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

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September 10, 2018

Abstract

This paper examines whether the rapidly growing firm patenting activity in China is associated with real economic outcomes by building a unique dataset uniting detailed firm balance sheet information with firm patent data for the period 1998-2007. We find strong evidence that within-firm increases in patent stock are associated with increases in firm size, export, and more importantly, firm productivity and new product revenue share. Event studies of initial patent applications, using first-time patentees as the treatment group, and nonpatenting firms—selected based on the Propensity-Score Matching method—as the control group, also generate similar findings. State-owned enterprises have higher productivity-patenting elasticities than private firms. Changes in productivity associated with patenting, however, should not be interpreted as being caused by patenting, as our instrumental variable analysis does not indicate that patenting has a significant effect on productivity.

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

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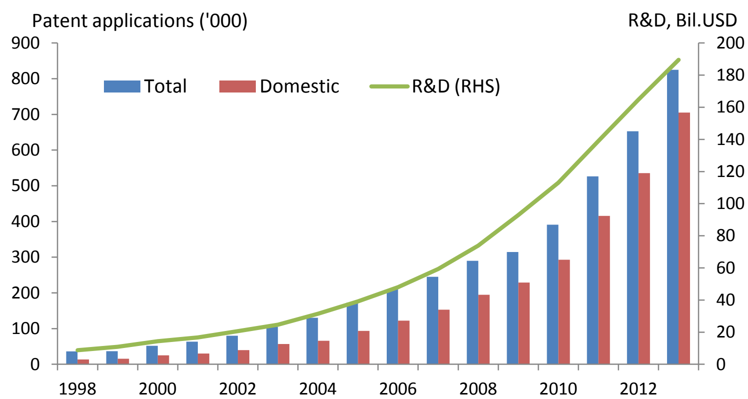
1 Introduction

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-to-GDP ratio 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, rose dramatically from 36 thousand in 1998 to 825 thousand in 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, question China's ability to innovate. They contend that China's prolific patent filings are simply a response to the ambitious government-set target. Without proper intellectual property rights, and under the dominance of inefficient and uninnovative SOEs, many argue that the incentive to invent is simply absent (e.g., World Bank, 2012; Thomson Reuters, 2014). The quality and real impact of many of these patents are in doubt.

Is technology advancement, as manifested by the patent explosion, associated with real productivity growth in China? The answer to this question is of first-order policy importance and provides valuable insight into China's transition from an investment-led to a more innovation-based growth model (Zilibotti, 2017). This paper addresses the question by examining, at the micro level, whether Chinese firm patenting is associated with real improvement in firm productivity and other economic performance. Patents and patent statistics are often used as valuable indicators of new ideas intended to produce innovation and to measure firm R&D successes in industrialized economies (e.g., Hall et al., 2001; Bloom and Van Reenen, 2002; Hall et al., 2005; Jaffe, 1986; Griliches, 1981). Such studies also help in evaluating the quality of Chinese patents, and inform future works using Chinese patent statistics which aspects of economic activity they actually capture, and how they compare to evidence in industrialized economies. We also investigate which factors determine firms' patenting behaviors in China, and whether the patenting behaviors of state-owned firms are different from their private-owned peers'.

This paper begins by building a unified dataset combining firm patenting data from China's State Intellectual Property Office (SIPO) and firm production and balance sheet data from China's Surveys of Industrial Enterprises (SIE). Using firm names, we develop annual links between patent assignees and firms included in the SIE. The constructed data cover more than 260 thousand 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.

In line with previous studies that use data from industrialized economies, we find that the distribution of patent activities across Chinese firms (both in terms of patent stock and scope) is highly skewed. Only 9 percent of all firms in the merged data applied for patents, accounting for 38 percent of value added, 42 percent of capital stock, and 27 percent of employment. Among these patenting 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 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 (36 percent) of firms filing patents in China.

To understand which firm characteristics are associated with patenting, we first estimate a count data model of patents based on the Negative Binomial specification. We find that younger, larger firms, and firms with more R&D investments, patent more. SOEs tend to file fewer patents than POEs, while exporting firms are more innovative than nonexporting firms. Firms that are new to patenting innovate less. Lastly, firm-specific leverage ratios tend to have negative effects on firm patenting.

We then compare the *within-firm* elasticity of firm productivity (and other production performance) to changes in patent stock (the accumulated number of patent applications) and patent scope (the total number of distinct technological fields in which the firm has applied for patents). We find strong evidence that within-firm changes in patent stock and scope are significantly and positively associated with productivity improvement, where productivity is measured by various approaches. The elasticities of productivity to changes in patent stock are 0.018, 0.014, 0.051, and 0.028 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 almost 2 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), although elasticities are often highest for utility model patents.

In line with these findings, we also observe that significant real economic changes are associated with firms' initial patent applications. In a before-and-after study, we find that, after applying for patents for the first time, firms experience significant increases in productivity, size, new product shares, and exports, but undergo falls in markups. In 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 coincide with first-time patenting events. The significant effect tends to take place with a one-year lag.

Detailed firm-level data also inform our understanding of the roles various factors may play in contributing to the positive relationship between patent activity and a firm's production performance. In this paper, we specifically investigate whether a firm's ownership status plays any significant role, as it is a uniquely important element in understanding firm performance in China (see Song et al., 2011; Zhu, 2012; Hsieh and Song, 2015; Chang et al., 2016). Somewhat surprisingly, we find that the aforementioned positive association between patent application and productivity growth is stronger for SOEs than for their private-owned peers. Although SOEs tend to be less innovative, increases in their patent stocks are associated with more improvements in productivity. Using DID analysis, we find that the SOE reform appears to have improved the productivity elasticity of patenting for SOEs more than that of private firms. Given the well-documented misallocation of resources between SOEs and private enterprises (e.g., Wei et al. 2017), this discrepancy could be the result of the considerable support SOEs receive from the government, as well as their access to low bank loans.

Lastly, a firm's patenting behavior is not exogenous. Factors that contribute to the application of more patents may simultaneously affect firm productivity. To provide further insight on the causality, we adopt an instrumental variable (IV) analysis. We identify one particular external driver of firm innovation as an instrument, the initial prefecture-level IPR protection, which is exogenous to firm patenting, but should not contribute to firm productivity growth directly. IPR protection in China matters at the local level, due to the lack of forum shopping and the clustering of industries (see Fang et al., 2017). Consistent with Fang et al. (2017), we find that regional variations in local IPR protection scores do, indeed, help explain variations in firms' patenting behaviors. Our instrumental variable analysis, however, shows no significant positive effect from patenting on firm productivity growth. Our results suggest that Chinese firms' patents are meaningful proxies for real innovative activity, as they are associated with real significant changes in firm productivity and other performance, but should not be interpreted as having a causal effect on firm productivity.

Related Literature The practice of using patent data for economic research on productivity and innovation dates back to Schmookler and Brownlee (1962), followed by Griliches and Schmookler (1963) and Scherer (1965). Previously reliable patent data were only available in industrialized economies, where attempts have been made to combine patent data with firm production data. Recently, Balasubramanian and Sivadasan (2011) developed a detailed concordance between NBER patent data and U.S. Census data to examine the consequences of firm patenting. Our paper is the first to use a Chinese firm-production-patent data combination to evaluate the impact of firm innovation on productivity growth. We observe many similarities between Chinese patent data and the U.S. observations, but also point out important differences in the following sections.

This paper contributes to the growing literature on various aspects of Chinese firm innovation.

