北京大学中国经济研究中心
China Center for Economic Research
讨论稿系列
Working Paper Series

E2019005 2019-05-29

Measuring China’s Patent Quality: Development and Validation of ISR Indices

Philipp Boeing and Elisabeth Mueller
May 2019

Because China has become one of the largest applicants of PCT patents, it is of interest to compare the quality of Chinese and non-Chinese applications. We extend a quality index based on internationally comparable citation data from international search reports (ISR) to consider foreign, domestic, and self citations. Whereas foreign citations show that Chinese PCT patent applications reach only a third of the non-Chinese quality benchmark, the extension towards domestic and self citations suggests a higher quality level that converges to or even surpasses the benchmark. We investigate these differences based on firm-level regressions and find that in China, only foreign citations, but not domestic and self citations, have a significant and positive relation to R&D stocks. Using Germany as a representative country without policy support for patenting, we show that all three citations types may be used as economic indicators if policy distortion is not a concern. Our results show that domestic and self citations suffer from an upward bias in China and should be employed with caution if they are to be interpreted as a measure of patent quality.

Keywords: patent quality, cross-country comparison, China

JEL classification: O34, O3

Measuring China's Patent Quality: Development and Validation of ISR Indices

Philipp Boeing[*] and Elisabeth Mueller[**]

May 2019

Because China has become one of the largest applicants of PCT patents, it is of interest to compare the quality of Chinese and non-Chinese applications. We extend a quality index based on internationally comparable citation data from international search reports (ISR) to consider foreign, domestic, and self citations. Whereas foreign citations show that Chinese PCT patent applications reach only a third of the non-Chinese quality benchmark, the extension towards domestic and self citations suggests a higher quality level that converges to or even surpasses the benchmark. We investigate these differences based on firm-level regressions and find that in China, only foreign citations, but not domestic and self citations, have a significant and positive relation to R&D stocks. Using Germany as a representative country without policy support for patenting, we show that all three citations types may be used as economic indicators if policy distortion is not a concern. Our results show that domestic and self citations suffer from an upward bias in China and should be employed with caution if they are to be interpreted as a measure of patent quality.

Keywords: patent quality, cross-country comparison, China

JEL classification: O34, O3

[*] ZEW – Leibniz Centre for European Economic Research, Mannheim, Germany and Peking University, China Center for Economic Research (CCER), Beijing, China, Email: boeing@zew.de
[**] German Graduate School of Management and Law, Heilbronn, Germany and ZEW – Leibniz Centre for European Economic Research, Mannheim, Germany, Email: elisabeth.mueller@ggs.de

Acknowledgements: We acknowledge valuable feedback from Loren Brandt, Can Huang, Xibao Li, Georg Licht, Xielin Liu, Alan Marco, Pierre Mohnen, Kazuyuki Motohashi, Russell Thomson, Beth Webster, Miaojie Yu and Xiaobo Zhang. We thank conference and seminar participants at the Academy of Management Conference 2016, ZEW Conference on Economics of Innovation and Patenting 2015, ZEW SEEK Conference 2015, OECD IP Statistics for Decision Makers 2015, Sino-German Workshop in Hangzhou 2015, APIC 2015, Peking University, Tsinghua University, Fudan University, Swinburne University of Technology, Zhejiang University, University Duisburg-Essen, Chinese Academy of Science, Chinese Academy of Social Science, and Chinese State Information Center for helpful discussion. We thank (former) patent examiners from China's Patent Office, the European Patent Office, IP Australia, and the German Patent and Trademark Office as well as Carlo Pandolfi, Director International Co-operation at European Patent Office, for sharing their insights with us. Any errors remain those of the authors.

1. Introduction

As the Chinese economy becomes increasingly innovation-driven, research and development (R&D) expenditures and patent applications have significantly increased. China's ratio of gross expenditures for R&D to GDP has overtaken that of the European Union, and in gross R&D expenditure China is projected to overtake the USA around 2020 (OECD 2014). China is already leading in patent applications (World Bank 2016) and ranks second in applications made under the Patent Cooperation Treaty (PCT) (WIPO 2018). In recent years, China's patent applications have risen disproportionately against its R&D expenditures, resulting in decreasing R&D inputs per patent.

The Chinese government uses patent targets, subsidies, and other policy instruments to incentivize applications. The National Patent Development Strategy (2011-2020) targets 75 thousand PCT patent applications in 2020, which would make China the leading PCT applicant country (WIPO 2018). It is well documented that patent subsidies are a driver of patent quantity in China (Chen and Zhang 2019, Dang and Motohashi 2015, Li 2012), and also support international and PCT applications. Additionally, there are other policy instruments, such as tax allowances, that increase the expected value of patenting for the applicant and may thereby incentivize more applications.

Typically, patent applications are determined by R&D inputs and the expectation that the economic value of a patent exceeds its cost (Griliches 1990). Following the theoretical argument that a cost reduction, e.g. through subsidies, disproportionately incentivizes patents of marginal value (de Rassenfosse and Jaffee 2018), the increase in China's patent quantity may have happened to the detriment of patent quality.

The empirical assessment of China's patent quality is challenging. One issue is that China's patent office does not publicly disclose citation data that is widely used to measure patent quality (Harhoff et al. 1999). Moreover, even if citations were observable, further problems arise. Citation inflation through an increase in subsidy-induced, low quality patent applications may introduce an upward bias on this quality measure. To perform a comprehensive analysis of China's patent quality we validate domestic citations in comparison to foreign ones, which are invariant to China's economic policy, as economic indicators. International comparability of citation data is ensured by restricting the analysis to citations generated by international search reports (ISRs) in the PCT system.

We extend the original ISR index (Boeing and Mueller 2016), which is based on foreign citations, by adding domestic and self citations. Whereas the use of foreign citations shows that

Chinese PCT patent applications reach only a third of the non-Chinese quality benchmark, the extension towards domestic and self citations suggests a higher quality level that converges to or even surpasses the international benchmark. We investigate these differences based on firm-level regressions and find that in China, only foreign citations, but not domestic and self citations, are a valid indicator of patent quality. Using Germany as a representative country without patent subsidies, we show that all three citations types may be used as economic indicators if policy distortion is not a concern. In conclusion, our results show that in China, domestic and self citations suffer from an upward bias and should be employed with caution if they are to be interpreted as a measure of patent quality. Our findings also support the argument by Goodhart (1975) and Lucas (1976) that indicators fail as reliable measures if they become the target of policy.

The remainder of the paper is organized as follows. In section 2 we explain relevant details of the PCT system. In section 3 we discuss the properties of citation types and extend the ISR indices. In section 4 we describe our data and define our variables. In section 5 we show the descriptive analysis of patent quality and the present the validation of our indices. In section 6 we discuss our results and the wider applicability of the indices. Finally, section 7 concludes.

2. The PCT system

The PCT system offers applicants international protection of inventions in up to 148 countries (WIPO 2015a). It is increasingly used by applicants worldwide, amassing a total of about 214,500 PCT filings in 2014 (WIPO 2015a). As applicants choose only more valuable inventions for protection in numerous foreign countries, PCT applications are more homogeneous than a mixture of national and international applications.

Applications are filed with a competent Receiving Office (RO), which is determined according to the home country of the applicant. For example, Chinese applicants must file PCT applications with the Chinese Patent Office (SIPO) as the RO. SIPO is also the only competent office to act as an International Search Authority (ISA). The designated ISAs publish the international search report (ISR) 18 months after the priority date. Globally, the search for prior art is highly concentrated: the top five ISAs were responsible for more than 95% of ISRs in

2014 (European Patent Office (EPO) 38.8%, Japanese Patent Office (JPO) 20.0%, Korean Patent Office (KPO) 14.9%, SIPO 13.5%, USPTO 10.6% (WIPO 2015a, p. 74f.)).[1]

ISRs contain references to prior art. In the PCT system, applicants are encouraged to provide references to prior art. The description of the application should "indicate the background art which, as far as known to the applicant, can be regarded as useful for the understanding, searching and examination of the invention, and, preferably, cite the documents reflecting such art" (Rule 5 of WIPO 2016b).[2] However, in the PCT system it is ultimately the examiner who determines which references are included in the ISR. Such selected references are an appropriate measure of patent quality as they constitute an evaluation by a third party – namely by the examiner – of the technical and legal relationships among patents. Furthermore, examiner citations show a much stronger correlation with patent value than applicant citations (Hegde and Sampat 2009).

