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Could government lead the way? Evaluation of China's patent subsidy policy on patent quality

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ABSTRACT: As China aimed to transform her growth into an innovation-driven model, we study the impact of China's effort to promote technology inventions. By linking to Google Patents, we compile a comprehensive set of patent quality indicators. Based on Chinese provincial panel data from 1995 to 2010, we find that the effect of the implemented patent subsidy policies on quantity, as well as various quality metrics of patents, was significantly positive. Moreover, the explanation power of subsidy policies on both patent quantity and quality diminished as time goes by. We also find that the effect of these policies depended on the growth rate of experienced innovators rather than entrants. Since the implemented policies we study in this paper were designed to focus on subsidizing expenses incurred during the patenting process, our results show that the provided partial funding led the way for improving China's patent quality.

JEL classification: O31, O34, O38.
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Abstract

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1 Introduction

This paper is motivated by the unprecedented surge of patenting in China.[1] Grants for Chinese invention patents began to rise in the year 1999 (in either absolute or rate terms). The annual growth rate of China's invention patent grants between 1995 and 1998 was around 0.35% per year, but jumped to 42% per year between 1999 and 2010 (Figure 1). One may wonder whether such a dramatic rise in China's invention patents signals the increase of innovation quality and the development of innovation ability. Moreover, China was going through a series of important institutional transitions at the time of the patent surge. The Chinese government started highlighting the role of the patent system in promoting technology innovation in 1997. Shanghai launched patent subsidy policies (PSP) in 1999, which was quickly followed by other local governments. In this paper, we are interested to find out the impact of these subsidy policies: whether they had a significant impact and whether the impact was permanent.

[Figure 1 about here]

From the perspective of public policy, if the impact of subsidy policies on the quality of patents can be estimated more accurately, then it will be much more useful for policymakers to understand the effectiveness of the implemented policies and design ones that raise the quality of patents and nurture creativity. We find that the implemented patent subsidy policies were designed to only subsidize expenses incurred during the patenting process and did not cover R&D expenditures during the pre-patenting stage. Thus, is it possible that such partial funding implies the possibility of local governments only leading the way for improving patent quality rather than being the main driver?

Why do we care about the resulted Chinese patent quality in China's effort to promote technology innovation? First, patent quality indicators are important metrics of invention outputs besides patent quantity measures. Patent quality can help reveal research efficiency, and provide more

[1]There are three types of patents in China: invention patent, utility model patent, and design patent. Because of the technological importance of inventions, we will focus on granted invention patents. All patents in this paper refer to invention patents.

insights for innovation capacity, technological change, and productivity growth. If the quality of Chinese patents has kept pace with the increase of its volume, then it is possible that China is transforming herself from a technological follower to a technological leader and is achieving its goal of catching-up with developed countries. Second, some assert that although China is ramping up its patent applications, their value is questionable. As a matter of fact, unlike other patent offices which have well-documented data on patent qualities, CNIPA (China National Intellectual Property Administration, previously known as SIPO) releases very limited information for the quality of its patents. If we can provide some remedies to these data drawbacks, then the question over Chinese patent quality can be better addressed. Third, it is obvious that innovators have to confront much higher uncertainty and use more research input to produce patents of good quality. Therefore, to reduce the market failure in innovation, more incentives should be given to the quality of patents, rather than the quantity of patents.

This paper makes two key contributions. Our first contribution is to provide a multi-facet toolbox for assessing China's patent quality based on a unique and comprehensive database. By linking the Chinese patent database (released by CNIPA, 1985- 2012) with Google Patents database[2] containing forward citations and claims, our database not only overcomes the shortcoming of CNIPA data, but also allows us to analyze multiple patent quality metrics. We build upon Suzuki (2011) and separate the quality of patents into technological quality (including forward citations, claims, and the number of inventors) and economic quality (including withdrawal rate and renewal rate). Our second contribution is to evaluate the impact of patent subsidy policies on the quality of China's invention patents using two-way fixed effects regression as our identification strategy. Based on provincial panel data from 1995 to 2010, we find that the effect of patent subsidy policies by provincial governments on the technological quality of Chinese patents was significantly positive, whereas the effect on the economic quality of Chinese patents was inconclusive. Moreover, we find that the overall effect of patent subsidy programs on patent quantity and quality growth diminished as time goes by, indicating that the effect of the implemented programs on the growth of patenting innovation was not long-lasting.

[2]http://www.google.com/patents

We also made two discoveries in this paper. Our first discovery is to find the relative importance of the dynamic effects of government subsidy. We separate the impact of government subsidy programs into short-run adjustments (or shocks) and long-run (or persistent) impacts. We find that it takes time for the effect of subsidy programs to stabilize. Short-run adjustments on both quantity and (technological) quality takes at least five years to approach the long-run impact. Our second discovery is to find the special role played by experienced innovators in China. Our results demonstrate that the effect of patent subsidy policies on the technological quality of patents depended on the growth rate of experienced innovators, rather than the growth rate of entrants. Our discoveries pointed to the possibility of the government only leading the way for building innovation capacity. The enduring growth in quality originated more from the innovators themselves, especially experienced innovators.

We contribute to an important stream of research on examining patent quality by providing a comprehensive set of useful measures for Chinese patents. Since Chinese patent data have no commonly used indicators of patent quality, several attempts have been made to reflect the quality characteristics of Chinese patents using other metrics. The pioneering work of Li (2012) used patent grant rate to show the dynamic changes of Chinese invention patent quality from 1998 to 2006, while Dang and Motohashi (2015) analyzed the invention patent quality of Chinese industrial enterprises using the number of nouns in patent claims. Some studies were based on patent renewal period data to track the economic value of Chinese expired invention patents, such as Zhang and Chen (2012) and Zhang et al. (2014). Studies that used forward citations were compiled from patents filed abroad. From the PATSTAT database, Fisch et al. (2016) used the number of forward citations received by 155 Chinese leading universities from 1991 to 2009, and Fisch et al. (2017) used citation lag of a small stratified sample of China's invention patents with priority years between 2000 and 2010. However, we think that adopting a simple quality indicator of patents or relying on a selected sample of patents filed abroad is not sufficient to provide information about the overall quality features of inventions in China. To reduce the measured variance in quality and overcome the drawback of Chinese patent data, we collect information on claims and forward citations using Google Patents.

In addition, we use multiple indicators, including the number of inventors, withdrawal rate, and renewal rate, to analyze the dynamic quality features of Chinese invention.

We also contribute to another important stream of literature focusing on the influence of government subsidy on the explosive surge of patents in China. Previous studies have found that the explosion of patent filings at CNIPA was driven by factors other than underlying innovative behavior (Huang et al., 2017; Prud'homme and Zhang, 2019), including government subsidies that encourage patent filings directly (Eberhardt et al., 2017; Li, 2012). Similar results were found using Chinese industrial enterprise patenting data (Dang and Motohashi, 2015). Although Fisch et. al (2016) found that subsidy programs promoting research excellence were a significant driver of patent quantity and quality, their study covered only the top 155 universities in China. Unlike the prior studies which largely focused on the impact of patent subsidy programs on the rise of patenting volume, this paper provides a systematic framework to investigate whether and how the patent subsidy policies influence the quality of patented innovations in China. Thus, we fill the gap in the literature by providing a comprehensive examination of the influence of policy on patent quality.

The rest of the paper is organized as follows. Section 2 reviews the measurement of patent quality and shows the summary statistics of the quality features of invention patents in China. Section 3 describes the implementation and evaluation of patent subsidy programs. Section 4 presents the data and empirical results. Section 5 contains the results of a number of robustness tests. Section 6 concludes.

2 Quality Features of Invention Patents

It is well known that patents vary enormously in their value. Since patents are seldom marketed, their actual value is in general unobserved. Therefore, various indicators have been used to adjust for variation in the quality of patents (Lanjouw and Schankerman, 2004; Trajtenberg, 1990). One of the widely used indicators is the number of forward citations, which reflects the technological importance of the patent. Other important indicators that have been used include the number of claims in the patent application (Tong and Frame, 1994), the number of inventors (Wuchty et al., 2007), withdrawal rate (Long and Wang, 2016), patent value based on patent renewal fee (Zhang et al., 2014), and novelty of patents (Jia et al., 2019).

2.1 Chinese Patent Quality Dataset

Our study of Chinese invention patent quality is based on the CNIPA database and Google Patents. The CNIPA database provides a rich description of all patent applications that have been filed at CNIPA since 1985 and offers some patenting information at the provincial level. However, the shortcoming of this database is that it includes no commonly used patent quality measures such as patent forward citations and the number of claims. Google Patents, fortunately, provides these two measures for all Chinese patent applications by combing through the patent application documents. Moreover, Google Patents updates forward citation data of each patent according to the information on backward citation. We thus link it with the CNIPA database. Specifically, Google Patents records patent information based on the publication number, and each webpage records one patent application.[3] It is noted that according to the Chinese invention patent publication number system, one invention patent may have two types of publication number: unexamined patent publication (ends with "A") and granted patent publication (ends with "B"). Thus, if the invention patent is granted, there could be cases where one patent has two web pages in Google Patents, where the claims information can be recorded differently.[4] In order to obtain full information of patent citation and claims, the web pages of both publication numbers are crawled and cleaned.

For the invention patents issued before 1989 and issued between July 2007 and August 2016, we match Google Patents with the CNIPA database using the publication number. However, for applications published between 1990 and July 2007, the CNIPA database only records the unexamined patent publication number. We fix the problem by crawling the entire Chinese invention patent during this period on Google Patents to obtain full information of patent citation, claims,

[3]For instance, see https://www.google.com/patents/CN101728830B, which has a total of 3 claims and 2 backward citations.

[4]For example, application CN200910114583 was published as CN101728830A (https://www.google.com/patents/CN101728830A) first and then given a granted patent publication number CN101728830B (https://www.google.com/patents/CN101728830B) after it was granted. Moreover, there are fewer claims on the granted patent number page, which is probably narrowed down because of the substantial examination.

and application number. Since almost all of the invention patents in the CNIPA database are found in Google Patents, we can use the patent application number to get a perfect match.

This is a novel database, some of the papers that also use this database include Sun et al. (2019), Sun et al. (2021), and Howell et al. (2020). However, we are the first to examine the effect of provincial patent subsidy programs on patent quality using this database.

2.2 Indices for Chinese Invention Patent

We utilize our unique database and use five metrics to measure the quality of China's invention patents. We build upon Suzuki (2011) and separate the quality of patents into technological quality and economic quality. Forward citations, claims, and the number of inventors are considered in this paper to be mainly associated with technological quality, while withdrawal rate and renewal rate are thought to be more correlated with economic quality. We also examine the number of invention patent applications and the number of invention patent grants to measure the change in quantity of China's patenting innovation output. Among the two, number of grants represent the filtered quantity by the examination office. We discuss the special features of these five quality metrics from CNIPA in the following sections.

2.2.1 Technological Quality: Forward Citations, Patent Claims, and Number of Inventors

Forward citations occur when the patent is fundamental to subsequent innovations. Therefore, a larger number of forward citations is often associated with the patent having higher quality, which is theoretically and empirically confirmed by Griliches (1990), Trajtenberg (1990), and Jaffe et al. (2002).

Considering that more than 50% of forward citations of an invention patent occur within the first 5 years (Nagaoka et al., 2010), we study patents filed between 1985 and 2010 but include citations up to August 2016 so that even a patent filed in 2010 can have a large proportion of the forward citations in its entire life. This helps largely reduce the problems of underestimation for younger patents due to the truncation of forward citations.

Figure 2 presents the average number of forward citations received by an invention patent filed in China from 1985 to 2010. There was clearly an increasing trend for the average forward citations in China in the period of 26 years. The average number of forward citations rose from 1.2 pieces in 1986 to 2.5 pieces in 2002, indicating progress in the technological quality of Chinese invention. Even for most recent years, such as 2010, for an average invention, there were 1.9 pieces of forward citation although its forward citations could only be observed within five years, compared to thirty years for the inventions filed in 1985. In other words, the increasing trend could be more obvious if all inventions have the same length of citation span.