Hu and Jefferson (2009) study the factors behind the explosion of China's patent applications for large and medium enterprises and conclude that, since 2000, they have been driven by a combination of rising foreign direct investment, changing ownership structures in Chinese industry, and propatent legislation. In their follow-up research, Hu et al. (2017) relate the recent 2007-11 patent surge to noninnovation-related motives for acquiring patents, such as government R&D subsidy programs (as discussed in Chen et al., 2018). Using data on R&D investment and patent information, Wei et al. (2017) discuss the drivers of China's innovation growth and identify the potential misallocation of R&D resources, given that innovation productivity is higher for private firms than for SOEs, while the latter receive more government subsidies. Similarly, 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 U.S. Based on publicly listed Chinese firms, Boeing et al. (2016) also find that private firms have higher R&D returns, in terms of productivity growth, than SOEs. Our work, although also sheds light on the internal and external drivers of patenting, focuses more on the impact of patenting on firms' economic performances.

Lastly, using microeconomic perspectives, this paper contributes to the recent empirical studies on China, as a variety of firm-level data have been made available (e.g., Hsieh and Klenow, 2009; Brandt and Zhu, 2010; Brandt et al., 2012). Brandt et al. (2012) is the first to estimate firm-level TFPs for China's manufacturing firms, discovering that TFP growth dominated input accumulation in contributing to output growth in manufacturing sectors. Our paper utilizes recently available firm patent data and investigates whether the surge in patenting behavior has contributed to the observed TFP growth. Drawing upon a recently developed method—based on Ackerberg et al. (2015)—that addresses the functional dependence issues in Olley and Pakes (1996) and Levinsohn and Petrin (2003), we find that Chinese firm patenting is, indeed, associated with productivity growth. Our results also 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).

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 (patent stock, scope, and status) and production performance. Section 4 investigates the role of state ownership, and Section 5 studies whether changes in productivity could be attributed to patenting. Section 6 concludes.

2 Institutional Background, Data and Measurement

2.1 China's Patent System

China's patent law was first introduced in 1984, and has since been amended several times to comply with international standards and to facilitate its development into an innovative economy. 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 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 during our sample period.

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

[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.

for a long time (i.e., pharmaceutical or biotech). Utility patents account for 31 percent of the total patent applications in our 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 accounted for the largest share of patent applications, 43 percent, in our 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 United States in the same year.

2.2 Data Description

The patent application data are obtained from China's National Bureau of Statistics (NBS). The data cover the universe of patent applications from 1985 to 2011 and contain detailed information (e.g., application number; filing, publishing, and granting dates; title; technological class; assignee; inventor; and patent agency) on each patent. The information we use in this paper is patent ID, patent title, and its associated International Patent Classification (IPC), the application date, and the name (assignee) and address of the applicant (usually a firm or an institution).

Firm-level data come from China's SIE, which was conducted annually by the NBS between 1998 and 2007. The SIE 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 "above-scale" firms—SOEs and non-SOEs with annual revenues of 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. (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 SIE 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.[2] 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 comprehensive firm-patent matched dataset that links the patent data to SIE firm data. Since the two datasets use different firm identification systems, we match them by firm name (i.e.,"firm name" in SIE data and "assignee name" in patent data), and verify the match using location information ("provincial proxy number"). Among all the matched firms in our SIE sample, 29,284 firms applied for patents at least once since the patent law's establishment in China—we call these firms "patenting firms" or "patentees" 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 Column (3) of Table I, about 2 percent of firms in our SIE sample applied for patents in 1998, accounting for 7 percent of the total applications that year. The percentage of firms filing for patents in the SIE sample increased to about 3.4 percent by the end of the sample in 2007. A similar trend is observed in the share of matched patents in total nationwide patent 7.3 percent in 1998 to 16.5 percent in 2007 (see Column (6)).

Two factors contribute to the low representation of SIE firms in SIPO patent data: (a) the majority of patents in China are filed by educational and research institutions that are not linked to firms, and (b) the firms included in the SIE are all above-scale firms. Since most innovating

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

Table I: Matching SIE Data and Patent Data

	Our Sample						NBS CSY
Year	No. of firms in SIE	No. of matched firms filing patent	%	Total Patents in SIPO	Patents by matched firms	%	Patents by large-medium firms
	(1)	(2)	(3)=$\frac{(2)}{(1)}$	(4)	(5)	(6)=$\frac{(5)}{(4)}$	(7)
1998	100,126	1,981	1.98	91,014	6,638	7.29	6,317
1999	106,312	2,507	2.36	125,996	9,693	7.69	7,884
2000	106,236	2,875	2.71	132,160	11,509	8.71	11,819
2001	121,884	3,475	2.85	151,184	14,728	9.74	15,339
2002	133,919	4,287	3.20	173,164	22,208	12.82	21,297
2003	155,725	5,196	3.34	220,019	29,092	13.22	31,382
2004	234,522	6,511	2.78	236,928	37,820	15.96	42,318
2005	233,505	7,015	3.00	316,984	46,608	14.70	55,271
2006	262,263	8,814	3.36	368,536	66,423	18.02	69,009
2007	298,152	10,152	3.41	485,399	80,270	16.54	95,905

firms are large, the second factor may not be as important. 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 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.

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 2 percent to 36 percent (Column (1)), they account for a relatively large share of the industry's value-added, ranging from 10 percent to 80 percent (Column (2)). This is consistent with the stylized facts documented in previous studies using industrial country observations: relatively few firms own patents, but they are large firms that dominate economic activity. There is also large heterogeneity across industries: 36 percent of firms in the medical sector applies for at least one patent in a given year, while only 2 percent of firms in apparel, footwear, and caps are patent-owning firms. Among the 29 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

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 (Mil.RMB) (4)	Patents per Firm (5)	% of SOE (6)
13	Processing of Foods	5.9	17.5	302	46	0.50	21.6
14	Food	20.2	40.2	937	104	1.27	19.8
15	Beverage	21.9	52.3	727	209	1.25	31.0
16	Tobacco	30.5	80.9	91	166	1.53	90.9
17	Textile	3.9	14.1	932	224	1.51	25.9
18	Apparel, Footwear and Caps	2.4	10.5	390	52	1.69	9.0
19	Leather	4.0	10.5	200	20	1.12	7.8
20	Timber	5.6	13.5	185	16	0.95	17.6
21	Furniture	10.7	20.2	499	39	1.81	5.5
22	Paper making	4.8	22.3	153	110	0.57	17.6
23	Print, Reproduction of media	6.1	23.3	104	29	0.55	23.7
24	Articles for Culture, Edu. and Sports	16.6	27.5	1,059	33	2.68	6.1
25	Petroleum Processing	8.8	43.9	107	155	0.78	44.0
26	Raw Chemical	12.0	34.1	1,282	960	0.78	26.2
27	Medical	36.1	60.2	1,200	745	0.86	26.7
28	Chemical Fibers	10.4	45.4	91	58	0.95	35.3
29	Rubber	13.5	31.8	208	134	0.70	21.7
30	Plastics	10.8	20.6	696	93	0.79	9.9
31	Nonmetallic Mineral	6.5	16.8	922	192	0.93	24.5
32	Pressing of Ferrous Metals	5.7	61.3	581	1,198	2.46	48.1
33	Pressing of NonFerrous Metals	9.1	42.3	353	219	1.13	37.0
34	Metal Products	13.3	27.2	1,209	216	0.95	12.6
35	General Purpose Machinery	18.7	42.0	2,170	945	0.82	23.6
36	Special Purpose Machinery	28.1	50.9	2,066	849	0.95	27.9
37	Transport Equipment	18.8	54.9	2,622	2,729	1.55	33.8
39	Electrical Machinery and Equipment	22.3	50.1	5,000	2,199	1.95	13.2
40	Computers and Other	23.3	48.3	6,759	4,533	3.99	22.3
41	Instruments	33.0	40.2	1,019	350	1.15	23.4

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 stock in that industry per year, and Column (4) presents the total value of R&D expenditure per year. Column (5) shows the average number of patent filed per 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.