It is important to note that even though national patent offices act as ISAs, the examiners of the different offices follow the same strict examination rules from WIPO when drafting an ISR (WIPO 2016a). As we exclusively consider ISR citations, we rule out heterogeneity in national examination procedures and assure the comparability of citations.[3] The search guidelines explain in detail how citations are to be selected by the examiners (WIPO 2016a, §15.67-15.72). Examiners are encouraged to cite only the most relevant documents and, in the case that several members of one patent family are available, to cite documents in the language of the application (WIPO 2016a, §15.69). Due to the strict search rules defined by WIPO, the citation-bias of patent examiners against foreign prior art is adequately addressed.

Against this regulatory background, Michel and Bettels (2001) report insights from actual examination practices and discuss the comparability of ISR citations for statistical analysis. They point out that the USPTO's mean number of citations generated per domestic application is three times larger than the corresponding mean at the EPO. However, when these

[1] Note that applicants from the USA can file applications with numerous other offices than USPTO, e.g. EPO, JPO, and KPO. Thus, the number of searches for prior art at the respective ISAs is not directly indicative of the respective country's level of PCT applications.

[2] The PCT rules strike a balance between the regulations of the US Patent and Trademark Office (USPTO) and the European Patent Office (EPO). Whereas the USPTO requires applicants to provide references to all relevant prior art that they are aware of, the EPO requires only that examiners, and not applicants, carry out this task (Michel and Bettels 2001).

[3] The international phase ends 30 months after the priority date and applications enter the national phase in which national patent offices perform additional search and examination before making the grant decision. Citations in the national phase may differ from ISR citations as the former follow national guidelines. In order to restrict the citations to one institutional setting, we do not consider citations generated during the national phase for our quality indices.

offices function as ISAs, the difference largely disappears and the authors recommend ISR citations generated within the PCT system for the purpose of cross-country comparisons. While one cannot rule out idiosyncratic deviations from WIPO’s regulations by individual examiners, there seems to be no indication of systematic deviation by individual ISAs. Having provided regulatory and empirical arguments favoring ISR citations generated via the PCT system for cross-country comparison, we next define how these citations are employed in ISR indices.

3. Index definition

The patent system provides several measures that have been used as quality indicators for patents. Among others, the number of references (backward citations), the existence of international applications, and the incidence of opposition filings have been used (Harhoff et al. 2003). It is generally accepted in the literature that forward citations provide the best approximation of patent quality (Jaffe and de Rassenfosse 2017, Gambardella et al. 2008, Reitzig 2004). That is, forward citations are a reflection of the technical value (Trajtenberg 1990) and the economic value (Harhoff et al. 1999) of inventions.

Using citations as an indicator of quality has shortcomings as the average citation counts vary by technology and by the priority year of the patent. The literature has advanced towards using normalized citation counts as suggested by Hall et al. (2001). The number of citations received by a given patent is divided by the average citation count of patents from the same technology and the same priority year. Thus, citation counts are made comparable. A limitation of this approach is that it is no longer possible to investigate how patent quality evolves over time. By construction, the average patent quality for each technology-priority cohort is equal to one.

In a further step Boeing and Mueller (2016) introduce the ISR index as a quality measure that extends current best practice of using normalized citations in three respects. First, they choose a benchmark for normalization that does not rely upon the patents to be analyzed. For example, if the analysis group is patents from a specific country, then the normalization benchmark can be set by the average citations of patents from all other countries, excluding the country of interest. The index allows the flexibility to choose a comparison group that is a good fit for the intended analysis. Because patent quality is measured relative to a comparison group, it is possible to measure quality changes over time. The index takes on a value of 100% if the quality level of the analysis group equals the quality level of the comparison group. Secondly, the index only uses citations generated by international search reports (ISRs) of PCT applications to achieve international comparability. Finally, the index is based only on citations produced by PCT applications from foreign countries (*F* citations), i.e. excluding PCT applications from the analysis group. This restriction ensures that citations are independent of the economic policy of the country whose patents are in the analysis group.

We extend the quality index from Boeing and Mueller (2016) by considering domestic citations (*D* citations), i.e. citations from patents of the country of the applicant, and self citations (*S* citations), i.e. citations from earlier patents of the applicant itself. Whereas invariance with respect to national policy can be an advantage of a quality index, the inclusion of domestic and self citations may provide a more comprehensive and better understanding of patent quality. In the following discussion, we lay out specific characteristics of foreign, domestic, and self citations and define the extended ISR quality indices.

Generally, foreign citations are understood as a measure of high quality because they indicate the international competitiveness of domestic inventions. Firms build on prior art from third countries given that the cited inventions are closer to the global technology frontier than inventions from their own country. In addition, a high share of foreign citations on domestic science shows that foreign firms seek to appropriate the results of domestic R&D (Tijssen 2001).

In contrast to international competitiveness proxied by foreign citations, domestic citations are rather a measure of an economy's technological self-reliance. Stronger reliance on domestic prior art may correspond to a higher level of development as there is less dependence on research conducted abroad. For example, Kang et al. (2014) study the Chinese and Korean telecommunication industry and find that, over time, firms increasingly cite prior art from their own country for standard-essential patents. As the diffusion of knowledge correlates negatively with geographical distance, it is useful to distinguish foreign and domestic citations because domestic citations are received earlier (Narin 1994, Jaffe et al. 1993, Jaffe and Trajtenberg 1999).

While foreign and domestic citations differ across international and national provenance of follow-up inventions, self citations examine follow-up inventions within organizations. Empirical studies tend to find that self citations are more valuable to firms than non-self citations (e.g., Hall et al. 2005, Deng 2008). Firms with more self citations are able to appropriate returns from earlier investment in R&D and signal the presence of "cumulative innovations" (Lanjouw and Schankerman 2004). Self citations may also be an indicator of "fencing" – which is prevalent when firms build an "IPR wall" around themselves (Belderbos and Somers 2015). Because foreign, domestic, and self citations characterize different origins of follow-up inventions, a more nuanced understanding of patent quality can be achieved by considering information from all three citation types.

3.1 Calculation of ISR indices

In the remainder of this section we define the extended ISR indices based on foreign, domestic, and self citations. To correctly apply the index, one must define two sets of patents: the analysis group and the comparison group. For example, if the quality of PCT applications of a specific country is to be analyzed, it is natural to choose the PCT applications from all other countries as comparison group. In this situation the indices reflect the relative positioning of the analysis country to the rest of the world.

The ISR indices are first calculated at the year-technology level. The information content of the indices increases monotonically by index type, first relying only on *F* citations, then also including *D* and *S* citations. The ISR index is defined at the level of year *t* and technology *k* as follows:

(1) $$ISR\ index_{(t,k)} = \frac{\frac{1}{N_{t,k}} \sum_{i=1}^{N_{t,k}} ISR\ citations_i}{\frac{1}{M_{t,k}} \sum_{i=1}^{M_{t,k}} ISR\ citations_j}$$

$N_{t,k}$ is the number of patents in the analysis group. $M_{t,k}$ is the number of patents in the comparison group. *ISR citations*$_i$ is the number of ISR citations received by patent *i* within the specified time window, e.g. 3 or 5 years.

In order to obtain the quality indices at the desired level of aggregation (e.g. country-, industry-, or firm-level), one has to multiply the year and technology specific indices with the number of applications per year and technology ($N_{t,k}$), sum over the products, and then divide by the number of patents in the aggregate (N).[4] Index values of above (below) 100% correspond to average patent quality above (below) the quality level of the comparison group.

(2) $$ISR\ index = \frac{1}{N} \sum_{t=1}^{T} \sum_{k=1}^{K} N_{t,k} * ISR\ index_{(t,k)}$$

We define three distinct ISR indices for patent quality. The *F* index is the original index as established by Boeing and Mueller (2016). It only considers non-self citations received by foreign countries, i.e. from countries other than the applicant country (*F* citations). The quality

[4] If a patent is allocated to more than one technology class, one has to apply fractional counting.

measurement of this index is exogenous with respect to domestic economic policy. In addition to *F* citations, the extended *FD* index also accounts for non-self citations of domestic origin (*D* citations). The measurement of this index is exogenous with respect to the patenting strategy of the applicant. The *FDS* index is the most comprehensive index as it also takes self citations (*S* citations) into account. There is a tradeoff between relying on more “neutral” sources of information and being more inclusive.