This finding is consistent with Fisch et al. (2016). They found that there has been a dramatic increase in forward citations of top 155 universities' inventions from 2000 to 2004, with an annual growth rate of 52%. Hu and Mathews (2008) used Chinese invention patenting records at the USPTO (United States Patent and Trademark Office) and demonstrated that the increase in forward citations is particularly significant since 2001. Zhu (2021) also documented the improvement of China's highly cited articles, exceeding the world's average level since 2015.

[Figure 2 about here]

Claims in the patent specification delineate the property rights protected by the patent. More claims means more technology contributions and solutions for the technical difficulties. Figure 2 shows the annual average number of claims for invention patents between 1985 and 2010. We can see that the number of claims for an average invention had a significant rising trend, from 4.2 in 1993 to 6.2 in 2010.

The number of inventors in the patenting is also an important determinant of the technological value of a patent. Compared to an individual inventor, multiple inventors can bring greater collective knowledge and effort for the innovation, especially in technological areas of high complexity and difficulty. Based on a comprehensive analysis of 2.1 million patents, Wuchty et al. (2007) found that teams produce more highly cited and higher impact research than individuals (solo inventors) do and this advantage is increasing over time. A similar pattern was observed in China. It can be seen from Figure 2 that the average number of inventors was 2.1 in 1995 and increased to 3.4 in 2010.

2.2.2 Economic Quality: Withdrawal and Renewal Rates

There are three kinds of patent application outcomes: granted, rejected and, withdrawn. The former two outcomes are determined by whether the patent satisfies the patentability requirements, and the last outcome depends on the tradeoff between the cost of application and expected profit from receiving the patent. The applicant will terminate the application if the expected revenue from the patent is less than the application cost. In other words, patents with lower economic value are more likely to be withdrawn by the applicants themselves. The withdrawal rate exhibits a significant decreasing trend since 1993, indicating that the expected economic quality of patent applications was rising (Figure A1 in Appendix).

We also include patent renewal data to examine other economic aspects of patent quality. Rational patentees make renewal decisions based on the value of the patent right obtained by renewal (Schankerman and Pakes, 1986). If the patent has little or no value, and as such, the patentee will cease to renew it. CNIPA charges tiered prices for the renewal of patent rights and increases the renewal fee every three years.[5] Therefore, the longer a patent right is kept, the greater its economic value/quality. It should be noted that only a small number of valuable patents are kept until the patent expiration date, which provides a useful channel to observe the variation of economic quality among patents. Several studies (Zhang and Chen, 2012; Zhang et al., 2014) have attempted to estimate the value of invention patents in China using renewal payment model based on expired invention patent data of CNIPA (1985-2009) and found that patent value from Chinese owners is much lower than that of overseas owners (U.S., Japan, and European countries).

We used cessation information to identify which patents are in force for different durations and calculated separate renewal rates (Figure A2 in Appendix). We assigned the number of applications in a given year as the denominator. For the numerator, we tabulated the number of filed patents

[5]900 yuan will be charged each year for the first three years, and then 1200 yuan, 2000 yuan, 4000 yuan, 6000 yuan, 8000 yuan each year for the 4-6 years, 7-9 years, 10-12 years, 13-15 years, and 16-20 years respectively.

that were approved eventually in the given year with more than 5 years between the application date and the cessation date to calculate the 5-year renewal rate (Chart (a)). In Chart (b), we replace the application date with grant date and recalculate the numerator. It is easy to infer that the second renewal rate is smaller than the first one since the approbations of patents take time. The renewal rates show a marked rise since the early 1990s, indicating that the economic quality for an average invention patent was rising in recent years. Since cessation rate and renewal rate are two sides of the same coin, we chose to only use renewal rate in our model to represent one of the dimensions of economic quality.

3 Patent Subsidy Policies and Invention Patent Quality

3.1 The Implementation of Patent Subsidy Policies in China

As China became a member of WTO, the government became aware of the importance of intellectual property rights and began to encourage patenting. The patent subsidy policies we study in this paper were launched by provincial governments starting at the end of the 1990s following the guidelines issued by the central government. Local governments initiated the implementation of patent promotion policies to motivate and help inventors to increase both the quantity and quality of patent applications by cultivating the strength of inventors in science and technology to achieve self-dependent intellectual property. Among these patent promotion policies, a batch of subsidy measures that reimburse expenses related to the patenting process was implemented.

Since the guidelines contained neither quantitative targets nor suggested policy instruments, each local government was free to choose the timing to launch PSP and the forms of subsidies. This can be seen from the large variations in the timing, the design, and the amount of subsidies across different provinces. Shanghai was the first to launch patent subsidy policies in 1999 to promote patenting invention in its jurisdiction. Beijing, Tianjin, Guangdong, Jiangsu, and Chongqing quickly followed. By the end of 2007, 30 provincial-level governments had launched some patent subsidy programs (Figure 1). Details of the implemented patent subsidy programs vary between provinces.

After studying the patent subsidy policies including revised ones (94 documents in total)[6], we find that each province designed policies to support innovation and patenting according to their own needs. Some governments launched PSP late and mainly focused on subsidizing application fees (such as Ningxia). Other governments chose to offer additional grant-contingent subsidies to award the higher quality patents. The wide variation and heterogeneity among PSP across provinces implies decentralization of policies implemented during this time period. The launch years of PSP and selected policies is summarized in Table A1 in Appendix. Our observation of the vast regional difference echoes the discussion in Li (2012) and Dang and Motohashi (2015).

From public government documents, we reached three interesting observations. First of all, invention patents have priority over the other two types of patents. Some provinces issued patent subsidy documents stipulating that only payments made during the application, grant and/or maintenance stages of invention patents can be reimbursed. Moreover, invention patents were given higher amounts of reimbursement compared with the actual payment for patent application processing and related attorney fees.

Second of all, it is interesting to know that not all of the fee items were compensated. Thus it is impossible for the patent applicant to obtain extra benefits exceeding its costs through government subsidies. Take Shanghai for example, 80% of the actual payment during the application of domestic invention patents were reimbursed. In Beijing, the reimbursement standard for each domestic invention patent is no more than 950 yuan for the application fee and 1200 yuan for the substantial examination fee. Over 70% of provinces treated filing fees and substantial examination fees (only eligible for the invention patent) as the funding target, leaving the applicants to make payments for annual fees, surcharge for claims, pages in excess of a specified number, and agent fees. In most cases, applicants can only apply for the reimbursement of filing fees after CNIPA has accepted the patent application and filing fees have already incurred. However, in some provinces, such as Zhejiang, Shandong, Yunnan, Hebei, Anhui, and Hubei, only after the patent was granted by CNIPA, can the filing fees and/or substantial examination fees incurred be partly reimbursed. Patent subsidy

[6]The policy documents were mainly collected from www.pkulaw.cn, www.lawyee.net, and government official websites.

policies were designed to only subsidize expenses incurred during the patenting process and did not cover expenditures during the R&D stage. Such partial funding indicates that the governments are only leading the way for patenting innovation rather than being the main driver.

Lastly, we find that patent subsidy policies adopted the principle of giving priority to excellence. All units and individuals were encouraged to procure patent rights for their inventions that meet the patent application requirements. However, constrained by limited funds, not all patent holders in the jurisdiction were eligible for applying for the reimbursement. The most common funding form is to set higher funding standards for the big enterprises and business groups who have self-dependent intellectual property, such as Patent Pilot Enterprise (*shi-dian*) and Patent Demonstration Enterprise (*shi-fan*). In addition, many provinces also prioritize excellence by promoting applicants in areas with High-and-New Technology (*gao-xin-ji-shu*), or certain strategic industries that are in line with the comparative advantages of the province. On the other hand, local governments set lower funding standards for ordinary patent applicants. Patent Pilot Enterprise and Patent Demonstration Enterprise were carefully selected through the process of expert review, discussion, and consultation. Only those with outstanding performances in technology innovation can be authorized and become the nurture and development focal of the provincial-level patent work. Aside from prioritizing excellence, some provinces set up funding to reward the patent award receivers both at the central and the provincial level to inspire inventors to produce important patents.

We compare the dynamics of propensity to patenting between experienced innovators and entrants in Table A2 in Appendix (experienced innovators are defined as in Section 4.3). From Table A2 we find that both the number of applicants and applications have increased with the length of PSP treatment. Moreover, experienced innovators continue to outpace entrants over time. In the first treatment year, the experienced innovator submitted 3.51 times applications of the entrants' applications on average, which is increased to as much as 5.33 times of the entrants' applications after ten years of PSP treatment. Therefore, it is possible that PSP can increase patent quality by encouraging experienced innovators to file for high-quality patents.

3.2 The Evaluation of Patent Subsidy Policies on Invention Patent Quality

As demonstrated in the literature by Li (2012) and Dang and Motohashi (2015), China's patenting volume increased much faster than R&D and the puzzle of why Chinese patenting has grown so much cannot be solved by merely looking at the effect of R&D. To solve this puzzle, we incorporate the impact of patent subsidy policies on the propensity to patent and hence on the quantity and quality of Chinese patents.

Patent subsidy policies and other government support for innovation-related activities has been justified on the basis of correcting for market failures or solving the difficulty of appropriating all the returns to an innovation. It is argued that with positive externalities, the private sector invests less in innovation than is socially desirable. Hence, the government needs to provide incentives to the private sector to compensate for the gap between the private and social returns to innovation to ensure that the social optimum is achieved.

China's patent subsidy policies also aim at lowering the cost of applying for patent protection. However, the influence of patent subsidy programs on the average level of patent quality is unclear. On the one hand, patent subsidy programs can lower patenting costs for innovators. On the other hand, patent subsidy programs attract a large number of inexperienced innovators who may produce patent applications with low quality, thus resulting in a lowered average patent quality at the aggregate level.

[Table 1 about here]

To examine whether patent subsidy policies improve the average quality of invention patents in China, we first compare changes in the quality of invention patents at the provincial level before and after patent subsidy programs. Table 1 presents the descriptive statistics of invention patent quantity and quality. As shown by the t-tests, it is apparent that both the number of patent applications and grants increased significantly with patent subsidy programs. Moreover, patent quality measured by the number of patent forward citations, patent claims, and inventors also increased significantly with the launch of patent subsidy programs. In addition, we find a decline in the withdrawal rate and a rise in the renewal rate.

We focus on whether the changes of invention patent quality were affected by patent subsidy policies. Considering that it takes time for information on the patent subsidy programs to be diffused, we follow the concept in Li (2012) and use two variables to measure the effect of patent subsidy programs. A binary variable ($PSP1$) is used to identify the persistent effect or long-run effect of patent subsidy policies (β_ℓ), which takes a value of 1 after the province launches its patent subsidy program and 0 otherwise. The second variable ($PSP2$) is used to represent the short-run adjustment to the long-run effect (β_s).

$$PSP1_{it} = \begin{cases} 0, & \text{if } t < t_0 \\ 1, & \text{otherwise} \end{cases} \tag{1}$$

$$PSP2_{it} = \begin{cases} 0, & \text{if } t < t_0 \\ -\lambda^{(t-t_0)}, & \text{otherwise} \end{cases} \tag{2}$$

The impact of subsidy programs is not instantaneous or constant; time is required for the information about the launch of subsidy programs in a province to be communicated to potential innovators. It is more likely that any positive or negative effect of subsidy programs will increase after the actual launch date. In contrast to Li (2012), $PSP2$ takes the general geometric form of $-\lambda^{(t-t_0)}$ in our framework, where t_0 is the year when the province first launches the program. In this paper, we allow the short-run adjustment of the subsidy program to approach the long-run effect with different speeds of geometric depreciation by the parameter λ, which is set to 0.6 for our baseline results. Our construction allows for a bigger deviation between short-run shock and long-run impact when subsidy programs are first launched, mirroring the commonly-observed uncertainty around new policies. Figure 3 exhibits how the speed of short-run adjustment approaching long-run impact differs by different values of λ. We discuss the reasonable range of λ in Section 5.