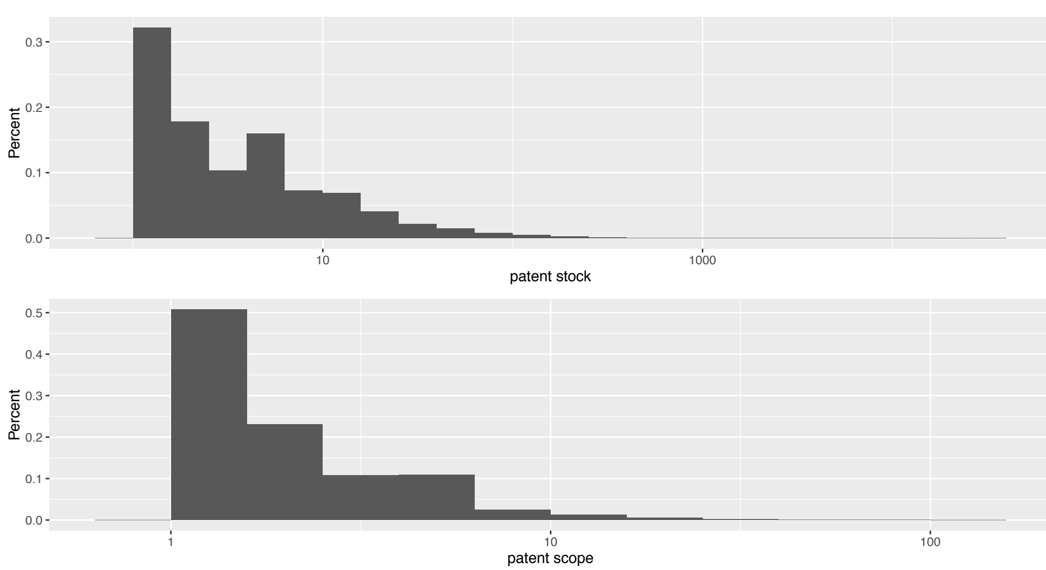
R&D expenditure, found in Column (4)). Since industries also differ in firm concentration, the top three industries boasting the highest number of patent applications per firm are slightly different from the previous list: computers, manufacturing of articles for culture education, and sports and pressing of ferrous metals. 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.

2.3 Measurement

Innovation We use three indicators—patent stock, patent scope 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: $s^j_{it} = p^j_{it} + s^j_{i,t-1}$. Firm i's total patent stock is then $S^i_t = \sum_j s^j_{i,t}$. SIPO classifies each patent into one of the six-digit technology-based patent categories. A firm's patent scope, N_t, is defined as the number of technological categories in which it has filed for patents to date (i.e., the dimension of the vector $(s^j_{i,t})_{j \in J}$). 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 ($\{S_i\}_i$) and patent scopes ($\{N_i\}_i$) in the last year of the sample (2007). The distributions of stock and scope are both highly skewed. While an average firm has a stock of 13.2 patents, a median firm has only three patent applications. Among the 29,284 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.

Figure II: Histogram of patent stock and patent scope (in log)



Notes: The Figure presents firm distribution across patent stock and patent scope. Patent stock is calculated as accumulated count of patents the firm has applied up to 2007, and patent scope is defined as the number of distinct technological categories in which a firm has applied for patent.

Production The SIE 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 (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 SIE, instead of fixed investment, each firm reports the value of fixed capital stock at the original purchase price. These book values are the sums 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).[3] 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 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

[3] If a firm listed in the SIE 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 SIE. The real initial capital stock is then obtained by deflating the nominal capital stock with the investment deflator in that year.

the aggregate value added.

Ownership Following Hsieh and Song (2015), we use two variables in the SIE 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:

$$\ln V^j_{it} = \lambda_1 \ln S^j_{it} + \lambda_2 \ln K^j_{it} + \lambda_3 \ln L^j_{it} + \mu_i + \gamma_{j,t} + \varepsilon^j_{it}. \tag{1}$$

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:

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

where s^{l}_{it} is the expenditure share of labor input, $w_{it}L_{it}/P_{it}Q_{it}$, and $\widehat{\theta}^{l}_{it}$ 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 Patenting Behavior

Before evaluating the impact of patenting on firm performance, we first ask what factors account for Chinese firms' patenting behaviors. 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:

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

where S_{it} is the patent stock of firm i, i.e. a count of the number of patents that firm i has applied for up to 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 total patent applications for firm i at year $t-1$, $P_{it-1} > 0$, and zero otherwise.[4] The vector X_{it} stands for other control variables, including the log of the R&D expenditure (when available), sales, age, exporting firm dummies, SOE dummies, and dummies for firms who are new to patenting (defined as firms whose first patent applications are less than five years old), as well as the leverage ratio measured by the ratio of total liabilities to total assets. Lagged observations for X_{it} are included to mitigate endogeneity issues. We also 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.[5] Unfortunately, R&D expenditure data are only available for three years in the SIE: 2001, 2005 and 2006. We are thus unable to construct firm-level R&D stocks and unable to control for R&D in the panel regression.

Table III presents both the cross-section regression estimates based on observations in 2006 and 2007 ($t = 2007$) and the panel regression estimates using the entire sample period. According to the cross-section estimation results in Panel A, R&D investment contributes positively and significantly to patent stock. This positive relationship between R&D input and innovation output is consistent with findings in previous literature (Hu and Jefferson, 2009). Compared to other firms in the same industry, firms with higher sales have more patents and, by design, firms that have recently begun patenting have fewer patents. Exporting firms have larger patent stock than nonexporting firms. SOEs have fewer patent stocks than POEs. Finally, financial constraint does not seem to play a significant role in determining patenting behavior across firms.

Panel B examines within-firm changes using panel regressions. Since there is strong persistence in patenting behavior, Columns (4)-(6) each include a lagged dependent variable, $S_{i,t-1}$. Sales and firms' exporting statuses retain positive and significant coefficients. As a firm ages, it becomes less innovative. Unlike the cross-section outcome, once previous patent stocks are controlled for, firms who are new to innovation actually prove to be more innovative than established firms, indicating that innovation rates are higher for new patenting firms. Naturally, when firm fixed effects are

[4] 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.

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

Table III: Determinants of Patent Stock, Negative Binomial Model

Dept. Var.	**A. Cross-section (2007)** S_{2007}		**B. Panel (1998-2007)** S_t			
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln R\&D_{t-1}$	0.054***	0.054***	–	–	–	–
(s.e.)	[0.002]	[0.002]				
$\ln sales_{t-1}$	0.375***	0.375***	0.413***	0.095***	0.090***	0.089***
(s.e.)	[0.006]	[0.006]	[0.002]	[0.001]	[0.001]	[0.001]
age_{t-1}	-0.004***	-0.004***	-0.006***	-0.003***	-0.002***	-0.001***
(s.e.)	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
D_t^{SOE}	-0.068***	-0.068***	-0.110***	-0.020***	-0.001	-0.004
(s.e.)	[0.025]	[0.025]	[0.009]	[0.005]	[0.005]	[0.005]
D_t^{EX}	0.239***	0.238***	0.251***	0.042***	0.039***	0.038***
(s.e.)	[0.017]	[0.017]	[0.007]	[0.004]	[0.004]	[0.004]
D_t^{New}	-0.214***	-0.214***	-0.175***	0.090***	0.075***	0.077***
(s.e.)	[0.021]	[0.021]	[0.008]	[0.005]	[0.005]	[0.005]
$Leverage_{t-1}$		-0.02				-0.019***
(s.e.)		[0.030]				[0.007]
$\ln S_{t-1}$				0.857***	0.860***	0.862***
(s.e.)				[0.001]	[0.002]	[0.002]
Pre-sample FEs					0.103***	0.099***
(s.e.)					[0.005]	[0.005]
Firm FEs	No	No	No	No	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	No	No	Yes	Yes	Yes	Yes
Number of obs	195,366	195,366	1,460,537	1,460,537	1,460,537	1,460,537

Notes: Dependent variable is overall patent counts. Estimation is conducted using the Negative Binomial model. Standard errors (in brackets) allow for serial correlation through clustering by firm. A full set of year dummies, industry dummies are included all panel regressions and industry dummies are included in the cross section regressions. Columns (5) – (6) 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.

controlled for by using the presample mean approach, an SOE status is no longer significant, as few firms change their ownership statuses. Finally, as in Fang et al. (2017), we find that leverage ratios appear to have negative impacts on innovation.