4. Variable definition and data

4.1 Index definition for China

In our application of the index we choose PCT applications from China as analysis group and non-Chinese PCT applications as comparison group. Our indices provide information on whether the strong increase in China’s patent quantity influenced the average patent quality. The comparison of Chinese PCT applications to the non-Chinese benchmark allows for an assessment of the average quality of Chinese PCT applications relative to the rest of the world. We choose a time period of 3 years as our citation window, and we define technologies at the 3-digit level of the IPC classification.

4.2 Data sources

Beginning with China’s patent expansion in 2001, we observe all PCT applications with priority years between 2001 and 2009 using the EPO Worldwide Patent Statistical Database (PATSTAT Version April 2013). During the priority year, the applicant can file applications for the same invention at additional patent offices. Applications are allocated to countries according to the address of the first applicant. We only consider citations from distinct pairs of citing and cited patent families and identify self citations based on DOCDB standard names from PATSTAT and the EEE-PPAT applicant name harmonization (Magerman et al. 2006). To categorize patents according to technology, we use the 3-digit technology class level of the IPC classification and apply fractional counting to apportion patents that belong to more than one technology class. Given the typical trade-off between precision and timeliness characteristic of work with patent citations, we restrict the citation window to a still informative three years to capture more recent dynamics.

To validate ISR indices, we calculate these indices at the firm level and evaluate them against firm characteristics. Our Chinese firm-level data consists of all firms listed at the stock exchanges in Shanghai and Shenzhen between 2001 and 2009.[5] Due to government stock issuance quotas, the sample mainly includes domestic large- and medium-sized firms from manufacturing industries and the coastal region, whereas other industries and inland regions are represented to a lesser extent.[6] The balance sheet information is compiled from DATASTREAM and the Chinese databases CSMAR, RESSET, and WIND. As the coverage of R&D expenditures in these databases is rather incomplete before 2007, supplementary information on reported R&D expenditures has been collected from the universe of annual reports accessible via the Chinese CNINFO database.

In addition to R&D information, we also observe a firm's number of employees, age, ownership, industry affiliation, and the provincial GDP per capita. All variables in monetary values have been deflated using China's GDP deflator from the World Bank. Finally, we merge patent data with the firm panel data following the procedure detailed in Boeing et al. (2016).

4.3 Descriptive statistics

Table 1 presents descriptive statistics for firm-year observations with above zero PCT applications. We calculate the average index over all PCT applications filed by a firm in a given year. The *F* index, *FD* index, and *FDS* index have a mean of 43.3%, 76.4%, and 87.5%, respectively. Employing the perpetual investment method, we follow the standard in the literature and compute the R&D stock assuming a 5% annual growth rate of R&D and an annual depreciation rate of 15% (Hall et al. 2010). The R&D stock has a mean of 488 million RMB and a median of 30.4 million RMB.[7] The PCT intensity is calculated as the application stock depreciated by an annual rate of 15% and scaled by thousand employees. This variable proxies the accumulated experience in international patenting. PCT applicants are relatively large and rather young: the median of employees is 3126 and the median age is 11 years. To reflect China's economic reforms, we broadly differentiate between firms with and without state ownership and find that, according to this distinction, 41.7% of observations are from private firms. We account for regional heterogeneity in China's economic development by GDP per capita at the provincial level. Table A1 in the appendix shows pairwise correlations of the variables.

[5] Data for listed firms is commonly used to investigate the innovation performance of firms, e.g. see Autor et al. (2017) for the US; Aghion et al. (2005) for Europe; and Fang et al. (2018) for China.

[6] Only domestic firms are listed on the A-share board of the stock exchanges of Shanghai and Shenzhen. According to the definition of the China Securities Regulatory Commission, a firm is considered domestic if the percentage of total shares held by foreign parties does not exceed 20%.

[7] In the regression analysis we will take the log of the R&D stock + 1 RMB, because some observations have zero R&D.

Table 1: Firm characteristics

Variable	Mean	Median	S.D.	Min.	Max.	Obs.
F index	43.3	0	135.2	0	1350.4	451
FD index	76.4	0	154.2	0	923.7	451
FDS index	87.5	0	139.4	0	890.4	451
R&D stock (million RMB)	487.9	30.4	2183.6	0	25001	451
PCT intensity	3.443	0.825	8.443	0.005	100	451
Employees	20237	3126	68680	10	539168	451
Age	11.5	11	5.1	1	29	451
Private ownership	0.417	0	0.494	0	1	451
Provincial GDP per capita (RMB)	30996	29447	15786	5905	66006	451

Note: Statistics based on firms with at least one PCT application. ISR indices are calculated as averages of annual patent applications and are expressed as percentages. Observations are at the firm-year level.

5. Empirical analysis

The Chinese government relies on patent targets and policy instruments to incentivize applications. In 2020, the National Patent Development Strategy (2011-2020) targets 75 thousand PCT patents applications, which would make China the world leading country in PCT applications. It is well documented that patent subsidies have contributed to the increase in patent quantity (Chen and Zhang 2019, Dang and Motohashi 2015, Li 2012), and there are also subsidies to support international and PCT applications.[8] In addition, other policy instruments, such as tax allowances, may indirectly change the cost or value of patenting and thereby contribute to more applications.[9] Goodhart (1975) and Lucas (1976) point out that indicators may fail as reliable measures if they become the target of policy. Along these lines it is meaningful that patent applications have risen faster than R&D expenditures in recent years (Figure A1), resulting in decreasing R&D inputs per patent (Figure A2).

Our concern is that China may experience a "citation inflation" (Marco 2007). Given that a patent is applied for if the expected value exceeds the cost of patenting, a cost reduction, e.g. through subsidies, disproportionately incentivizes marginal, low-quality patents (Griliches 1990, de Rassenfosse and Jaffee 2018). Hence, China's policy not only increases the quantity

[8] Most programs reimburse application fees and additionally award granted patents. Subsidies for international applications are typically larger (Li 2012). In 2009 the Ministry of Finance launched a program that explicitly supports PCT patents. Applications in up to five countries are subsidized with a maximum of 100,000 RMB each (ca. 14,600 USD, exchange rate of 31.12.2009) but more support is possible for projects involving significant innovation. Subsidies mainly cover fees for patent agents, examination and renewal. Song et al. (2016) calculates that in ten provinces the amount of subsidies even exceed actual fees once common rebates are taken into account, which makes filing applications profitable regardless of the patent's expected economic value.

[9] One example is the High New Technology Enterprise (HNTE) Program, which lists patents in force as an eligibility criterion (Garcia et al. 2016). Because the program offers a tax reduction for accredited firms, the expected value of patenting increases for HNTE applicants.

of patents but simultaneously incentivizes applications of lower quality. A citation inflation would compromise the validity of Chinese citations as an economic indicator of patent quality. If more patents are filed that can cite existing prior art and if the average value of the citing patents declines, then the explanatory power of citations as quality indicators is weakened. Hence, Chinese *D* and *S* citations generated by policy-induced low-quality applications might fail as reliable measures of patent quality and introduce an upward bias of the *FD* and *FDS* indices. In contrast, the non-Chinese *F* citations and the *F* index are independent from China's economic policy and not subject to this bias. In section 5.1 we provide a descriptive analysis of the ISR indices. In section 5.2 we use regression analysis to test the validity of citations and indices. Section 5.3 reports several robustness tests.

5.1 Descriptive analysis of patent quality

The differences between the *F*, *FD*, and *FDS* indices are striking (Table 2). With a mean of 32.1%, the *F* index shows that China's PCT patent quality is significantly below that of the non-Chinese comparison group, which consists mainly of high-income countries.[10] Over time this mean declines from 44.9% to 30.4%. In contrast, the means of the *FD* (61.6%) and *FDS* (90.0%) indices show that China's quality level is approaching that of the comparison group and over time converges to or even surpasses it. A key insight is that, in global comparison, Chinese firms rely disproportionately on domestic and internal technologies. The rising focus on domestic prior art corresponds to a decoupling from the international innovation system, while the rise in self citations may be a reflection of firms working in silos. Overall, we find that the three indices offer different conclusions regarding the quality level and the quality evolution of Chinese patents.

