China's Rising IQ (Innovation Quotient) and Growth: Firm-Level Evidence*

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Abstract

This paper examines whether the rapidly growing firm patenting activity in China is associated with productivity growth, and whether this association changes after the introduction of patent subsidy programs and differs across ownership types. We first build a unique dataset uniting detailed firm balance sheet information with firm patent data for the period 1998-2007. We find strong evidence that both within-firm increases in patent stock and initial patenting event (using nonpatenting firms selected based on the propensity-score matching method as the control group) are associated with increases in total factor productivity. Patent subsidy programs sequentially implemented across Chinese provinces weaken this positive association over time. State-owned enterprises (SOEs) have higher productivity-patenting elasticities than private firms, especially after 2001.

Keywords: innovation; growth; patent; R&D; productivity; state-owned enterprises; China

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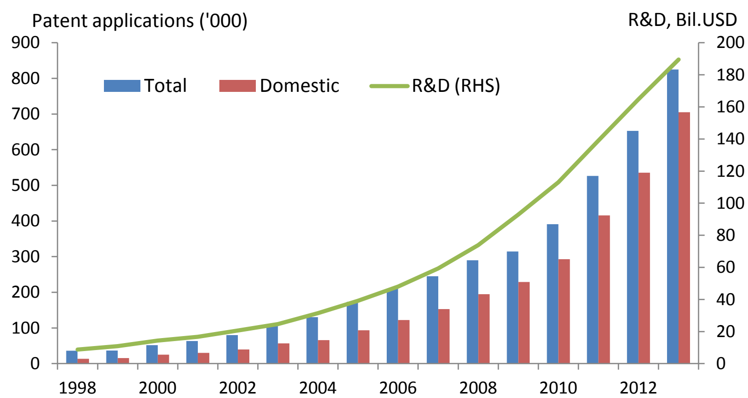
1 Introduction

The last two decades have witnessed astonishing growth in China's innovation input and output. R&D spending increased by 22 percent per year during 1998-2013, reaching 190 billion USD in 2013. By 2014, China's R&D expenditure, as a ratio of GDP, had exceeded the OECD average, although its GDP per capita was just one-fifth of the average OECD economy (Wei et al., 2017). Innovation output, measured by the number of domestic applications for invention patents, grew by almost 23-fold from 1998 to 2013, surpassing Japan and the United States in 2011 (Figure I). Accompanying the rising innovation performance is China's spectacular growth, which is often attributed to its productivity improvement. Zhu (2012), for example, finds that total factor productivity growth has contributed to about 80 percent of China's per capita GDP growth for the 1978-2007 period.

Figure I: Invention-patent applications and R&D expenditure in China



Source: National Bureau of Statistics of China, State Intellectural Property Office of China

The soaring number of patents held by Chinese firms (such as Huawei and Lenovo), the rapid accumulation of R&D stocks, and the success of large internet and telecom companies (such as Alibaba and Tencent) have led some to conclude that China has leaped into the world innovation frontier. Skeptics, on the other hand, contend that China's prolific patent filings are simply a response to the government-set target and various subsidies. With weak intellectual property rights (IPR) protection (Zhao, 2006), and under the dominance of inefficient and uninnovative SOEs, many question if the rapid upsurge in patenting is "fiction" (*Economist*, Dec 11th 2014) or represents real changes in the technological capability and competitive edge of Chinese firms.

While a number of recent studies have strived to unravel what is behind China's explosive growth in R&D and patents (Hu and Jefferson, 2009; Li, 2012; Hu et al., 2017; Chen et al., 2018), this paper poses different questions: Is China's patent explosion associated with real productivity growth? And does the association differ across ownership types and change after the introduction of patent subsidy programs? Answers to these questions are of both policy and economic interests, as they provide valuable insight into China's transition from an investment-led to a more innovation-based growth model (Zilibotti, 2017) and the impact of past patent subsidy programs on the "quality" of patents—where quality is evaluated by their relationship with productivity. In addition, as patent statistics are often used as indicators of innovation and R&D successes in developed economies (e.g., Griliches, 1981; Jaffe, 1986; Hall et al., 2001; Bloom and Van Reenen, 2002; Hall et al., 2005; Aghion et al., 2005; Balasubramanian and Sivadasan, 2011), our work also informs future works using Chinese patent statistics whether they are able to meaningfully capture firm's innovative and economic activity and how they are compared with evidence in advanced economies.

We address these questions by presenting evidence at the firm level using a unified dataset merging firm patenting data obtained from China's National Bureau of Statistics (NBS) with firm production and balance sheet data from Annual Surveys of Industrial Enterprises in China (ASIEC) which include all "above-scale" firms. Our main results are that *within-firm* changes in the patent stock of innovating firms (intensive margin) and firms' initial patent applications (extensive margin) are both significantly and positively associated with Total Factor Productivity (TFP) improvement in China. The TFP-patent elasticity, on average, is even higher than that observed in the U.S. This positive association, however, weakens over time throughout our sample period of 1998-2007, which could be related to the patent subsidy programs that were launched sequentially across different provinces and municipalities in China. The improvement in firms' productivity associated with a given change in patent stock drops when these government-led incentives for patenting are in place. Somewhat surprisingly, compared to their privately-owned peers, changes in patent stocks of state-owned enterprises (SOEs) are associated with more improvement in measured productivity, even though they produce less patent per yuan spent in R&D. This elasticity gap between ownership types is especially significant after 2001 and increases over time towards the end of the sample. Our followup analyses seem to suggest that it is not because SOEs enjoy better IPR protection, or receive more subsides from the government, or are less financially constrained, or benefit more from China's accession to WTO. Since the divergence between the TFP-patent elasticity for SOEs and that for POEs emerges after SOE reforms, it suggests that SOE reforms might have contributed to the above observation.

Our analysis proceeds as follows. First, using firm names, we develop annual links between patent applicants and firms included in the ASIEC. The matched data cover more than 1/4 million firms and almost 1.5 million firm-year observations from 1998 to 2007, representing the majority of nonindividual, nonresearch-institution, and nongovernment patentees during this period. Using this unified database, we first document some stylized facts about Chinese firms' patenting behavior. In line with observations in developed economies, we find that the distribution of patent activities across Chinese firms is highly skewed. Only 9 percent of all firms in the merged sample applied for patents, accounting for 38 percent of value added, 42 percent of capital stock, and 27 percent of employment. Among these patent-filing firms, 6 percent engage in innovation in multiple four-digit industries, accounting for 91 percent of overall patents. Patenting firms are, in general, significantly larger in size than nonpatenting firms. They also tend to be older, have higher capital-to-labor ratios, and higher shares of new products in sales. Patenting behavior is also highly heterogeneous across industries for the merged above-scale firms. For example, an average firm files 20 times more patents in the computer industry than that in the least innovative food processing industry. The medical industry has the highest fraction (39 percent) of firms filing patents in China; while in industry of apparel, footwear, and caps, only 3 percent of firms ever filed patents.

To understand which firm characteristics are associated with patenting in China, we then estimate a count data model of patents based on the Negative Binomial specification. We find that younger and larger firms, and firms with more R&D investment, patent more. SOEs tend to file fewer patents than POEs, while exporting firms are more innovative than nonexporting firms.

We then compute the within-firm elasticity of firm productivity (and other production performance) to changes in patent stock (i.e. the accumulated number of patent applications). The elasticities of productivity to changes in patent stock are 0.017, 0.014, 0.039, and 0.026 log points for labor productivity, the Solow Residual, the OLS estimate of Total Factor Productivity (TFP), and the Ackerberg et al. (2015) measure of TFP, respectively. These elasticities are surprisingly higher and more significant than those observed in the U.S., as documented in Balasubramanian and Sivadasan (2011). The elasticity of the new product revenue share is 1.5 percent and significant, implying that innovation is also associated with the introduction of new products in China. Significantly positive changes in other production outcomes, such as size (output, value added, capital stock, and employment) and exports are also observed, but not for factor intensity or markup. Although firm entry and exit are definitely important phenomena in a fast-growing economy like China's, and often have far-reaching implications, considering only the surviving firms does not alter our findings, and the estimated elasticities are even larger than the baseline estimates. These findings also hold across different patent types (invention patent, utility model patent, and design patent) with comparable elasticities.

In line with these findings, we also observe that significant real economic changes are associated with firms' initial patent applications. Based on a difference-in-differences (DID) analysis, using first-time patentees as the treatment group, and nonpatenting firm—selected based on the Propensity-Score Matching (PSM) method—as the control group, we find that significant improvements in productivity, size, new product shares and exports, are associated with first-time patent application events. The significant effect tends to take place after a year from the initial patenting.

We then examine the dynamics of the contribution of patent to productivity growth by allowing the patent elasticity of TFP to vary year by year. Our results show that this contribution declines steadily over time. We investigate whether the weakening elasticity over time is because more and more patent applications are induced by government-led patent fee subsidy programs and hence embody less innovation value and are less correlated with TFP growth. During our sample period (1998-2007), various patent subsidy programs were rolled out sequentially across different provinces in China. Employing data on different introduction years of the programs across various regions (Li, 2012), we find that it is indeed the case. When the patent subsidy program is in place, the elasticity drops on average by 0.017 log point, implying a significant reduction in the TFP-patent elasticity.

Next we investigate whether a firm's ownership status plays any significant role, as ownership is a uniquely important element in understanding firm performance in China (e.g., Hsieh and Klenow, 2009; Song et al., 2011; Zhu, 2012; Chang et al., 2016). We find that the aforementioned positive association between patent application and productivity growth is significantly stronger for SOEs than for their private-owned peers, especially after 2001. This result is not driven by firm entry and exit, neither by changes in firm ownership. This finding is to some extend unexpected, especially considering that SOEs are generally regarded as uninnovative and less effective with their R&D investment.

To understand this somewhat surprising result, we carry out the following further analyses. First, since the conventional role of patents is to deter copying and pre-empt unauthorized entry, patent may generate IPR protection value for the firms in addition to its technological value. To test whether it is the higher protection value enjoyed by SOEs that contributes to the above observation, we turn into another alternative measure of technology—R&D expenditure. Unfortunately, the ASIEC data we have access to only provide R&D expenditure for three years—2001, 2005, and 2006. Nevertheless, when both R&D and patents are included in the estimation of TFP returns to innovation, with the first approximating the unobserved technology and the second representing the IPR protection premium, we observe that the TFP return to R&D is again significantly higher for SOEs while the TFP return to patent application is non-differentiable between SOEs and POEs. This evidence suggests that the higher TFP return to SOEs' patents does not come from the patent premium but may reflect true technological value of SOEs innovation.

Second, since this divergence of TFP-patent elasticities between SOEs and POEs emerges after 2001, coinciding with China's accession to WTO, we next investigate whether this event disproportionately benefits exporting SOEs and drives the above result. However, when splitting SOEs into exporting and nonexporting SOEs, we fail to see significant differences. The elasticity of nonexporting SOEs is still significantly higher than the elasticity of POEs.

Third, given the well-documented misallocation of resources between SOEs and private enterprises, this discrepancy could be the result of the considerable credit support SOEs receive from the government, as well as their favorable access to bank loans (which might reflect in their higher leverage ratios). We test the role of government subsidy and leverage ratio in explaining the TFP-patent elasticity, but find that both are insignificant in explaining the elasticity gap associated with the ownership status.

Since the gap emerges following a sequence of SOE reforms, it suggests that the SOE reform might have contributed to the observation. Under the slogan "Grasp the Large and Let Go of the Small", Hsieh and Song (2015) has shown that reforms intended to strengthen large SOEs, but privatized or closed loss-making SOEs, and have contributed positively to TFP growth. In addition, they document that TFP growth of SOEs was faster than that of private firms for our sample period. Similarly, our analysis also shows that these large innovating SOEs experienced higher TFP growth than innovating POEs, suggesting that the SOE reform may have improved both SOEs' innovating behavior and TFP growth, as well as the relationship between these two.

Our results that Chinese firms' patents are associated with real significant changes in firm productivity and other performance suggest that they are meaningful proxies for real innovative activity. However, it should not be interpreted as patenting having a causal effect on firm productivity. In fact, a firm's patenting behavior is not exogenous. Factors that contribute to the patent applications may simultaneously affect firm productivity. When we attempt to provide some insight on the causality using the initial perceived strength of prefecture-level IPR protection as an instrumental variable (IV) in an IV analysis, we find that there is no significant causal effect of patent application on firm productivity growth.

Related Literature This paper contributes to several strands of literature. First, it is related to the large literature using patent data for economic research on productivity and innovation, which dates back to Schmookler and Brownlee (1962), Griliches and Schmookler (1963), and Scherer (1965). The empirical evidence so far has been concentrated in advanced economies, where high-quality patent data are available and attempts have been made to combine them with firm production data. For example, Balasubramanian and Sivadasan (2011) developed a detailed concordance between NBER patent data and U.S. Census data to examine the consequences of firm patenting. Similar research on developing economies, however, is scant. To our knowledge, this is the first paper evaluating the quality of Chinese patents by examining the relationship between patents and

TFP using a large firm-level dataset matched with patent statistics. We observe many similarities between Chinese patent data and the U.S. observations, but also point out important differences in the following sections. Our results thus support the previous literature that uses patents as meaningful proxies of innovation. In addition, the positive association between patents and productivity growth validates the prevailing approach in the literature, which uses changes in TFP or the introduction of new products as measures of Chinese firm innovation (e.g., Aghion et al., 2015).