[Figure 3 about here]

Applying the framework of knowledge production function (Pakes and Griliches, 1984) into estimating patent production function for filings and grants (Hu and Jefferson, 2009; Li, 2012; Dang and Motohashi, 2015), we estimate a patent *quality* production function with our unique database. The quantity and quality outcome of invention patent applications is the dependent variable and a two-way fixed effects panel regression is specified as follows:

$$Pmeasure_{it} = \beta_0 + \beta_\ell\,(PSP1_{it}) + \beta_s\,(PSP2_{it}) + \theta X_{it} + province_i + year_t + \varepsilon_{it}, \tag{3}$$

$Pmeasure_{it}$ is measured by two quantity variables and five quality metrics introduced in Section 2.2 for province i in year t. The total number of invention applications ($lnApps$) and the total number of invention grants ($lnGrants$) measures patent quantity. The remaining five metrics assess different dimensions of patent quality. We take logarithms of the three quality variables: total number of claims ($lnClaims$), total number of forward citations ($lnFwd$), and total number of inventors ($lnInventors$).

Withdrawal and renewal rates enter equation (3) as ratios. We measure the withdrawal rate by taking the ratio of "the total number of withdrawals of the applied invention patents in year t of province i" to "the total number of applied invention patents in year t of province i". This index is denoted by $Rwithdrawal$. We measure the (5-year) renewal rate by taking the ratio of "the total number of granted invention patents in year t of province i that are active for 5 years or longer" to "the total number of granted invention patents in year t of province i". This index is denoted by $Rrenewal5$. [7]

The vector X_{it} contains 2 control variables. The control variables represent alternative explanations of China's patent surge. R&D expenditure is one of the most important factors of generating patents. Following the econometric literature on estimating the relationship between R&D and patents (Hausam et al., 1984; Crepon and Duguet, 1997; Li, 2012; Dang and Motohashi, 2015), we use real R&D expenditure with one year lag to control the effect of R&D (in logarithm, denoted by

[7] Let us make the definition clearer by a simple example. Suppose Patent A applied in year 2000 and was granted, then subsequently terminated the patent in year 2005. Patent A would be classified as being active for 5 years. Take one step further, if a province in year 2000 had 500 patent applications that were granted, among the 500 patents, 150 remained active for 5 years. Then, *Rrenewal5* for this province in year 2000 is $\frac{150}{500} = 30\%$.

$L.lnRD$). Since there are patent promotion policies on tax rebates for R&D expenses, this variable can help account for policies that targeted the pre-patenting stage. As for the second control, foreign direct investment (FDI) inflow represents technological opportunities brought by foreign firms for domestic firms to imitate and innovate, contributing to overall innovative performance (Hu and Jefferson, 2009; Zhang and Rogers, 2009). We take its logarithm and denote by *lnFDI*.[8]

The variables $province_i$ and $year_t$ indicate the province fixed effects and year fixed effects respectively. The year fixed effects account not only for the observed institutional change that coincided with the patent surge, but also takes into account the overall quantity change in patents. Moreover, this control can also help account for the Chinese legal environment as another force that helped foster the patent surge. ε_{it} is the error term.

4 Estimation and Results

Our analysis is based on a comprehensive dataset constructed from multiple official sources. Specifically, the exact launch year for patent subsidy programs for each province was gleaned from the series of annuals of Chinese Intellectual Property Rights which record important policies and practices of intellectual property management every year for each local government. Patent information was collected from Chinese CNIPA and Google Patents. Information on R&D expenditure was gathered from the series of Chinese Science & Technology Statistical Yearbooks.[9] The remaining data were collected from Chinese Statistical Yearbooks which provide rich information on direct investment in China to construct FDI stock.

4.1 Pre-treated Trend Test

It is not necessarily the case that provinces that are lagging in patenting become the first or last provinces to implement PSP. We find that there are no clear patterns between the ranking of

[8]Following Hall and Mairesee(1995), the depreciation rate of FDI was set at 15%, and the interest rate was set at 5%.

[9]China started the statistics of R&D expenditure at the provincial level in 1999. Consequently, we use the internal expenditure of scientific and technological activities to represent the innovation input at the provincial level from 1995 to 1998.

invention patent grants per 10,000 people and the launch year of PSP (Figure A3 in Appendix).[10] In addition, there is no clear association of PSP launching with economic variables in each province as shown by Dang and Motohashi (2015).

To assess the credibility of our empirical specification, a test between the treated and the controlled is used to see whether there are any significant differences in the pre-treatment trend. If the pre-treated trend between the treated group and the control group is parallel, then it is valid to consider β_s and β_ℓ as the short-run shock and persistent effect of patent subsidy programs. We use the sub-sample before the launching of patent subsidy programs as our test base, i.e. 84 observations in total from 1995 to 1998. The test equation is:

$$Pmeasure_{it} = \alpha_0 + \alpha_1 \left(trend_t\right) + \alpha_2 \left(trend_t \times treated_i\right) + \eta X_{it} + province_i + \rho_{it}, \tag{4}$$

where $trend_t$ is equal to $t - 1994$. $treated_i$ is a dummy variable of being treated or not, X_{it} is the set of controls, η_i is the treated province fixed effect, ρ_{it} is the error term.

[Table 2 about here]

To guarantee the variation of $treated_i$ and the distribution of the sample, we set the provinces which launched patent subsidy programs before 2001 as the treated group. That is to say, $treated_i$ equals to 1 if the province was treated before 2001 (6 treated provinces in total) and 0 otherwise. Table 2 shows the coefficient of the interaction term ($trend_t \times treated_i$) is insignificant, no matter what kind of invention patent quality measures is used, indicating that there is no systematic difference in pre-trends across treated and control provinces.

The results are robust across different definitions for $treated_i$. We performed the pre-treated trends test for (a) $treated_i$ equals to 1 if the province was treated before 2002 (12 treated provinces in total) and 0 otherwise, (b) $treated_i$ equals to 1 if the province was treated before 2003 (18 treated provinces in total) and 0 otherwise, and (c) $treated_i$ equals to 1 if the province was treated before

[10] There is no clear associations when we look at the relationship between PSP launch year and ranking of GDP per capita, ranking of GDP growth, or ranking of tax income growth in year 2000.

2004 (23 treated provinces in total) and 0 otherwise. The results were almost the same as shown in Table 2.

4.2 Baseline Results

The results from our estimation model equation (3), using various metrics of invention patents as the outcome variable, are shown in Table 3. Regression results reveal a positive and statistically significant correlation between patent subsidy policies and patent quantity. We also find that coefficients of $PSP1$ stay significantly positive in columns (3)-(5), which indicate that implementing patent subsidy programs has a persistent impact on technological quality. Coefficients of $PSP2$ on these metrics of invention patents are also consistently positive, which indicates short-run adjustments take place when these policies were implemented. Therefore, we find that time is indeed needed for the full effect of these subsidy programs to show. It is likely that there is a lot of noise when subsidy programs are first launched, thus it takes time for the effect of subsidy programs to stabilize. The overall effect of patent subsidy programs on patent quality, expressed as $\exp(\beta_\ell - \beta_s \lambda^{(t-t_0)})$, remains positive.

Columns (6)-(7) report estimated coefficients of patent subsidy programs on the economic quality of invention patents. The coefficients of both $PSP2$ and $PSP1$ on the ratio of withdrawal and renewal are statistically insignificant. The results suggest that whether a patent subsidy policy was implemented is uncorrelated with the economic quality of invention patents. As a matter of fact, the withdrawal decision during the application of patenting is often viewed as a rational choice of the patentee, which reflects the tradeoff between potential economic benefits of excluding others from exploiting an invention and the costs of preparing, filing, and maintaining the invention patent. In our study, this argument is supported and validated by the insignificant coefficient of patent subsidy policies on the ratio of patent withdrawal. Second, we find a similar relationship between patent subsidy and the ratio of renewal. Again, assuming that renewal decisions are based on economic criteria, patentees will renew their patents only if the value of holding them an additional year exceeds the cost of renewal. From our analysis, we believe patent applicants have their own rational judgment on the economic or market value of the invention patents, which is not much influenced by the government's patent subsidy programs.

The different impact of subsidy programs on the different dimensions of patent quality is an interesting finding. Potential patentees have more incentives to apply and come up with innovations of better technological qualities due to the launch of subsidy programs, but the market mechanism for patent withdrawal and renewal has not been altered. Using data from CNIPA, Long and Wang (2016) also found that patent promotion policies have a positive effect on invention patent applications and approvals. The authors used rates of approval, withdrawal, and renewal as quality measures. They found no correlation between the policies and quality of invention patents (though they do find a significant negative relationship with utility and design patents), echoing our findings for subsidy policies on the economic quality of patents.

[Table 3 about here]

The contribution of lagged one year R&D expenditure to the quality of invention patent is mixed. According to columns (1)-(5) of Table 3, it can be seen clearly that coefficients of R&D are statistically significant, indicating that more innovation input will increase both quantity and quality. Moreover, as shown in column (6), the coefficient of R&D on the ratio of patent withdrawal becomes significantly negative, implying that the invention patents with a larger amount of R&D input produce better economic quality and the patentees will have a lower possibility to withdraw their applications. However, whether the patentees renew their invention patents after grant through paying the annual fee is independent of prior R&D input. As shown clearly in the table, the elasticity of patent quality with respect to R&D expenditure is less than 1 in all cases. This result is in line with the literature (Hausman et al., 1984; Hu and Jefferson, 2009; Li, 2012; Hu et al., 2017). Thus, R&D expenditure alone would not be able to explain the whole story of the dramatic increase in patents.

In terms of the impact of FDI stock, it is found to be significantly negative only for some patent indicators. These findings demonstrate that the inflow of FDI is likely to compete for the technological dominance and resources (such as new ideas and inventors) with the domestic innovator and produce a negative impact on the number of patent claims and patent inventors.

For the five patent metrics that were impacted significantly in Table 3, we are interested in understanding how fast the short-run adjustment of PSP stabilizes. Panel A in Table 4 reports the effect size of the overall effect of PSP by program launch duration. Panel B shows the impact of PSP on different patent metrics for different launch durations normalized by the impact in the 11^{th} year. Take column (1), impact on patent applications, for example. Our results show that the effect in the 1^{st} year is only 59.1% of the effect in the 11^{th} year, and the short-run adjustment stabilizes around the 7^{th} year. A similar convergence pattern emerges for other patent metrics as well, all exhibiting a lagged effect from program launch and stabilizing after at least five years. The difference in convergence speed may be due to the way the patent subsidy programs were designed. It is relatively easier to respond to subsidies by increasing applications and adding inventors to the research team, we thus see a higher starting point and faster convergence speed for these two metrics. The other three metrics, especially forward citations, largely depend on how latecomers evaluate the patented innovation. Therefore, these quality metrics show a lower starting point and slower convergence speed, indicating more time is needed for the nudge from the government to translate into a more-lasting impact.

[Table 4 about here]

In Table 5, we present the explanation power of patent subsidy policies on the variation of patent measures. Panel A looks at the explanation power of PSP from the perspective of partial η^2. η^2 describes the ratio of variance explained in the dependent variable ($Pmeasure$) by a predictor (treatment of PSP) while controlling for other variables, making it analogous to R^2. We use a 3-year moving average to smooth out the noise to see the trend over time more clearly. Panel B represents the explanation power of PSP from the perspective of the proportion of growth multiple of patent measures explained by PSP. We find that the short-run adjustments stabilize around the 7^{th} year in Table 4, we thus examine the provinces that launched subsidy programs for at least 7 years and up to 10 years. We tabulate the provinces according to the length of patent subsidy program implementation. For example, provinces that launched for ten years include Shanghai, Beijing, Tianjin, Guangdong, Jiangsu, and Chongqing. These six provinces will also be included in the observations for the tabulation of provinces that launched subsidy programs for nine, eight, and seven years. Both Panel A and Panel B in Table 5 show that the explanation power of PSP has declined, either by years since program launch or by calendar year, indicating the effect of these policies were not long-lasting and the growth we observed in patent measures do not depend solely on subsidy "shocks".

