Dissertation

The effects of universities on innovation and productivity in China: An empirical analysis

carried out for the purpose of obtaining the degree of Doctor rerum socialium oeconomicarumque (Dr. rer. soc. oec.), submitted at TU Wien, Faculty of Mechanical and Industrial Engineering, by

Marcin BOROWIECKI

Registration number: 0405559

under the supervision of

Univ.Prof. Dr. Karl-Heinz Leitner

Institute of Management Science

reviewed by

Prof. Martin Andersson	Univ. Prof. Dr. Hardy Hanappi
Blekinge Institute of Technology	Vienna University of Technology
Department of Industrial Economics	Institute for Math. Methods in Economics
Valhallavägen 1, 371 79 Karlskrona	Wiedner Hauptstrasse 6-8, 1040 Wien
Sweden	Austria

This work was supported by the Austrian Institute of Technology within the Framework of the Innovation and Sustainability – Knowledge and Talent Development Programme.

I confirm, that going to press of this thesis needs the confirmation of the examination committee.

Affidavit

I declare in lieu of oath, that I wrote this thesis and performed the associated research myself, using only literature cited in this volume. If text passages from sources are used literally, they are marked as such.

I confirm that this work is original and has not been submitted elsewhere for any examination, nor is it currently under consideration for a thesis elsewhere.

Vienna, June, 2019

Marcin Borowiecki

Acknowledgments

My special thank goes to my supervisor Prof. Dr. Karl-Heinz Leitner for his guidance and insightful comments throughout the preparation of this thesis. I also want to thank PD Dr. Thomas Scherngell, who provided me with his mentorship, and Prof. Dr. habil. Josef Fröhlich, who gave me the opportunity of working on this exciting project. My thank also goes to the team at the Innovation Systems Department at the Austrian Institute of Technology for the great atmosphere and their support. The exchange of ideas and programming codes was critical for the success of this thesis.

I would like to give special thanks to Prof. Yuanjia Hu from the University of Macau for his insightful comments, access to Chinese data and his hospitality during my research stay in Macau. I also want to thank Prof. Gary Jefferson at Brandeis University for letting me work with him during my research stay in Boston and for access to Chinese data, which gave the thesis the necessary empirical foundation.

On a more personal note, I have many more people to thank, all those that have shared days and evenings with me during my PhD, with especial thanks to Patrick, Rafael, Iris, Manuela, Kathi, Schifteh, Stefan, and Talita. And of course, my love Chus, who has been supporting me throughout these years and who inspired me to pursue this PhD. I all too often neglected him and my little Pepe while working on this thesis.

I dedicate this book to my parents, Małgorzata Debska and Jan Debski, who showed me love and supported me throughout my whole life. If I got to this point, it is thanks to you!

Kurzfassung

Gegenstand dieser Arbeit ist die Rolle von Universitätsforschung für innovations- und produktivitätsbasiertes Wachstum in China. Der technologische Wandel erhöht den Druck auf Unternehmen, externes Universitätswissen für eigene Innovationsaktivitäten und Produktionsprozesse zu verwenden. In Schwellenländern wie China kommt hinzu, dass Unternehmensforschung schwach ausgeprägt ist, was zu einer größeren Bedeutung von externem Universitätswissen führt. Um Aufschluss über die Rolle von Universitätsforschung für industrielle Innovation und Produktivtät zu erlangen, untersucht die vorliegende empirische Arbeit ausgewählte Transferkanäle zwischen Universitätsforschung und Industrie: Lizenzierung von Hochschulpatenten, Vertragsforschung mit der Industrie, sowie Wissensspillover (entgeltloser Wissenstransfer) zwischen Universitäten und Unternehmen. Die Arbeit untersucht erstens die Auswirkungen von Wissensspillover – gemessen anhand von geographischer Nähe zu Hochschulpatentaktivitäten, auf regionale industrielle Innovationsaktivität und Produktivität in China. Die Arbeit untersucht außerdem, inwieweit universitäre Forschung und Entwicklung (FuE) mit der Lizenzierung von Hochschulpatenten und der Vertragsforschung mit der Industrie im Zusammenhang steht. Die verwendete Datengrundlage beruht auf einem Industriezensus, Patenten sowie einer Universitätsumfrage für 261 Präfekturen und 28 Provinzen in China im Zeitraum zwischen 1998 und 2007. Die Ergebnisse zeigen, dass der Anstieg von Hochschulpatenten in einem positiven Zusammenhang mit der Zunahme von Industriepatenten und Industrieproduktivität in der gleichen Präfektur steht – was auf lokale Wissensspillover deutet, während keine signifikanten Spillovereffekte von Hochschulpatentaktivität auf andere Präfekturen gefunden werden. Die Ergebnisse zeigen zudem, dass Reformen des chinesischen Hochschulpatentsystems - ein exogener Schock, der zu einem Anstieg von Hochschulpatenten führte - einen positiven Einfluss auf die Zahl der Industriepatente und auf das Produktivitätsniveau in China hatte. Die Zahl der Industriepatente stieg nach den Reformen jährlich um 1,4% an – im Vergleich zur Periode vor den Reformen, während das Produktivitätsniveau jährlich um 1,6% anstieg. Die Ergebnisse deuten zudem auf einen stärkeren Effekt von Hochschulreformen auf neu gegründete Unternehmen (im Vergleich zu etablierten Unternehmen) und Unternehmen im Privatbesitz (im Vergleich zu Unternehmen im Staatsbesitz) an. Bei den direkten Transferkanälen zeigt sich, dass das Wachstum der universitären Umsatzerlöse aus der Patentlizenzierung mit einem Anstieg der universitäre FuE-ausgaben für Grundlagenforschung zusammenhängt, während die Ergebnisse gegen einen Einfluss der universitäre FuE-ausgaben für angewandte Forschung auf Technologietransfer sprechen.