[10] In 2013, 87% of PCT applications came from high-income countries, 12% from upper-middle-income countries (thereof 10% from China) and only 1% from lower-middle-income countries (WIPO 2015b).

Table 2. Quality of Chinese PCT patent applications

	F index	*FD* index	*FDS* index	PCT patent applications
2001	44.9	37.3	36.3	793
2002	34.2	32.0	30.1	1060
2003	38.8	35.3	31.8	1368
2004	34.4	27.7	32.0	1948
2005	41.0	38.8	44.5	3321
2006	30.7	42.4	51.5	4649
2007	29.0	55.3	72.6	5799
2008	29.8	76.3	112.0	6159
2009	30.4	89.1	151.8	9641
Total	32.1	61.6	90.0	34738

Note: Mean values for *F* index, *FD* index, and *FDS* index displayed as percentages. The first column is a replication from Boeing and Mueller (2016). Observations are at the patent level.

The variation of indices across six technology areas is displayed in Figure A3. Patents in the field of electrical engineering, which constitute the majority with 57% of China's PCT applications, also exhibit the largest difference between the *F* index (27.5%) and the *FDS* index (97.6%). The dominance of electrical engineering is related to ZTE and Huawei, two globally operating ICT firms that together file one third of Chinese PCT applications. Additional analysis shows that both firms receive fewer foreign citations than the average Chinese applicant but, consistent with their large size, exhibit considerably more self citations. Applications in the second largest field, chemistry, display the smallest difference between the *F* index (38.4%) and the *FDS* index (49.3%). This variation is in consistent with the typical citation behavior in complex vs. discrete technologies. The differences in the remaining technology areas – mechanical engineering, consumer goods and construction, instruments, and process engineering – fall somewhere in the middle.

Because variation in the indices is not only determined by Chinese patents, but also by the non-Chinese comparison group, we investigate average citations for both groups separately in Table 3. We find that the decline of the *F* index over time is a result of the decrease in the average number of citations obtained by Chinese PCT applications relative to the stable number obtained by the comparison group. Similarly, the increases of the *FD* and *FDS* indices are due to increases in the average citations obtained by Chinese PCT applications, whereas the average citations obtained by the non-Chinese comparison group are stable over time. We are not aware of any large-scale policy programs outside of China that may inflate the benchmark during our observation period. Hence, variation in the indices is mainly a reflection of Chinese dynamics against non-Chinese stability.

Table 3: Average citations for Chinese and non-Chinese PCT patent applications

	Average citations					
	F citations		*F* and *D* citations		*F*, *D*, and *S* citations	
	CN patents	Non-CN patents	CN patents	Non-CN patents	CN patents	Non-CN patents
2001	0.131	0.276	0.165	0.424	0.217	0.587
2002	0.079	0.249	0.108	0.371	0.144	0.528
2003	0.085	0.241	0.112	0.348	0.148	0.499
2004	0.074	0.224	0.088	0.317	0.143	0.448
2005	0.091	0.230	0.126	0.323	0.199	0.442
2006	0.074	0.258	0.154	0.364	0.262	0.495
2007	0.075	0.292	0.235	0.414	0.407	0.545
2008	0.077	0.302	0.311	0.431	0.627	0.580
2009	0.076	0.292	0.325	0.426	0.781	0.576
Total	0.079	0.276	0.234	0.396	0.473	0.536

Note: Non-Chinese patents weighted according to the technology distribution of China. The values of "Chinese patents" and "non-Chinese patents" are the numerator and denominator values of the indices respectively. Observations are at the patent level.

Our descriptive analysis shows that using different quality indices may lead to opposing conclusions regarding the level and development of the quality of Chinese PCT applications. These results demonstrate the importance of evaluating patent quality based on a valid indicator. While *F* citations are superior in their invariance with respect to national policy, the probability of obtaining *F* citations may decrease in a country's share in global PCT applications. However, the exclusion of domestic citations penalizes China less than other countries.[11,12] Analysis of the index components corroborates that increases in the *FD* and *FDS* indices are driven by *D* and *S* citations from China's rapidly rising PCT applications. An important distinction to make is whether domestic citations are inflated by policy-induced low quality patents, or whether they adequately reflect China's rising innovation capacity. In the following subsection we therefore validate different citation types as indicators of patent quality.

[11] To account for the inverse effect of China's rising share of global PCT applications on China's citation probability, we divide the *F* index by China's share of global PCT applications in a given year. The values of the *F* index change only marginally, e.g. to 45.8 in 2001 and 32.0 in 2009. Note that a country's increasing share of global PCT applications does not mechanically induce a downward trend of the *F* index for that country. For example, the Republic of Korea's global share of PCT applications has increased from 2% in 2001 to 6% in 2009 and its *F* index increased from 74.4 to 80.4 (Boeing and Mueller 2016). In the meantime, China's share (2% in 2001 and 5% in 2009) remained far below the share of other leading PCT countries, e.g. the US (40% in 2001 and 29% in 2009).

[12] Quantifying the effect of language bias, Boeing and Mueller (2016) show that China's average ISR index based on *F* citations increases only modestly from 32.1% to 35.6% after taking the bias into account. As core elements of PCT applications are published in English – i.e. abstract, title, search report, and text of drawings – negative bias that results from Chinese-only language elements is negligible.

5.2 Index validation

Following the simple model by Griliches (1990), a patent application is stochastically determined by the amount of R&D devoted to the respective research project and the expectation that the economic value of patenting exceeds the cost of patenting. Given that the patent premium remains stable and that the level of current and past R&D expenditures, i.e. the R&D stock, increases the technological success of research projects, an increase in the number of patents is understood as an increase in economically valuable knowledge. The production of knowledge $\dot{K}$ depends on R&D $(\dot{K} = R + u)$, and the patent count P depends on $\dot{K}$ $(P = a\dot{K} + v)$, where the random components u and v are independent of each other. Hence, the validity of P as an indicator of $\dot{K}$ depends on the relative magnitude of v. Once R is used as a substitute of unobserved $\dot{K}$ $(P = aR + au + v)$, the relationship between P and R provides a lower bound of the validity of P as an indicator of $\dot{K}$.

Let P_{it} denote a patent indicator of firm i in year t, which is assumed to depend on firm-specific variables in X_{it}, the log of the R&D stock r_{it}, industry fixed effects ϕ_j and year fixed effects τ_t in the following way:

(3) $$P_{it} = \alpha_0 + X_{it}\beta + \gamma r_{it} + \phi_j + \tau_t + \varepsilon_{it}$$

In this setting, a significant γ would reject the null hypothesis that P_{it} is not a valid measure for economically valuable knowledge. The vector of characteristics X_{it} includes the PCT stock scaled by employees to proxy the accumulated experience in international patenting, the log number of employees to control for firm size effects, the log of firm age, and a dummy to control for private ownership. Furthermore, we account for heterogeneity in the economic development across provinces by the log of provincial GDP per capita.

The literature often estimates models similar to equation (3), where P_{it} either is a patent count (Pakes and Griliches 1984), a citation-weighted patent count (Aghion et al. 2013), a normalized citation count (Hall et al. 2001), or average citations per patent (Bessen 2008, Blind et al. 2009). While the number of patents is associated with the magnitude of research effort, citation-weighted patent count combines the scale of effort with a measure of success (Jaffe and de Rassenfosse 2017). The measure of citation-weighted patent count is defined as patents multiplied by the raw number of citations received. The measure normalized citation count is a refinement of raw citation counts, as it uses citations that are normalized to eliminate technology and year differences. Studies with focus on China are up to now only available for P_{it} as a simple patent count. They tend to find a patent-R&D elasticity that is considerably lower as compared to OECD countries (Chen and Zhang 2019, Hu et al. 2017, Hu and Jefferson 2009).

