among large firms or among small firms.

In panel B we replace the interaction term by interacting it with two size dummies, a small-size dummy and a large-size dummy. A treated firm is defined as small sized if its total assets right before the access year are below the median value among all treated firms getting access in the same year; otherwise, it is defined as large sized. Two size dummies are defined accordingly. When *Patent1_dum* is examined, the coefficients on *Post*Treatment*Large size* and *Post*Treatment*Small size* are both negative and significant. It seems that these large firms were on average not large enough and still financially constrained. The significance among large firms is somewhat consistent with the R&D resource reallocation story as large firms are more likely to initially have innovation capacity. It is interesting to find that when *HQ_pat_dum* is used as the dependent variable, the interaction coefficient is significant only among large firms. One possible explanation is that it is too demanding for small firms to produce invention patents with top citations given that small firms generally have low innovation capacity. Consequently, while the likelihood of a small firm having any invention patents is negatively influenced by the PBL access, the likelihood of having any invention patents with top citations is not.

With the above findings, we tend to think that it is more important to further explore the negative effect among treated firms initially having invention patents. We thus perform additional heterogeneity analyses with the sample restricted to treated firms initially having invention patents along with their matched control firms.

The hypothesis of R&D resource reallocation is conditioned on firms' scale expansion, implying that the ratio of the PBL amount to investment expenditures (i.e., investment coverage by the loan) is an important factor. If the loan can only cover a small portion of a firm's investment, the PBL access effect should be weakened. We simply assume that a firm's investment scale is proportional to its fixed assets and use fixed assets as the denominator. We do not have the data on the loan amount of each PBL. Alternatively, we use the count of pledged patents as the proxy. The ratio is thus defined as the count of pledged patents over a firm's fixed assets right before the access year. We then divide the treated firms into two groups by the median of the ratio and generate two corresponding dummies, *Low coverage* and *High coverage*. We rerun the baseline regressions by replacing *Post*Treatment* with *Post*Treatment*Low coverage* and *Post*Treatment*High coverage*. As shown in panel C, no matter which dependent variable is used, the coefficient on *Post*Treatment*High coverage* is significantly negative while the coefficient on *Post*Treatment*Low coverage* is less significant and much smaller in magnitude. It supports the view that the investment coverage by the PBL is important to firms' innovation decisions.

If our story of R&D resource reallocation is true, one should expect the adverse effect to be more pronounced among those treated firms expanding their scale more aggressively. The reason is that when a firm is expanding more aggressively, more R&D resources would be diverted from high-quality innovation. To measure the extent of a firm's expansion upon its PBL access, we use the annual change of its fixed assets in the access year. We then divide the treated firms into two groups by the median of this ratio and generate two corresponding dummies, *Low expansion* and *High expansion*. We rerun the baseline regressions by replacing *Post*Treatment* with *Post*Treatment*Low expansion* and *Post*Treatment*High expansion*. As shown in panel D, the coefficient on *Post*Treatment*High expansion* is much larger in magnitude and also more significant than the coefficient on *Post*Treatment*Low expansion*. It is particularly so when *HQ_pat_dum* is used as the dependent variable. It is consistent with our hypothesis that the adverse effect is more pronounced when firms expand their scale more aggressively.

Last, we perform the heterogeneity analysis of industry types. In high-tech industries, innovation competition is more intense. Consequently, the opportunity cost to innovate less is high: a firm may put itself in a very bad situation when its competitors catch up by innovating more. In this aspect, firms in high-tech industries would be less likely to reallocate their R&D resources. Regarding the extent of financial constraints, on the one hand, firms in high-tech industries are involved in more innovation activities, the output of which is less likely to be collateralized, making it harder for these firms to obtain bank loans. On the other hand, high-tech firms, once meeting certain conditions, can enjoy a preferential corporate income tax rate of only 15% and receive strong support from local governments (Chen, Liu, Suárez Serrato, & Xu, 2021), resulting in more internal funds available to finance their innovation. Consequently, it is ultimately an empirical question whether the adverse effect is more pronounced among high-tech firms or not.