Second, this paper contributes to the growing literature on various aspects of China's innovation activity. Most empirical studies use aggregate secondary data at the provincial level (e.g., Cheung and Ping, 2004; Li, 2012). A few studies using disaggregated firm-level data focus on listed firms (e.g. Choi et al., 2011; Lin et al., 2010; Boeing et al., 2016) or large and medium size enterprises (e.g., Hu and Jefferson, 2009; Hu et al., 2017) or are limited to a particular region (Lei et al. 2012). One exception is Xie and Zhang (2015), which document several basic patterns of Chinese firm patenting behavior by making a similar effort as ours of matching ASIEC and SIPO data at the firm level.

Many existing works study the factors behind the explosion of China's R&D expenditure and patent applications. For example, based on large and medium size enterprises data, Hu and Jefferson (2009) find that a combination of rising foreign direct investment, changing ownership structures in Chinese industry, and pro-patent legislation contributed to China's patent boom during 1995-2001. In their follow-up research, Hu et al. (2017) relate the more recent 2007-11 patent surge to noninnovation-related motives for acquiring patents. Consistent with ours, they find the positive correlation between patents in force and labor productivity becomes weaker over time. However, their patent data are only available for three years. Li (2012) finds that patent subsidy programs, together with R&D intensification and a pro-patent legal change fostered the jump in Chinese patents from 1995 to 2007. Recently using a difference-in-differences approach, Fang et al. (2017) find that patent filing increases after SOE privatizations and this increase is larger in areas with strong IPR protection, suggesting that institutions matter for innovation. Chen et al. (2018) analyze the effects of tax cuts for R&D and find large responses of reported R&D and increase in firm productivity.

Third, this paper also adds to a recent literature differentiating innovation behavior of firms with different ownership. Using publicly listed Chinese firms data, Boeing et al. (2016) find that throughout their entire sample period of 2001-2011 POEs are more effective with their R&D spending in increasing TFP. However, for the earlier period of 2001-2006 they find a higher TFP-returns of patents for SOEs than POEs, in line with our result, although this observation is reversed for their later sample period when policy-induced patenting strategies were introduced. Wei et al.

(2017) find that innovation productivity is higher for private firms than for SOEs, while the latter receive more government subsidies, and identify the potential misallocation of R&D resources. Corroborating our evidence, Wei et al. (2017) also argue that the Chinese patent explosion is associated with a real, robust improvement in patent quality, based on patent approval rates and comparisons between Chinese patent citations and those of other countries that are patenting in the United States.

The rest of the paper is organized as follows: Section 2 provides an institutional background on China's patent system and describes the data construction and measurement of key variables. Section 3 presents evidence on the determinants of patent activity and examines the relationship between changes in a firm's patent activity and production performance. Section 4 discusses the over time change of the relationship mentioned above and provides the evidence of its link to the introduction of patent subsidy programs. Section 5 investigates the role of state ownership, and Section 6 studies whether changes in productivity could be attributed to patenting. Section 7 concludes.

2 Institutional Background, Data, and Measurement

2.1 China's Patent System

China's patent law was first introduced in 1984, put into effect the second year, and has since been amended several times (September 1992, August 2000, and December 2008) to comply with international standards and to facilitate its development into an innovative economy. China's State Intellectual Property Office (SIPO) grants three types of patents: invention patents, utility model patents, and design patents. Broadly speaking, an invention patent protects technical solutions or improvements relating to products or processes, while the utility model patent covers mostly the structures and shapes of mechanical structures, and design patents cover new designs, shapes, patterns, or colors, which are rich in aesthetic appeal and fit for industrial application.

An invention patent in China corresponds to the U.S. utility patent. Similar to those required in other major patent offices in the world, invention patent applicants must submit relevant documents, such as clear and comprehensive descriptions of the inventions and reference materials, so that examiners may carry out the "Substantive Examination" of the applications in terms of novelty, inventiveness, and industrial applicability.[1] It takes approximately three to five years for

[1]Novelty, in particular, means that, before the filing date, no identical invention or utility model patents have been publicly disclosed in any publication, or have been publicly used or made known to the public anywhere in the world. Furthermore, there should be no other earlier-filed Chinese application that describes an identical invention or utility model patent, even if its publication date is after the date of filing of the present case.

an application to complete prosecution. Once granted, invention patents have a duration of 20 years. 26 percent of total patent applications are submitted for invention patents in our matched sample.

Applications for utility model patents (similar to petty patents) are only subject to novelty tests and have practical uses. The inventiveness requirements for utility model patents is lower than that of invention patents, and utility patents can be obtained as quickly as within 12 months after filing. These patents are preferred for structural products that have relatively short product lives or relatively low technology hurdles (i.e., competitors may easily reverse engineer or copy the technology). The term for a utility model patent in China is 10 years from the application date. By contrast, an invention patent provides twice the duration of protection and is more useful for a product that requires an extended development period or that will remain commercially valuable for a long time (i.e., pharmaceutical or biotech). Utility patents account for 31 percent of the total patent applications in our matched sample.

The design patent application does not require substantive examination and is only subject to a formality examination. The patented design must be distinctly different from existing designs, or combinations of existing design features, and must not conflict with the lawful rights acquired by others prior to the date of application. The approval time/period, starting from the filing date, is usually between three and eight months. A design patent can be granted for up to 10 years. Design applications account for the largest share of patent applications, 43 percent, in our matched sample.

China now is one of the most litigious countries in the world when it comes to intellectual property enforcement. In 2001, only 1,597 infringement actions had been filed. By 2010, that number had risen to 5,700, compared with the 3,605 patent infringement actions filed in the U.S. in the same year.

2.2 Patent Subsidy Programs

In the past couple decades, Chinese governments at various levels have introduced different policy initiatives to promote technology innovation, R&D and patent applications. The key national initiatives, such as the Long and Medium Term Science and Technology Plan (for the period of 2006-2020) and the 12th Five-year Plan of Science and Technology Development (for the period of 2011-2015), took place outside our sample period, and hence their impact cannot be analyzed using our dataset. There were, however, province-level patent subsidy programs sequentially introduced between 1999 and 2007 across different regions in China, and we investigate their impact on the quality (i.e. the measured TFP-return of patent) of patent filed afterwards.

The data on different launching years of patent subsidy programs in each province or municipality in China are obtained from Li (2012), which extracts these dates from the series of Annuals of Chinese Intellectual Property Rights that record key policies and practices of intellectual property management for each local government.[2] Shanghai was the first municipality that launched policy initiatives in 1999 to stimulate local innovators to apply for patent by setting up a special fund to subsidize costs and fees associated with patent application, substantial examination, and maintenance. These subsidies are independent of the technology class, or the potential economic value of inventions. In the following year, five other provinces and municipalities—Beijing, Chongqing, Guangdong, Jiansu, and Tianjing—followed suit. By the end of 2007, 29 out of 30 provinces in mainland China had launched a patent subsidy program. Table X in the Appendix lists the starting year of these programs for each province.

Li (2012) argues that patent subsidies significantly reduce the cost of seeking patent protection and thus increase the overall payoff of patenting for potential patentees. As evident from the aggregate data, patent applications jumped immediately after the program was enforced in each area. The regional disparity in the timing of these programs is consistent with the observed patterns of Chinese patenting across regions.

2.3 Data Description

The patent application data are obtained from China's National Bureau of Statistics (NBS). The dataset includes patents applied as of Oct 24, 2011 in China. The database contains 5,987,061 observations, including 2,124,619 invention patents, 2,088,790 utility model patents, and 1,773,652 design patents. A typical entry of patent contains the following information: application number, patent name, applicant, inventor, filing and publishing dates, its main International Patent Classification (IPC) number, filing agency's name and associated institution, applicant's address, and patent origin (provinces in China or other countries).

Firm-level production and financial data come from the ASIEC for the period 1998-2007, which was conducted annually by the NBS. The ASIEC is the most comprehensive firm-level dataset in China and has been widely used in the literature (e.g., Hsieh and Klenow, 2009; Brandt et al., 2012; Aghion et al., 2015). It is described in detail in Du et al. (2012). The survey covers all state-owned and non-state-owned "above-scale" firms—firms with annual revenues above 5 million RMB (approx. 0.7 million USD)—in the industrial sector, including mining, manufacturing, and public utilities. Although the data do not include all firms (especially small ones), Brandt et al.

[2]Not only the initial year of these programs differ across regions, the monetary incentives (e.g., the budget available for subsidies and the rules for reimbursement) provided by the programs also vary. Unfortunately, the detailed information on the latter is not available.

(2012) show that these firms account for most of the economic activity in China. Most firm-level production variables (such as output, value added, sales, etc.) in the dataset line up very closely with the corresponding aggregate variables in the Chinese Statistical Yearbook.

The ASIEC data were cleaned following the procedures outlined in Brandt et al. (2012). To construct the firm panel, we first use a firm's unique registration ID to match the firm over time. For a firm that cannot be matched directly by its ID (probably as a result of a merger, acquisition, or restructuring), its name, address, phone number, etc., are used to match it over time.[3] The result is a 10-year unbalanced panel of firms. To handle other potential mismeasurement issues, we drop the following from our sample: (i) observations with missing key variables, such as total assets, net values of fixed assets, sales, and values added; (ii) firms with reported sales below 5 million RMB; and (iii) firms with fewer than 10 employees. In addition, following Cai and Liu (2009), and guided by the generally accepted accounting principles, we delete observations if any of the following rules is violated: (i) total assets must be higher than current assets; (ii) total assets must be larger than total fixed assets; (iii) total assets must be larger than the fixed assets' net values; and (iv) the year of establishment must be valid. Since our analysis relies on panel techniques, firms with fewer than four consecutive years of data are also excluded. This leaves a final sample of 263,111 firms for the merged sample period 1998–2007. The overall panel is unbalanced, as we keep new entrants and exiters in the sample. Results using a balanced panel are sometimes reported in the following sections for comparison.

We then create a firm-patent matched dataset that links the patent data to ASIEC firm data. Since the two datasets use different firm identification codes, following Liu et al. (2015) we match them by firm name (i.e.,"firm name" in ASIEC data and "assignee name" in patent data), and double-check the matching results with the firms' location information.[4] Among all the matched firms in our ASIEC sample, 29,198 firms applied for patents at least once since the patent law's establishment in China—we call these firms "patenting firms" or "patentees" (see Column (2) of Table I). Firms that had never filed patents before the end of our sample period (2007) are labeled "nonpatenting firms" or "nonpatentees". In total, the matched production-patent data contain 198,414 firm-year observations from 1998 to 2007. As shown in Columns (3) and (6) of Table I, on average about 9 percent of firms in our ASIEC sample are innovating firms (i.e. matched to

[3] About 95 percent of firms from 1998 to 2007 are identified by registration ID, while the rest are matched based on other information.

[4] We use exact name match between the names of the firms in the patent data and the names of the firms in the ASIEC, both in Chinese characters. Admittedly, this procedure may drop some patenting firms due to spelling errors or different abbreviations of the names in one or both of the datasets. However, this procedure guarantees no mis-match. We prefer this method than fuzzy matching method which can potentially lead to mismatch. For our propose, as long as firms are randomly dropped (e.g. firms whose patents tend not to relate to their performance are not systematically dropped), this procedure should not bias our result.

Table I: Matching ASIEC Data and Patent Data

Year	Our Sample						NBS CSY
	No. of firms in ASIEC	No. of patentees		Total patents by enterprises	Patents by matched industrial firms		Patents by large-medium firms
	(1)	(2)	(3)=$\frac{(2)}{(1)}$	(4)	(5)	(6)=$\frac{(5)}{(4)}$	(7)
1998	100,126	5,242	5%	20,090	6,638	33%	6,317
1999	106,312	7,103	7%	29,446	9,693	33%	7,884
2000	106,236	8,762	8%	32,802	11,509	35%	11,819
2001	121,884	11,027	9%	39,308	14,728	37%	15,339
2002	133,919	13,459	10%	45,084	22,208	49%	21,297
2003	155,725	16,375	11%	62,829	29,092	46%	31,382
2004	234,522	20,634	9%	64,169	37,820	59%	42,318
2005	233,505	23,776	10%	77,951	46,608	60%	55,271
2006	262,263	26,539	10%	89,171	66,423	74%	69,009
2007	298,152	29,198	10%	131,152	80,270	61%	95,905

at least one patent application up to a given year), whose patents account for about half of the total patent applications by enterprises (see Column (4), data are from NBS). The rest of patent applications are filed by below-scale firms, or firms in other industries (other than manufacturing, mining and public utilities), or by firms that fail to be matched to the ASIEC sample. To assess the quality of our match at the aggregate level, we compare the number of patent applications made by large- or medium-sized industrial firms—summarized and reported by the NBS's China Statistical Yearbook (Column (7))—to the number of patent applications in our matched data (Column (5)). The numbers are close, especially considering the trends, suggesting that our matched data are representative in terms of capturing patents by large- or medium-sized industrial firms.

The match of the patenting data with the ASIEC firms naturally drops patent-filing below-scale firms, whose patent applications may have different association with firm's performance than that of the above-scale firms. All our analyses below are based on above-scale firm sample, and hence our results should not be generalized to all innovating firms in China.