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 XII 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 SIE 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).

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 and patent scope are both associated with significant increases in all outcome variables under consideration. For example, a 10 percent increase in patent stock implies approximately 1.5 percent increases in real output and value added, similar rises in capital and employment, and a 4 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 0.28 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 0.20 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 0.51 percent. Patent stock's impact on the Solow residual and labor productivity is smaller at 0.14 percent and 0.18 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

Table IV: Patent Stock, Patent Scope and Firm Production Performance

	A. Patent Stock			B. Patent Scope		
	ln(S)	(s.e.)	R^2	ln(N)	(s.e.)	R^2
A. Overall Panel						
Productivity						
Labor prod	0.018***	(0.005)	0.85	0.024***	(0.008)	0.85
Solow Residual	0.014*	(0.007)	0.78	0.018*	(0.011)	0.78
OLS-FE	0.051***	(0.007)	0.89	0.067***	(0.010)	0.89
$\text{TFP}^{ACF,CD}$	0.020***	(0.005)	0.91	0.031***	(0.007)	0.91
$\text{TFP}^{ACF,Translog}$	0.028***	(0.006)	0.94	0.041***	(0.008)	0.94
Markup	0.044	(0.113)	0.17	0.600	(0.631)	0.17
Size						
Output	0.155***	(0.006)	0.93	0.206***	(0.010)	0.93
Value added	0.152***	(0.008)	0.87	0.200***	(0.011)	0.87
Capital stock	0.142***	(0.007)	0.95	0.182***	(0.010)	0.95
Employment	0.137***	(0.006)	0.93	0.182***	(0.009)	0.93
Other						
Capital-labor ratio	0.005	(0.006)	0.86	0.000	(0.009)	0.86
New product share	1.946***	(0.248)	0.73	2.825***	(0.331)	0.73
Export shipment	0.402***	(0.034)	0.85	0.577***	(0.049)	0.85
Number of obs	142,717					
B. Balanced Panel						
Productivity						
Labor prod	0.025	(0.015)	0.85	0.040*	(0.021)	0.85
Solow Residual	0.024	(0.015)	0.79	0.038*	(0.022)	0.79
OLS-FE	0.062***	(0.016)	0.91	0.089***	(0.023)	0.91
$\text{TFP}^{ACF,CD}$	0.025*	(0.013)	0.92	0.036*	(0.019)	0.92
$\text{TFP}^{ACF,Translog}$	0.039***	(0.014)	0.95	0.048**	(0.019)	0.95
Markup	0.44	(0.485)	0.14	0.477	(0.538)	0.14
Size						
Output	0.159***	(0.019)	0.93	0.221***	(0.027)	0.93
Value added	0.160***	(0.022)	0.89	0.221***	(0.031)	0.89
Capital stock	0.137***	(0.018)	0.96	0.182***	(0.025)	0.96
Employment	0.135***	(0.016)	0.93	0.181***	(0.024)	0.92
Other						
Capital-labor ratio	0.003	(0.016)	0.84	0.001	(0.023)	0.84
New product share	2.921***	(0.571)	0.69	4.080***	(0.857)	0.69
Export shipment	0.509***	(0.094)	0.84	0.689***	(0.148)	0.84
Number of obs	26,310					

Notes: The dependent variables are patent stock ($S^j_{i,t}$) in Panel A, and patent scope ($N^j_{i,t}$) in Panel B. All dependent variables, except for the new product share, are logged. All regressions control for firm and four-digit industry 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.

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/scope, controlling for firm fixed effects and industry-year fixed effects. As shown in Table IV, a 10 percent increase in patent stock raises the share of a new product by about 19 percent, suggesting that innovation is also associated with new product development in China. Similarly, when firms' patent scopes increase (firms patenting in more sectors), they also become larger, more productive, export more, and, as expected, produce more new products.

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 and scope 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.

3.2.2 Different Types of Patents

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 SIPO. 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 Table V. Increases in all types of patent stocks are positively and significantly associated with increases in productivity, size, new products' revenue shares, and exports. However, most of the elasticities' magnitudes are notably smaller for the most inventive type (invention patents). Rises in patent scopes across all categories are also found to increase with firm performance and there are no significant differences between productivity coefficients.

Table V: Patent Stock, Patent Scope and Firm Production Performance: Different Patent Types

	Invention		Utility Model		Design	
	β	(s.e.)	β	(s.e.)	β	(s.e.)
			A. Patent Stock			
Productivity						
Labor productivity	0.014	(0.012)	0.021**	(0.008)	0.008	(0.009)
Solow Residual	-0.002	(0.015)	0.027***	(0.010)	-0.005	(0.012)
OLS-FE	0.032**	(0.014)	0.066***	(0.009)	0.031***	(0.012)
$\text{TFP}^{ACF,CD}$	0.019**	(0.009)	0.019***	(0.007)	0.008	(0.008)
$\text{TFP}^{ACF,Translog}$	0.019*	(0.010)	0.025***	(0.008)	0.024***	(0.009)
Markup	-0.079	(0.165)	0.062	(0.192)	1.741	(1.792)
Size						
Output	0.127***	(0.015)	0.170***	(0.008)	0.139***	(0.010)
Value added	0.114***	(0.017)	0.174***	(0.010)	0.129***	(0.012)
Capital stock	0.113***	(0.015)	0.144***	(0.009)	0.137***	(0.010)
Employment	0.113***	(0.011)	0.149***	(0.008)	0.131***	(0.011)
Other						
Capital-labor ratio	0.000	(0.014)	-0.004	(0.008)	0.007	(0.010)
New product (share)	2.165***	(0.639)	2.566***	(0.282)	0.943***	(0.353)
Export shipment	0.318***	(0.073)	0.502***	(0.041)	0.346***	(0.053)
			B. Patent Scope			
Productivity						
Labor productivity	0.029*	(0.017)	0.028**	(0.011)	0.023*	(0.014)
Solow Residual	0.012	(0.022)	0.017	(0.014)	0.014	(0.019)
OLS-FE	0.059***	(0.021)	0.068***	(0.013)	0.068***	(0.018)
$\text{TFP}^{ACF,CD}$	0.037***	(0.013)	0.035***	(0.010)	0.027**	(0.012)
$\text{TFP}^{ACF,Translog}$	0.037***	(0.013)	0.034***	(0.010)	0.055***	(0.014)
Markup	-0.079	(0.165)	0.062	(0.192)	1.741	(1.792)
Size						
Output	0.186***	(0.020)	0.215***	(0.012)	0.243***	(0.014)
Value added	0.173***	(0.025)	0.207***	(0.015)	0.227***	(0.019)
Capital stock	0.156***	(0.022)	0.190***	(0.012)	0.206***	(0.017)
Employment	0.157***	(0.016)	0.187***	(0.010)	0.220***	(0.014)
Other						
Capital-labor ratio	-0.001	(0.021)	0.003	(0.011)	-0.014	(0.018)
New product (share)	2.936***	(0.820)	3.105***	(0.395)	2.891***	(0.602)
Export shipment	0.555***	(0.090)	0.662***	(0.062)	0.523***	(0.082)

Notes: The independent variables are patent stock ($S^j_{i,t}$) in Panel A, and patent scope ($N^j_{i,t}$) in Panel B. Patents of different types—invention patent, utility model patent and design—are used for different columns. All regressions control for firm and four-digit industry 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.

3.3 First-Time Patenting Firms

This section adopts an event study approach to examine what happens to a firm's production performance after it changes its patenting status, that is, when it applies for a patent for the first time.