[Table 5 about here]

4.3 Heterogeneity of Patent Subsidy Policies and Patentees

We identify in the paper two channels that could explain our findings. The first is the heterogeneity of patent subsidy policies. The other is the heterogeneity of patentees. Local governments tend to give priority to excellence, that is, local governments screen the applicants when allocating subsidies. Given the level of R&D, governments encourage innovators' attention to patent the results of R&D. Afterwards, it is the thriving experienced innovators who are driving the increase in quality of patented innovation. Although the dollar amount of PSP can be small as compared to the huge cost of R&D, PSP provides incentives for innovators to file patent applications, allowing high-quality innovation to appear in the patent pool.

4.3.1 Heterogeneity of Patent Subsidy Policies

Patent subsidy policies cover a wide range of costs and fees during the patenting process. We identified subsidies that promote and prioritize excellence. We found two types of subsidies that are most in line with this policy goal: explicit province-specific subsidies that target excellence ($TargetPSP$) and grant-contingent subsidies ($GrantPSP$).[11] We emphasize "province-specific" because almost all provinces have projects resonating national level Patent Pilot/ Demonstration Enterprise programs, however, it does not guarantee province-specific subsidies targeting these high-quality applicants. We consider all subsidies that give additional benefits to granted applications

[11] We thank the anonymous referee for suggesting us to explore further the heterogeneity of patent subsidy policies across provinces.

as grant-continent awards, including one-time awards when granted and subsidies that only apply to applicants with grants (such as maintenance fee and examination fee subsidies).

We have also identified policies that aim at subsidizing fees for using patent agents ($AgentPSP$), who offer professional services in improving the writing quality of patent applications. The acquired services are quite expensive compared to others fees incurred during the application process. Thus, applicants are serious about patenting when they secure services from patent agents.

For all three policies we identified, we construct dummy variables to indicate whether and when the policies were implemented. Variation in the subsidy amount is not captured due to the limitation in public government documents. $TargetPSP$ is set to 1 if a province has explicit province-specific policies for Patent Pilot and/or Demonstration Enterprises, and/or excellence; otherwise we set to 0. Similarly, $GrantPSP$ and $AgentPSP$ are set to 1 if a province has explicit policy; otherwise we set to 0. The three policies are summarized in Table A1 in Appendix. We focus only on the patent metrics that have been found to be statistically significant in Section 4.2 for our regression analysis in the section.

[Table 6 about here]

We construct short-run adjustments and long-run effects of PSP as in the baseline model, using "1" at the end to denote long-run and "2" at the end to denote short-run (for example, $TargetPSP1$ for long-run effects and $TargetPSP2$ for short-run adjustments). From Table 6 we find that the long-run effect of $TargetPSP$ is the only one that remains significant for all of the patent measures when considering different combinations of patent subsidy policies. The results imply that giving priority to excellence is associated with the increase in quality.

4.3.2 Heterogeneity of Patentees: Experienced Innovators

The institutional background as described above implies that patent subsidy policies may exert different impacts on high-quality and low-quality patents. We consider the following quantile regression to examine this hypothesis:

$$Pmeasure_{it,\tau} = \beta_{0,\tau} + \beta_{\ell,\tau}\left(PSP1_{it}\right) + \beta_{s,\tau}\left(PSP2_{it}\right) + province_i + \epsilon_{it,\tau}, \tag{5}$$

where τ represents the quantile level (we examine τ at 10%, 25%, 50%, 75%, and 90% quantile). We calculate the quantiles based on the rank in patent quantity and quality of applicants who filed patents in province i at year t. From Table 7 we find that for quantiles at and below 50%, the effect of PSP is smaller for the patent quality of applicants at the lower quantile and bigger for the patent quality of applicants at the higher quantile for most of the patent measures.[12]

[Table 7 about here]

We conduct further empirical analysis of policy effects to test whether the patent subsidy policies were implemented mainly through the experienced innovators as documents demonstrate.[13] Intuitively, if experienced innovators were the biggest beneficiaries of patent subsidies, then these selective patent subsidies can produce a positive feedback mechanism. By reducing the cost of patent filings, subsidy policies increased the incentive of experienced patentees in the long run, thus finally producing more high-quality inventions. In most cases, those who insist on patenting are more likely to be better innovators. Therefore, we consider the persistent effects of the subsidy programs in this section.

Based on whether the patentee insisted on patenting activities, we separate the patentees into *entrants* (new innovators, normally small and medium enterprises) and *experienced innovators*. We define the patentees who only filed in year t as entrants and the patentees who filed patents at year $t-1$ and year t as experienced. We add four variables to our baseline regression model: the growth rate of entrants ($Rentrant_{it}$) and its interaction term with patent subsidy programs

[12] We do not have data on R&D and FDI at the quantile level. From summary statistics, there is little variation for the 10% and 25% quantiles, and the variation is more pronounced after the 50% quantile. Thus results in Table 7 are not available for most $Pmeasure_{it,\tau}$ before the 50% quantile.

[13] For example, Beijing issued preferential patent subsidy policies during 2000-2002 for institutions and individuals that have filed a substantial amount of patent applications. During 2007-2010, the policies further specified that when the applicant has filed more than 100 invention patent applications in a given year, an additional 1000 yuan will be subsidized for each application, and 1500 yuan for each granted application.

($PSP1_{it} \times Rentrant_{it}$), the growth rate of experienced innovators ($Rexp_{it}$) and its interaction term with patent subsidy programs ($PSP1_{it} \times Rexp_{it}$).

$$\begin{aligned} Pmeasure_{it} = \beta_0 + \beta_\ell PSP1_{it} + \beta_s PSP2_{it} + \beta_1 Rentrant_{it} + \beta_2 Rexp_{it} \\ + \beta_3 PSP1_{it} \times Rentrant_{it} + \beta_4 PSP1_{it} \times Rexp_{it} + \theta X_{it} + province_i + year_t + \varepsilon_{it} \end{aligned} \quad (6)$$

Panel A in Table 8 presents the estimation results of model (6). Both $Rentrant_{it}$ and $Rexp_{it}$ have significantly positive impacts on the quality of invention patent, indicating that the surge of patentees, both experienced innovators and entrants, has a noticeable impact on the technological quality of China's invention patents. Moreover, the estimated coefficients of $PSP1_{it} \times Rexp_{it}$ are significant and positive, whereas the coefficients of $PSP1_{it} \times Rentrant_{it}$ are insignificant, confirming our hypothesis that the positive persistent impact depends on the growth rate of experienced innovators rather than entrants. Note that the coefficients of $\mathrm{PSP1}_{it}$ become mostly insignificant after the inclusion of $PSP1_{it} \times Rexp_{it}$ and $PSP1_{it} \times Rentrant_{it}$. It indicates that there is no quality difference in the long term between the treated group and the control group when the growth rate of experienced innovators is held constant at zero.

[Table 8 about here]

Our results remain robust when we relax our definition of experienced innovators to be patentees that filed patents at time t and $t-2$ (Table A3 in Appendix).[14] Our results are also robust when we examine the interaction between experienced innovators and $TargetPSP$ (Panel B of Table 8).

Our findings imply that prioritizing experienced innovators is more effective in producing important inventions, and the government can build innovation capacity through experienced innovators in the long run. In other words, PSP improves the quality of invention patents through helping experienced innovators survive and prosper. Our results further imply that public policies could

[14] We thank the anonymous referee for suggesting this robustness test and providing further discussion in making a clearer interpretation of this mechanism. Results remain robust when we relax further our definition of experienced innovators to be those that filed patents at time t and $t-3$. Regression results are available upon request.

also be designed to nurture the inexperienced innovators in order to help create a bigger pool of experienced innovators. By doing so, the government not only can help encourage experienced innovators to prosper, but also improve the general construction of national innovation capacity.

5 Robustness Checks

Robustness Check A: Placebo Test

One potential problem in our empirical results is whether our empirical design identifies the exact effect of patent subsidy programs. In order to validate the identification of the treatment effect, we have conducted the placebo test as follow: First, we generate one-year lead value of the patent subsidy programs ($F.PSP1_{(i,t)} = PSP1_{(i,t+1)}$). Based on the sample without a real patent subsidy program or treatment, we regress the outcome variables on the pseudo patent subsidies variable ($F.PSP1_{(i,t)}$) and other controls as Table 3. If coefficients of $F.PSP1_{(i,t)}$ are statistically insignificant, it can be inferred that only the true treatment can have a significant impact on patent quality. We also tried the two-year and three-year lead value of the patent subsidy programs. Panel A in Table 9 reports the results of the placebo test. The estimated coefficients of the pseudo patent subsidy programs are found to be statistically insignificant on all of the patent measures, implying that the quantity and quality of invention patents can only be affected if PSP was implemented.

[Table 9 about here]

Robustness Check B: Exogeneity of Control Variables

Another potential problem is whether the control variables, especially R&D input, are exogenous to patent subsidy policies. We examine this by checking the results with or without control variables. As can be seen from Panel B in Table 9, the coefficients tell the same story as Table 3. Since the estimated impact of PSP on patent quality (β_ℓ and β_s) exhibit similar magnitudes and statistical significance, we conclude that the policies are indeed exogenous to control variables.

Robustness Check C: Adjustment parameter

In our model, we set the adjustment parameter (λ) to be 0.6. Here, we examine λ via two criteria. First of all, we compare the convergence patterns across different models with values of λ to find a reasonable range. We find that $\lambda \leq 0.4$ results in insignificant impacts of PSP on patent quantity and quality, and $\lambda = 0.9$ leads to a convergence pattern similar to the dynamic DID model and the Interaction-weighted (IW) estimators following Sun and Abraham (2020). Secondly, we examine the overall effect of PSP relative to the effect of R&D in the long run with different values of λ. We verify that λ should take on values less than or equal to 0.7 to have the effect of R&D dominate in the long run, consistent with the implications of Li (2012).

[Table 10 about here]

According to both the convergence pattern and the long-run effect of PSP relative to R&D, we have validated that our baseline model is within the reasonable range of $0.5 \leq \lambda \leq 0.7$. Regression results with $\lambda = 0.5$ are reported in Table 10, with the estimated policy effects very similar to that of Table 3.[15]

Robustness Check D: More Controls and City-level Regression[16]

We also introduce more control variables for robustness check. Although policies subsidizing R&D are partially controlled by the lagged R&D ($L.lnRD$) in our baseline model, we follow Long and Wang (2016) to add a control variable of patent-relevant tax rebate policies (dummy variable, denoted as *pattax*, details reported in Table A1 in Appendix). We also control for other potential variables: provincial population size (in logs, denoted as *lpop*) and the number of college students (in logs, denoted as *lcollege*).[17] Regression results are reported in Table 11 Panel A. We find that

[15]We thank the anonymous referee for suggesting Sun and Abraham (2020) as an important reference to the calibration of λ. When changing our model formulation to the multiplicative inverse function $1/(t - t_0 + 1)$, we were able to replicate the results in Li (2012). Moreover, we find that results under $0.5 \leq \lambda \leq 0.7$ include the results of Li (2012). Figures for comparison of convergence pattern, tables for comparison of overall effect between PSP and R&D in the long run, and results for $\lambda = 0.7$ are available upon request.

[16]We thank the anonymous referee for suggesting us to conduct robustness checks on control variables and expanding our observations in the regression analysis by going to a lower level.

[17]We chose to not control for high school students since it is highly correlated with the number of college students.

the coefficients of $PSP1$ and $PSP2$ remain positive and significant. Although we do not exhaust all possible policies announced by the government that could impact R&D, our effort to include $pattax$ shows that our baseline result can remain robust when introducing more policy variables.