We first report some basic statistics about firm innovation and production distribution across two-digit industries in China. Table II presents the economic and innovation activities of patenting firms by industry. Columns (1) and (2) show the importance of these firms. Although the proportion of firms within each industry that apply for patents is small, ranging from 3 percent to 39 percent (Column (1)), they account for a relatively large share of the industry's value-added, ranging from 11 percent to 82 percent (Column (2)). This is consistent with the stylized facts documented in previous studies using industrial country observations: relatively few firms file patents, but they are firms that dominate economic activity. There is also large heterogeneity across industries: 39 percent of in-sample firms in the medical sector applies for at least one patent in a given year, while only 3 percent of firms in apparel, footwear, and caps are patent-filing firms. Among the 30 two-digit industries, computers, electrical machinery, and transport equipment are the top three most innovative industries, both in terms of aggregate innovation output (the industry's total number of patent applications per year, found in Column (3)) and innovation input (industry-level annual R&D expenditure, found in Column (4)). Since industries also differ in firm concentration, the top three industries boasting the highest number of patent applications per firm (see Column (5)) are slightly different from the previous list: computers, manufacturing of articles for culture, education, and sports and pressing of ferrous metals. Finally, Column (6) shows the share of SOE firms in each industry. There is no apparent relationship between the dominance of state ownership and innovation at the industry level. In addition, since only above-scale firms are matched to patent data, the selection based on scale could potentially also generate the cross-industry heterogeneity observed above, and hence should be interpreted with caution.

2.4 Measurement

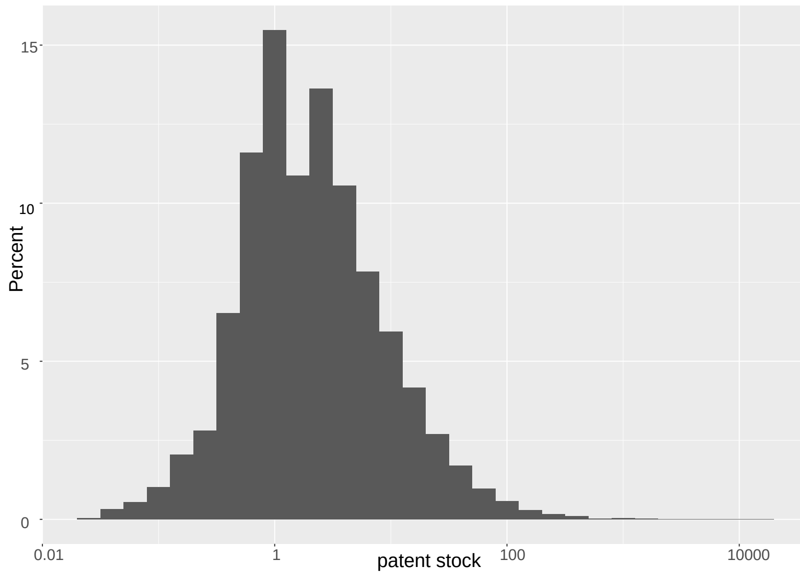
Innovation We use two indicators—patent stock and patent status in a given year—to evaluate a firm's innovation outcome. Let $p^j_{i,t} > 0$ denote the number of patents filed by firm i in category j in year t. The total number of patents the firm applied for in year t is then $P^i_t = \sum_j p^j_{i,t}$. Patent stock in category j ($s^j_{i,t}$) is the accumulated count of patents the firm has applied for up to year t subject to a 15% depreciation rate that is standard in the literature: $s^j_{it} = 0.85 \times s^j_{i,t-1} + p^j_{it}$. Firm i's total patent stock is then $S^i_t = \sum_j s^j_{i,t}$. A firm's patent status becomes one from the year it filed for its first patent; otherwise, its patent status is zero.

Figure II presents the distribution of firms' patent stocks ($\{S_i\}_i$) in the last year of the sample (2007), which is highly skewed. While an average firm has a stock of 13.2 patents, a median firm has only three patent applications. Among the 29,198 firms with positive patent stock in our matched data, the majority of the innovating firms (29.2 percent) have only one patent each. A few outliers (about 1.38 percent of firms in the matched dataset) have applied for more than 100 patents.

Production The ASIEC firm-level dataset contains detailed information about firms' balance sheets and income statements. We use data on income statements such as sales, value added, export shipments, employments, capital stocks, wages, total intermediate inputs, profits, and interest costs to evaluate firm performance and construct the various measures of firm productivity. Balance sheet data on firms' assets and liabilities are useful for measuring firms' credit constraints as well. Since a firm's registration date is also available, we can calculate its age by the difference between the current year and the registration year.

Each firm belongs to an industry according to the four-digit Chinese Industry Classification

Figure II: Histogram of patent stock (in log)



Notes: The Figure presents firm distribution across patent stock, which is calculated as accumulated count of patents a firm has applied up to 2007 subject to a 15% depreciation rate.

(CIC) system, which resembles the U.S. Standard Industrial Classification (SIC) system. In 2003, the Chinese classification system was revised to incorporate more details for some industries, while some other industries were merged. To make the industry codes comparable across the entire sample period, we adopt a harmonized classification system, created by Brandt et al. (2012), to group industries into more aggregated levels to ensure consistency before and after 2003.

In the ASIEC, instead of fixed investment, each firm reports the value of fixed capital stock at the original purchase price. These book values are the sum of nominal values from different years, and therefore should not be used directly. Following the general practice for estimating real capital stock (e.g., Brandt et al., 2012), we use perpetual inventory method in this study. We first impute the real initial capital stock of a firm, depending on whether it was established before or after 1998 (the beginning year of our data sample).[5] We then back out nominal capital stock year by year by adding annual nominal fixed investment, which is the change in nominal capital stock between years, assuming an annual depreciation rate of 9 percent. Finally, we deflate annual investment using the investment price deflator developed by Perkins and Rawski (2008).

Another adjustment we made to the data is related to the reported annual employment and wages. The median labor share of value added in our sample is roughly 25 percent, which is

[5]If a firm listed in the ASIEC was established after 1998, the initial nominal capital stock is the book value of capital stock that the firm reports for the first time. If a firm was established before 1998, initial capital stock is calculated using information from the 1993 Annual Enterprise Survey to construct estimates of the nominal capital stock's the average growth rate between 1993 and the year that this firm first appears in the ASIEC. The real initial capital stock is then obtained by deflating the nominal capital stock with the investment deflator in that year.

significantly lower than the aggregate labor share in the manufacturing sector, reported in the Chinese input-output tables and national accounts (about 50 percent). Following the procedure suggested by Hsieh and Klenow (2009), in our productivity estimation, we assume that nonwage benefits are a constant fraction of a firm's wage compensation, where the adjustment factor is calculated such that the sum of imputed benefits and wages across all firms equals 50 percent of the aggregate value added.

Ownership Following Hsieh and Song (2015), we use two variables in the ASIEC data to classify firm ownership. First, the data provide the share of a firm's registered capital owned by the state, a private person, a collective, a foreigner, or a legal person. A legal person is either another firm or simply a holding company. Second, the data classify the "controlling shareholder" of a firm as the state, a collective, a private person, or a foreigner. We define a firm as state owned if it satisfies one of the following requirements: 1) the registered capital held by the state exceeds 50 percent, or 2) the controlling shareholder for the legal person is the state.

Productivity To estimate productivity, we first deflate all nominal variables using corresponding price deflators. In the absence of firm-specific price deflators, we use detailed four-digit industry-specific input and output deflators from Brandt et al. (2012) and Brandt et al. (2017). For the sake of robustness and comparability with the literature, we measure productivity in the following five ways.

The first measure is the widely used labor productivity, which is calculated as real value added per employee. Given China's low labor share in production, omitting capital is unlikely to provide an accurate estimate of firm productivity. In our analysis, we give greater weight to the other productivity measures. The second measure we consider is the traditional Solow residual. It is constructed as changes in real value added minus the factor share weighted sum of changes in capital stock and employment. $\ln TFP^S_{it} = \ln Y^j_{it} - \alpha_{jt} \ln L^j_{it} - (1-\alpha_{jt}) \ln K^j_{it}$, where i represents the firm and j represents the two-digit industry to which the firm belongs. Y, L, and K indicate real value added, employment, and real capital stock, respectively. Labor share, α_{jt}, is then calculated as the share of wage bill in industry j's nominal value added. Solow-residual-based TFP requires information on the share of factor inputs and can introduce measurement errors. In addition, it assumes perfect competition in both input and output markets. Otherwise, the constructed TFP may reflect monopolist rent, as it is the residual of real value added after subtracting factor inputs. Thus, as a third measure, we follow Bloom and Van Reenen (2002) and consider the residual from the OLS regression of real value added on capital and employment with firm fixed effects and industry-year fixed effects:

$$\ln V_{it}^{j} = \lambda_1 \ln S_{it}^{j} + \lambda_2 \ln K_{it}^{j} + \lambda_3 \ln L_{it}^{j} + \mu_i + \gamma_{j,t} + \varepsilon_{it}^{j}. \tag{1}$$

However, estimating the production function using the OLS-FE approach does not control for unobserved productivity shocks, which are potentially correlated with inputs, leading to endogeneity issues. Failing to control for them would cause inconsistent estimates of a firm's production function. To deal with this endogeneity issue, we follow the method proposed by Olley and Pakes (1996), Levinsohn and Petrin (2003), and further developed by Ackerberg et al. (2015) (ACF hereafter) to handle the functional dependence problem. Here we consider two production function specifications: a generalized translog specification which is our preferred specification and a Cobb-Douglas production form. The two estimates are denoted by $TFP^{ACF,translog}$ and $TFP^{ACF,CD}$, respectively. Appendix A provides further details on the estimation procedure.

Markup As was mentioned, since the individual firm's price deflator is unavailable, our TFP measure is calculated based on nominal value added deflated by the industry-specific price deflator. Since the deflator is common across all firms within the same industry, the observed cross-firm TFP variations, following the aforementioned estimation methods, may simply reflect differences in the prices charged by different firms. To obtain further insight, we investigate how firm-specific markups change with patent stocks. To uncover firm-level markups, we follow the recent work of De Loecker and Warzynski (2012), who derive the equilibrium markup from a firm's cost minimization problem and express markup in terms of output elasticity of input and input share:

$$m_{it} = \widehat{\theta}_{it}^{l} (s_{it}^{l})^{-1}, \tag{2}$$

where s_{it}^{l} is the expenditure share of labor input, $w_{it}L_{it}/P_{it}Q_{it}$, and $\widehat{\theta}_{it}^{l}$ is the estimated output elasticity on labor input (see Appendix B for more details on the derivation).

3 Patent Stock and Firm Performance

3.1 Determinants of Chinese Firms' Patenting Behavior

Before evaluating the relationship between firm patenting with firm performance, we first ask what factors account for Chinese firms' patenting behaviors. As argued in Hu et al. (2017), if patenting decision is driven by technological advancement, as opposed to non-innovation related incentives that affect the propensity to apply for patent, one should expect a tight link between R&D input and patent application. Therefore, studying the determinants of Chinese firms' patenting provides another way to evaluate the significance of Chinese patents.

Since the patent count data are highly dispersed across firms, we estimate a version of the Negative Binomial model to analyze the patent count data:

$$P_{it} = \exp(\alpha_1 D_{it} \ln P_{it-1} + \alpha_2 D_{it} + \beta' X_{it-1} + \mu_i + \tau_t + \varepsilon_{i,t}), \tag{3}$$

where P_{it} is the patent application count of firm i at time t. Following Bloom et al. (2013), we control for both dynamics and fixed effects by adopting a Multiplicative Feedback Model. D_{it} is a dummy variable that equals one when $P_{it-1} > 0$, and zero otherwise.[6] Since there is strong persistence in patenting behavior, this lagged dependent variable, $P_{i,t-1}$ is included. The vector X_{it} stands for other control variables, including the log of the R&D expenditure (when available), sales, age, exporting firm dummies and SOE dummies (and their interaction with R&D). Lagged observations for X_{it} are included to mitigate endogeneity issues. We control for time and industry dummies. We also use the "presample mean scaling" method, as in Blundell et al. (1999), to control for firm fixed effects in some of the panel regressions.[7] Unfortunately, R&D expenditure data are only available for three years in the ASIEC that we have access to: 2001, 2005 and 2006, hampering the construction of time series of firm-level R&D stocks. Following Wei et al. (2017), we control for R&D expenditures from these three years in some regressions.[8]

Table III presents both panel regression estimates based on the three years with R&D data (Panel A) and using the entire sample period (Panel B). According to Panel A, R&D investment contributes positively and significantly to patent applications. This positive relationship between R&D input and innovation output is consistent with findings in previous literature (Hu et al., 2017). Compared to other firms in the same industry, larger firms with higher sales and younger firms apply for more patents. SOEs on average are less innovative than POEs as shown by lower patent applications. Finally, exporting firms file for more patents than nonexporting firms. These findings still hold when we examine the full sample (Panel B). Sales and firms' exporting status retain positive and significant coefficients. SOE status, on the other hand, remains to have a significantly negative effect on patenting behavior. As a firm ages, it becomes less innovative.

[6] The variance of the Negative Binomial is $\exp(x'\beta) + \alpha \exp(2x'_{it}\beta)$, allowing for the variance to be larger than the mean (α is the over-dispersion measure). This relaxes the restrictions imposed by the Poisson regression ($\alpha = 0$). Given that the unconditional mean of the patent count is much lower than its variance, the Negative Binomial Model is more appropriate than the Poisson Model. Moreover, we find that estimates based on the Poisson model yield qualitatively similar results, which is why we do not report them here.

[7] As discussed in Blundell et al. (1999), this method relaxes the strict exogeneity assumption required by the approach of Hausman et al. (1984).

[8] Only firms with R&D expenditure larger than 100 yuan are included in these panel analyses.