3.3.1 Baseline Analysis

The magnitude and statistical significance of change in performance after initial patenting event are evaluated by estimating the following two panel regressions:

$$\text{Before-and-After: } Y_{it}^{j} = \varphi_1 Switch_{it} + \mu_i + \varepsilon_{i,t}^{j}, \tag{5}$$

$$\text{Difference-in-Differences: } Y_{it}^{j} = \varphi_2 Switch_{it} + \mu_i + \gamma_{j,t} + \varepsilon_{i,t}^{j}, \tag{6}$$

where $Switch_{it} = 1$ if $t \geq t_0$ and t_0 is the first year that firm i filed for a patent.

First, in a before-and-after comparison in equation (5), we study firms who applied for patents for the first time during our sample period and compare their performance after the patenting event with their performance before the event. The estimated coefficient associated with the dummy variable $Switch_{it}$, φ_1, gives the estimated change in the outcome variable associated with first-time patenting. Second, to control for common industry trends and shocks, we specify a difference-in-differences regression in equation (6), which examines how firms' production outcomes change after first-time patenting compared to nonpatenting firms in the same four-digit industry. Here, the sample includes both first-time patenting firms and nonpatenting firms. The difference-in-differences estimates of the change in firm outcome are given by the coefficient φ_2. 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.

Table VI summarizes the estimates of φ_1 and φ_2 for each outcome variable under the two specifications. Except for markups and capital-labor ratios, φ_1 and φ_2 are estimated to be positive and significant (each at 1 percent) for all outcome variables, consistent with previous within-firm analyses. The magnitudes of the increases in productivity shown in the before-and-after analyses are much larger than those revealed in the difference-in-differences analyses, at around 0.4 log points, according to TFP measures. Firms' outputs and inputs (capital and employment) also experience significant jumps following the patenting status switches. In the case of the difference-in-differences analysis, based on our preferred measure of TFP, using the ACF method and translog

Table VI: First-time Patenting Firms: An Event Study

	A. Before-and-After			B. Difference-in-Differences		
	φ_1	(s.e.)	R^2	φ_2	(s.e.)	R^2
Productivity						
Labor productivity	0.448***	(0.014)	0.76	0.028***	(0.010)	0.82
Solow Residual	0.367***	(0.025)	0.63	0.024***	(0.013)	0.73
OLS-FE	0.669***	(0.016)	0.80	0.170***	(0.014)	0.83
$\text{TFP}^{ACF,CD}$	0.439***	(0.013)	0.82	0.039***	(0.009)	0.90
$\text{TFP}^{ACF,Translog}$	0.397***	(0.016)	0.85	0.043***	(0.009)	0.94
Markup	-0.617**	(0.241)	0.12	-0.501*	(0.304)	0.17
Size						
Output	0.664***	(0.016)	0.87	0.176***	(0.011)	0.90
Value added	0.669***	(0.016)	0.80	0.170***	(0.014)	0.83
Capital stock	0.463***	(0.018)	0.91	0.148***	(0.012)	0.93
Employment	0.216***	(0.013)	0.87	0.148***	(0.010)	0.89
Other						
Capital-labor ratio	0.247***	(0.016)	0.79	0.000	(0.012)	0.83
New product (share)	3.257***	(0.301)	0.61	1.673***	(0.333)	0.63
Export shipment	0.961***	(0.066)	0.78	0.490***	(0.061)	0.82
Number of obs		44,379			76,964	

Notes: The tables hows the results for before-and-after and difference-in-differences regressions, as specified in equations (5) and (6). The sample for Panel A includes only first-time patentees and the sample for Panel B includes both first-time patentees and all the nonpatentees. Panel A controls for firm fixed effects and Panel B controls for both firm and four-digit industry 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.

production specification, we find an increase of 0.04 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 0.18 log points, while the increases in capital and labor input are slightly smaller (in 0.15 and 0.15 log points, respectively). In addition, there is an approximately 2 percent increase in new product share in total revenue and an increase of 0.49 log points in export value. The markup coefficients in regressions are negative and only significant at the 10 percent level in equation (6). 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.

3.3.2 Matched Sample Analysis: TFP

While the baseline difference-in-differences approach specified in equation (6) allows for cleaner identification of the before-and-after changes of innovation, it 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, in this section, 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 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.[6] Appendix D explains the PSM method in more detail.

Panel A of Table VII 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 is in the treatment group, and zero otherwise. The result shows that all covariates,

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

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 VII 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 VII: Match Sample Analysis

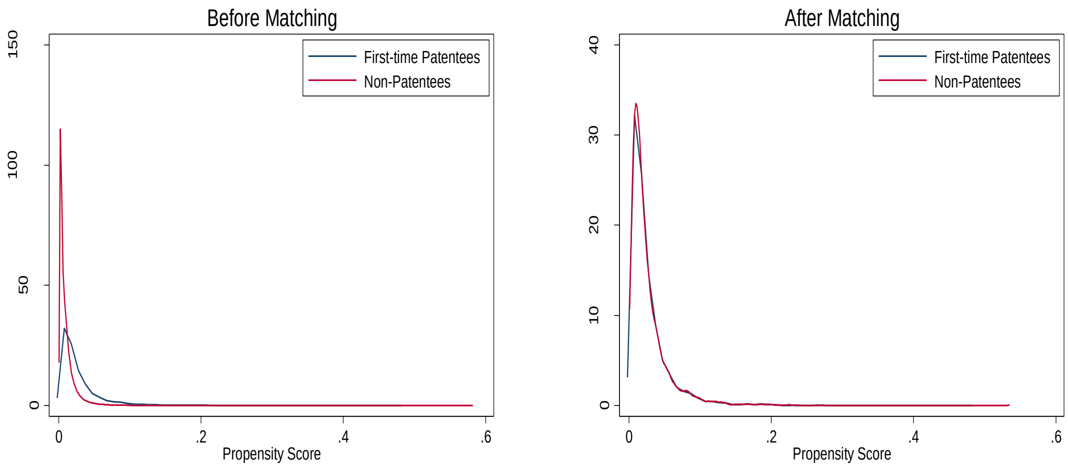
Variables	A: Probit	B: Differences in pre-patenting characteristics			
		First-time Patentees	Non-Patentees	Difference	t-statistic
$\ln(age_{it-1})$	0.020**	2.34	2.35	-0.01	0.43
	(0.008)				
$\ln(employment_{it-1})$	0.243***	5.64	5.64	0.01	0.81
	(0.006)				
D^{SOE}_{it-1}	0.043**	0.18	0.19	-0.01	0.28
	(0.018)				
D^{EX}_{it-1}	0.174***	0.45	0.45	0.00	0.86
	(0.014)				
$\ln TFP^{ACF,Translog}_{it-1}$	0.111***	2.10	2.08	0.02	0.55
	(0.008)				
$\Delta \ln TFP^{ACF,Translog}_{it-1}$	-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. *** indicates significance at 1%, ** significant at 5%, and * significant at 1%. Industry and year fixed effects are also controlled for. Panel B compares the pre-patenting mean of patenting treatment group and control group.

The postpatenting changes in production performance of all matched pairs are then compared using the difference-in-differences method. First, Panel A of Table VIII 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 Table VI, 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:

$$
\begin{aligned}
\ln Y_{it}^{j} \quad = & \sum_{z=-2\&-1,0,1,2+} \psi_1^z Patentee_{it}^{j} \times Switch_{it}^{z} + \\
& \sum_{z=-2\&-1,0,1,2+} \psi_2^z Switch_{it}^{z} + \psi_3 Patentee_{it}^{j} + \gamma_{j,t} + \varepsilon_{i,t}^{j},
\end{aligned}
\tag{7}
$$

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 VIII. 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-

Table VIII: 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		
$Patentee \times Switch^{-2\&-1}$	0.025*	0.009
	(0.015)	(0.015)
$Patentee \times Switch^{0}$	0.034*	0.027
	(0.018)	(0.019)
$Patentee \times Switch^{1}$	0.041**	0.044**
	(0.020)	(0.021)
$Patentee \times Switch^{2+}$	0.056***	0.066***
	(0.022)	(0.022)
$Patentee$	0.048**	0.006
	(0.020)	(0.021)
$Switch^{-2\&-1}$	-0.040***	-0.038**
	(0.014)	(0.016)
$Switch^{0}$	-0.076***	-0.095***
	(0.020)	(0.023)
$Switch^{1}$	-0.095***	-0.122***
	(0.023)	(0.026)
$Switch^{2+}$	-0.142***	-0.183***
	(0.032)	(0.036)
Number of obs	78,141	78,141
R^2	0.607	0.754

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 (7). 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.