[Table 11 about here]

Our baseline result is based on provincial data. In order to check the robustness of our estimation and the validity of our conclusions at a lower level, we reconsider our empirical analysis based on 4,313 city-year observations (consisting 314 cities that cover all of the provinces in our sample). Since only limited number of cities released data on R&D and FDI at the city level, we control instead $pattax$ and city-level population size. Both province and year fixed effects are controlled. Table 11 Panel B show that our baseline results remain robust.

6 Conclusions

China has aimed to transform her growth model from "high speed" to "high quality", and from factor-driven to innovation-driven. The contribution from inventions and innovation capability have become increasingly important. Since patents are the most commonly used indicator of the invention output and technological change, one may wonder whether such a dramatic rise of China's invention patents signals the increase of innovation quality and the development of innovation ability. We try to answer this question by linking CNIPA data with Google Patents data and analyze a comprehensive set of quality indicators for invention patents. We find a significantly positive effect by China's patent subsidy policy on the technological quality of patents, with short-run adjustments on both quantity and quality taking at least five years to approach the long-run impact.

In this paper we show that the influence (explanation power) of patent subsidy policies (PSP) on patent quantity and quality diminishes as time goes by, indicating that the government is only leading the way for improving patent quality. Afterwards, the innovation activity is mainly in the

We also chose to not use provincial-level GDP as a control since it is found to be highly correlated with lagged R&D, FDI, and population. Moreover, researchers have long questioned the accuracy of provincial-level GDP data in China.

hands of experienced innovators. We find that the influence of PSP depends on the growth rate of experienced innovators rather than entrants, which is consistent with the government's target for prioritizing the experienced patentees. The implemented patent subsidy policies we study in this paper were designed to only subsidize expenses incurred during the patenting process and did not cover expenditures during the R&D stage, thus it can be interpreted as merely a "guidance" by government since PSP focuses on increasing patenting propensity rather than R&D.

This research contributes to at least two lines of research. On the one hand, it presents the quality of China's invention patents as fully as possible based on the comprehensive patent information and enriches our understanding of its dynamic features. On the other hand, it contributes to the studies on the evaluation of the impact of patent subsidy programs on patent quality. As far as we know, no other paper examines the relationship between patent subsidy programs and the quality of patents, although lots of advanced countries have implemented similar programs as China.

It should be noted that China's patent quality problem still exists. With the introduction of patent subsidy policies, we show that the quality of China's invention patent increased with these policies. This does not mean that there is no patent quality problem in China. China still has a long way to go before she can establish herself as a dominant player in intellectual property and technology leadership. Some studies indicate that the average quality of China's patent is declining, mainly due to the low quality of utility model and design patent (Gao et al., 2011; Dong and He, 2015). Moreover, there is still a patent quality gap between China's invention patents and foreign invention patents (Boeing, 2016). These issues do not seem to be effectively addressed at present. Therefore, patent quality is worthy of further exploration in future research.

References

Boeing, P. (2016). The allocation and effectiveness of China's R&D subsidies- Evidence from listed firms. Research Policy, 45(9), 1774-1789.

Crepon, B., Duguet, E. (1997). Estimating the innovation function from patent numbers: GMM on count panel data. Journal of Applied Econometrics, 12(3), 243-263.

Dang, J., Motohashi K. (2015). Patent statistics: A good indicator for innovation in China? Patent subsidy program impacts on patent quality. China Economic Review, 35, 137-155.

Dong, T., He, H. (2015). On the patent quality: A special report about the implementation of utility mode and industrial design patent. Journal of Science Technology & Law, 220-305.

Eberhardt, M. , Helmers, C., Yu, Z. (2016). What can explain the Chinese patent explosion? Oxford Economic Papers, 69(1).

Fisch, C.O., Block, J.H., Sandner, P.G. (2016). Chinese university patents: Quantity, quality, and the role of subsidy programs. Journal of Technology Transfer, 41(1), 60-84.

Fisch, C.O., Sandner, P.G, Regner, L. (2017). The value of Chinese patents: An empirical investigation of citation lags. China Economic Review, 45, 23-34.

Gao, L., Li, M., Cheng, Y. (2011). Report on the Quality for Invention in China, Beijing Intellectual Property Rights Institute.

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. Journal of Economic Literature, 28(4), 1661-1707.

Hall, B.H., Mairesse, J. (1995). Exploring the relationship between R&D and productivity in French manufacturing firms. Journal of Econometrics, 65(1), 263-293.

Hausman, J., Hall, B.H., Griliches, Z. (1984). Econometric models for count data with an application to the patents-R&D relationship. Econometrica, 52 (4), 909-938.

Howell, A., Lin, J., Worack, S. (2020) Going out to innovate more at home: The impact of outward direct investments on Chinese firms' domestic innovation performance. China Economic Review, Volume 60, 101404.

Hu, A.G., Jefferson, G. H. (2009). A great wall of patents: What is behind China's recent patent explosion? Journal of Development Economics, 90(1), 57-68.

Hu, M., Mathews, J.A. (2008). China's national innovative capacity. Research Policy, 37(9), 1465-1479.

Hu, A.G., Zhang, P., Zhao, L. (2017). China as number one? Evidence from Chinas most recent patenting surge, Journal of Development Economics, 124, 107-119.

Huang, K.G., Geng, X., Wang, H. (2017). Institutional Regime Shift in Intellectual Property Rights and Innovation Strategies of Firms in China. Organization Science, 28(2): 355-377.

Jaffe, A.B., Lerner, J., Stern, S. (2002). Innovation Policy and the Economy, Volume 2.

Jia, N., Huang, K.G., Zhang, C.M. (2019). Public Governance, Corporate Governance and Firm Innovation: An Examination of State-owned Enterprises. Academy of Management Journal, 62(1): 220-247.

Lanjouw, J.O., Schankerman, M. (2004). Patent quality and research productivity: measuring innovation with multiple indicators. Economic Journal, 114(495), 441-465.

Li, X. (2012). Behind the recent surge of Chinese patenting: An institutional view. Research Policy, 41(1), 236-249.

Long, C.X., Wang, J. (2016). Evaluating Patent Promotion Policies in China: Consequences for patent quantity and quality. In: Economic Impacts of Intellectual Property-Conditioned Government Incentives (Edited by Prud'homme, D., Song, H.). Springer Singapore.

Nagaoka, S., Motohashi, K., Goto, A. (2010). Patent statistics as an innovation indicator. Handbook of the economics of innovation, Volume 2 (1st ed., Edited by Hall, B.H., Rosenberg, N.), 1083-1127, Elsevier B.V.

Pakes, A., Griliches, Z. (1984). Patents and R&D at the firm level: A first look. R & D, patents, and productivity. Vol. I. (pp. 5572). University of Chicago Press.

Prud'homme D., Zhang T. (2019) Chinese patenting trends and the role of the state. In: China's Intellectual Property Regime for Innovation. Springer, Cham.

Schankerman, M., Pakes, A. (1986). Estimates of the value of patent rights in European countries during the post-1950 period. The Economic Journal, 96(384), 1052-1076.

Sun, L., Abraham, S. (2020). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. Journal of Econometrics. *forthcoming*.

Sun, Z., Shi, L., Cheng, L. (2019). Strategic use of the second tier of the patent system: Evidence from parallel filings in China. Working paper.

Sun, Z., Lei, Z., Wright, B.D., Cohen, M., Liu, T. (2021). Government targets, end-of-year patenting Rush, and innovative performance in China. Nature. *forthcoming*.

Suzuki, J. (2011). Structural modeling of the value of patent. Research Policy, 40, 986-1000.

Trajtenberg, M. (1990). A penny for your quotes: Patent citations and the value of innovations. RAND Journal of Economics, 21(1), 172-187.

Tong, X., Frame, J. D. (1994). Measuring national technological performance with patent claims data. Research Policy, 23(2), 133-141.

Wuchty, S., Jones, B.F., Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. Science, 316(5827), 1036-1039.

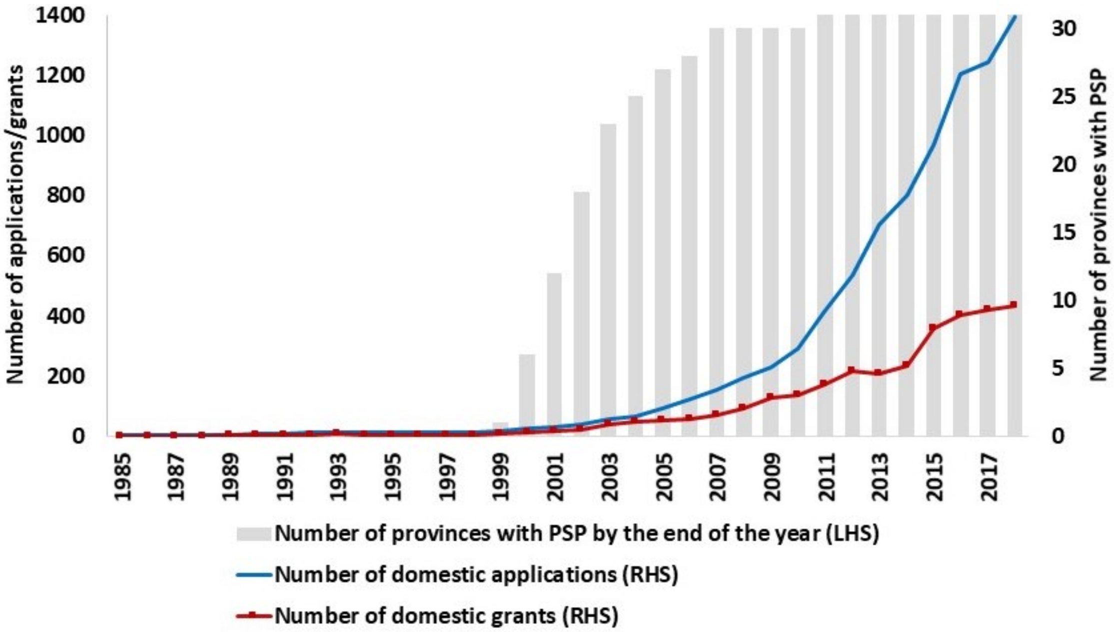
Zhang, G., Chen, X. (2012). The Value of Invention Patents in China: Country Origin and Technology Field Differences. China Economic Review, 23, 357-370.

Zhang, J., Rogers, J.D. (2009). The technological innovation performance of Chinese firms: The role of industrial and academic R&D, FDI and the markets in firm patenting. International Journal of Technology Management, 48(4), 518-543.

Zhang, G., Lv, X., Zhou, J. (2014). Private value of Patent Right and Patent Infringement: An empirical study based on patent renewal data of China? China Economic Review, 28, 37-54.

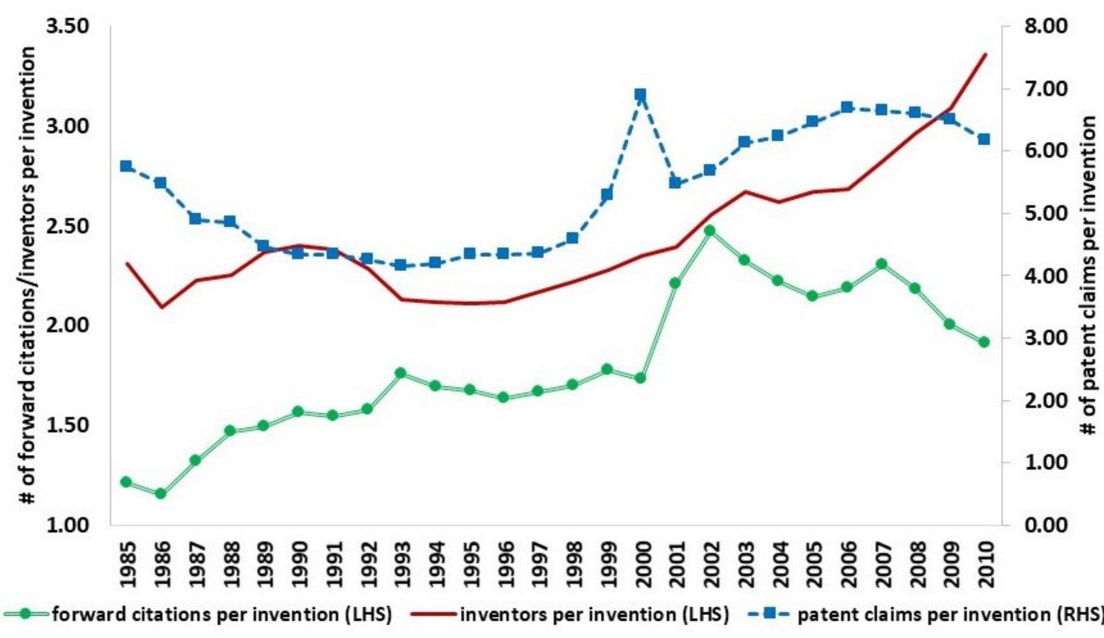
Zhu, T. (2021). Catching Up to America: Culture, Institutions, and the Rise of China. Cambridge: Cambridge University Press.