We thus rerun the baseline regressions by replacing the interaction term with its interactions with two industry dummies, a high-tech dummy and a non-high-tech dummy. A treated firm is defined as high-tech if it belongs to a high-tech industry based on its 3-digit industry code; otherwise, it is defined as non-high-tech; two industry dummies are defined accordingly. The results in panel E reveal a complicated picture. When *Patent1_dum* is examined, the coefficient on *Post*Treatment*High-tech* is much larger in magnitude than the coefficient on *Post*Treatment*Non-high-tech*. Whereas, when *HQ_pat_dum* is examined, the coefficient on *Post*Treatment*Non-high-tech* turns larger while the coefficient on *Post*Treatment*High-tech* turns insignificant. It seems that innovation competition in high-tech industries matters: upon scale expansion, high-tech firms rationally reallocate their R&D-related resources such that though overall invention patenting is adversely influenced, the higher quality portion is somewhat sustained.[30]

5. Other consequences

Our hypothesis also predicts that firms would tend to expand its capital with the PBL access. To test whether the firm's total assets substantially increased after the access, we rerun the baseline regressions by using the log of total assets in year *t* as the dependent variable. Accordingly, firm size is dropped from the control variables. As shown in Table 7, no matter whether control variables are included (column 2) or not (column 1), the coefficient on the interaction term remains significantly positive. Its magnitude in column 2 indicates that a firm's total assets would increase by 21% following its access to PBLs. Putting together, it suggests that an innovative firm, once obtaining PBLs, tends to expand its capital while producing less high-quality innovation.

One may be concerned that there is a positive mechanical relationship between the PBL access and total assets. Specifically, given that the firm-level data is based on balance-sheet reports and a firm's total assets are equal to its total debt plus owners' equity, the positive relationship between changes in debt and changes in assets may be mechanical. To rule out the possibility, we use the log of total sales as the dependent variable and rerun the regressions. As shown in columns 3 and 4 in Table 7, the coefficient on the interaction term remains significantly positive no matter we include control variables or not. Its magnitude in column 4 indicates that a firm's total sales would increase by 12.1% following its PBL access. Therefore, we are more confident that it is unlikely that the positive relationship between the PBL access and total assets is mainly driven by the mechanical relationship between total debt and total assets.

If our story is true, firms initially having invention patents are expected to expand their scale after the PBL access. If the size effect is insignificant among these firms, it would cast serious doubt on our main hypothesis. We thus repeat the regressions using *Post*-*Treatment*Having no invention patent* and *Post*Treatment*Having invention patents* to replace *Post*Treatment*. As shown in panel B, no matter which size measure is used, both coefficients are significantly positive with comparable magnitude, indicating that both types of

[30] So far, we use the subsample of treated firms initially having invention patents and their matched control firms to draw conclusions. One may be concerned that using a subsample may result in estimation bias. To check the robustness, in OA Table 8 we repeat the regressions of panels C to E in Table 6 by using the full matched sample and reach similar results.

Table 7
Size effects of PBL access.

	(1)	(2)	(3)	(4)
Dependent variable	Ln(TA)		Ln(Sales)	
Panel A. Average effect				
Post*Treatment	0.221***	0.210***	0.115***	0.121***
	(6.60)	(6.29)	(3.40)	(3.83)
Post	−0.073***	−0.059***	−0.049***	−0.059***
	(−5.51)	(−4.72)	(−3.51)	(−4.31)
Observations	9532	9532	9518	9518
Adjusted R^2	0.930	0.932	0.915	0.921
Panel B. Heterogeneous effects of initial innovation capacity				
Post*Treatment	0.242***	0.235***	0.122**	0.113**
*Having no invention patent	(5.30)	(5.12)	(2.28)	(2.29)
Post*Treatment	0.210***	0.195***	0.111***	0.126***
*Having invention patents	(4.86)	(4.57)	(2.76)	(3.33)
Post	−0.073***	−0.059***	−0.049***	−0.059***
	(−5.51)	(−4.72)	(−3.51)	(−4.31)
Observations	9532	9532	9518	9518
Adjusted R^2	0.930	0.932	0.915	0.921
Panel C. Heterogeneous effects of initial firm size				
Post*Treatment	0.186***	0.168***	0.074*	0.093**
*Large size	(4.62)	(4.36)	(1.81)	(2.34)
Post*Treatment	0.257***	0.253***	0.157***	0.150***
*Small size	(5.18)	(4.98)	(3.18)	(3.37)
Post	−0.073***	−0.059***	−0.049***	−0.059***
	(−5.50)	(−4.72)	(−3.51)	(−4.31)
Observations	9532	9532	9518	9518
Adjusted R^2	0.930	0.932	0.915	0.921
Control variables		Yes		Yes
Firm dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes

This table estimates the effect of the PBL access on firm size by using the matched sample. The variables are defined in OA Table 1. In columns 1 and 2, the dependent variable is the log of total assets. In columns 3 and 4, the dependent variable is the log of total sales revenues. For all regressions, standard errors are clustered at the firm level. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

firms expand after the PBL access.