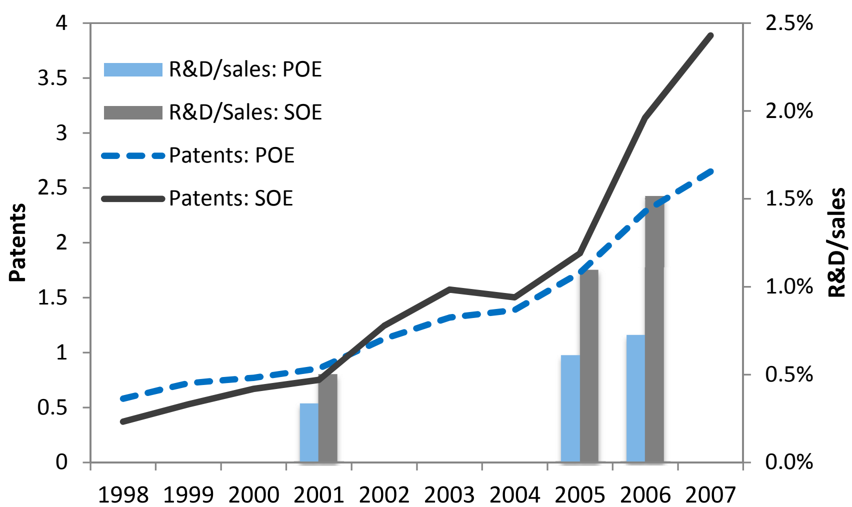
firm changes. Changes in firm production performances are significant, especially with regard to productivity, which is associated with changes in patent stock and status.

4 The Role of State Ownership

4.1 Patenting Behavior and Firm Production

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 (see Song et al., 2011). A simple comparison between an average SOE and an average POE (Figure IV) shows that SOEs and POEs filed similar numbers of patents per firm before 2001 and, starting in 2001, the former actually surpassed the latter. This is partly due to the fact that SOEs receive larger R&D resource allocations, as shown in the same graph. Consistent with the previous literature, the regression results presented in Table III suggest that SOEs are actually less innovative than POEs, once we control for size and R&D investment.

Figure IV: Patent Applications and R&D Intensity per Firm: SOE vs. POE



The next question is whether there are any significant differences between SOEs and POEs in terms of the relationships between their patenting behaviors and production performances. To answer this question, we run the following regression:

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

where as before, Y_{it} denotes the outcome variables listed in Table IV. D^{SOE} is a dummy variable taking the value to be one if the firm is state-owned and zero otherwise. Parallel to equation (1), we also estimate the OLS-FE measure of TFP by interacting ownership status with patent stock:

$$\ln V_{it}^{j} = \alpha \ln K_{it}^{j} + \beta \ln L_{it}^{j} + \lambda_1 \ln S_{it}^{j} + \lambda_2 D_{it}^{SOE} + \lambda_3 \ln S_{it}^{j} \times D_{it}^{SOE} + \mu_i + \gamma_{j,t} + \varepsilon_{it}^{j}. \tag{9}$$

Panel A in Table IX shows the estimation results for equations (8) and (9). As expected, SOEs are generally larger and have lower productivity levels than POEs. Surprisingly, the positive correlation between patent stock change and change in productivity is actually higher for SOEs (as suggested by the significantly positive estimates of λ_3), suggesting that SOEs are potentially better at adapting new in-house innovations to improve productivity. At the same time, for the same increases in patent stock, increases in size (e.g., output, value added, capital stock, and employment) and exports are smaller for SOEs than POEs. There are also no significant differences between SOEs and POEs in terms of changes in the new product shares associated with given patenting increases.

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 reform, which began in 1997 and gradually phased out after 2002. SOEs' inefficiency pushed the Chinese government to initiate a large-scale privatization of SOEs in 1997 under the slogan "Grasp the large, release the Small ." 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 went bankrupt (see Hsieh and Song, 2015). Thus, a significant fraction of less productive firms has switched from being state owned to privately owned.[7] 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 that excludes firms that switched ownership over our sample period. 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 (the "balanced and constant

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

Table IX: Patenting and Production Performance: SOEs vs. POEs

A: Patent and Firm Performance	$\ln S$	(s.e.)	D^{SOE}	(s.e.)	$\ln S \times D^{SOE}$	(s.e.)
Productivity						
Labor productivity	0.006	(0.005)	-0.150***	(0.016)	0.055***	(0.008)
Solow Residual	0.004	(0.007)	-0.104***	(0.021)	0.041***	(0.010)
OLS-FE	0.048***	(0.007)	-0.053***	(0.019)	0.014	(0.009)
$\text{TFP}^{ACF,CD}$	0.011**	(0.005)	-0.091***	(0.013)	0.041***	(0.007)
$\text{TFP}^{ACF,Translog}$	0.020***	(0.006)	-0.083***	(0.015)	0.035***	(0.008)
Markup	-0.169	(0.288)	2.337	(3.226)	0.759	(0.622)
Size						
Output	0.166***	(0.007)	0.084***	(0.018)	-0.047***	(0.009)
Value added	0.167***	(0.008)	0.111***	(0.021)	-0.062***	(0.012)
Capital stock	0.167***	(0.007)	0.201***	(0.022)	-0.108***	(0.009)
Employment	0.160***	(0.006)	0.234***	(0.018)	-0.101***	(0.009)
Other						
Capital-labor ratio	0.007	(0.007)	-0.034**	(0.016)	-0.006	(0.009)
New product (share)	1.877***	(0.270)	-0.105	(0.538)	0.270	(0.322)
Export shipment	0.431***	(0.036)	0.323***	(0.074)	-0.130***	(0.043)

B: Sample Selection Bias

Dependent Var.	$\text{TFP}^{ACF,Translog}$			
	A. Benchmark Sample	B. Balanced Panel	C. Constant Ownership	D. Balanced and Constant Ownership
$\ln S$	0.020***	0.023*	0.015**	0.011
(s.e.)	(0.006)	(0.014)	(0.007)	(0.007)
D^{SOE}	-0.083***	-0.135***	–	–
(s.e.)	(0.015)	(0.026)	–	–
$\ln S \times D^{SOE}$	0.035***	0.051***	0.054***	0.089***
(s.e.)	(0.008)	(0.014)	(0.014)	(0.027)
Number of obs	142,717	26,310	121,980	19,620
R^2	0.94	0.95	0.95	0.95

Note: Panel A reports the regression results of specification (8) and (9). Panel B studies how the TFP-productivity relationship changes according to different sample selection, using the same specification as Panel A. All regressions control for firm 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.

ownership" sample).

Panel B in Table IX shows the estimation results of (8) based on our preferred TFP measure—TFP^{ACF,Translog}, using four different samples: the benchmark sample, balanced panel, constant ownership, and balanced and constant ownership samples. We are most interested in the coefficient of the interaction term, $\ln(S) \times SOE$ (λ_3), which captures how patent growth relates to growth in TFP differently for SOEs and POEs. This coefficient is positive and significant at the 1 percent level for each of the four samples examined. In addition, the coefficient is the highest for the most restricted sample (balanced and constant ownership), implying that it is the act of "grasping the large" rather than "releasing the Small" that drives the result. Using alternative TFP measures do not alter these results.