Abstract of the Dissertation

This thesis analyses the role of university research for innovation- and productivity-led growth in China. Technological change increases the pressure on firms to use external university knowledge for their own innovation activities and production processes. In the context of China's with its weak industrial R&D basis, universities gain on importance as sources of external knowledge for industry. To assess the contributions of universities to industrial innovation and productivity, the empirical analysis focuses on selected channels linking university research to industry: Licensing of university patents, joint research with industry, and knowledge spillovers (non-remunerated knowledge transfer) between universities and industry. First, this thesis provides empirical evidence on the effects of university spillovers – measured based on geographical proximity to university patent activity, on local industrial innovation and productivity, as well as on spillover effects to other regions in China. Second, the thesis examines the extent to which university R&D relates to licensing of university patents and contract research with industry – two direct channels linking university research to industry. Additional analyses assess the occurrence of trade-offs between contract research and patent licensing. The analysis is based on industrial census, patent, and university survey information for 261 prefectures and 28 provinces in China between 1998 and 2007. The findings show that increases in university patents are positively associated with increases in industrial patents and industrial total factor productivity (TFP) in the same prefecture, while evidence for spillover effects from university patent activity to other prefectures is weak. The findings further show that pro-patent university reforms – an exogenous shock that led to increased university patent activity, had a positive impact on industrial patent numbers and TFP levels. Industry experienced an annual increase in patent numbers of 1.4%, and an increase of 1.6% in TFP levels after the reforms relative to before. Differences exist across firm ownership and newly established firms and incumbent firms: The impacts of reforms were larger for newly established enterprises than for incumbent enterprises and for privately-owned enterprises than for state-owned enterprises. Regarding channels linking university research to industry, the results reveal that growth in university revenues from patent licensing is associated with growth in university R&D expenditures on basic research, while evidence for the role of R&D expenditures on applied research is weaker. Trade-offs between patent licensing and contract research do not reveal themselves.

Keywords: Universities; Total Factor Productivity; Innovation; Spillovers; Intellectual Property Reforms; Patent Licensing; Contract Research; Technology Transfer; China

Table of Content

1. Introduction

Motivation

The Chinese government increasingly recognises the benefits of university research for supporting industrial innovation and productivity, which are key for the county's economic transition towards a knowledge-based economy. It is well documented that universities contribute to increases in the human capital and stronger pro-democratic attitudes of their students (e.g. Valero and Van Reenen, 2019; Moretti, 2004). Beyond direct contributions of universities to higher education, university increase innovation and productivity in the private sector through knowledge spillovers (e.g. Belenzon and Schankerman, 2013) and their direct contributions to innovation, including licensing of university inventions (Jensen and Thursby, 2001) and joint research with industry (Hall, Link, and Scott, 2003). Knowledge spillovers from university research denote the benefits of university research to firms not responsible for the original investment in the creation of this research (e.g. Scherngell, Borowiecki and Hu, 2014). Empirical research has shown that R&D collaboration with university researchers improved enterprises' innovation performance (Robin and Schubert, 2013; Maietta, 2015), entry into new technological fields (Hall et al., 2003), and productivity of high-tech start-ups (Motohashi, 2005). Data collected by researchers on the establishment of new universities points to significant spillover effects of university research on patent activity and productivity of their local economies (e.g. Toivanen and Väänänen, 2016; Kantor and Whalley, 2014; Andersson, Quigley, and Wilhelmsson, 2009). However, the existing empirical literature is largely based on findings from developed economies. China differs significantly from developed economies in that the country has a weak legacy of private R&D and only recently established legal frameworks for the protection of intellectual property rights (IPR). The different economic and institutional context limits our understanding of the effects of universities on innovation and productivity in China.

China is an interesting case to analyse the effects of university research on innovation and productivity in an emerging economy context. The country's tremendous catching-up process in terms of productivity over the past decades is well documented. Between 1978 and 2007, China managed to maintain an average annual growth rate of total factor productivity (TFP) of 5.5 per cent (Zhu, 2012). At the same time, industrial survey data shows that many Chinese enterprises lacked R&D capacities, which was a serious barrier to further productivity improvements (e.g. Hu, Jefferson, and Jinchang, 2005). In order to compensate for their limited in-house R&D, many Chinese firms pursued an innovation strategy that relied on collaborations with universities (Motohashi and Yun, 2007). Having realised the potential benefit of science and technology for economic development, the Chinese government boosted public investment in Chinese universities (Zhou, 2015; Zhang, Patton, and Kenney, 2013) and strengthened the institutional framework supporting technology transfer between universities and industry (Hu and Jefferson, 2009; OECD, 2008).