Figure 1: The surge of China's invention patents



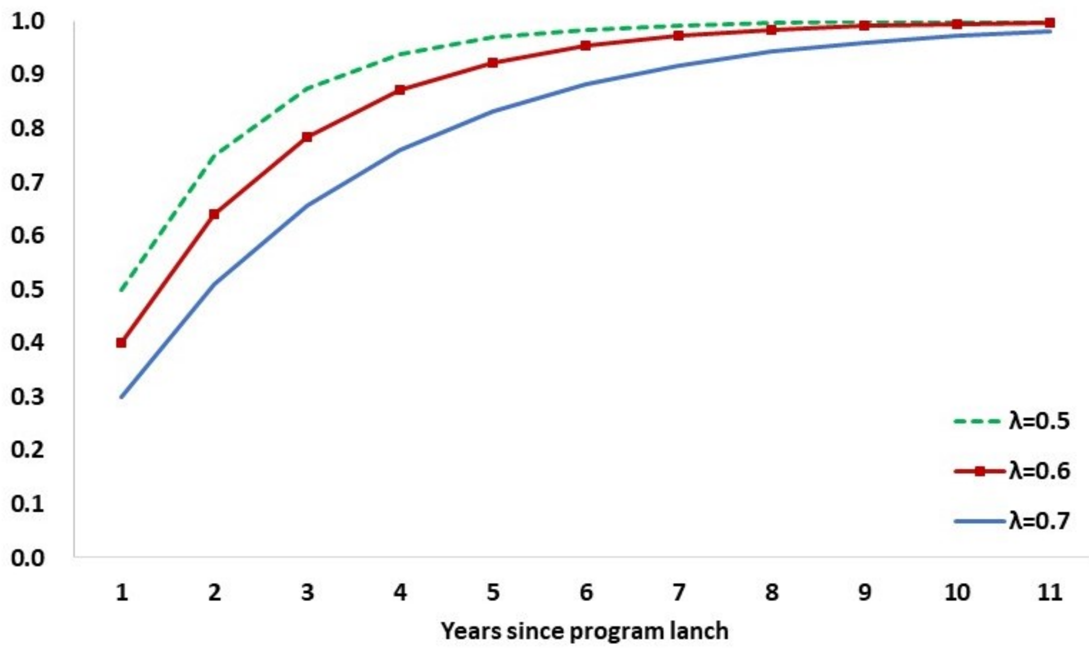
Data source: Authors' calculation based on data of CNIPA, Google Patents, and incoPat.

Figure 2: Quality of China's invention patents



Data source: Authors' calculation based on data of CNIPA, Google Patents, and incoPat.

Figure 3: Different geometric speeds of short-run adjustments approaching long-run impact



Notes: Simulated by fixing $\beta_\ell = \beta_s = 1$.

Table 1 Descriptive Statistics

Variables	Full sample (N=421)		Without subsidy (N=189)		With subsidy (N=232)		t-test	
	mean	stdev	mean	stdev	mean	stdev	t	p-value
# of applications	2,329	4,481	494	505	3,824	5,594	-8.57	0
# of grants	1,116	2,206	235	279	1,833	2,764	-8.36	0
# of forward citations	5,238	10,085	956	1,114	8,726	12,518	-8.93	0
# of claims	15,811	37,111	2,358	3,057	26,770	47,200	-7.48	0
# of inventors	7,180	14,025	1,215	1,421	12,039	17,412	-8.97	0
withdrawal rate	0.42	0.11	0.48	0.1	0.38	0.09	12.74	0
renewal rate (5-year)	0.53	0.16	0.4	0.11	0.63	0.12	-19.40	0

Table 2 Pre-treated Trends Test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	lnApps	lnGrants	lnClaims	lnFwd	lnInventors	Rwithdrawal	Rrenewal5
L.lnRD	-0.122	0.063	-0.132	-0.208	-0.096	-0.089	-0.071
	[0.182]	[0.219]	[0.202]	[0.325]	[0.218]	[0.062]	[0.080]
lnFDI	0.349*	0.361	0.217	0.491	0.523**	-0.006	0.067
	[0.188]	[0.227]	[0.209]	[0.337]	[0.225]	[0.064]	[0.083]
trend	0.072**	0.171***	0.079**	0.119**	0.097***	-0.037***	0.027**
	[0.029]	[0.035]	[0.032]	[0.052]	[0.035]	[0.010]	[0.013]
trend ×	-0.003	-0.014	0.024	-0.045	0.01	-0.008	0.004
treated	[0.044]	[0.052]	[0.048]	[0.078]	[0.052]	[0.015]	[0.019]
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	84	84	84	84	84	84	84
adj. R^2	-0.232	0.093	-0.198	-0.312	-0.169	-0.067	-0.268

Notes: Robust standard errors are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3 Baseline Results: $\lambda = 0.6$

	(1) lnApps	(2) lnGrants	(3) lnClaims	(4) lnFwd	(5) lnInventors	(6) Rwithdrawal	(7) Rrenewal5
PSP2	0.532**	0.630***	0.531**	0.627***	0.565***	-0.015	-0.036
	[0.206]	[0.198]	[0.193]	[0.196]	[0.196]	[0.034]	[0.031]
PSP1	0.407*	0.467**	0.437**	0.474**	0.452**	-0.014	0.01
	[0.200]	[0.183]	[0.212]	[0.175]	[0.198]	[0.036]	[0.036]
L.lnRD	0.417**	0.543***	0.461**	0.456**	0.397**	-0.056**	0.021
	[0.178]	[0.187]	[0.178]	[0.179]	[0.164]	[0.024]	[0.028]
lnFDI	-0.218*	-0.235**	-0.228*	-0.184	-0.185*	0.017	0.021
	[0.122]	[0.110]	[0.116]	[0.112]	[0.098]	[0.021]	[0.013]
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	421	421	421	421	421	421	421
adj. R^2	0.891	0.906	0.908	0.921	0.940	0.593	0.821

Notes: Robust standard errors are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4 Impact of subsidy measured by effect size of overall effects and convergence pattern

Panel A: Effect size of overall effect

Years since program launch	(1) Applications	(2) Grants	(3) Claims	(4) Forward citations	(5) Inventors
1	0.88***	0.85***	0.91***	0.86***	0.89***
	[0.07]	[0.07]	[0.10]	[0.06]	[0.07]
2	1.09***	1.09***	1.13***	1.10***	1.12***
	[0.11]	[0.10]	[0.14]	[0.09]	[0.11]
3	1.24***	1.27***	1.28***	1.28***	1.28***
	[0.17]	[0.15]	[0.20]	[0.14]	[0.17]
4	1.34***	1.39***	1.38***	1.40***	1.39***
	[0.21]	[0.20]	[0.25]	[0.19]	[0.22]
5	1.40***	1.47***	1.44***	1.48***	1.46***
	[0.25]	[0.23]	[0.28]	[0.22]	[0.26]
6	1.44***	1.52***	1.48***	1.53***	1.50***
	[0.27]	[0.26]	[0.30]	[0.25]	[0.28]
7	1.47***	1.55***	1.51***	1.56***	1.53***
	[0.28]	[0.27]	[0.31]	[0.26]	[0.29]
8	1.48***	1.57***	1.52***	1.58***	1.55***
	[0.29]	[0.28]	[0.32]	[0.27]	[0.30]
9	1.49***	1.58***	1.53***	1.59***	1.56***
	[0.29]	[0.28]	[0.32]	[0.27]	[0.30]
10	1.49***	1.58***	1.54***	1.60***	1.56***
	[0.30]	[0.29]	[0.32]	[0.28]	[0.31]

Panel B: Convergence pattern

Years since program launch	(1) Applications	(2) Grants	(3) Claims	(4) Forward citations	(5) Inventors
1	58.7%	53.5%	59.1%	53.8%	56.7%
2	72.7%	68.6%	73.4%	68.8%	71.3%
3	82.7%	79.9%	83.1%	80.0%	81.5%
4	89.3%	87.4%	89.6%	87.5%	88.5%
5	93.3%	92.5%	93.5%	92.5%	93.0%
6	96.0%	95.6%	96.1%	95.6%	95.5%
7	98.0%	97.5%	98.1%	97.5%	97.5%
8	98.7%	98.7%	98.7%	98.8%	98.7%
9	99.3%	99.4%	99.4%	99.4%	99.4%
10	99.3%	99.4%	100.0%	100.0%	99.4%

Notes: Robust standard errors are in brackets. *** indicate significance at the 1% level. Overall effect is defined as $exp(\beta_\ell - \beta_s 0.6^{t-t_0})$. All reported effect size in Panel A have a p-value of 0.00. Panel B is calculated using the overall effect of the 11^{th} year since PSP launch as base.

Table 5 Explanation power of patent subsidy policies on the variation of patent measures

Panel A: 3-year moving average of partial η^2 (by calendar year, t)

Calendar year	Observations	(1) Applications	(2) Grants	(3) Claims	(4) Forward citations	(5) Inventors
2001-2003	29	18.7%	20.3%	28.0%	22.7%	20.0%
2004-2006	29	17.7%	19.7%	21.3%	17.3%	13.7%
2007-2009	29	13.3%	14.0%	12.0%	13.7%	10.7%

Panel B: Proportion of growth multiple explained by PSP (by years since program launch, $g = t - t_0$, for $g \geq 1$)

Years since program launch	Observations	(1) Applications	(2) Grants	(3) Claims	(4) Forward citations	(5) Inventors
7	22	36.1%	41.9%	29.4%	31.5%	25.0%
8	18	30.8%	35.9%	23.5%	26.8%	19.6%
9	12	21.1%	24.2%	16.5%	19.9%	13.2%
10	6	12.3%	14.4%	14.2%	16.4%	10.2%

Notes: $\eta^2 = \frac{\delta^2{}_{treatment}}{\delta^2{}_{total}}$. We sum up the partial η^2 of PSP1 and PSP2 to find the total variation explained by patent subsidy policies. We follow equation (3) to calculate Panel B according to program launch year ($g = t - t_0$ for $g \geq 1$). Proportion of growth multiple explained by PSP= overall effect of PSP_{g-1} / Growth multiple of $Pmeasure_g$. Growth multiple of $Pmeasure_g$ is the ratio between the level of $Pmeasure_g$ and the level of $Pmeasure_1$. Overall effect of PSP can be found in Table 4 Panel A. Results are similar when we do not consider the possible lagged effect of PSP.