4.2 SOEs and Innovation Quality

The previous section documents the surprising finding that SOEs tend to be better at associating new patents with TFP growth than POEs. However, as previously discussed, not all patents are of the same quality. In this section, we differentiate patents by type and investigate which type of patents SOEs are particularly good at adapting. As discussed in Section 2, in China, an invention patent usually needs to meet higher, stricter requirements than the other two patent types (utility model and design), and is generally expected to be of higher quality. We redo all analyses in Section 4.1 for these three different types of patents individually. In order to save space, we have not reported the detailed results here, but have explained them below.

The fact that TFP^{ACF,Translog} elasticity is higher for SOEs with respect to patent stock is particularly significant for utility model and design patents. While still positive, this elasticity is not significant when considering only invention patents. This observation indicates that SOEs tend to be more successful than POEs at associating innovation with productivity growth for lower-quality patents.

4.3 The Impact of the SOE Reform

The above results suggest that SOEs are better than POEs at associating changes in innovation with productivity growth. However, the analyses summarized by regressions (8) and (9) do not address whether firm ownership has any causal effect on how innovation is transformed into productivity growth, since ownership statuses are not exogenously determined. This section uses the nationwide SOE reform as a "natural experiment" to understand whether SOE reforms have disproportionately improved patent-productivity elasticities for SOEs.

As shown in Figure IV, before 2002, an average SOE filed fewer patent applications than an average POE. However, SOEs surpassed POEs in 2003, and the gap has been widening ever since. Note that the SOE reform took place during 1998-2001. We use the reform as an exogenous event and adopt a difference-in-differences estimation strategy to investigate whether SOE reform has a heterogeneous effect on the relationship between productivity growth, depending on the firm's ownership status. Our empirical specification is as follows:

$$\begin{aligned}\ln TFP_{it}^{j} \;=\;& \phi_1 \ln S_{it}^{j} + \phi_2 D_{it}^{SOE} + \phi_3 Post\_reform_t + \phi_4 \ln S_{it}^{j} \times D_{it}^{SOE} + \phi_5 \ln S_{it}^{j} \times Post\_reform_t + \\ & \phi_6 D_{it}^{SOE} \times Post\_reform_t + \phi_7 \ln S_{it}^{j} \times D_{it}^{SOE} \times Post\_reform_t + \mu_i + \gamma_{j,t} + \varepsilon_{it}^{j}, \qquad (10)\end{aligned}$$

where $Post\_reform_t$ is an indicator variable equal to one for the post-reform period, i.e., $t \geq 2002$. SOE versus POE status (embodied by the SOE dummy) provides the first layer of difference. The before and after comparison of SOE reform (embodied by the $Post\_reform$ dummy) provides the second layer of difference.

Table X shows results for the DID specification of equation (10), using TFP^{ACF,Translog} as the dependent variable for each of the four samples mentioned above. Besides showing similar results to those in previous sections, the table reveals that TFP is higher during the postreform period. The significantly positive coefficient of interaction term $SOE \times Post\_reform$ reform indicates that SOEs' TFPs have been increasing more rapidly than the POEs' after the SOE reform. After the reform, SOEs began catching up with POEs in terms of productivity. This finding correlates with the main findings in Hsieh and Song (2015).

The coefficient of interest, ϕ_7, captures how productivity growth responds to changes in patent stock differently for SOEs and POEs during the postreform period relative to the prereform period. It is estimated to be positive, but insignificant, for the benchmark sample and the constant ownership sample, but significant for the balanced panel and balanced and constant ownership panel. This finding implies that, considering only the surviving firms (which are most likely large), SOE reform significantly improves a SOE's ability to adapt new innovations to boost productivity, as opposed to POEs. In other words, the reform not only allows SOEs to catch up with POEs in terms of TFP level—as emphasized in Hsieh and Song (2015)—but also makes them better firms with regard to transforming innovation into within-firm productivity growth.

Why are TFP-patent elasticities higher for SOEs? Casual observations point to the differences

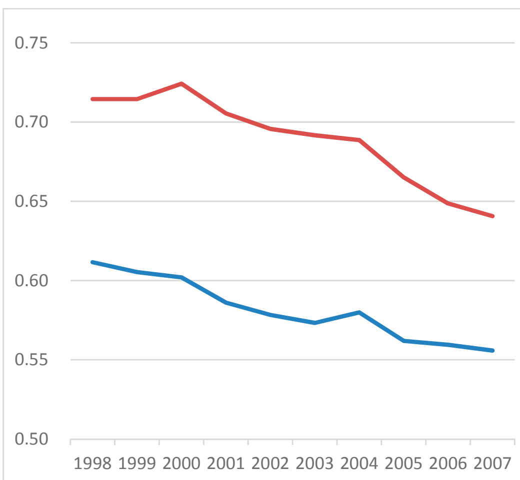
Table X: The Role of SOE Reform

Dependent variable	TFP^{ACF,Translog}			
	A. Full	B. Balanced Panel	C. Constant Ownership	D. Balanced and Constant Ownership
$\ln S_{it}$	0.142***	0.137***	0.142***	0.127***
(s.e.)	[0.008]	[0.013]	[0.009]	[0.016]
D_{it}^{SOE}	-0.182***	-0.223***	–	–
(s.e.)	[0.026]	[0.036]	–	–
$Post\_reform_t$	0.258***	0.396***	0.251***	0.385***
(s.e.)	[0.013]	[0.019]	[0.013]	[0.021]
$\ln S_{it} \times D_{it}^{SOE}$	0.036***	0.043***	0.025	0.046
(s.e.)	[0.011]	[0.016]	[0.020]	[0.034]
$\ln S_{it} \times Post\_reform_t$	-0.015***	-0.038***	-0.015**	-0.037***
(s.e.)	[0.006]	[0.008]	[0.006]	[0.008]
$D_{it}^{SOE} \times Post\_reform_t$	0.110***	0.081**	0.114***	0.105**
(s.e.)	[0.024]	[0.035]	[0.029]	[0.041]
$\ln S_{it} \times D_{it}^{SOE} \times Post\_reform_t$	0.005	0.029*	0.021	0.046**
(s.e.)	[0.012]	[0.015]	[0.014]	[0.020]
Number of obs	142,717	26,310	121,980	19,620
R^2	0.93	0.93	0.94	0.93

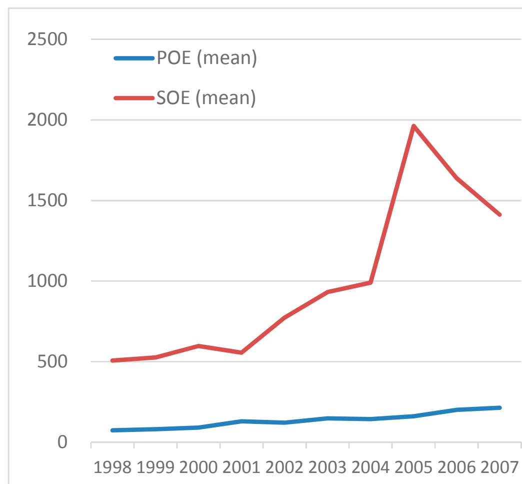
Note: This table show regression coefficients based on specification (10). Panel A employs the whole sample of firms. The sample for Panel B includes only firms that exist from the beginning to the end of the sample period; thus it is a balanced panel. The sample for Panel C includes only firms that have never changed its ownership status and the sample for Panel D comprises only firms that are included in both Panels B and C. All regressions control for firm and four-digit industry-year fixed effects. 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.

in access to financing and subsidies. Research has shown that SOEs have much easier access to the credit market, especially after the SOE reform, and receive more subsidies from the government (see Song et al., 2011, Chang et al., 2016). As shown in Panel (a) of Figure V, in our merged data, the average SOEs' leverage ratio has been significantly higher than the average POEs' for the entire sample period, with the average ratio being 0.69 for SOEs and 0.58 for POEs. Panel (b) demonstrates that an average SOE receives a significantly higher number of subsidies from the government than an average POE does, and the gap has been increasing over time, especially after the SOE reform.[8] More funding and less financial constraint allow firms to take advantage of knowledge capital and to convert new ideas into productivity improvements quickly. Evaluating the impacts of these preferential government policies is beyond the goal of this paper, but could be explored in the future work.