3.2 Within-Firm Changes in Patent Stock and Firm Performance

3.2.1 Baseline Analysis

This section examines the relationship between a firm's patenting behavior and the associated changes in its production performance. A patenting firm is the one that is matched with at least one assignee in the patent data (including firms that filed for patents before our sample starting year, 1998). The average patenting firm in China tends to be much larger than the average nonpatenting firm (see Table IX in Appendix C). Output, value added, capital stock and employment are generally greater by a factor of 3-5. They are also older, exhibit higher capital-to-labor ratios, export more, and have significantly higher revenue shares that are associated with new products. The simple mean comparison, however, does not suggest that the average patenting firm has a higher productivity level and markup than the average nonpatenting firm.

We now examine how within-firm *changes* in patent stock are related to *changes* in firm production and productivity, based on the following regression specification controlling for firm fixed effects and industry-year fixed effects:

$$\ln Y_{it}^{j} = \beta \ln S_{it}^{j} + \mu_i + \gamma_{j,t} + \varepsilon_{it}^{j}, \tag{4}$$

where Y_{it}^{j} is the outcome variable, such as various measures of productivity, sales, and employment, for firm i; S_{it}^{j} is the firm's patent stock at t; and j indicates the unique industry the firm belongs to as reported in the ASIEC database. The inclusion of firm fixed effects, μ_i, controls for time-invariant heterogeneity at the firm level. As every firm is classified into one of the four-digit industries, detailed four-digit industry-year fixed effects, $\gamma_{j,t}$, control for industry-specific shocks or trends that can affect both firm patenting and the dependent variables simultaneously (e.g., demand shocks). We also control for province fixed effects in all of our regression analyses.

Table II: Economic and Innovation Activity of Patenting Firms By Industry

CIC	Manufacturing Industry	% of firms (1)	% of Value added (2)	Patents (3)	R&D (4)	Patents per firm (5)	% of SOE (6)
13	Processing of Foods	6.7	18.7	274	0.13	0.49	21.4
14	Food	22.8	42.4	917	0.32	1.32	19.7
15	Beverage	24.7	53.6	698	0.68	1.28	32.0
16	Tobacco	31.9	82.2	83	0.47	1.40	91.3
17	Textile	4.4	14.7	869	0.62	1.50	25.7
18	Apparel, Footwear and Caps	2.8	11.3	350	0.16	1.61	9.0
19	Leather	4.6	11.1	198	0.05	1.15	7.4
20	Timber	6.6	14.6	165	0.05	0.93	18.0
21	Furniture	12.3	21.8	424	0.12	1.73	5.6
22	Papermaking	5.3	23.3	147	0.31	0.57	17.7
23	Print, Reproduction of media	6.9	24.7	101	0.09	0.56	23.8
24	Articles for Culture, Edu. And Sports	18.4	28.9	1,036	0.10	2.78	5.9
25	Petroleum Processing	10.3	46.8	101	0.49	0.79	45.0
26	Raw Chemical	13.4	35.7	1,222	2.94	0.79	26.2
27	Medical	39.0	61.5	1,109	2.20	0.84	26.8
28	Chemical Fibers	11.6	46.9	88	0.17	0.97	36.0
29	Rubber	15.1	33.4	201	0.43	0.71	21.8
30	Plastics	12.1	21.7	641	0.25	0.79	9.7
31	Nonmetallic Mineral	7.2	17.7	878	0.51	0.94	24.6
32	Pressing of Ferrous Metals	6.7	63.3	566	3.88	2.49	48.4
33	Pressing of NonFerrous Metals	10.6	45.0	314	0.65	1.11	36.5
34	Metal Products	15.0	29.1	1,136	0.66	0.96	12.4
35	General Purpose Machinery	20.7	44.1	1,986	2.87	0.81	23.7
36	Special Purpose Machinery	30.9	53.3	1,869	2.64	0.95	28.0
37	Transport Equipment	21.0	56.6	2,530	8.22	1.60	34.1
39	Electrical Machinery and Equipment	24.4	51.8	4,810	7.08	2.02	13.0
40	Computers and Other	25.4	50.1	6,518	13.62	4.33	22.6
41	Instruments	35.6	41.8	953	1.04	1.18	23.6
42	Art craft and Other	9.0	19.3	503	0.05	1.70	3.8

Notes: Column (1) shows the percentage of firms within each industry that apply for patent(s). Column (2) shows the share of industry value added accounted by these firms. Column (3) presents total number of patent applications in that industry per year, and Column (4) presents the total value of R&D expenditure (in billion RMB) in that industry per year. Column (5) shows the average number of patents filed per patenting firm in that industry and the share of SOEs among the innovating firms is shown in Column (6). All statistics reported in this table are averaged across years in our sample, except for Column (4) where R&D data are only available for three years—2001, 2005 and 2006.

Table III: Determinants of Patent Applications, Negative Binomial Model

Indept. Var.	A. With R&D for three years			B. Full sample without R&D	
	(1)	(2)	(3)	(4)	(5)
$\ln R\&D_{t-1}$	0.071***	0.070***	0.067***		
(s.e.)	(0.008)	(0.009)	(0.009)		
$\ln sales_{t-1}$	0.154***	0.154***	0.150***	0.187***	0.184***
(s.e.)	(0.009)	(0.009)	(0.009)	(0.004)	(0.004)
age_{t-1}	-0.005***	-0.005***	-0.004***	-0.004***	-0.004***
(s.e.)	(0.001)	(0.001)	(0.001)	0.000	0.000
D_t^{SOE}	-0.138***	-0.151	-0.166	-0.071***	-0.061***
(s.e.)	(0.027)	(0.106)	(0.106)	(0.014)	(0.014)
D_t^{EX}	0.056**	0.056**	0.058**	0.051***	0.051***
(s.e.)	(0.024)	(0.024)	(0.024)	(0.011)	(0.011)
$D_{it} \ln P_{t-1}$	0.498***	0.498***	0.491***	0.459***	0.452***
(s.e.)	(0.010)	(0.010)	(0.010)	(0.005)	(0.005)
$D_t^{SOE} \ln R\&D_{t-1}$		-0.002	-0.006		
(s.e.)		(0.013)	(0.013)		
Pre-sample FEs			0.208***		0.153***
(s.e.)			(0.038)		(0.016)
Firm FEs	No	No	Yes	No	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
Observations	38,565	38,565	38,565	1,197,426	1,197,426

Notes: Dependent variable is patent application counts. Estimation is conducted using the Negative Binomial model. Standard errors allow for serial correlation through clustering by firm. A full set of year dummies, industry dummies are included all panel regressions. Columns (1) – (3) include only three year observations as R&D expenditures are only observed for three years in our data. Columns (3) and (5) include the pre-sample mean scaling approach used to estimate fixed effects of firms following Blundell, Griffith, and Van Reenen (1999). Robust standard errors clustered at the four-digit industry level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table IV: Patent Stock, First-time Patenting and Firm Production Performance

Dept. Var.	A. Overall Panel		B. Balanced Panel		C. Different Types: Invention		C. Different Types: Utility		C. Different Types: Design		D. First-time Patentee (DID)	
	$\log S$	(s.e.)	$\log S$	(s.e.)	$\log S$	(s.e.)	$\log S$	(s.e.)	$\log S$	(s.e.)	Switch	(s.e.)
Productivity												
Labor prod	0.017***	(0.004)	0.022**	(0.010)	0.023**	(0.009)	0.019***	(0.006)	0.012*	(0.007)	0.0340***	(0.009)
Solow Residual	0.014**	(0.005)	0.018*	(0.010)	0.01	(0.012)	0.020***	(0.007)	0.006	(0.009)	0.0369**	(0.011)
OLS-FE	0.039***	(0.005)	0.040***	(0.011)	0.039***	(0.012)	0.045***	(0.007)	0.034***	(0.008)	0.0775***	(0.011)
$\text{TFP}^{ACF,CD}$	0.019***	(0.004)	0.023***	(0.009)	0.028***	(0.007)	0.020***	(0.005)	0.011*	(0.006)	0.0532***	(0.008)
$\text{TFP}^{ACF,Translog}$	0.026***	(0.004)	0.031***	(0.009)	0.030***	(0.007)	0.024***	(0.005)	0.027***	(0.007)	0.0664***	(0.008)
Markup	0.074	(0.100)	0.312	(0.339)	-0.021	(0.105)	0.093	(0.152)	0.002	(0.131)	-0.523	(0.317)
Size												
Output	0.112***	(0.005)	0.100***	(0.012)	0.114***	(0.012)	0.118***	(0.006)	0.124***	(0.008)	0.185***	(0.011)
Value added	0.108***	(0.006)	0.097***	(0.014)	0.104***	(0.014)	0.117***	(0.008)	0.116***	(0.009)	0.168***	(0.013)
Capital stock	0.093***	(0.005)	0.079***	(0.011)	0.091***	(0.012)	0.094***	(0.006)	0.109***	(0.007)	0.106***	(0.012)
Employment	0.095***	(0.005)	0.078***	(0.010)	0.091***	(0.010)	0.099***	(0.006)	0.112***	(0.008)	0.151***	(0.010)
Other												
Capital-labor ratio	-0.002	(0.004)	0	(0.010)	-0.001	(0.010)	-0.006	(0.005)	-0.004	(0.008)	-0.0449***	(0.011)
New product share	1.481***	(0.181)	1.987***	(0.358)	1.694***	(0.468)	1.727***	(0.192)	1.344***	(0.305)	2.523***	(0.311)
Export shipment	0.295***	(0.026)	0.319***	(0.055)	0.305***	(0.057)	0.347***	(0.028)	0.290***	(0.042)	0.534***	(0.057)

Notes: The dependent variables are patent stock ($S_{i,t}^{j}$) in Panel A–C and a dummy variable indicating first-time patenting event in Panel D. All dependent variables, except for the new product share, are logged. The sample for Panel A–C includes only firms that have ever filed for patent and the sample for panel D includes both first-time patentees and all the nonpatentees. All regressions control for firm, four-digit industry, and province fixed effects. The constant terms are omitted to save space. Robust standard errors clustered at the four-digit industry level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A in Table IV reports the estimation results. It shows that Chinese firm patenting is associated with positive, statistically significant changes in production and productivity within firms. Except for the capital-labor ratio and markup, increases in patent stock are associated with significant increases in all outcome variables under consideration. For example, a 10 percent increase in patent stock implies approximately 1 percent increases in real output and value added, similar rises in capital and employment, and a 3 percent increase in export value.

More importantly, all productivity measures point to the same conclusion: patenting is also significantly correlated with an increase in firm productivity. Our preferred measure of productivity, $TFP^{ACF,translog}$, increases by 0.26 percent annually on average for a 10 percent increase in patent stock. The other measures of productivity show similar patterns. $TFP^{ACF,CD}$ increases by 0.19 percent for a 10 percent increase in patent stock. Using the OLS-FE measure, a 10 percent increase in patent stock raises a firm's TFP by 0.39 percent. Patent stock's impact on the Solow residual and labor productivity is smaller at 0.14 percent and 0.17 percent, respectively. These observations are especially striking when compared with the U.S. evidence. Using U.S. firm-level data, Balasubramanian and Sivadasan (2011) report the elasticity of OLS-FE based productivity to changes in patent stock as 0.0152, about one-third of our estimate using the same productivity measure. Their elasticity, based on the Solow residual, is insignificant and, again only one-third of the elasticity estimated in this study.

As previously mentioned, one concern is that increases in measured productivity could reflect increases in markups, as the price deflators used to calculate productivity are common across firms in the same industry. Table IV, however, shows that there is no significant correlation between changes in innovation and changes in markup.

Innovation is often associated with the creation of new products. We thus also regress the share of new products in total revenue on patent stock, controlling for firm fixed effects, industry-year fixed effects, and province fixed effects. As shown in Table IV, a 10 percent increase in patent stock raises the share of a new product by about 15 percent, suggesting that innovation is also associated with new product development in China.

Firm entry and exit dynamics could potentially affect the relationship between patenting and production. However, when restricting the sample to firms that operate throughout the whole sample period (as in Panel B of Table IV), we find similar results. Increases in patent stock remain associated with significant increases in TFP, firm size, new product revenue shares, and export shipments. The elasticities are even larger for this restricted sample.

Not all patents are created equal. The empirical studies using patent data in industrial countries quantify patent quality using forward/backward citations, which, unfortunately, are not available in the Chinese patent dataset obtained from NBS. One way to differentiate patents is by type. Invention patents generally possess greater innovation value, as they have to meet the "Substantive Examination", whereas utility model and design patents stress practical use. Here, we reestimate equation (4) using subsamples of these three patent types. The regression results are presented in Panel C of Table IV. Increases in all types of patent stocks are positively and significantly associated with increases in various measures of productivity, size, new products' revenue shares, and exports. Most of the elasticities' magnitudes associated with productivity are notably larger for the most inventive type (invention patents).

Lastly, a few points worth mention here. First, since below-scale patent-filing firms are not covered the sample, the above findings are limited to relatively large Chinese firms. To obtain a rough understanding on how the results may differ if small firms were to be considered, we examine among the above-scale firms how TFP-patent elasticities compare between below-median sales firms and above-median sales firms. It turns out that the elasticity for smaller firms is insignificant and lower than that for larger firms which is significantly positive. This implies that the overall TFP-patent elasticity might be smaller than reported here if all firms in the economy are considered. Second, we do not have information on whether a specific patent application is granted in our data set. Suppose granted patents are generally of higher quality and thus presumably correlate more with productivity than unapproved ones. Then our result would provide a lower bound of the estimates for granted patents. Third, since firms may not file for patent immediately after a successful innovation for some reason, the effect of a firm's innovation on productivity may have materialized before the firm applies for patent. Indeed, when regressing the (log) TFP on lead patent stocks using the same regression specification (4), we find that the coefficients of lead patent stocks are significant up to three periods and deteriorate afterwards.