Additionally, if our story is true, one should expect that scale expansion after the PBL access happens among both small firms and large firms as we have found that among both types of firms the PBL access negatively influences the likelihood of having high-quality innovation. We thus repeat the regressions using *Post*Treatment*Small size* and *Post*Treatment*Large size* to replace *Post*Treatment*. As shown in panel C, when the log of total assets is used as the dependent variable, both coefficients are significantly positive and the magnitudes are comparable, indicating that both types of firms are expanding after the PBL access. It also confirms our previous argument that these large firms are on average financially constrained.[31]

It is no doubt a disaster in the long run if an innovative firm gives up doing any high-quality innovation. Nevertheless, it is interesting to figure out whether such a strategy results in higher returns in the short run or not. We thus use the return on assets (ROA) as the dependent variable and rerun the regressions. As shown in Table 8, the coefficient on the interaction term remains insignificant no matter whether we include control variables or not. Therefore, we conclude that the PBL access does not results in higher profitability, suggesting that firms' switching from innovation investment to capital investment may not be the best strategy even in the short run.

6. Discussion and conclusion

Consistent with the R&D resource reallocation hypothesis, we document that in China the access to short-term PBLs negatively influences firms' high-quality innovation propensities. We provide further evidence by documenting that this negative effect is more pronounced among firms initially having innovation patents, particularly when the PBL covers a larger portion of firm investment and when these firms expand more aggressively. We confirm the scale expansion effect by finding that the PBL access positively influences firms' subsequent scale.

From the practitioners' point of view, such a negative effect on firm innovation is somewhat disappointing because their major purpose of promoting PBLs is to boost small firms' innovation by alleviating their financial constraints. However, one can view it in a positive manner; that is, by alleviating an innovative firm's financial constraints, the loan access actually allows the firm to better

[31] It is interesting to find that the efficiency of production expansion seems lower among large firms. When the log of total sales is examined, the coefficient on *Post*Treatment*Large size* is smaller in magnitude than that on *Post*Treatment*Small size*.

Table 8
The effect of PBL access on profitability.

	(1)	(2)
Dependent variable	ROA	
Post*Treatment	−0.009	−0.002
	(−1.22)	(−0.29)
Post	0.013***	0.010***
	(3.34)	(2.61)
Control variables		Yes
Firm dummies	Yes	Yes
Year dummies	Yes	Yes
Observations	9532	9532
Adjusted R^2	0.669	0.676

This table estimates the effect of the PBL access on firms' profitability by using the matched sample. The variables are defined in OA Table 1. The dependent variable is the ROA. For all regressions, standard errors are clustered at the firm level. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

enforce its capital investment. Policy makers thus should not simply blame these firms for their deviation from high-quality innovation, but better understand the underlying rationales of this deviation and adjust the policy accordingly to better serve small innovative firms' long-term interest.

Our findings also suggest that the situation of only offering short-term loans needs to be improved before innovative firms can be better balanced between innovation and capital investment. In the short run, one potential improvement is to compensate when banks agree to issue long-term loans; the other is to provide loan guarantees to alleviate the refinancing risk related to short-term loans. In the long run, the improvement should be focused on the institutional development; that is, a developed legal system and bank regulations that tolerate long-term loan issuing can better serve the interest of an economy's long-term growth by distributing more long-term debt to innovative firms.