Figure V: State Ownership, Financial Constraint and Subsidies



(a) Leverage



(b) Subsidy

5 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

[8] Aghion et al. (2015) note a similar pattern in terms of the percentages of SOEs and POEs that received positive subsidies. The share rose from 14 percent in 1998 to 25 percent in 2007 for SOEs, compared to 8 percent in 1998 to 12 percent in 2007 for POEs.

the firm, also have direct impacts on productivity. This section, however, attempts to address the endogeneity of patent stock in the baseline specification (4) by considering a specific external driver of firm innovation as an instrumental variable, namely, IPR protection.

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.[9] As explained in Fang et al. (2017), due to the Chinese Intellectual Property Law's requirements and most Chinese firms' domestic market focus, Chinese IPR protection matters at *local* level.[10] 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. Another advantage of this local IPR protection measure is that it is based on a detailed survey of legal professionals (such as judges, IPR lawyers, and corporate executives), and thus reflects the perceived quality of IPR protection, which directly affects the incentive to innovate.[11]

Consistent with their findings, we also find that firms tend to have higher innovation rates in cities with higher IPR protection scores, suggesting that local IPR protection can be a valid 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.[12] 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 XI 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. Other firm-specific internal drivers of innovation are also controlled for in Column

[9] Special thanks to Lily Fang for sharing local IPR protection score data, which span from 2002 to 2007 for 66 prefectures in China. For a more detailed description of the IPR data, see Fang et al. (2017).

[10] 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.

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

[12] 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.

(2). Both regressions show that higher scores of initial IPR protection significantly increase firms' subsequent innovation rates. The F-statistic is above 10, suggesting that the initial local IPR protection is a valid instrument.

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

A. First Stage:	$\Delta \ln(PS)$		*B. Second Stage*:	$\Delta \ln(TFP^{ACF,Translog})$			
	(1)	(2)		(3) OLS	(4) IV	(5) OLS	(6) IV
Initial IPR	0.048***	0.062***	$\Delta \ln(PS)$	0.037***	0.007	0.043***	-0.046
	(0.014)	(0.013)		(0.013)	(0.486)	(0.013)	(0.382)
age		-0.002***	age			0.000	0.000
		(0.000)				(0.000)	(0.001)
ln(emp)		0.041***	ln(emp)			-0.009*	-0.005
		(0.002)				(0.005)	(0.016)
D^{SOE}		0.017*	D^{SOE}			0.005	0.007
		(0.009)				(0.014)	(0.016)
D^{EX}		0.000	D^{EX}			-0.001	-0.001
		(0.006)				(0.009)	(0.009)
F-stat	12.04	21.65					
Number of obs	15,118	15,118	Number of obs	15,118	15,118	15,118	15,118
R^2	0.038	0.067	R^2	0.044	0.043	0.044	0.043

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 XI presents the second-stage cross-section regression instrumental variable estimates in Columns (4) and (6), which are compared with the results of the benchmark OLS regression using the same samples in Columns (3) and (5).[13] The cross-sectional results based on OLS show significantly positive relationships between changes in patent stock and productivity, consistent with the baseline fixed effect panel regression results reported in Table IV, although the point estimates of elasticity are somewhat larger in magnitude. A 10 percentage point increase in patent stock is associated with an approximately 4 percentage point increase in TFP in 2007, compared to the average 2-3 percent increase in TFP during 1998-2007. However, Columns (4) and (6) present an ambiguous picture of patenting's causal impact on productivity. The instrumented cross-section results indicate that innovation does not produce any significant effect on productivity, with or without controlling for other firm-specific characteristics. The insignificant effect associated with the instrumental variable estimation

[13]The Chinese regional IPR data we obtained are available only from 2002, and for just 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.

scheme is consistent with the hypothesis that the least squares estimate could be positively biased by endogenous patenting activity.

6 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 patentees using the propensity score matching approach to construct a control group also show similar effects following an initial patent application. Our analysis suggests that Chinese firm patenting is associated with real, statistically significant changes within firms, including changes in productivity and new products' revenue shares, which is consistent with the existing literature which uses patenting statistics from industrialized economies. We document the somewhat surprising observation that SOEs are better than POEs at associating patenting with productivity growth, although this observation is confined to lower-quality patents. SOEs' easier access to financing and the government-led SOE subsidy program might be the reasons behind this finding.

However, this positive patenting-productivity relationship should not necessarily be interpreted as causal. Underlying drivers of innovation can simultaneously affect production outcomes. Indeed, using the prefecture-level IPR protection score as a valid instrument for firm patenting, we find that patenting has no significant 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 to estimate TFP. To allow for more a flexible production function, we consider a translog value added production specification:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_{kk} k_{it}^2 + \beta_{ll} l_{it}^2 + \beta_{kl} k_{it} l_{it} + \omega_{it} + \epsilon_{it} \tag{11}$$

where y_{it}, k_{it} and l_{it} are the value added, capital, and labor of firm i 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:

$$m_{it} = f_t(k_{it}, l_{it}, \omega_{it}). \tag{12}$$

Assuming strict monotonicity, equation (12) can be inverted such that $\omega_{it} = f^{-1}(k_{it}, l_{it}, m_{it})$. Substituting this back into the production function, we get

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_{kk} k_{it}^2 + \beta_{ll} l_{it}^2 + \beta_{kl} k_{it} l_{it} + f_t^{-1}(k_{it}, m_{it}, l_{it}) + \epsilon_{it}. \tag{13}$$

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

$$\Phi_{it} \equiv \beta_k k_{it} + \beta_l l_{it} + \beta_{kk} k_{it}^2 + \beta_{ll} l_{it}^2 + \beta_{kl} k_{it} l_{it} + f_t^{-1}(k_{it}, m_{it}, l_{it}). \tag{14}$$

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 (14), 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

$$\widehat{\omega}_{it} = \widehat{\Phi}_{it} - (\beta_k k_{it} + \beta_l l_{it} + \beta_{kk} k_{it}^2 + \beta_{ll} l_{it}^2 + \beta_{kl} k_{it} l_{it}). \tag{15}$$

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:

$$\widehat{\beta} = arg\min_{\beta} \frac{1}{T}\frac{1}{N}\sum_{t=1}^{T}\sum_{i=1}^{N}\xi_{it}(\beta)\begin{pmatrix} k_{it} \\ l_{it-1} \\ k_{it}^2 \\ l_{lt-1}^2 \\ k_{it}l_{it-1} \end{pmatrix} \tag{16}$$

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:

$$Q_{it} = Q_{it}(K_{it}, L_{it}, \omega_{it}). \tag{17}$$

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:

$$Lag(K_{it}, L_{it}, \lambda_{it}) = r_{it}K_{it} + w_{it}L_{it} + \lambda_{it}(Q_{it} - Q_{it}(.)), \tag{18}$$

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

$$\frac{\partial Lag_{it}}{\partial L_{it}} = w_{it} - \lambda_{it}\frac{\partial Q_{it}(.)}{\partial L_{it}} = 0, \tag{19}$$

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:

$$\theta_i = \frac{\partial Q_{it}(.)}{\partial L_{it}}\frac{L_{it}}{Q_{it}} = \frac{1}{\lambda_{it}}\frac{w_{it}L_{it}}{Q_{it}}. \tag{20}$$

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 (20) as

$$\theta_i = \mu_{it}\frac{w_{it}L_{it}}{P_{it}Q_{it}}. \tag{21}$$

Based on equation (21), 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:

$$\mu_{it} = \theta_i\frac{P_{it}Q_{it}}{w_{it}L_{it}}. \tag{22}$$

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 XII.

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

Table XII: 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.

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 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 VIII.

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