Table 6 Heterogeneous patent subsidy policies

	(1)	(2)	(3)	(4)	(5)
	lnApps	lnGrants	lnClaims	lnFwd	lnInventors
$TargetPSP2$	0.424**	0.344*	0.309	0.342*	0.344*
	[0.204]	[0.183]	[0.205]	[0.185]	[0.171]
$TargetPSP1$	0.423**	0.324**	0.302*	0.315**	0.316**
	[0.163]	[0.149]	[0.165]	[0.147]	[0.144]
$AgentPSP2$	0.125	0.222	0.286*	0.057	0.171
	[0.174]	[0.132]	[0.165]	[0.138]	[0.155]
$AgentPSP1$	0.193	0.268	0.303	0.184	0.226
	[0.192]	[0.173]	[0.192]	[0.170]	[0.175]
$GrantPSP2$	-0.068	0.096	-0.080	0.084	-0.016
	[0.203]	[0.191]	[0.177]	[0.205]	[0.158]
$GrantPSP1$	-0.094	0.084	-0.079	0.074	0.011
	[0.231]	[0.212]	[0.222]	[0.214]	[0.197]
L.lnRD	0.447***	0.596***	0.505***	0.511***	0.442***
	[0.157]	[0.176]	[0.169]	[0.172]	[0.148]
lnFDI	-0.197*	-0.208*	-0.218*	-0.158	-0.162*
	[0.112]	[0.111]	[0.119]	[0.107]	[0.092]
Observations	421	421	421	421	421
adj. R^2	0.894	0.905	0.908	0.918	0.939

Notes: Robust standard errors are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. We control for province and year fixed effects.

Table 7 Heterogeneous impact of patent subsidy policies on patent quality: quantile regression

	(1) lnApps	(2) lnGrants	(3) lnClaims	(4) lnFwd	(5) lnInventors
Panel A: quantile = 10%					
PSP2	–	–	0.041	0.039	–
	–	–	[0.056]	[0.040]	–
PSP1	–	–	0.090**	0.005	–
	–	–	[0.037]	[0.005]	–
Panel B: quantile = 25%					
PSP2	–	–	0.145***	0.207	0.132***
	–	–	[0.050]	[0.373]	[0.036]
PSP1	–	–	0.247***	1.880***	0.086***
	–	–	[0.038]	[0.264]	[0.023]
Panel C: quantile = 50%					
PSP2	0.123**	0.001	0.219***	0.172***	0.464***
	[0.046]	[0.001]	[0.046]	[0.047]	[0.061]
PSP1	0.079***	-0.002	0.405***	0.394***	0.555***
	[0.028]	[0.002]	[0.032]	[0.040]	[0.036]
Panel D: quantile = 75%					
PSP2	0.452***	0.466***	0.263***	0.122***	0.513***
	[0.058]	[0.066]	[0.044]	[0.040]	[0.049]
PSP1	0.605***	0.539***	0.426***	0.338***	0.616***
	[0.038]	[0.036]	[0.035]	[0.027]	[0.030]
Panel E: quantile = 90%					
PSP2	0.657***	0.422***	0.398***	0.214***	0.587***
	[0.050]	[0.051]	[0.044]	[0.040]	[0.060]
PSP1	0.801***	0.544***	0.579***	0.477***	0.733***
	[0.033]	[0.035]	[0.036]	[0.034]	[0.044]
Observations	421	421	421	421	421

Notes: For the cells marked "–", regression analysis could not be conducted since there is no variation among the observations. Robust standard errors are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. We control for province fixed effects for all quantile regressions in the table.

Table 8 Heterogeneous patentees: The role of experienced innovators

Panel A: *PSP*

	(1) lnApps	(2) lnGrants	(3) lnClaims	(4) lnFwd	(5) lnInventors
PSP2	0.514**	0.616***	0.515**	0.614***	0.547***
	[0.197]	[0.187]	[0.188]	[0.180]	[0.182]
PSP1	0.278	0.357*	0.306	0.362**	0.317
	[0.212]	[0.199]	[0.216]	[0.176]	[0.197]
Rentrant	0.232**	0.304***	0.254**	0.550***	0.365***
	[0.111]	[0.081]	[0.122]	[0.124]	[0.086]
Rexp	0.090*	0.089	0.129***	0.184**	0.105**
	[0.046]	[0.061]	[0.043]	[0.067]	[0.045]
PSP1 × Rentrant	0.102	0.063	0.146	-0.067	0.06
	[0.231]	[0.209]	[0.300]	[0.193]	[0.218]
PSP1 × Rexp	0.480***	0.403**	0.454**	0.443**	0.507***
	[0.171]	[0.168]	[0.173]	[0.172]	[0.164]
L.lnRD	0.403**	0.533***	0.446**	0.456**	0.385**
	[0.172]	[0.183]	[0.172]	[0.172]	[0.159]
lnFDI	-0.214*	-0.234**	-0.225*	-0.186	-0.184*
	[0.123]	[0.109]	[0.116]	[0.112]	[0.097]
adj. R^2	0.896	0.911	0.912	0.929	0.945

Panel B: *TargetPSP*

	(1) lnApps	(2) lnGrants	(3) lnClaims	(4) lnFwd	(5) lnInventors
$TargetPSP2$	0.495***	0.439***	0.400**	0.432***	0.423***
	[0.162]	[0.140]	[0.156]	[0.133]	[0.127]
$TargetPSP1$	0.320*	0.270*	0.196	0.257*	0.225
	[0.159]	[0.142]	[0.153]	[0.138]	[0.139]
Rentrant	0.341***	0.361***	0.380***	0.577***	0.433***
	[0.107]	[0.087]	[0.122]	[0.127]	[0.075]
Rexp	0.134***	0.126**	0.159***	0.218***	0.148***
	[0.043]	[0.052]	[0.038]	[0.057]	[0.039]
$TargetPSP1$ × Rentrant	-0.131	-0.049	-0.135	-0.155	-0.085
	[0.206]	[0.222]	[0.248]	[0.218]	[0.210]
$TargetPSP1$ × Rexp	0.716***	0.599**	0.755***	0.723***	0.751***
	[0.257]	[0.230]	[0.263]	[0.240]	[0.235]
L.lnRD	0.422***	0.561***	0.480***	0.479***	0.412***
	[0.146]	[0.165]	[0.153]	[0.158]	[0.138]
lnFDI	-0.179*	-0.204*	-0.200*	-0.156	-0.156*
	[0.099]	[0.100]	[0.102]	[0.094]	[0.080]
adj. R^2	0.899	0.907	0.911	0.927	0.943

Notes: Robust standard errors are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. We control for province and year fixed effects in Panel A and B. Each of the regressions reported has 421 observations.

Table 9 Robustness checks: Placebo test and exogeneity of control variables

Panel A: Placebo test

	(1) lnApps	(2) lnGrants	(3) lnClaims	(4) lnFwd	(5) lnInventors	(6) Rwithdrawal	(7) Rrenewal5
Panel A1: 1 year lead (N=188)							
F.PSP1	0.020	0.016	0.063	-0.04	-0.001	-0.013	0.018
	[0.043]	[0.054]	[0.059]	[0.051]	[0.050]	[0.014]	[0.022]
Panel A2: 2 year lead (N=187)							
F2.PSP1	0.058	0.045	0.165	-0.093	0.011	-0.032	0.044
	[0.103]	[0.131]	[0.142]	[0.124]	[0.117]	[0.033]	[0.055]
F2.PSP2	0.106	0.082	0.210*	-0.053	0.099	-0.025	0.030
	[0.093]	[0.118]	[0.119]	[0.110]	[0.100]	[0.032]	[0.050]
Panel A3: 3 year lead (N=186)							
F3.PSP1	-0.056	-0.036	-0.003	-0.131	-0.139	-0.026	0.045
	[0.091]	[0.112]	[0.135]	[0.107]	[0.106]	[0.029]	[0.044]
F3.PSP2	0.009	0.000	0.074	-0.041	-0.047	-0.024	0.029
	[0.077]	[0.104]	[0.110]	[0.093]	[0.086]	[0.024]	[0.037]

Panel B: Exogeneity of control variables

	(1) lnApps	(2) lnGrants	(3) lnClaims	(4) lnFwd	(5) lnInventors	(6) Rwithdrawal	(7) Rrenewal5
PSP2	0.593***	0.713***	0.600***	0.698***	0.625***	-0.024	-0.031
	[0.198]	[0.192]	[0.188]	[0.190]	[0.189]	[0.034]	[0.029]
PSP1	0.459**	0.546***	0.497**	0.543***	0.506***	-0.024	0.020
	[0.181]	[0.176]	[0.191]	[0.170]	[0.182]	[0.034]	[0.035]
Observations	421	421	421	421	421	421	421
adj. R^2	0.878	0.889	0.897	0.911	0.933	0.578	0.819

Notes: Robust standard errors are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. We control for province and year fixed effects in Panel B.

Table 10 Robustness check: $\lambda = 0.5$

	(1) lnApps	(2) lnGrants	(3) lnClaims	(4) lnFwd	(5) lnInventors	(6) Rwithdrawal	(7) Rrenewal5
PSP2	0.506**	0.590***	0.503**	0.590***	0.538***	-0.007	-0.036
	[0.202]	[0.192]	[0.195]	[0.188]	[0.189]	[0.036]	[0.030]
PSP1	0.364*	0.410**	0.392*	0.419**	0.407**	-0.007	0.012
	[0.191]	[0.171]	[0.211]	[0.160]	[0.185]	[0.036]	[0.034]
L.lnRD	0.433**	0.563***	0.477**	0.475**	0.414**	-0.057**	0.02
	[0.179]	[0.188]	[0.179]	[0.181]	[0.165]	[0.024]	[0.028]
lnFDI	-0.218*	-0.235**	-0.228*	-0.185	-0.186*	0.017	0.021
	[0.122]	[0.112]	[0.117]	[0.112]	[0.098]	[0.021]	[0.014]
Observations	421	421	421	421	421	421	421
adj. R^2	0.889	0.904	0.907	0.919	0.938	0.593	0.821

Notes: Robust standard errors are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. We control for province and year fixed effects.

Table 11 Robustness checks: More controls and city-level regression

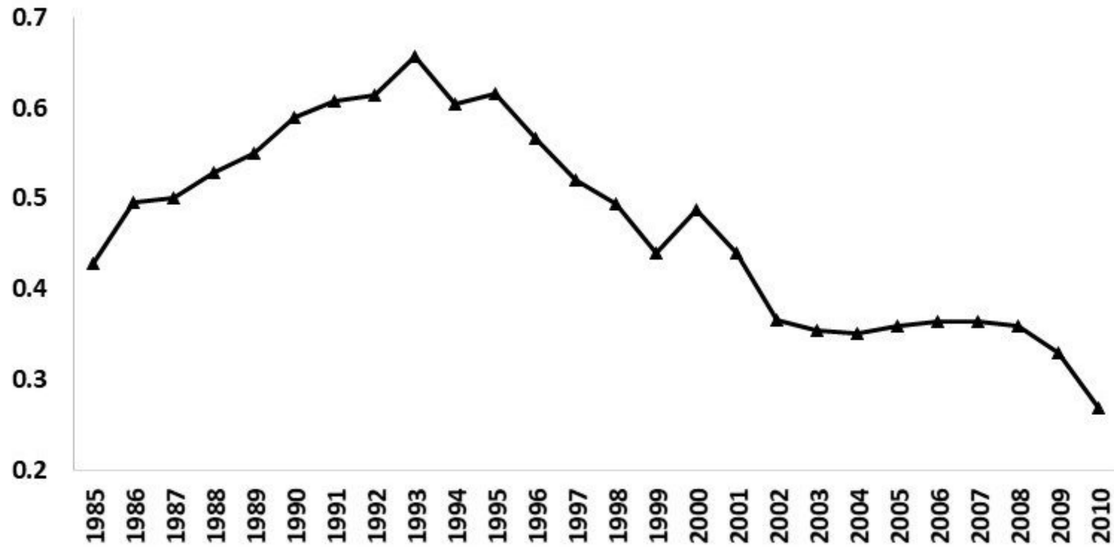
Panel A: More controls					
	(1)	(2)	(3)	(4)	(5)
	lnApps	lnGrants	lnClaims	lnFwd	lnInventors
PSP2	0.468**	0.587***	0.470**	0.573***	0.523**
	[0.204]	[0.194]	[0.194]	[0.185]	[0.191]
PSP1	0.394**	0.459**	0.426**	0.462***	0.444**
	[0.189]	[0.174]	[0.197]	[0.161]	[0.185]
pattax	0.358**	0.302***	0.370***	0.360***	0.312**
	[0.139]	[0.105]	[0.128]	[0.127]	[0.115]
L.lnRD	0.401**	0.538***	0.436***	0.461***	0.392**
	[0.161]	[0.175]	[0.156]	[0.162]	[0.152]
lnFDI	-0.195*	-0.237***	-0.216**	-0.176*	-0.191**
	[0.095]	[0.085]	[0.086]	[0.090]	[0.081]
lpop	1.546*	0.744	1.402	1.020	0.689
	[0.826]	[0.909]	[0.962]	[0.749]	[0.744]
lcollege	0.118	0.097	0.179	0.049	0.101
	[0.113]	[0.121]	[0.130]	[0.112]	[0.094]
Observations	421	421	421	421	421
adj. R^2	0.903	0.911	0.916	0.927	0.943