3.3 First-Time Patenting Firms: Differences-in-Differences Analysis

This section adopts an event study approach to examine what happens to a firm's production performance when it applies for patent for the first time. We estimate the following difference-in-differences regression to examine the magnitude and significance of change in performance after initial patenting event compared to nonpatenting firms in the same four-digit industry:

$$Y_{it}^{j} = \varphi_2 Switch_{it} + \mu_i + \gamma_{j,t} + \varepsilon_{i,t}^{j}, \tag{5}$$

where $Switch_{it} = 1$ if $t \geq t_0$ and t_0 is the first year that firm i filed for a patent. Different from the previous section, the sample includes both first-time patenting firms and nonpatenting firms.[9]

Panel D of Table IV summarizes the estimates of φ_2 for each outcome variable. Except for markups and capital-labor ratios, φ_2 is estimated to be positive and significant (each at 1 percent) for all outcome variables, consistent with previous within-firm analyses. Based on our preferred measure of TFP, using the ACF method and translog production specification, we find an increase of 0.07 log points in TFP for patenting firms compared with nonpatenting firms in the same industry. The relative increases in output and value added are both in the magnitude of 0.17-0.19 log points, while the increases in capital and labor input are slightly smaller (in 0.11 and 0.15 log points, respectively). In addition, there is an approximately 2.5 percent increase in new product share in total revenue and an increase of 0.53 log points in export value. The markup coefficients in regressions are negative and not significant. Furthermore, its R^2 is low compared to those of other outcome variables. We view these results as evidence of the insignificance of the relationship between patent stock and markup, which helps to validate TFP measures in these specifications.

Matched Sample Analysis The difference-in-differences approach specified in equation (5) requires the strong assumption that, prior to initial patenting, patenting firms follow similar trajectories in outcome variables as those of nonpatenting firms in the same industry. To ensure that the difference in production outcome is caused by a change in firm innovation status rather than a preexisting difference in firm performance, here, we improve the baseline difference-in-differences analysis by adopting a matched sample analysis.

First, for each first-time patentee, we identify a matching nonpatenting firm using the Propensity-Score Matching (PSM) method. Based on the findings in Table III, we specify a list of matching covariates as key determinants of patenting status: firm size, age, ownership, and export status. Since we are most interested in a firm's productivity change after initial patenting, we also include the level and growth rate of $TFP^{ACF,Translog}$ as one of the matching characteristics to ensure that the treatment firm and matched control firm follow similar productivity patterns before first-time patenting. Then, each patenting firm is paired with a nonpatenting firm in the same industry-year, which is selected so as to have the closest distance in prepatenting characteristics to the patenting firm.[10] Appendix D explains the PSM method in more details.

Panel A of Table V checks whether the covariates selected are important determinants of change in patenting status. In the Probit model, the dependent variable is a dummy that equals one if a firm

[9]Since our panel spans just over 10 years, we include only firms that have at least three-year observations before and after switching from being nonpatenting firms to patenting firms.

[10]The results are largely unchanged when more than one nonpatenting firms are matched with a given patenting firm as control groups.

is in the treatment group, and zero otherwise. The result shows that all covariates, except for TFP growth, are, indeed, significant determinants of first-time patenting status. Having never patented before, firms are more likely to start innovating if they are larger, more mature, or productive, or if they are exporting/SOE firms operating in the same industry-year. Panel B in Table V checks the validity of our matching procedure by showing the matching balance test, which is based on a pairwise t-test comparison between treatment firms and matched control firms. There are no significant differences between the key determinants of patenting likelihoods across the treatment and control samples. The propensity scores' density plots for the treatment and control groups before and after matching further confirm that the matching procedure provides a solid foundation for the difference-in-differences estimation (Figure III).

Table V: Match Sample Analysis

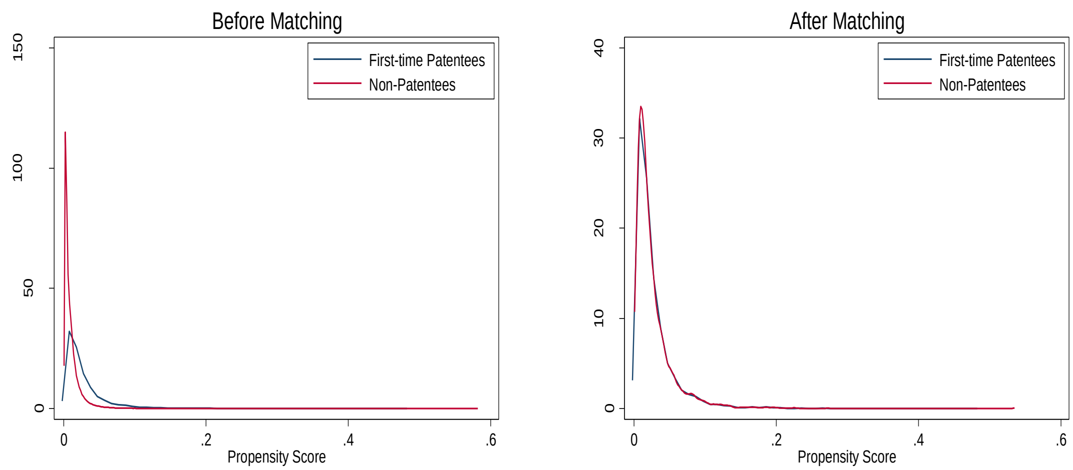
Variables	A: Probit	B: Differences in pre-patenting characteristics			
		First-time Patentees	Non-Patentees	Difference	t-statistic
$\ln(age_{it-1})$	0.020**	2.34	2.35	-0.01	0.43
	(0.008)				
$\ln(employment_{it-1})$	0.243***	5.64	5.64	0.01	0.81
	(0.006)				
D_{it-1}^{SOE}	0.043**	0.18	0.19	-0.01	0.28
	(0.018)				
D_{it-1}^{EX}	0.174***	0.45	0.45	0.00	0.86
	(0.014)				
$\ln TFP_{it-1}^{ACF,Translog}$	0.111***	2.10	2.08	0.02	0.55
	(0.008)				
$\Delta \ln TFP_{it-1}^{ACF,Translog}$	-0.014	0.04	0.04	0.00	0.81
	(0.010)				
Observations	434,692				

Notes: Panel A tests whether covariates chosen for matching are significant determinants of the first-time patenting status. It shows the coefficients of the Probit regression results. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Industry, location and year fixed effects are also controlled for. Panel B compares the pre-patenting mean of patenting treatment group and control group.

The post-patenting changes in production performance of all matched pairs are then compared using the difference-in-differences method. First, Panel A of Table VI reports the average treatment effect in a univariate difference-in-differences analysis (see Appendix D for more details). The results are qualitatively similar to the benchmark difference-in-differences results in Panel D of Table IV, but the elasticities are larger. Relative to the nonpatenting peers in the same industry-year, first-time patentees experience an average increase of around 7 percent in $TFP^{ACF,Translog}$, and around 6 percent in $TFP^{ACF,CD}$ per year in the three years following initial innovation.

To explore the time-series dimension of the difference-in-differences analysis, we run the follow-

Figure III: Propensity Score Density Plots



ing regression using both the treatment and control groups:

$$\begin{aligned} \ln Y_{it}^{j} \quad = \quad & \sum_{z=-2\&-1,0,1,2+} \psi_1^z Patentee_{it}^{j} \times Switch_{it}^{z} + \\ & \sum_{z=-2\&-1,0,1,2+} \psi_2^z Switch_{it}^{z} + \psi_3 Patentee_{it}^{j} + \gamma_{j,t} + \varepsilon_{i,t}^{j}, \end{aligned} \tag{6}$$

where $Patentee$ is a dummy that equals one for the treatment firms, and zero for control firms. $Switch_{it}^{z}$ is a dummy that equals one if a matched-pair's observation is from z years before or after the initial patenting year and zero otherwise. Here, for each matched pair, $z = -2\& - 1, 0, 1$, and $2+$, denoting one and two years before the initial patenting date, the year in which the firm first applies for a patent, the first year after the application, and the second and third years after the initial patenting. $\gamma_{j,t}$ captures the industry-year fixed effects. We have included only observations starting from three years before the initial patenting year and ending three years after patenting.

The results are shown in Panel B of Table VI. First, the regression analysis confirms that our PSM-based match was valid, as the coefficient of the interaction term, $Patentee \times Switch^{-2\&-1}$ is not statistically significant for the case of TFP^{ACF,Translog}, since TFP^{ACF,Translog} is one of the matching characteristics. More interestingly, it provides additional insight into the timing of firms' TFP increases after initial patent application. Significant differences in TFP growth between a first-time patentee and nonpatentee firm appear one year after patenting, and become even larger during the second and third years.

The evidence from first-time patentees further confirms the findings in the analysis of within-firm changes. Changes in firm production performances are significant, especially with regard to

Table VI: Patenting and TFP: Difference-in-Differences Analysis (PSM)

	$\text{TFP}^{ACF,CD}$	$\text{TFP}^{ACF,Translog}$
A. Univariate Analysis		
Diff-in-Diff	0.058***	0.071***
	(0.011)	(0.014)
Number of obs	48,964	48,964
B. Regression Analysis		
$Patentee \times Switch^{-2\&-1}$	0.024*	0.008
	(0.014)	(0.015)
$Patentee \times Switch^{0}$	0.032*	0.025
	(0.018)	(0.018)
$Patentee \times Switch^{1}$	0.043**	0.046**
	(0.020)	(0.020)
$Patentee \times Switch^{2+}$	0.056***	0.065***
	(0.021)	(0.022)
$Patentee$	0.037**	0.001
	(0.018)	(0.020)
$Switch^{-2\&-1}$	-0.040***	-0.039**
	(0.013)	(0.015)
$Switch^{0}$	-0.077***	-0.096***
	(0.020)	(0.022)
$Switch^{1}$	-0.100***	-0.127***
	(0.023)	(0.026)
$Switch^{2+}$	-0.148***	-0.190***
	(0.032)	(0.036)
Number of obs	78,141	78,141
R^2	0.627	0.765

Notes: This table reports difference-in-differences analyses using propensity-score matched samples. Panel A reports the average change in TFP in the three years following (and including) the intial patenting of the treatment group compared with that of the control group. The details of this analysis is in Appendix D. Panel B reports regression analyses of the treatment and the control groups' TFP, as specified in equation (6). The constant terms are omitted to save space. Robust standard errors clustered at the four-digit industry level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

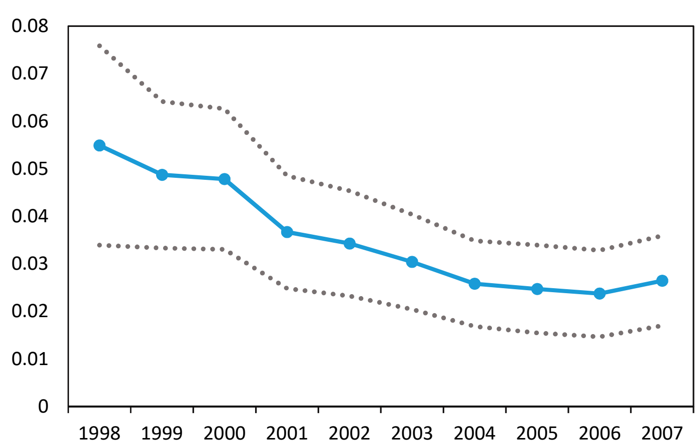
productivity, which is associated with changes in patent stock and status.

4 Overtime Changes and the Role of Patent Subsidy Programs

As discussed in Section 2.2, during our sample period of 1998-2007, different provinces across China sequentially introduced patent subsidy programs which have been found to cause the increase in the number of patent filings for Chinese firms (Li 2012 and Lei et al. 2012), as they largely reduce the cost of seeking patent protection and increase the overall return of patenting. If patent applications were induced by government policies rather than by commerical proposes, it is reasonable to expect their relationship with firm real production performance would be rather weak. Furthermore, if the share of patent applications induced by policies rises over time, as these policies were gradually launched across different regions and it takes time for information about such a program to spread among firms, we would expect the positive relationship between TFP and patents to deteriorate with time.

To examine how the relationship between patent application and productivity growth changes over time, we augment regression (4) with the interaction terms between the year dummy and $\ln S$. The year-specific elasticity is then calculated as the sum of the coefficient of $\ln S$ and that of the corresponding interaction term. Figure IV presents the time variations in the elasticity. We find that the previous speculation is indeed the case: the TFP-patent elasticity has declined as time elapses, although it is positive and significant throughout the entire sample period.

Figure IV: Overtime Changes in Patent Elasticity of TFP



Notes: The solid line presents the dynamics of the estimated elasticity of changes in TFP to within-firm changes in patent stock. The two dotted lines indicates the upper and lower bound of 95% confidence intervals.