In Table 4 we estimate equation (3) with the ISR indices as the dependent variable. We use a Tobit model because there is censoring from below at zero as the latent variable citations is only observed when patents are above zero but remains unobserved otherwise. We start with the F index in column (1) and find that γ is positive and highly significant. We transform the coefficient of 0.166 into a marginal effect of 0.034 to derive an intuitive interpretation of the size of the effect. The Tobit model has the structure of a linear-log model, i.e. the dependent variable is in linear form and the regressor of interest, the R&D stock, is in logarithms. Because an increase of the R&D stock by 1% corresponds to an increase in the log of the R&D stock by 0.01, we multiply the marginal effect of 0.034 by 0.01 to arrive at the unit change in the index that is caused by a 1% increase in the R&D stock. Thus, we find that a 1% increase in the R&D stock corresponds to an increase in the quality index by 0.00034, or by 0.034 percentage points. When interpreted relative to the mean of the F index (0.433 or 43.3%), a 1% increase in R&D stock leads to an increase in patent quality of about 0.1%. This result confirms a positive and economically important relationship between the R&D stock and patent quality.

Moving on to the interpretation of the control variables, we find a positive and highly significant impact for PCT intensity. Patent quality shows a positive relationship with a firm's experience in filing international patents.

Table 4: Tobit model

	(1)	(2)	(3)	(4)	(5)
	F index	*FD* index	*FDS* index	*D* index	*S* index
R&D stock (log)	0.166***	0.036	-0.005	-0.090	-0.120
	(0.061)	(0.034)	(0.026)	(0.115)	(0.077)
PCT intensity	0.141***	0.060*	0.039**	0.141	0.144***
	(0.048)	(0.034)	(0.017)	(0.094)	(0.042)
Employees (log)	0.298	0.215	0.217**	0.875*	1.126***
	(0.222)	(0.144)	(0.095)	(0.509)	(0.336)
Age (log)	-0.951	-0.165	-0.038	0.427	0.067
	(0.671)	(0.439)	(0.292)	(1.636)	(0.928)
Private ownership (0/1)	0.641	-0.128	-0.061	-0.898	-0.062
	(0.674)	(0.441)	(0.292)	(1.442)	(0.996)
Provincial GDP per capita (log)	-0.486	-0.223	-0.407	-0.212	-1.298
	(0.629)	(0.456)	(0.340)	(1.457)	(1.105)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	451	451	451	451	451
Log pseudo likelihood	-350.75	-545.66	-608.07	-485.34	-491.37

Note: Analysis is at the firm-year level. Standard errors are clustered at the firm-level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels.

In column (2) the dependent variable is the *FD* index and γ becomes substantially smaller and insignificant. In column (3) with the *FDS* index as the dependent variable γ is close to zero and insignificant. With the addition of self citations to the index we find a positive and significant coefficient for firm size. This is to be expected as larger firms have more prior art they can cite. In columns (4) and (5) we restrict the index to *D* and *S* citations, respectively, and neither index has a significant relationship with R&D stock. For self citations we again confirm a positive and highly significant correlation with firm size. The main result is that only *F* citations, but not *D* or *S* citations, provide a valid measure of patent quality.[13]

5.3 Robustness tests

In this section we challenge our main results in several robustness tests. First, in Table 5 we report results for a Heckman selection model that allows firms to select to be PCT applicants. The model fits the two independent processes of filing patents and receiving citations. The proper specification requires an exclusion restriction that explains selection but is no

[13] Our results for the validation of the different citation types do not hinge on the use of average patent quality as dependent variable. We also computed the outcome variable P_{it} based on citation-weighted patent counts and normalized citation counts. The results remain very similar when we re-estimate the regressions presented in Table 4 based on the alternative dependent variables.

explanatory factor in the outcome equation. We use the number of employees relative to the industry mean as an exclusion restriction, following the rationale that relatively larger firms are more likely to file PCT applications, whereas relative firm size is no determinant for average patent quality. The positive and at the 1%-level significant coefficient of the exclusion restriction supports this rationale (column 1).[14]

The outcome equations for patent quality show only a significant influence of the R&D stock for the *F* index (column 2) but not for the indices that include *D* and *S* citations (columns 3-6). Our main results are therefore confirmed by the selection model. The positive values of rho and the inverse mills ratio (IMR) confirm a positive correlation of the error terms in the selection and outcome equations. Under the assumption of a correctly specified model, the null hypothesis of no selection bias can be tested with a t-test on the IMR (Wooldridge 2010, p.806). The insignificance of the IMR suggests that unobservable firm characteristics are unlikely to induce selection bias.

Table 5: Heckman two-step selection model

	(1)	(2)	(3)	(4)	(5)	(6)
	PCT application (0/1)	*F* index	*FD* index	*FDS* index	*D* index	*S* index
	1st stage	2nd stage	2nd stage	2nd stage	2nd stage	2nd stage
Relative firm size	0.007*** (0.001)					
R&D stock (log)	0.023*** (0.004)	0.034*** (0.013)	0.020 (0.014)	0.005 (0.013)	-0.004 (0.032)	-0.018 (0.023)
IMR		0.318 (0.390)	0.547 (0.448)	0.500 (0.392)	1.091 (0.992)	0.231 (0.711)
X_{it}	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Rho		0.237	0.348	0.363	0.315	0.095
Observations	12575	451	451	451	451	451

Note: Analysis is at the firm-year level. X_{it} includes the stock of PCT applications by thousand employees, the log of employees, the log of age, a dummy for private ownership, and the log of provincial GDP per capita. IRM is the inverse mills ratio. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels.

We perform additional specification tests because several studies have shown that the result of Heckman models can be sensitive to misspecification (e.g. Lennox et al. 2012 and Certo et al. 2016). First, we calculate the correlation of the IMR with the other regressors of the

[14] The selection equation also shows a positive and highly significant effect of the R&D stock on the probability of filing at least one PCT application. Filing PCT applications is also more likely for private-ownership and firms in provinces with a higher GDP per capita. Note that we omit the regressor PCT intensity in the first stage because of high correlation with the probability of having at least one PCT application.

outcome equation. High multicollinearity implies that the IMR does not contain substantial information that is not already included in the other regressors. In such a situation, an insignificant IMR would not reliably indicate the absence of selection bias. With an average correlation of 0.295 we can reject this concern. This result together with the highly significant exclusion restriction in the selection equation suggests that the exclusion restriction is strong enough to detect selection bias if present. Second, we lag the exclusion restriction “relative size” by one period to test robustness with respect to changes in the restriction. The results for R&D stock in the outcome equations remain almost identical and the exclusion restriction remains significant at 1%. Third, we investigate whether the results of the outcome equation change when selection is not controlled for. If an insignificant IMR is the result of model misspecification, then results with and without selection correction can still diverge. For the Heckman selection model, we obtain a marginal effect for the R&D stock of 0.034 in column (2), which is in fact identical to the marginal effect in the Tobit model. Overall, we find that our results are not compromised by possible selection bias.

In a second robustness test, reported in Table 6, we exploit the panel properties of our data for identification. Because of inconsistency of the Tobit fixed effects estimator, Cameron and Trivedi (2005, p.800) recommend a random effects Tobit model with the Chamberlain-Mundlak device.[15] This estimator achieves consistent results even if the time-invariant error term is not independent from the time-variant regressors. For additional controls, the regression specification includes the average value of time-variant regressors, $\bar{X}$. Again, the size of γ declines as we extend the indices from *F* to *FD* to *FDS* and the significance levels decline from 5%, to marginally significant at 10%, to insignificant. For indices only based on *D* or *S* citations γ remains insignificant.

[15] We also follow the advice of one referee and employ the pantob program, which implements the estimators developed in Honore (1992) and allows for estimating truncated and censored panel data models with fixed effects. The results are confirmative of our main findings reported in Table 4: γ is estimated at 0.221 and the regressor is significant at the 5% level for the F index. The estimates for all alternative indices are insignificant.

Table 6: RE Tobit model with Chamberlain-Mundlak device

	(1)	(2)	(3)	(4)	(5)
	F index	*FD* index	*FDS* index	*D* index	*S* index
R&D stock (log)	0.163** (0.074)	0.108* (0.056)	0.042 (0.037)	0.080 (0.185)	-0.171 (0.123)
X_{it}	Yes	Yes	Yes	Yes	Yes
Chamberlain-Mundlak device: $\overline{X_\iota}$	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	451	451	451	451	451
Log likelihood	-345.61	-537.28	-596.32	-473.04	-476.77

Note: Analysis is at the firm-year level. X_{it} includes the stock of PCT applications by thousand employees, the log of employees, the log of age, a dummy for private ownership, and the log of provincial GDP per capita. Bootstrapped standard errors with 50 repetitions. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels.