So far, due to higher financing costs, PBLs in China are not sustainable without governments' subsidies. In the long run, to make such a financial instrument viable, a well-functioned market for patents is needed so that patents can be more efficiently priced and transferred. With such a well-functioned market, patents would be more generally accepted as collateral by banks and thus innovative firms' refinancing risks would become lower. Moreover, thanks to the market efficiency, the informational difficulty of identifying high-quality innovative firms would be alleviated as owning valuable (i.e., highly priced) patents can be regarded as a reliable signal. Such a cost-efficient identification of high-quality innovative firms would be helpful not only to banks when loans are considered but also to public servants when innovation promotion policies, such as R&D subsidies, are implemented.

Unlike previous literature, several recent studies have demonstrated the importance of external debt providers (e.g., Acharya & Xu, 2017) and particularly of banks (e.g., Hochberg et al., 2018; Mann, 2018) for firms' innovation activities. Given the uncertain and often lengthy progress of innovation projects, a long-term collaboration is an important feature of such bank-firm relationships. The lack of long-term bank-firm relationships in China might explain why the issuance of PBLs appears to be an exception in Chinese bank lending rather than a common business practice like in more industrialized economies such as the U.S. and European countries.

When PBLs become available, firms with innovation success will be further rewarded.[32] If firms' innovation success rates are exogenously determined and firms' innovation propensities are unrelated to the PBL access, there would be a ratchet effect in the long run: the PBL availability makes firms with higher innovation success rates continuously better off by capturing more financial resources, whereas making firms with lower innovation success rates worse off. However, the above assumptions may not be valid. First, our major results imply that such a reward may not be accumulative as firms with PBLs are less likely to produce high-quality innovation. Consequently, it makes the situation complicated and such a reward may not transfer into a ratchet effect in the long run. Second, essentially, this paper investigates what a firm is going to do after obtaining a short-term loan (unlikely to be renewed) through patent pledge. During our examination period, the persistency of the PBL availability was still doubtful as it was at the trial stage. Without a time-persistent expectation of PBL availability, the ratchet effect may not exist. It is thus ultimately an empirical question whether such a ratchet effect exists. At the current stage we are unable to obtain data with a longer examination period to answer this question. We thus put it in our future research agenda once data become available.

Our study focuses on firms' short-term reaction to their PBL access. Therefore, it is still inconclusive how the PBL access would influence these firms in the long run. Future research can extend our study by tracking these firms over a longer period of time. Additionally, when detailed information on PBL contracts becomes available, many related research questions can be fully explored. For example, it is interesting to figure out how the structure of PBL contracts is influenced by patent quality and firm characteristics. It is also interesting to know how valuable each collateralized patent on average is and how large the related heterogeneity is.

[32] From an ex-ante perspective, the availability of PBLs tends to stimulate firms' innovation as it provides an additional benefit from innovation; that is, patent applications, once granted, can now be used as collaterals to obtain loans. Such a stimulation effect is not only valid for firms who already obtained PBLs but also valid for firms who did not. Since we have included the control group, such a stimulation effect is supposed to be controlled for.

Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chieco.2023.101918.

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Appendix A. Appendix

Appendix Table 1
Estimations using different thresholds to define high-quality innovation.

	(1)	(2)	(3)	(4)
Dependent variable	HQ_pat15_dum		HQ_pat25_dum	
Post*Treatment	−0.046**	−0.044**	−0.086***	−0.084***
	(−2.48)	(−2.40)	(−4.33)	(−4.22)
Post	0.020**	0.019**	0.023**	0.022**
	(2.12)	(2.02)	(2.44)	(2.31)
Control variables		Yes		Yes
Firm dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observations	9532	9532	9532	9532
Adjusted R^2	0.290	0.290	0.310	0.310

This table estimates the effect of the PBL access on other measures of firms' high-quality innovation propensity by using the matched sample. The variables are defined in OA Table 1. The dependent variables are *HQ_pat15_dum* and *HQ_pat25_dum*, respectively. For all regressions, standard errors are clustered at the firm level. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Appendix Table 2
The effect of PBL access on high-quality innovation propensity, robustness check.

	(1)	(2)
Dependent variable	Patent1_3y_dum	
Post*Treatment	−0.084***	−0.085***
	(−3.38)	(−3.40)
Post	0.012	0.012
	(1.05)	(1.06)
Control variables		Yes
Firm dummies	Yes	Yes
Year dummies	Yes	Yes
Observations	9532	9532
Adjusted R^2	0.378	0.378

This table estimates the effect of the PBL access on firms' high-quality innovation propensity by using *Patent1_3y_dum* as the dependent variable. We restrict the sample to the matched sample. The variables are defined in OA Table 1. For all regressions, standard errors are clustered at the firm level. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Appendix Table 3
The effect of PBL access on low-quality innovation propensity.