To test whether the erosion in the TFP-patent elasticity is indeed related to the patent subsidy policies, we run the following regression utilizing the different timing of the enforcement of the policies across provinces:

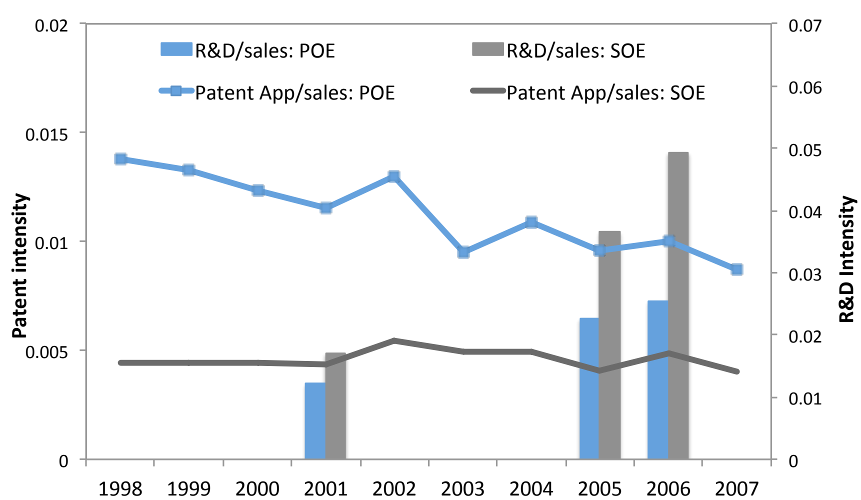
$$\ln TFP_{it}^{j} = \delta_1 \ln S_{it}^{j} + \delta_2 D_{it}^{PATSUB} + \delta_3 D_{it}^{PATSUB} \ln S_{it}^{j} + \mu_i + \gamma_{j,t} + \varepsilon_{it}^{j}, \quad (7)$$

where $D_{it}^{PATSUB} = 1$ if the subsidy program is introduced in that province before or in year t, and otherwise zero. We focus on our preferred TFP measure—TFP^{ACF,Translog}. δ_3 thus measures the policy-induced change in the TFP-patent elasticity. Column (1) of Table VII shows that δ_3 is significantly negative. 10 percent increase in patent stock is associated with 0.43 percent TFP growth before the introduction of the patent subsidy policy, while it is associated with 0.26 percent after the policy is launched. The introduction of patent subsidy decreases the TFP-patent elasticity by 0.17 percent, indicating that the quality of applied patents has declined.

5 The Role of State Ownership

A unique feature of the Chinese economy is the prevailing existence of SOEs, which are often viewed as less productive than POEs, and not completely driven by profit maximization purposes (Song et al., 2011). A simple comparison between an average SOE and an average POE presented in Figure V reveals that despite lower R&D intensity, POEs generally have higher patent intensity (number of patent applications-to-sales ratio). Thus, consistent with Wei et al. (2017), the average SOE produces much lower patents per yuan of R&D.

Figure V: Innovation Behavior: SOEs vs. POEs



Note: The figure compares R&D expenditure-to-sales ratio and patent application-to-sales ratio of an average patenting SOE with an average patenting POE. R&D expenditure data are available for only three year in our dataset.

Table VII: The Role of Patent Subsidy and State Ownership

Indept. Var.	Patent Subsidy Program (1)	SOEs vs. POEs: Baseline (2)	Selection (3): A. Balanced Panel	Selection (3): B. Constant Ownership	Selection (3): C. Balanced & Constant	Including R&D (4)	Exporting Status (5)	Subsidy (6)	Leverage (7)
$\ln S$	0.043***	0.019***	0.020**	0.018***	0.017	0.012	0.019***	0.017***	0.013***
	(0.006)	(0.004)	(0.009)	(0.005)	(0.012)	(0.008)	(0.004)	(0.004)	(0.005)
$D^{PATSUB}\ln S$	-0.017***								
	(0.007)								
D^{PATSUB}	0.035***								
	(0.005)								
$D^{SOE}\ln S$		0.029***	0.035***	0.029**	0.044**	0.016		0.029***	0.029***
		(0.006)	(0.010)	(0.011)	(0.022)	(0.013)		(0.006)	(0.006)
D^{SOE}		-0.057***	-0.082***	–	–	-0.083***		-0.057***	-0.057***
		(0.011)	(0.018)	–	–	(0.024)		(0.011)	(0.011)
$D^{SOE}\ln R\&D$						0.010**			
						(0.004)			
$\ln R\&D$						0.008***			
						(0.002)			
$D^{XSOE}\ln S$							0.029***		
							(0.007)		
$D^{NXSOE}\ln S$							0.023***		
							(0.008)		
D^{XSOE}							-0.021		
							(0.015)		
D^{NXSOE}							-0.078***		
							(0.012)		
$SUB\ln S$								0.003	
								(0.003)	
SUB								0.011*	
								(0.006)	
$LEV\ln S$									0.011***
									(0.004)
LEV									0.000
									(0.006)
R^2	0.943	0.943	0.948	0.945	0.952	0.969	0.943	0.943	0.943
N umber of obs	142,717	142,717	26,310	121,980	19,620	53,166	142,717	142,717	142,717

Note: Dependent variable is TFP^{ACF,Translog}. Column (1) reports the regression results of specification (7) and Columns (2)-(3) report the results based on equation (8). Columns (4)-(7) build on regression (8) by adding additional explanatory variables. All regressions control for firm, province and four-digit industry-year fixed effects. The constant terms are omitted to save space. Robust standard errors clustered at the four-digit industry level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

The natural question is whether there is any significant difference between SOEs and POEs in terms of the relationship between their patenting behavior and productivity growth. To answer this question, we run the following regression:

$$\ln TFP_{it}^{j} = \lambda_1 \ln S_{it}^{j} + \lambda_2 D_{it}^{SOE} + \lambda_3 D_{it}^{SOE} \ln S_{it}^{j} + \mu_i + \gamma_{j,t} + \varepsilon_{it}^{j}, \tag{8}$$

where D^{SOE} is a dummy variable that equals one if the firm is state-owned and zero otherwise.

Column (2) in Table VII shows the estimation results for regression specification (8). As expected, SOEs generally have lower productivity levels than POEs as demonstrated by the negative and significant λ_2. Surprisingly, the positive correlation between changes in patent stock and changes in productivity is actually higher for SOEs (as shown by the significantly positive estimates of λ_3), suggesting that SOEs are potentially better at adapting new in-house innovations to improve productivity.

Sample Selection Bias First, we investigate whether this observation is simply an outcome of sample selection bias. There are two sources of selection bias. First, POEs are generally more dynamic: more POEs enter and exit the market than SOEs do. It is possible that some innovative, but small, POEs may not have survived and were dropped from the sample. To control for this possibility, we rerun the regression (8) using a balanced panel of surviving firms. Second, our sample period (1998-2007) covers an important period of reform in China, the SOE reforms, which began in late 1990s and were gradually phased out after 2001. Except for large SOEs in strategic sectors (e.g., energy, electricity, telecommunications, and banking), the majority of small-to-medium SOEs were either privatized or closed (Hsieh and Song, 2015). Thus, a significant fraction of less productive firms has switched from being state owned to privately owned. These firms may appear as POEs in the latter part of the sample, thereby biasing the SOE-POE comparison. To address the selection bias generated by changes in ownership status, we rerun regression (8) for a more restricted sample excluding firms that switched ownership over our sample period.[11] We label the sample "constant ownership". Finally, to correct for both firm dynamics and ownership-switching biases simultaneously, we consider a sample that includes only surviving firms that never changed ownership over the sample period ("balanced and constant ownership").

Columns (3.A)-(3.C) in Table VII show the estimation results based on three different samples: the balanced panel, constant ownership, and balanced and constant ownership samples: λ_3 is positive and significant for each of the three samples examined. In addition, the coefficient is

[11] Among the 142,717 firms in our merged patent-ASIEC sample, 20,737 of them changed ownership, accounting for 14.5 percent of the firms in the benchmark sample.

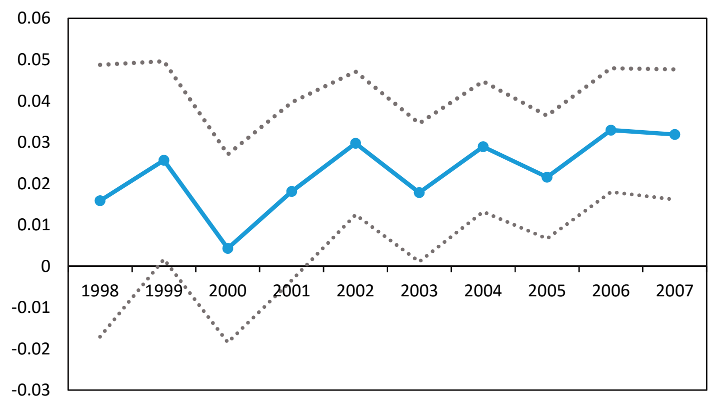
the highest for the most restrictive sample (balanced and constant ownership). Using alternative TFP measures do not alter these findings. Moreover, when we differentiate patents by types and investigate which types of patents SOEs are particularly good at adapting, we find that λ_3 is significantly positive for all three types, with a slightly higher value for design patent applications.

Biased Patent Protection The finding that SOEs are better than POEs at associating new innovation with productivity growth may be somewhat surprising given that SOEs are known to be less innovative and less efficient. Since the conventional role of patents is to deter copying and to pre-empt unauthorized entry, patent applications may generate IPR protection value for the patenting firm in additional to its technological value. Hence, one concern is that the higher TFP-patent elasticity for SOEs simply reflects the better legal protection enjoyed by SOEs. Especially, it has been argued that in the absence of effective IPR protection, state ownership acts as an alternative mechanism providing protection against expropriation through administrative measures by the government or through the courts, which often rule in their favor (Snyder, 2011). To test if it is the biased IPR protection that drives the result, we extend regression (8) by including two additional control variables: R&D and its interaction with the SOE dummy. The idea is to use this alternative measure of technology—R&D expenditure—to approximate the unobserved technology and to use patent stock to represent the IPR protection premium. Unfortunately, the ASIEC data we have access to only provide R&D expenditure for three years—2001, 2005, and 2006. Nevertheless, Column (4) of Table VII shows the estimation result: the coefficient of $\ln S \times D^{SOE}$ is no longer significant, but the coefficient of the interaction term between R&D and SOE dummy is positive and significant. This evidence suggests that the higher TFP return to SOEs' innovation does not seem to come from the patent premium but may reflect their technological value.

Biased Effect of Trade Liberalization Has the TFP-patent elasticity always been higher for SOEs than for POEs through the whole sample period? By introducing triple interaction terms between $\ln S$, SOE dummy, and year dummies into regression (8), we find that the SOE–POE gap is especially significant after 2001 and increases slightly over time towards the end of the sample (Figure VI), somewhat coinciding with the divergence in patenting behavior that we observed between ownership types in the data.

A major event took place around 2001: China's WTO accession. To explore that if trade liberalization has benefited exporting SOEs disproportionately more than POEs in terms of the higher measured TFP return of innovation, we divide SOEs into exporting SOEs (indicated by dummy variable D^{XSOE}) and nonexporting ones (D^{NXSOE}) in regression (8). Column (5) of Table VII shows that both exporting SOEs and non-exporting SOEs observe similarly significantly higher

Figure VI: Overtime Changes in TFP-patent elasticity gap between SOEs and POEs



Notes: The solid line presents the dynamics of the estimated elasticity of changes in TFP to within-firm changes in patent stock. The two dotted lines indicates the upper and lower bound of 95% confidence intervals.

elasticities than the privately-owned firms, indicating that accession to WTO does not have direct biased effect on TFP-patent elasticity towards SOEs. However, it is worth noting that this finding does not preclude the indirect effect of trade liberalization through, for example, input-output linkages. Specifically, Li et al. (2015) argue that the external demand boosted by the WTO access benefits upstream SOEs by allowing them to extract more rents from competitive and liberalized downstream exporting industries and enjoy higher profitability after 2001. Similar reasoning applies here although formal testing of this specific channel goes beyond the scope of this paper.

Biased Access to Credit and Subsidies Starting in the late 1990s, Chinese government implemented credit policies encouraging favorable lending to SOEs, especially those in heavy industries. Research has shown that SOEs have easier access to the credit market, enjoy higher leverage, pay lower interest rates, and receive more subsidies from the government than the non-SOEs (Song et al., 2011; Chang et al., 2016; Bai et al., 2018). In our merged data, an average innovating SOE enjoys higher leverage ratio than an the average POE for the entire sample period, with the average ratio being 0.69 for SOEs and 0.58 for POEs. In addition, the share of SOEs that received positive subsidies rose from 14 percent in 1998 to 25 percent in 2007, compared to 8 percent to 12 percent for POEs. More funding and less financial constraint can potentially allow SOEs to better take advantage of existing knowledge capital and to convert new ideas into productivity improvements more effectively.

To examine whether the biased access to subsidies (credit), we add in regression (8) an interaction term between $\ln S$ and an indicator SUB (LEV) which takes the value to be one if a firm received an above-median subsidy income (leverage ratio) or zero otherwise. Column (6) in

Table VII demonstrates that although government subsidy itself is significant in explaining TFP growth, it is not significant in explaining the difference in the TFP-patent elasticities of SOEs and POEs. More importantly, controlling for subsidy does not affect the magnitude of the coefficients of $D^{SOE} \ln S$, suggesting that differential treatment in subsidies cannot explain away the higher elasticity of $\ln S$ in driving productivity observed in SOEs. Controlling for the interaction between patent stock and leverage ratio (Column (7)) generates similar result. While leverage ratio does have significant impact on how firms associate new patents with TFP growth, it does not explain why SOEs are better at this than POEs.

Our analysis above shows that this SOE-POE elasticity gap is not because SOEs enjoy better IPR protection that POEs, or directly benefit more from China's accession to WTO, or have better access to credit and government subsides, or are less financially constrained. Since the significant SOE-POE gap starts to emerge and become significant post-2001, the timing seems to follow the dramatic SOE reforms between 1997-2001. As documented in Hsieh and Song (2015), the SOE reforms, featuring the slogan "Grasp the Large, Let Go of the Small", transformed the large SOEs into profit-maximizing firms under the state control and led to higher TFP growth of the state-owned firms than the privately-owned ones during that period. Consistently, in our innovating firm sample, we find that annual TFP growth of innovating SOEs was on average 1.8 percent faster than that of the innovating POEs for our sample period, even though the share of SOEs declined from 45 percent in 1998 to 15 percent by 2007. More robust analysis on the role of SOE reform is beyond the scope of this paper, but the casual observation suggests that the SOE reform may have improved both SOEs' innovating behavior and TFP growth, as well as the relationship between these two.