Panel B: City-level regression					
	(1)	(2)	(3)	(4)	(5)
	lnApps	lnGrants	lnClaims	lnFwd	lnInventors
PSP2	0.139	0.287***	0.367***	0.409**	0.214*
	[0.097]	[0.107]	[0.120]	[0.171]	[0.127]
PSP1	0.184*	0.358***	0.409***	0.456***	0.330***
	[0.095]	[0.105]	[0.118]	[0.167]	[0.125]
pattax	0.244***	0.194**	0.155	0.272**	0.112
	[0.076]	[0.084]	[0.094]	[0.134]	[0.100]
lpop	1.216***	1.314***	1.410***	1.495***	1.480***
	[0.023]	[0.025]	[0.028]	[0.040]	[0.030]
Observations	4,313	4,313	4,313	4,313	4,313
adj. R^2	0.660	0.634	0.625	0.492	0.612

Notes: Robust standard errors are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. We control for province and year fixed effects in Panel A and B.

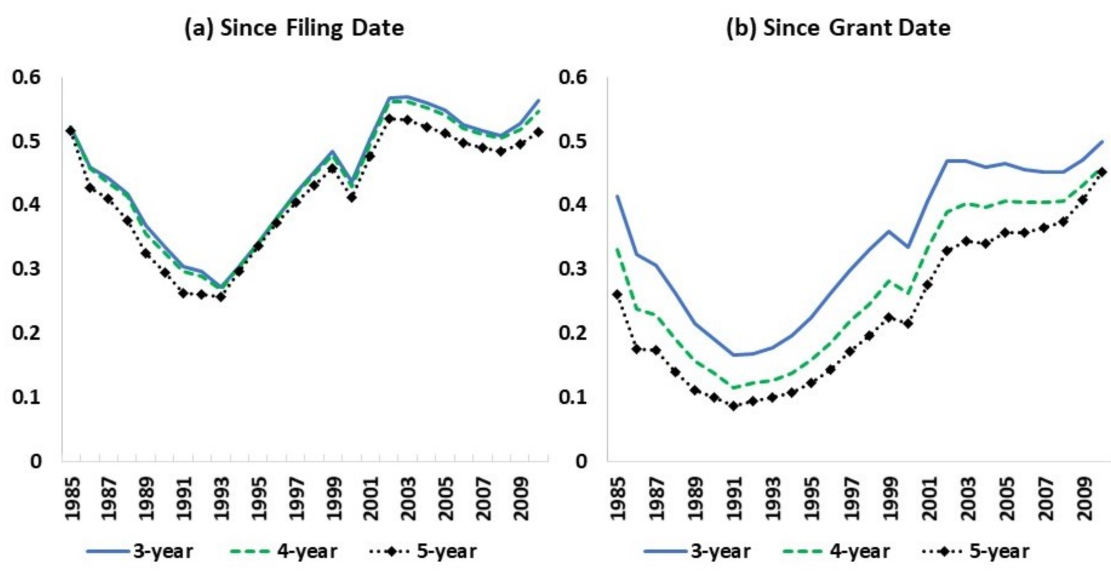
Appendix

Figure A1: Withdrawal rate of China's invention patents



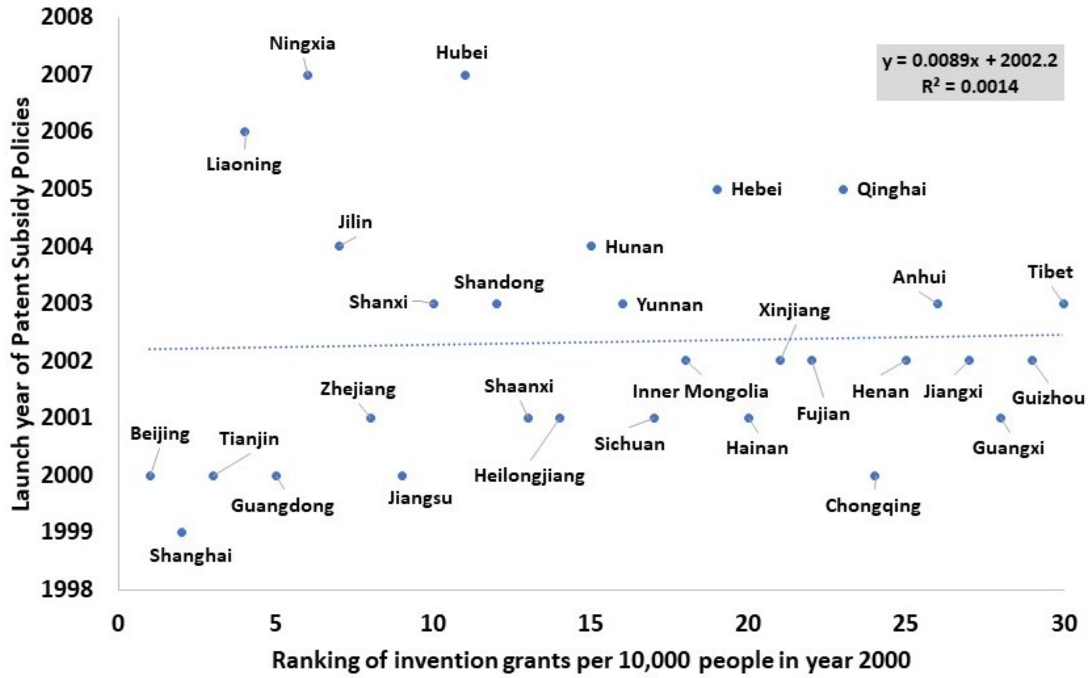
Data source: Authors' calculation based on data of CNIPA, Google Patents, and incoPat.

Figure A2: Renewal rate of China's invention patents



Data source: Authors' calculation based on data of CNIPA, Google Patents, and incoPat.

Figure A3: Patent subsidy policy launch year and ranking of invention grants per 10,000 people in year 2000



Data source: Authors' calculation based on data of public government documents and CNIPA.

Table A1 Heterogeneity of patent-relevant policies across provinces

Province	PSP launch year	$TargetPSP$	$GrantPSP$	$AgentPSP$	$pattax$
Shanghai	1999	1(2003-)	1	0	1(2000-)
Beijing	2000	1	0	1(2002-)	1(2005-)
Chongqing	2000	0	1	0	1(2007-)
Guangdong	2000	1(2003-)	0	1(2003-)	1(1995-)
Jiangsu	2000	1	0	0	1(2009-)
Tianjin	2000	1	0	1	0
Guangxi	2001	0	1	1(2003-)	0
Hainan	2001	0	0	0	0
Heilongjiang	2001	1	1	0	0
Sichuan	2001	1	0	0	0
Shaanxi	2001	1(2003-)	1(2003-)	1(2003-)	0
Zhejiang	2001	1	1(2006-)	0	0
Fujian	2002	1(2008-)	1(2006-)	0	0
Guizhou	2002	0	0	0	0
Henan	2002	1	1	1	0
Inner Mongolia	2002	0	0	1	0
Jiangxi	2002	1(2006-)	0	1	0
Xinjiang	2002	1(2003-)	1	0	0
Anhui	2003	1(2010-)	1	0	1(2005-)
Shandong	2003	1	1	0	0
Shanxi	2003	1	0	0	0
Tibet	2003	0	1(2004-)	1(2004-)	0
Yunnan	2003	1(2004-2008), 0(2009-)	1	0	0
Hunan	2004	1	1(2007-)	0	0
Jilin	2004	1	1	0	1(1999-)
Hebei	2005	1(2010)	1	0	0
Qinghai	2005	0	0	1(2006-)	1(2009-)
Liaoning	2006	1	1	0	1(1997-)
Hubei	2007	0	1	0	1(1998-)
Ningxia	2007	1	0	0	0

Notes: Summarized from public government documents by authors. Gansu launched PSP in 2011, thus not included in our sample. $TargetPSP$ refers to explicit subsidies that target excellence, $GrantPSP$ refers to grant-contingent subsidies, $AgentPSP$ refers to policies that aim at subsidizing fees for using patent agents, and $pattax$ identifies patent-relevant tax rebate policies.

Table A2 Dynamics of propensity to patent

	Number of applicants		Number of applications		Applications per applicant		
Years since program launch	Exp (1)	Entrant (2)	Exp (3)	Entrant (4)	Exp (5)	Entrant (6)	Ratio (5)/(6)
1	2,480	11,239	12,583	16,244	5.07	1.45	3.51
2	3,131	12,982	20,806	18,953	6.65	1.46	4.55
3	3,961	15,686	26,304	23,676	6.64	1.51	4.40
4	4,900	17,658	34,330	28,150	7.01	1.59	4.39
5	5,449	18,143	41,777	29,146	7.67	1.61	4.77
6	5,960	20,010	54,212	34,795	9.10	1.74	5.23
7	7,258	22,065	69,217	39,326	9.54	1.78	5.35
8	8,203	23,905	80,484	45,253	9.81	1.89	5.18
9	8,342	22,626	89,973	45,293	10.79	2.00	5.39
10	8,956	21,642	97,253	44,085	10.86	2.04	5.33

Notes: Authors' calculation based on data of public government documents and CNIPA. Experienced innovator (denoted as "Exp") in this table is defined as a patentee filed patents at time t and $t-1$. Applicants and applications in Gansu province are excluded since Gansu launched patent subsidy policies in 2011.

Table A3 Generalized definition of experienced innovators

	(1) lnApps	(2) lnGrants	(3) lnClaims	(4) lnFwd	(5) lnInventors
PSP2	0.495**	0.600***	0.498**	0.593***	0.529***
	[0.189]	[0.183]	[0.181]	[0.175]	[0.175]
PSP1	0.251	0.339*	0.289	0.339*	0.297
	[0.204]	[0.192]	[0.206]	[0.170]	[0.191]
Rentrant_2	0.268**	0.319**	0.278*	0.585***	0.386***
	[0.127]	[0.125]	[0.141]	[0.186]	[0.134]
Rexp_2	0.107	0.056	0.126**	0.110	0.092
	[0.065]	[0.094]	[0.057]	[0.098]	[0.055]
PSP1 $\times$ Rentrant_2	-0.122	-0.139	-0.051	-0.289	-0.159
	[0.255]	[0.231]	[0.326]	[0.261]	[0.256]
PSP1 $\times$ Rexp_2	0.685***	0.569**	0.598***	0.612***	0.679***
	[0.193]	[0.211]	[0.178]	[0.191]	[0.168]
L.lnRD	0.400**	0.530***	0.444**	0.453**	0.382**
	[0.173]	[0.184]	[0.176]	[0.174]	[0.162]
lnFDI	-0.221*	-0.237**	-0.232*	-0.191	-0.190*
	[0.122]	[0.109]	[0.116]	[0.114]	[0.098]
Observations	421	421	421	421	421
adj. R^2	0.896	0.910	0.912	0.928	0.944

Notes: Robust standard errors are in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Experienced innovator in this table is defined as a patentee filed patents at time t and $t-2$. We control for province and year fixed effects.