Third, we exclude the largest PCT applicant, ZTE, and re-estimate Table 4. The significance levels remain unchanged and the marginal effect in column (1) is very similar (results not reported). Thus, we could confirm that the results are not dominated by a single PCT champion.

So far we have argued that the validity of *D* and *S* citations may suffer from a subsidy-induced inflation of low quality patents and citations in China. Therefore, in our final robustness test we aim to scrutinize the validity of indices in a context without subsidies. While we cannot identify the before-and-after subsidy setting in China, we can turn to Germany as a country without patent subsidies. The German firm-level data comes from the Mannheim Innovation Panel (MIP) and includes about 3000 firms. Table A3 shows the ISR indices based on PCT applications filed by the German firms between 2001 and 2009. While the averages between indices increase monotonically from the *F* to *FD* and *FDS* index, the averages within indices remain rather stable over time. Assuming that the *FDS* index is unbiased in the German setting, the results suggest that Germany's patent quality narrowly oscillates around the non-German comparison group.

We estimate equation (3) based on the German firm-level data. Because the relationship between R&D and patent quality may differ between industries, we weight the observations according to the Chinese industry composition to make results more comparable across countries. Table 7 replicates the main estimations reported in Table 4. Parameter γ is positive and significant in all six columns. When we interpret the marginal effects relative to the mean of the indices, we find that a 1% increase in the R&D stock corresponds to an increase in patent quality of 0.1% for the *F* index, the same magnitude as for Chinese firms. Thus, the *F* index, which is exogenous to economic policy, gives the same result in both countries. In a context without subsidies, we find that all three citation types are valid measures for patent quality.

Table 7: Tobit model for German firms

	(1)	(2)	(3)	(4)	(5)
	F index	*FD* index	*FDS* index	*D* index	*S* index
R&D stock (log)	0.279***	0.182***	0.160***	0.532**	0.401***
	(0.071)	(0.047)	(0.036)	(0.223)	(0.102)
PCT intensity	0.021***	0.014***	0.011***	0.096***	0.044***
	(0.004)	(0.003)	(0.002)	(0.018)	(0.005)
Employees (log)	0.174	0.104	0.058	1.323***	0.547***
	(0.116)	(0.082)	(0.059)	(0.404)	(0.138)
Age (log)	-0.150	-0.147	-0.161*	-0.150	-0.571**
	(0.169)	(0.120)	(0.091)	(0.555)	(0.223)
Eastern Germany (0/1)	-1.689***	-1.358***	-0.995***	-3.066	-1.060
	(0.548)	(0.419)	(0.294)	(1.983)	(0.733)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	1844	1844	1844	1844	1844
Log pseudo likelihood	-2423.46	-2648.96	-2737.52	-2360.49	-2330.26

Note: Analysis is at firm-year level. Standard errors clustered at the firm-level. Observations are weighted according to the Chinese industry composition. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels.

6. Discussion

China's increase in patent quantity is partially driven by application targets, patent subsidies, and other policy instruments. An important question is whether citations have been inflated by policy-induced, low quality patents or provide an adequate reflection of China's rising innovation capacity. Based on our analysis we fail to confirm that Chinese *D* and *S* citations are a valid measure for economically valuable knowledge. In contrast, non-Chinese *F* citations, which are independent from China's economic policy, provide a valid indicator. We replicate the analysis in a context without subsidies and the significance of all indices shows that, when policy distortion is not a concern, all citations types are valid measures. Our findings support the argument by Goodhart (1975) and Lucas (1976) that indicators fail as reliable measures if they become the target of policy. In contrast to the *F* index, the *FD* and *FDS* indices are upward biased in China.

More generally, in settings without policy distortion all three ISR indices can be used to maximize the information content provided by forward citations. Beyond the analysis of PCT patents, ISR citations may be used to measure the quality of national patents because prior art search for PCT applications is not restricted to previous PCT applications, but rather it encompasses the patent literature from a large number of patent offices. The indices are versatile in their application as they can be used to analyze patent quality at various levels, e.g. at the country, industry, or firm level.

In future research it would be of interest to investigate for Chinese firms whether the quality of patent applications is related to measures of firm performance, such as total factor productivity or profitability.

7. Conclusion

In recent years China's patent applications have risen faster than R&D expenditures, resulting in decreasing R&D inputs per patent. Given that this patent expansion is policy-driven, we validate domestic citations in comparison to foreign ones, which are invariant to China's policy, as economic indicators. We derive internationally comparable citation data from ISRs and use foreign, domestic, and self citations to perform a comprehensive analysis of patent quality.

Whereas foreign citations show that Chinese PCT patent applications reach only a third of the non-Chinese quality benchmark, the extension towards domestic and self citations suggests an increasing quality level that is closer to the international benchmark. The rising focus on domestic prior art corresponds to a decoupling from the international innovation system, while the rise in self citations emphasized a focus on prior art from within the organization. However, the differences among indices can also be the result of a policy-driven citation inflation. We investigate these differences based on firm-level regressions and find that only foreign citations, but not domestic and self citations, are a valid indicator of patent quality. Using Germany as a representative country without patent subsidies, we show that all three citations types may be used as an economic indicator if policy distortion is not a concern. Our results emphasize that Chinese citations suffer from an upward bias and should be employed with caution if they are to be interpreted as a measure of patent quality.

References

Aghion, P., Bloom, N., Blundell, R., Griffith, R., Howitt, P., Competition and innovation: An inverted-U relationship. *The Quarterly Journal of Economics* **120**, 701-728 (2005).

Aghion, P., Van Reenen, J., Zingales, L., Innovation and institutional ownership. *American Economic Review* **103**, 277–304 (2013).

Autor, D., Dorn, D., Hanson, G., Pisano, G., Shu, P.,Foreign Competition and Domestic Innovation: Evidence from U.S. Patents. National Bureau of Economic Research Working Paper No. 22879 (2017).

Bacchiocchi, E. and Montobbio, F., International knowledge diffusion and home-bias effect: do USPTO and EPO patent citations tell the same story. *Scandinavian Journal of Economics* **112**, 441-470 (2010).

Belderbos, R. and Somers, D., Do technology leaders deter inward R&D investments? Evidence from regional R&D location decisions in Europe. *Regional Studies* **49,** 1805-1821 (2015).

Bessen, J., The value of U.S. patents by owner and patent characteristics. *Research Policy* **37**, 932-945 (2008).

Blind, K., Cremers, K., and Mueller, E., The influence of strategic patenting on companies' patent portfolios. *Research Policy* **38**, 428-436 (2009).

Boeing, P. and Mueller, E., Measuring patent quality in cross-country comparison. *Economics Letters* **149**, 145-147 (2016).

Boeing, P., Mueller, E., and Sandner, P., China's R&D explosion – analyzing productivity effects across ownership types and over time. *Research Policy* **45**, 159-176 (2016).

Cameron, C., Trivedi, P., Microeconometrics, Methods and Applications. (Cambridge University Press, 2005).

Certo, S. T., Busenbark, J. R., Woo, H. S. and Semadeni, M., Sample selection bias and Heckman models in strategic management research. *Strategic Management Journal* **37**, 2639-2657 (2016).

Chen, Z., Zhang, J., Types of patents and driving forces behind the patent growth in China. *Economic Modelling* (forthcoming).

Chinese Ministry of Finance, "Interim measures for the administration of special funds for subsidizing a foreign patent application" (Publication No. 567, 2009).

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

de Rassenfosse, G., Jaffe, A. B., Are patent fees effective at weeding out low-quality patents? *Journal of Economics and Management Strategy* **27**, 134-148 (2018).

Deng, Y., The value of knowledge spillovers in the US semiconductor industry. *International Journal of Industrial Organization* **26**, 1044-1058 (2008).

Fang, L., Lerner, J., Wu, C., Qi, Z., Corruption, government subsidies, and innovation: Evidence from China. Harvard Business School Working Paper 19-03, Cambridge, MA (2018).