6 Does Patenting *Cause* Productivity Growth?

A firm's patenting decision is not random. Its patent activity can be an endogenous outcome of its size, productivity, exports, etc. Therefore, productivity changes having been associated with patenting are not necessarily caused by patenting. Ascribing any causal relationship between productivity and patenting is challenging, as most drivers of innovation, internal or external to the firm, also have direct impacts on productivity. This section attempts to shed some light on whether patenting causes productivity growth by considering a specific external driver of firm innovation as an instrumental variable, namely, IPR protection.

More specifically, we use a survey-based prefecture-level IPR protection index published in the annual Urban Competitiveness Report by the Chinese Academy of Social Sciences. The surveys were conducted in 66 prefectures across 25 Chinese provinces between 2002 and 2011. The local IPR protection score is calculated based on a survey of legal professionals (such as judges, IPR lawyers, and corporate executives), which follows the same format as "The Competitivenss of Cities" report by the World Economic Forum. It asks the respondents to rate three areas related to local IPR enforcement, including the length of time it takes for courts to resolve IP disputes, the cost of resolution as a share of the value of the IP, and the fairness of court decisions. The prefecture-specific score is then constructed as the average score across individual responses and across the three areas normalized by the maximum scores across all 66 prefectures.

Despite the widely shared perception that China has a poor record regarding IPR protection in general, Fang et al. (2017) show that local IPR protection in China does matter; it strengthens firms' incentives to innovate, especially for POEs. As explained in their paper, due to the Chinese Intellectual Property Law's requirements and most Chinese firms' domestic market focus, Chinese IPR protection matters at *local* level.[12] This contrasts sharply with the U.S. experience, in which plaintiffs can choose the court to file lawsuits (e.g., forum shopping), making the local legal environment less relevant. One advantage of this local IPR protection measure is that it reflects the perceived quality of IPR protection, which directly affects the incentive to innovate.[13]

Consistent with their findings, we also find that patent stocks tend to increase faster for firms located in cities with higher IPR protection scores, suggesting that local IPR protection can be a useful instrument. One concern, however, is that local IPR protection itself can evolve endogenously in response to innovating firms' demands for better protection, thereby introducing reverse causalities. To mitigate this concern, we use the initial local IPR protection (i.e., the first year the IPR score is available, which is 2002) as the instrumental variable for firms' end-of-sample changes in patent stocks in a cross-section analysis.[14] Again, we focus on the impact of patenting on within-firm changes in productivity, which is measured by $TFP^{ACF,Translog}$.

Panel A of Table VIII shows the results of the first-stage regression, in which the increase in (log) patent stock in 2007 is regressed on the initial IPR protection score of the prefecture where the firm is located. Since firm, industry-year, and province fixed effects cannot be controlled for in

[12]The Chinese Intellectual Property Law requires that a lawsuit only be filed either in the plaintiff's location of residence or where the violation occurred (i.e., the defendant). 80 percent of the IPR cases in the Chinese Judicial Case Database involve plaintiffs and defendants from the same province. In addition, international patent filing is still scarce, and most companies focus on the domestic market.

[13]Alternative measures of IPR protection are often based on plaintiff win rates in provincial courts or the media's IPR coverage in official newspapers (see Ang et al. 2014). These measures may capture the severity of IPR infringements and violations rather than the degree of IPR protection.

[14]Since innovation usually takes place long before patent application, to avoid the reverse causality issue mentioned earlier, IPR protection scores going back several years would be more valid instruments than those with one- or two-year lags. Ideally, we would like to run a panel regression as is used for the baseline, using long-lagged IPR to instrument the first differenced (log) patent stock. However, the short span of the sample does not allow for this empirical strategy.

this cross-section regression, other firm-specific internal drivers of innovation and prefecture-specific characteristics that might also affect patent applications (such as local GDP per capita, and number of high education institutions) are also included. The reduced form result shows that higher scores of initial IPR protection significantly increase firms' subsequent innovation rates. And as expected, younger and larger firms are more innovative. Prefectural characteristics such as higher income level and more higher education institutions both increase innovation rate. The KP F-statistic is above 10.

Table VIII: Patenting and TFP: An IV Analysis, 2007

A. First Stage:	$\Delta \ln(S)$	*B. Second Stage*:	$\Delta \ln(TFP^{ACF,Translog})$	
			OLS	IV
	(1)		(2)	(3)
Initial IPR	0.086***	$\Delta ln(S)$	0.023***	0.036
	(0.024)		(0.007)	(0.284)
age	-0.003***	age	0.000	0.000
	(0.000)		(0.000)	(0.001)
ln(emp)	0.061***	ln(emp)	-0.008*	-0.011
	(0.004)		(0.004)	(0.018)
D^{SOE}	0.025	D^{SOE}	0.004	0.011
	(0.016)		(0.011)	(0.016)
D^{EX}	-0.002	D^{EX}	-0.001	0.001
	(0.009)		(0.008)	(0.009)
lnGDPpc	0.017**	lnGDPpc	-0.019***	-0.026**
	(0.009)		(0.006)	(0.011)
institutions	4.443**	institutions	-5.687***	-5.290**
	(2.096)		(1.763)	(2.508)
KP-F	14.61			
observations	14,835		20,875	14,835

Notes: This table reports the first stage (Panel A) and second stage (Panel B) results of the instrumental cross-sectional analysis. The constant terms are omitted to save space. Robust standard errors clustered at the four-digit industry level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

We then compare the responses of firm-level productivity to patent activity across Chinese prefectures with varying initial levels of IPR protections. Panel B of Table VIII presents the second-stage cross-section regression instrumental variable estimates in Column (3), which are compared with the results of the benchmark OLS regression using the same sample in Column (2).[15] The cross-sectional results based on OLS show significantly positive relationships between changes in patent stock and productivity with similar point estimates of elasticity as baseline fixed effect panel regression results reported in Table IV. A 10 percentage point increase in patent stock is associated with an approximately 2.3 percentage point increase in TFP in 2007, compared to the average 2-3

[15] The Chinese regional IPR data we obtained are available only from 2002, and for 25 provinces (instead of the entire 31 provinces in China). Some firms in our benchmark sample are no longer included here. To ensure comparability, we report the benchmark results using the same sample years and firms.

percent increase in TFP during 1998-2007. However, Column (3) presents an ambiguous picture of firm patenting's causal impact on productivity. The instrumented cross-section results indicate that innovation does not produce any significant effect on productivity. The insignificant effect associated with the instrumental variable estimation scheme is consistent with the hypothesis that the least squares estimate could be positively biased by endogenous patenting activity.

7 Conclusion

Is firm patenting in China accompanied by real changes in firm production performance, especially firm productivity? This paper answers the question by constructing a unique dataset uniting detailed firm balance sheet data with patent application data for the period 1998-2007. We find compelling evidence that increases in patent stock are associated with increases in firm size (output, sales, and employment), export performance, and more interestingly, firm productivity and the revenue share of new products. The associated improvement in productivity is even higher than that found in a prior study using U.S. data. Event studies based on first-time patent applicants using the propensity score matching approach to construct a control group also show similar effects following an initial patent application.

We also find that this positive relationship between innovation and productivity becomes weaker over time, which can be explained by the negative effect of government patent subsidy on the quality of patent applications. In addition, somewhat surprisingly, SOEs are found to be better than POEs at associating patenting with productivity growth. This SOE-POE elasticity gap is not because SOEs enjoy better IPR protection, or directly benefit more from China's accession to WTO, or have better access to credit and government subsides, or are less financially constrained. As this elasticity gap between ownership types is especially significant after 2001 and increases over time towards the end of the sample, it may suggest that the SOE reform, featuring the slogan "Grasp the Large, Let Go of the Small", might have contributed to strengthening of the innovation-productivity association of the large innovating state-owned firms. In fact, in our innovating firm sample, we find that TFP growth of innovating SOEs was faster than that of the innovating POEs.

The positive patenting-productivity relationship for Chinese firms in the period of 1998-2007 should not be interpreted as causal. Underlying drivers of innovation can simultaneously affect production outcomes. Indeed, using the prefecture-level IPR protection score as an instrument for firm patenting, we find that patenting has no significant causal effect on productivity changes. Overall, we conclude that Chinese firm patents are meaningful proxies for real innovative activities, since changes in patenting behaviors (patent stock or patent status) are significantly associated with real changes in production and productivity.

Appendix A Estimating TFP using ACF Method

To control endogeneity issues caused by unobserved productivity shocks, we follow De Loecker and Warzynski (2012) and use ACF method to estimate TFP. To allow for more a flexible production function, we consider a translog value added production specification:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_{kk} k_{it}^2 + \beta_{ll} l_{it}^2 + \beta_{kl} k_{it} l_{it} + \omega_{it} + \epsilon_{it} \tag{9}$$

where y_{it}, k_{it} and l_{it} are the value added, capital, and labor of firm i at time t in logarithms. ω_{it} is the unobserved productivity shocks, and ϵ_{it} represents the *i.i.d.* shocks including measurement errors or unforecastable shocks that are not correlated with inputs k_{it} and l_{it}. Assume that the demand for material input, m_{it}, is decided either at the same time or after l_{it} is chosen. This implies that we can express the material input as:

$$m_{it} = f_t(k_{it}, l_{it}, \omega_{it}). \tag{10}$$

Assuming strict monotonicity, equation (10) can be inverted such that $\omega_{it} = f^{-1}(k_{it}, l_{it}, m_{it})$. Substituting this back into the production function, we get

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_{kk} k_{it}^2 + \beta_{ll} l_{it}^2 + \beta_{kl} k_{it} l_{it} + f_t^{-1}(k_{it}, m_{it}, l_{it}) + \epsilon_{it}. \tag{11}$$

Treating f_t^{-1} non-parametrically, we define the composite term as

$$\Phi_{it} \equiv \beta_k k_{it} + \beta_l l_{it} + \beta_{kk} k_{it}^2 + \beta_{ll} l_{it}^2 + \beta_{kl} k_{it} l_{it} + f_t^{-1}(k_{it}, m_{it}, l_{it}). \tag{12}$$

Employing a third-order polynomial approximation for f_t^{-1}, we first regress y_{it} on m_{it}, k_{it}, and l_{it} and their higher-order terms according to equation (12), and obtain estimates of the expected value added, $\widehat{\Phi}_{it}$ from the predicted values.

Next, we assume that productivity follows an exogenous first-order Markov process in the form of $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$. For any given values of $\beta \equiv \{\beta_k, \beta_l, \beta_{kk}, \beta_{ll}, \beta_{kl}\}$, we compute the implied $\widehat{\omega}_{it}$ according to

$$\widehat{\omega}_{it} = \widehat{\Phi}_{it} - (\beta_k k_{it} + \beta_l l_{it} + \beta_{kk} k_{it}^2 + \beta_{ll} l_{it}^2 + \beta_{kl} k_{it} l_{it}). \tag{13}$$

We then regress the $\widehat{\omega}_{it}$ on the its lag non-parametrically to obtain the implied $\xi_{it}(\beta)$. Here we employ a second-order polynomial approximation for $g(.)$.

Based on the assumptions that (a) capital is decided one period ahead, and therefore, does not respond to the current productivity shocks, and (b) lagged labor is also uncorrelated with current productivity shocks, we have the following moment conditions: $E(\xi_{it}k_{it}) = 0$, $E(\xi_{it}l_{it-1}) = 0$, $E(\xi_{it}k_{it}^2) = 0$, $E(\xi_{it}l_{it-1}^2) = 0$ and $E(\xi_{it}k_{it}l_{it-1}) = 0$. The vector of the production function parameters, β, are then estimated using the standard General Method of Moments (GMM) procedure:

$$\widehat{\beta} = arg \min_{\beta} \frac{1}{T}\frac{1}{N}\sum_{t=1}^{T}\sum_{i=1}^{N}\xi_{it}(\beta)\begin{pmatrix} k_{it} \\ l_{it-1} \\ k_{it}^2 \\ l_{lt-1}^2 \\ k_{it}l_{it-1} \end{pmatrix}. \tag{14}$$

The above algorithm is applied to every two-digit industry, using data from 1998-2007 to obtain each industry-specific $\widehat{\beta}$. Finally, the TFP of firm i is computed as $\ln TFP_{it}^{ACF,translog} = \widehat{\Phi}_{it}^{j} - \widehat{\beta}_k k_{it} - \widehat{\beta}_l l_{it} - \widehat{\beta}_{kk} k_{it}^2 - \widehat{\beta}_{ll} l_{it}^2 - \widehat{\beta}_{kl} k_{it} l_{it}$.

Finally, as a robustness check for our estimation of TFP using the ACF method, we also measure TFP following ACF, but using a Cobb-Douglas specification for the production function instead of a generalized translog specification. In this C-D specification estimation, we also employ a third-order polynomial approximation for f^{-1} and a second-order polynomial approximation for $g(.)$. We denote this alternative measure as $TFP^{ACF,CD}$ throughout our analysis.