	(1)	(2)	(3)	(4)
Dependent variable	Patent2_dum		Patent3_dum	
Post* Treatment	−0.005	−0.006	0.0001	−0.001
	(−0.18)	(−0.24)	(0.01)	(−0.04)
Post	−0.014	−0.013	−0.011	−0.011
	(−1.12)	(−1.06)	(−1.29)	(−1.36)
Control variables		Yes		Yes
Firm dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes

(*continued on next page*)

Appendix Table 3 (*continued*)

	(1)	(2)	(3)	(4)
Dependent variable	Patent2_dum		Patent3_dum	
Observations	9532	9532	9532	9532
Adjusted R^2	0.554	0.554	0.495	0.496

This table estimates the effect of the PBL access on firms' low-quality innovation propensity by using the matched sample. The variables are defined in OA Table 1. The dependent variables are *Patent2_dum* and *Patent3_dum*, respectively. For all regressions, standard errors are clustered at the firm level. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Appendix Table 4
Estimations controlling for city-year and industry-year fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	Patent1_dum				HQ_pat_dum			
Post*Treatment	−0.081***	−0.081***	−0.079***	−0.078***	−0.045**	−0.043**	−0.045**	−0.043**
	(−3.16)	(−3.13)	(−2.83)	(−2.77)	(−2.29)	(−2.21)	(−2.11)	(−2.01)
Post	0.011	0.011	0.012	0.011	0.019*	0.018*	0.016	0.015
	(0.95)	(0.92)	(0.94)	(0.89)	(1.91)	(1.80)	(1.57)	(1.43)
Control variables		Yes		Yes		Yes		Yes
Firm dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Indu-year FEs	Yes	Yes			Yes	Yes		
City-year FEs			Yes	Yes			Yes	Yes
Observations	9532	9532	9532	9532	9532	9532	9532	9532
Adjusted R^2	0.378	0.378	0.367	0.367	0.303	0.303	0.285	0.286

This table estimates the effect of the PBL access on firms' high-quality innovation propensity by including city-year dummies and industry-year dummies, respectively. We use the matched sample. The variables are defined in OA Table 1. The dependent variables are *Patent1_dum* and *HQ_pat_dum*, respectively. For all regressions, standard errors are clustered at the firm level. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Appendix Table 5
The effect of two-year lagged PBL access on high-quality innovation propensity.

	(1)	(2)	(3)	(4)
Dependent variable	Patent1_dum		HQ_pat_dum	
Post*Treatment	−0.096***	−0.096***	−0.114***	−0.111***
	(−2.60)	(−2.61)	(−3.94)	(−3.90)
Post	0.036***	0.037***	0.026***	0.024***
	(3.23)	(3.21)	(3.06)	(2.84)
Control variables		Yes		Yes
Firm dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observations	8528	8528	8528	8528
Adjusted R^2	0.374	0.374	0.292	0.292

This table estimates the effect of the PBL access on firms' high-quality innovation propensity by lagging the dummy *Post* by two years. We use the matched sample. The dependent variables are *Patent1_dum* and *HQ_pat_dum*, respectively. For all regressions, standard errors are clustered at the firm level. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Appendix Table 6
The effect of PBL access on high-quality innovation at the intensive margin.

	(1)	(2)	(3)	(4)
Dependent variable	Patent1		HQ_pat	
Post* Treatment	−0.337	−0.304	−0.328	−0.391
	(−1.26)	(−1.33)	(−1.01)	(−1.30)
Post	−0.271	−0.274	−0.095	−0.045
	(−1.42)	(−1.56)	(−0.43)	(−0.21)
Control variables		Yes		Yes
Firm dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observations	2514	2514	1683	1683
Pseudo R^2	0.549	0.553	0.468	0.473

This table estimates the effect of the PBL access on firms' high-quality innovation by using the matched sample. The variables are defined in OA Table 1. The dependent variables are *Patent1* and *HQ_pat*, respectively. Poison specifications are estimated. For all regressions, standard errors are clustered at the firm level. T-statistics are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

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