Gambardella, A., Harhoff, D., and Verspagen, B., The value of European patents. *European Management Review* **5**, 69-84 (2008).

Garcia, A., Jiang, J., Turley, C. and Wang, M., The evolving environment for intellectual property tax management in China, in: Prud'homme, D. and Song, H. (eds.), "Economic Impacts of Intellectual Property-Conditioned Government Incentives" (Springer, 2016).

Goodhart, C. A. E., Problems of monetary management: the U.K. experience. Papers in Monetary Economics (Reserve Bank of Australia, 1975).

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

Grupp, H. and Schmoch, U., Patent statistics in the age of globalization: new legal procedures, new analytical methods, new economic interpretation. *Research Policy* **28**, 377-396 (1999).

Hall, B. H., Mairesse, J., and Mohnen, P., Measuring the returns to R&D. in: Hall, B. H., and Rosenberg, N. (eds.), Handbook of the Economics of Innovation 2, 1033-1082 (North-Holland 2010).

Hall, B. H., Griliches, Z., Hausman, J. A., Patents and R&D: Is there a lag? *International Economic Review* **27**, 265-83 (1986).

Hall, B. H., Jaffe, A. B., and Trajtenberg, M., The NBER patent citation data file: Lessons, insights and methodological tools. National Bureau of Economic Research Working Paper No. 8498 (2001).

Hall, B. H., Jaffe, A. B., and Trajtenberg, M., Market value and patent citations. *RAND Journal of Economics* **36**, 16-38 (2005).

Harhoff, D., Narin, F., Scherer, F. M., and Vopel, K., Citation frequency and the value of patented inventions. *Review of Economics and Statistics* **81**(3), 511-515 (1999).

Harhoff, D., Scherer, F. M., and Vopel, K., Citations, family size, opposition and the value of patent rights. *Research Policy* **32**, 1343-1363 (2003).

Hegde, D. and Sampat, B., Examiner citations, applicant citations, and the private value of patents. *Economics Letters* **105**, 287-289 (2009).

Honore, B. Trimmed lad and least squares estimation of truncated and censored regression models with fixed effects. *Econometrica* **60**, 533-565 (1992).

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

Hu, G., Zhang, P., and Zhao, L., China as nunber one? Evidence from China's most recent patenting surge. *Journal of Development Economics* **124**, 107-119 (2017).

Jaffe, A. B., and de Rassenfosse, G., Patent citation data in social science research: Overview and best practices. *Journal of the Association for Information Science and Technology* **68**, 1360-1374 (2017).

Jaffe, A. B. and Trajtenberg, M., International knowledge flows: evidence from patent citations. *Economics of Innovation and New Technology* **8**, 105-136 (1999).

Jaffe, A. B., Trajtenberg, M., and Henderson, R., Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics* **63**, 577-598 (1993).

Kang, B., Huo, D., and Motohashi, K., Comparison of Chinese and Korean companies in ICT global standardization: essential patent analysis. *Telecommunications Policy* **38**, 902-913 (2014).

Lanjouw, J. and Schankerman, M., Protecting intellectual property rights: Are small firms handicapped? *Journal of Law and Economics* **47**, 45-74 (2004).

Lennox, C. S., Francis, J. R. and Wang, Z., Selection models in accounting research. *The Accounting Review* **87**, 589-616 (2012).

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

Lucas, R. E., Econometric policy evaluation: a critique, Carnegie-Rochester Conference Series on Public Policy. 1, 19-46 (1976).

Magerman, T., Looy, B.V., and Song, X., Data production methods for harmonized patent statistics: patentee name harmonization. Eurostat Working Paper and Studies, Luxembourg (2006).

Marco, A. C., The dynamics of patent citations. *Economics Letters* **94**, 290-296 (2007).

Michel, J. and Bettels, B., Patent citation analysis: a closer look at the basic input data from patent search reports. *Scientometrics* **51**, 185-201 (2001).

Narin, F., Patent bibliometrics. *Scientometrics* **30**, 147-155 (1994).

OECD, Frascati Manual 2015: Guidelines for collecting and reporting data on research and experimental development (OECD Publishing, 2015).

OECD, Main science and technology indicators (OECD, accessed 2016).

OECD, OECD science, technology and industry outlook 2014 (OECD Publishing, 2014).

Pakes, A., and Griliches, Z., Patents and R&D at the firm level: a first look, in: Griliches, Z. (ed.), "R&D, Patents, and Productivity" (University of Chicago Press, 1984).

Pistor, K. and Xu, C., Governing stock markets in transition economies: lessons from China. *American Law & Economics Review* **7**, 184-210 (2005).

Reitzig, M., Improving patent valuations for management purposes: validating new indicators by analyzing application rationales. *Research Policy* **33**, 939-957 (2004).

Scherer, F., The Propensity to patent. *International Journal Industrial Organization* **1**, 107-128 (1983).

Shane, H., Patent citations as an indicator of the value of intangible assets in the semiconductor industry. Mimeo, The Wharton School, University of Pennsylvania (1993).

Song, H., Li, Z., and Xu, D., The upsurge of domestic patent applications in China: is R&D expenditure or patent subsidy policy responsible?, in: Prud'homme, D. and Song, H. (eds.), "Economic Impacts of Intellectual Property-Conditioned Government Incentives" (Springer, 2016).

Tijssen, R. J. W., Global and domestic utilization of industrial relevant science: patent citation analysis of science–technology interactions and knowledge flows. *Research Policy* **30**, 35-54 (2001).

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

WIPO, Patent Cooperation Treaty – international search and preliminary examination guidelines (WIPO, 2016a).

WIPO, Patent Cooperation Treaty yearly review – the international patent system (WIPO, 2015a).

WIPO, Patent Cooperation Treaty yearly review 2017 – the international patent system (WIPO, 2017).

WIPO, Patent Cooperation Treaty yearly review 2018 – the international patent system (WIPO, 2018).

WIPO, Regulations under the Patent Cooperation Treaty (Publication WIPO, 2016b).

WIPO, WIPO statistics database. Last updated: January 2015 (WIPO 2015b).

World Bank, Science & technology indicators (World Bank, accessed 2016).

Wooldridge, J. M., Econometric analysis of cross section and panel data (MIT Press, 2010).

Appendix: Tables and Figures

Table A1: Pairwise correlations of Chinese firm characteristics

	1.	2.	3.	4.	5.	6.	7.	8.
1. *F* index								
2. *FD* index	0.552							
3. *FDS* index	0.425	0.753						
4. R&D stock (log)	0.045	0.067	0.094					
5. PCT intensity	0.049	0.022	0.043	-0.105				
6. Employees (log)	-0.033	0.010	0.035	0.235	-0.413			
7. Age (log)	-0.099	-0.014	0.055	0.105	0.054	-0.083		
8. Private ownership (0/1)	-0.007	-0.008	0.050	-0.000	-0.046	-0.042	0.263	
9. Provincial GDP per capita (log)	-0.072	0.020	0.024	0.131	0.100	0.130	0.063	0.025

Note: Statistics based on firms with at least one PCT application. ISR indices are calculated as averages of annual patent applications. Observations are at the firm-year level.