Appendix B Constructing Firm-Specific Markups

Our construction of firm-specific markups closely follows De Loecker and Warzynski (2012). Firm i at time t produces output using the following production technology:

$$Q_{it} = Q_{it}(K_{it}, L_{it}, \omega_{it}). \tag{15}$$

The only restriction we impose on Q_{it} to derive an expression of markup is that Q_{it} is continuous and twice differentiable with respect to its arguments.

Cost-minimizing producers consider the following Lagrangian function:

$$Lag(K_{it}, L_{it}, \lambda_{it}) = r_{it}K_{it} + w_{it}L_{it} + \lambda_{it}(Q_{it} - Q_{it}(.)), \tag{16}$$

where w_{it} and r_{it} denote a firm's input costs for labor and capital, respectively. The first-order condition with respect to labor input is

$$\frac{\partial Lag_{it}}{\partial L_{it}} = w_{it} - \lambda_{it} \frac{\partial Q_{it}(.)}{\partial L_{it}} = 0, \tag{17}$$

where the marginal cost of production at a given level of output is λ_{it} as $\dfrac{\partial Lag_{it}}{\partial Q_{it}} = \lambda_{it}$. Rearranging terms and multiplying both sides by $\dfrac{L_{it}}{Q_{it}}$, we can express labor elasticity, θ_i as:

$$\theta_i = \frac{\partial Q_{it}(.)}{\partial L_{it}} \frac{L_{it}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{w_{it} L_{it}}{Q_{it}}. \tag{18}$$

We define markup, μ, as the ratio of price over marginal cost, $\mu_{it} = \dfrac{P_{it}}{\lambda_{it}}$. Using this definition, we can rewrite equation (18) as

$$\theta_i = \mu_{it} \frac{w_{it} L_{it}}{P_{it} Q_{it}}. \tag{19}$$

Based on equation (19), once labor elasticity, θ_i, is obtained from the production function estimation, and the share of labor costs in total sales, $\frac{w_{it}L_{it}}{P_{it}Q_{it}}$, is measured using the data, a firm's markup can be constructed as follows:

$$\mu_{it} = \theta_i \frac{P_{it} Q_{it}}{w_{it} L_{it}}. \tag{20}$$

Regarding the translog production function, the estimated elasticity for labor is given by $\widehat{\theta}^l_{it} = \widehat{\beta}_l + 2\widehat{\beta}_{ll} l_{it} + \widehat{\beta}_{lk} k_{it}$.

Appendix C Summary Statistics

The summary statistics of production performance variables for patenting and nonpatenting firms are presented in Table IX.

Appendix D The Analysis of Propensity-Score Matching DID

Our difference-in-differences analysis hinges on the comparability of patenting and nonpatenting firms. To guarantee that the comparison is meaningful, we have to ensure that the treatment group (patenting firms) and control group (nonpatenting firms) are similar in terms of major firm characteristics. The PSM method serves this propose. Here, we lay out the PSM procedure as

Table IX: Patenting Firms vs. Nonpatenting Firms

Variable	**Patenting Firms** Mean	**Patenting Firms** Standard Deviation	**Nonpatenting Firms** Mean	**Nonpatenting Firms** Standard Deviation	**Difference**
Productivity					
Labor productivity	364.20	657.37	361.16	876.91	3.04
Solow Residual	2.12	1.14	2.22	1.12	-0.1***
$\text{TFP}^{ACF,CD}$	3.40	1.04	3.58	0.94	-0.17***
$\text{TFP}^{ACF,TL}$	2.21	1.43	2.60	1.43	-0.39***
Markup	1.55	48.06	1.81	20.47	-0.25***
Size					
Output	265,634	1,694,065	66,909	452,803	198,725***
Value added	74,104	499,630	17,381	100,343	56,722***
Capital Stock	108,754	902,112	20,844	143,504	87,910***
Employment	690	2,494	246	595	444***
Other					
Age	14.44	14.95	9.53	10.09	4.91***
Capital-labor ratio	114.34	387.31	85.12	239.31	29.22***
New product (share)	9.61	22.82	2.52	12.73	7.09***
Export shipment	48,511	739,047	15,683	239,913	32,828***
Number of obs	198,414		1,263,326		

Notes: This table displays the summery statistics of variables for patenting and non-patenting firms in our data. The last column shows differences in means for patenting and nonpatenting firms. *** indicates the difference is significant at 1% based on the t-test. The summary statistics for OLS-FE based TFP meausures are not available here as only changes in OLS-FE based TFP are meaningful by construction.

follows.

For each firm i, we define the treatment $D_i = 1$ if firm i applies for at least one patent, and as zero otherwise. We run the following Probit model to estimate the propensity score:

$$\Pr(D_i = 1 \mid X) = G(X),$$

where X={size, age, SOE dummy, exporter dummy, level and growth rate of TFP, industry dummy, and year dummy}, and $G(z) = \exp(z)/(1 + \exp(z))$.

For firm i in the treatment group, we define $p_i(x) = \Pr(D_i = 1 \mid X = x)$. Under the common support condition, we have $0 < p_i(x) < 1$. We then take the nearest matching approach to pick the "matched" non-treated firm j for treated firm i, based on the following criteria:

$$\|p_i - p_j\| = \min_{k \in \{D=0\}} \|p_i - p_k\| .$$

Define firm i's performances before and after the treatment (D_i) as $Y_i^a - Y_i^b$

$$Y_i^a - Y_i^b = \begin{cases} Y_i^a(1) - Y_i^b(1) & \text{for } D_i = 1 \\ Y_i^a(0) - Y_i^b(0) & \text{for } D_i = 0 \end{cases}$$

Based on the PSM, the average treatment effect of the treated group (patenting firms) $\beta = E\left[\left(Y_i^a(1) - Y_i^b(1)\right) - \left(Y_i^a(0) - Y_i^b(0)\right)\right]$can be calculated as

$$\hat{\beta} = \frac{1}{N}\left[\sum_{i=1}^{N}\left(Y_i^a - Y_i^b\right) - \sum_{j=1}^{N}\left(Y_j^a - Y_j^b\right)\right]$$

for any treatment firm i and control firm j. The results are reported in Panel A in Table VI.

Appendix E Year of Patent Subsidy Programs

Table X below lists the initial years the 29 (out of 30) Chinese provinces introduced the patent subsidy programs. The data source is Li (2012).

Table X: Launching Year of Patent Subsidy Programs in Each Province

Year	Provinces/Municipality
1999	Shanghai
2000	Beijing, Tianjin, Guangdong, Jiangsu, Chongqing
2001	Zhejiang, Heilongjiang, Guangxi, Hainan, Sichuan, Shaanxi
2002	Fujian, Jiangxi, Henan, Guizhou, Neimenggu, Xinjiang
2003	Shanxi, Anhui, Shandong, Yunnan, Tibet
2004	Jilin, Hunan
2005	Hebei, Qinghai
2006	Liaoning
2007	Ningxia

References

Ackerberg, D. A., Caves, K., Frazer, G., 2015. Identification Properties of Recent Production Function Estimators. Econometrica 83 (6), 2411–2451.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., Howitt, P., 2005. Competition and Innovation: An Inverted-U Relationship. The Quarterly Journal of Economics 120 (2), 701–728.

Aghion, P., Cai, J., Dewatripont, M., Du, L., Harrison, A., Legros, P., 2015. Industrial Policy and Competition. American Economic Journal: Macroeconomics 7 (4), 1–32.

Ang, J., Cheng, Y., Wu, C., 2014. Does Enforcement of Intellectual Property Rights Matter in China? Evidence from Financing and Investment Choices in the High Tech Industry. The Review of Economics and Statistics 96 (2), 332–348.

Bai, Y., Lu, D., Tian, X., 2018. Do financial frictions explain chinese firms saving and misallocation? Tech. rep., National Bureau of Economic Research.

Balasubramanian, N., Sivadasan, J., 2011. What Happens When Firms Patent? New Evidence from US Economic Census Data. The Review of Economics and Statistics 93 (1), 126–146.

Bloom, N., Schankerman, M., Van Reenen, J., 2013. Identifying Technology Spillovers and Product Market Rivalry. Econometrica 81 (4), 1347–1393.

Bloom, N., Van Reenen, J., 2002. Patents, Real Options and Firm Performance. The Economic Journal 112 (478), C97–C116.

Blundell, R., Griffith, R., Van Reenen, J., 1999. Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms. The Review of Economic Studies 66 (3), 529–554.

Boeing, P., Mueller, E., Sandner, P., 2016. China's R&D Explosion – Analyzing Productivity Effects across Ownership Types and Over Time. Research Policy 45 (1), 159–176.

Brandt, L., Van Biesebroeck, J., Wang, L., Zhang, Y., 2017. WTO Accession and Performance of Chinese Manufacturing Firms. American Economic Review 107 (9), 2784–2820.

Brandt, L., Van Biesebroeck, J., Zhang, Y., 2012. Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing. Journal of Development Economics 97 (2), 339–351.

Cai, H., Liu, Q., 2009. Competition and Corporate Tax Avoidance: Evidence from Chinese Industrial Firms. The Economic Journal 119 (537), 764–795.

Chang, C., Chen, K., Waggoner, D. F., Zha, T., 2016. Trends and Cycles in China's Macroeconomy. NBER Macroeconomics Annual 30 (1), 1–84.

Chen, Z., Liu, Z., Serrato, J. C. S., Xu, D. Y., 2018. Notching R&D Investment with Corporate Income Tax Cuts in China. Tech. rep., National Bureau of Economic Research.

Cheung, K.-y., Ping, L., 2004. Spillover effects of fdi on innovation in china: Evidence from the provincial data. China Economic Review 15 (1), 25–44.

Choi, S. B., Lee, S. H., Williams, C., 2011. Ownership and firm innovation in a transition economy: Evidence from china. Research Policy 40 (3), 441–452.

De Loecker, J., Warzynski, F., 2012. Markups and Firm-level Export Status. American Economic Review 102 (6), 2437–71.

Du, L., Harrison, A., Jefferson, G. H., 2012. Testing for Horizontal and Vertical Foreign Investment Spillovers in China, 1998–2007. Journal of Asian Economics 23 (3), 234–243.

Fang, L. H., Lerner, J., Wu, C., 2017. Intellectual Property Rights Protection, Ownership, and Innovation: Evidence from China. The Review of Financial Studies 30 (7), 2446–2477.

Griliches, Z., 1981. Market Value, R&D, and Patents. Economics Letters 7 (2), 183–187.

Griliches, Z., Schmookler, J., 1963. Inventing and Maximizing. The American Economic Review 53 (4), 725–729.

Hall, B. H., Jaffe, A., Trajtenberg, M., 2005. Market Value and Patent Citations. RAND Journal of Economics, 16–38.

Hall, B. H., Jaffe, A. B., Trajtenberg, M., 2001. The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools. Tech. Rep. W8498, National Bureau of Economic Research.

Hausman, J. A., 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.

Hsieh, C.-T., Klenow, P. J., 2009. Misallocation and Manufacturing TFP in China and India. The Quarterly Journal of Economics 124 (4), 1403–1448.

Hsieh, C.-T., Song, Z. M., 2015. Grasp the large, let go of the small:: The transformation of the state sector in china. Brookings Papers on Economic Activity (1), 3.

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, A. G. Z., Zhang, P., Zhao, L., 2017. China As Number One? Evidence from China's Most Recent Patenting Surge. Journal of Development Economics 124, 107–119.

Jaffe, A. B., 1986. Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits and Market Value. The American Economic Review 76 (5), 984–1001.

Lei, Z., Sun, Z., Wright, B., 2012. Patent subsidy and patent filing in china. University of California, Berkeley, mimeo.

Levinsohn, J., Petrin, A., 2003. Estimating Production Functions Using Inputs to Control for Unobservables. The Review of Economic Studies 70 (2), 317–341.

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

Li, X., Liu, X., Wang, Y., 2015. A model of china's state capitalism. Available at SSRN 2061521.

Lin, C., Lin, P., Song, F., 2010. Property rights protection and corporate r&d: Evidence from china. Journal of Development Economics 93 (1), 49–62.

Liu, Q., Lu, R., Lu, Y., Luong, T. A., 2015. Is free trade good or bad for innovation? University of International Business and Economics. University of Birmingham.

Olley, G. S., Pakes, A., 1996. The Dynamics of Productivity in the Telecommunications Equipment Industry. Econometrica 64 (6), 1263–1297.

Perkins, D. H., Rawski, T. G., 2008. Forecasting chinas economic growth to 2025. Chinas great economic transformation, 829–86.

Scherer, F. M., 1965. Firm Size, Market Structure, Opportunity, and the Output of Patented Inventions. The American Economic Review 55 (5), 1097–1125.

Schmookler, J., Brownlee, O., 1962. Determinants of Inventive Activity. The American Economic Review 52 (2), 165–176.

Snyder, N. W., 2011. Putting numbers to feelings: Intellectual property rights enforcement in china's courts-evidence from zhejiang province trademark infringement cases 2004-2009. Nw. J. Tech. & Intell. Prop. 10, xxviii.

Song, Z., Storesletten, K., Zilibotti, F., 2011. Growing Like China. American Economic Review 101 (1), 196–233.

Wei, S.-J., Xie, Z., Zhang, X., 2017. From "Made in China" To "Innovated in China": Necessity, Prospect, and Challenges. Journal of Economic Perspectives 31 (1), 49–70.

Xie, Z., Zhang, X., 2015. The patterns of patents in china. China Economic Journal 8 (2), 122–142.

Zhu, X., 2012. Understanding China's Growth: Past, Present, and Future. Journal of Economic Perspectives 26 (4), 103–24.

Zilibotti, F., 2017. Growing and Slowing down like China. Journal of the European Economic Association 15 (5), 943–988.