Table A2: ISR indices for Chinese firms

	F index	*FD* index	*FDS* index	Obs.
2001	60.3	85.3	94.2	53
2002	56.6	56.5	68.3	102
2003	42.6	53.0	48.5	159
2004	81.7	78.1	68.0	195
2005	56.0	69.9	56.0	347
2006	55.7	61.0	65.2	429
2007	46.7	74.1	102.4	710
2008	23.1	62.4	144.7	871
2009	18.7	61.4	152.5	2318
Total	33.1	64.4	122.0	5184

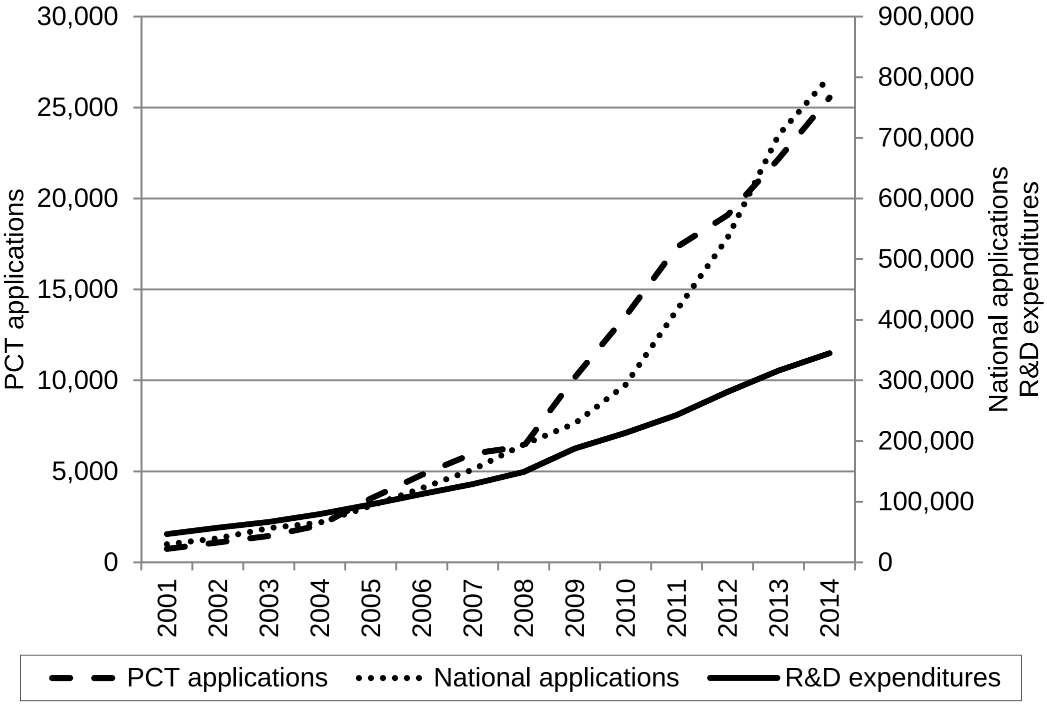
Note: Mean values displayed as percentages. Observations are at the patent level.

Table A3: ISR indices for German firms

	F index	*FD* index	*FDS* index	Obs.
2001	63.6	72.9	99.4	7054
2002	69.1	79.0	106.8	6753
2003	70.9	94.1	120.1	6194
2004	69.0	90.0	122.3	6475
2005	62.5	80.7	111.8	6738
2006	53.3	72.9	106.8	6952
2007	52.8	64.6	85.7	7486
2008	53.5	66.1	84.3	6623
2009	64.3	72.0	86.4	6601
Total	61.9	76.6	102.2	60876

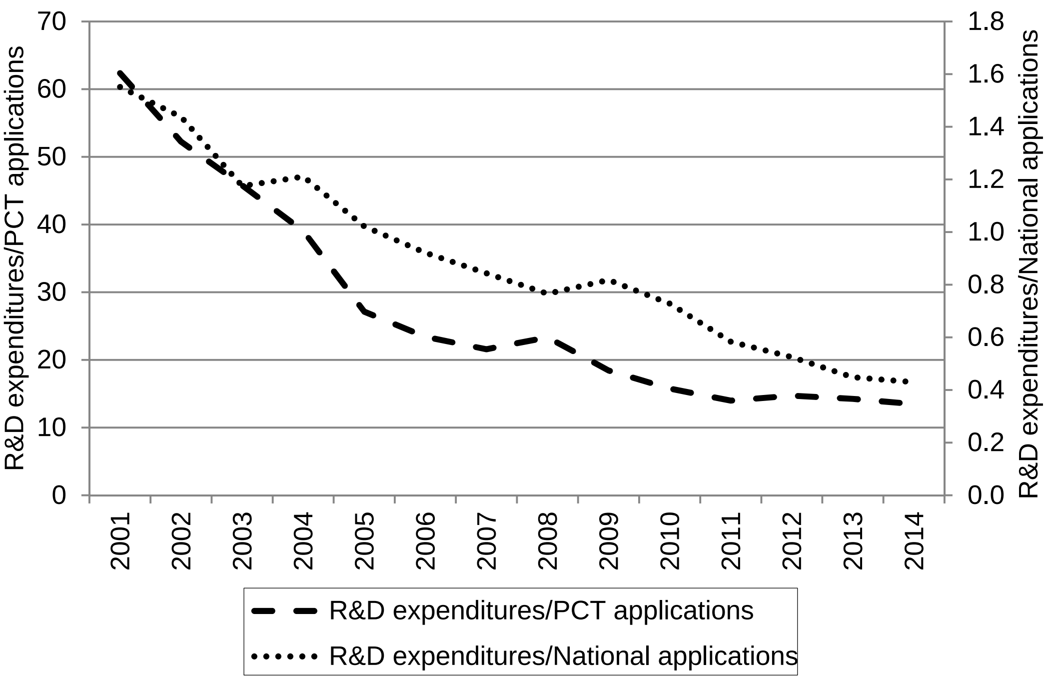
Note: Mean values displayed as percentages. Observations are at the patent level.

Figure A1: PCT patents, national patents and R&D expenditures



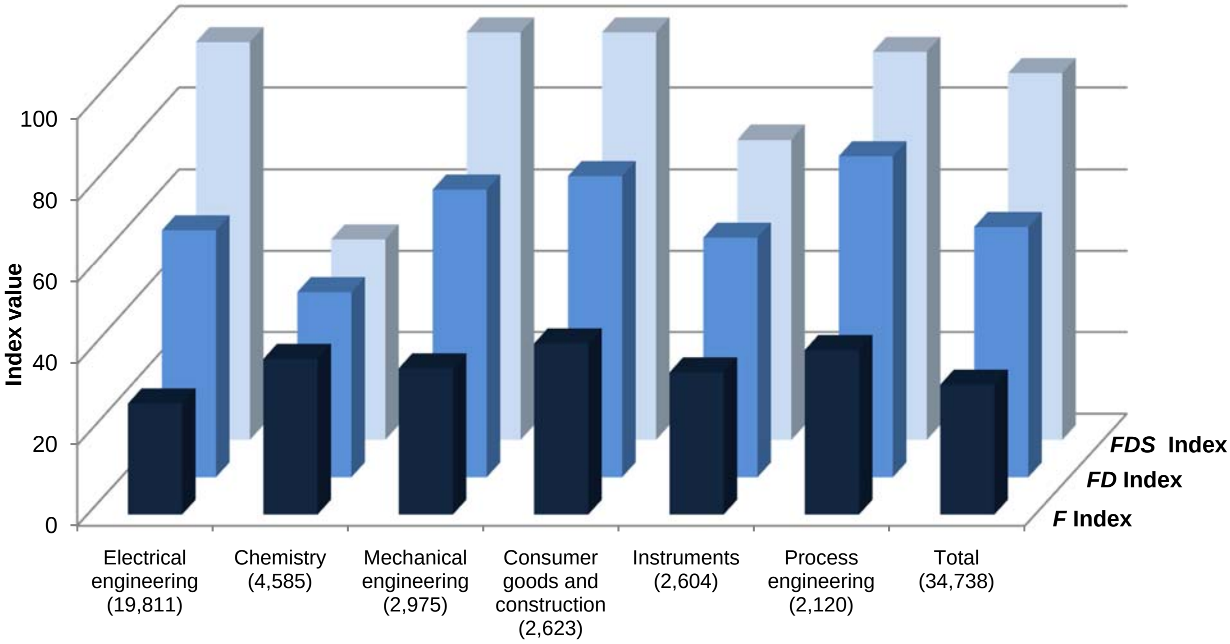
Note: R&D expenditures is Gross domestic Expenditure on Research and Development (GERD) as defined by OECD (2015), measured in million purchasing power parity USD in constant prices of 2010. National applications are national patent applications filed by residents. *Source*: OECD (2016), WIPO (2015a), World Bank (2016).

Figure A2: R&D expenditures to PCT patents and national patents



Note: R&D expenditures is Gross domestic Expenditure on Research and Development (GERD) as defined by OECD (2015), measured in million purchasing power parity USD in constant prices of 2010. National applications are national patent applications filed by residents. *Source*: OECD (2016), WIPO (2015a), World Bank (2016).

Figure A3: ISR indices by technology area



Note: Mean values for *F* index, *FD* index, and *FDS* index displayed as percentages for the six main technology areas (patent counts in parentheses). Observations are at the patent level.