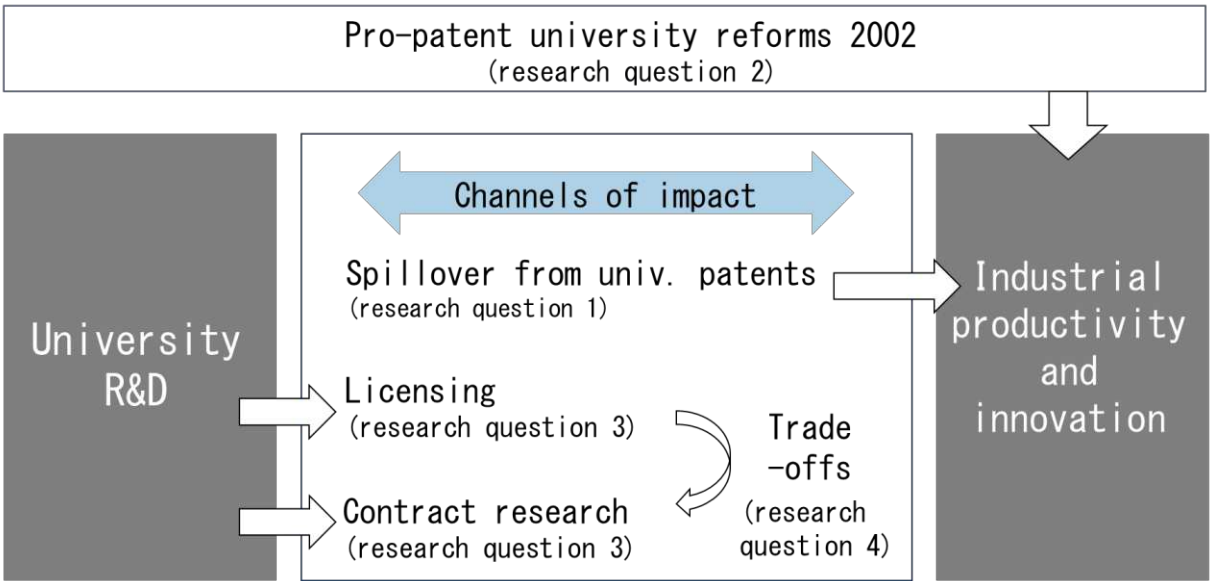
While there is an established body of empirical evidence on Chinese firm productivity (Brandt, Van Biesebroeck, and Zhang, 2012; Hu and Jefferson, 2009), industry patent activity (Böing, Müller, and Sandner, 2016; Dang and Motohashi, 2015), and formal science-industry R&D collaboration (Hong and Su, 2013; Motohashi and Yun; 2007), there is little research on the economic effects of universities in China.[1] There is agreement in literature that China experienced a surge in patent activity, both driven by university patents (Fisch, Block, and Sandner, 2016) and industry patents (Hu and Jefferson, 2009) after 2000, a period during which China's innovation systems underwent a radical transformation (OECD, 2008). During the same period, productivity of industrial enterprises increased (Böing et al., 2016; Hu and Jefferson, 2009). To date, however, the relationship between increases in industrial productivity and university research have not been systematically studied for China. Evidence on the contributions of universities to industrial innovation and productivity, as well as on channels linking university research to industry, will provide important insights into the role of public research for China's transition towards a knowledge-driven economy.

Research questions

The objective of this thesis is to provide empirical evidence on the contributions of university research to China's industrial productivity and innovation by means of investigating three channels linking university research and innovation (Figure 1.1): Spillover from university patents (as measured by means of geographical distance between industry and patent-active universities), licensing of university patents, and contract research with industry.

First, the thesis assesses the contributions of universities to increases in innovation and productivity in China between 1998 and 2007, thereby providing new insights on the role of university research in driving China's transition towards innovation- and productivity-based growth. It does so by means of a dataset that links Chinese patents to China's industrial enterprises and universities. In contrast to Glaeser and Lu (2018), it focuses on the effects of universities on industrial productivity – measured using total factor productivity (TFP), and innovation – measured based on patent activity. This gives rise to the following research question:

Figure 1.1. Channels of university impact under investigation



Research question 1: *What is the relationship between university patent activity and industry TFP and patent activity (i) within a prefecture, and (ii) in other prefectures in China?*

Studying the relationship between university patents and industry TFP and patents in the same prefecture provides insights on the potential effects of universities on their local economy, while the analysis of industry patent activity and TFP in other prefectures provides evidence on the crucial question whether universities generate spillovers to other prefectures in China. For the United States and Europe, studies report that the presence of research universities is positively associated with patent activity in neighbouring regions (Fischer and Varga, 2003; Anselin, Varga, and Acs, 1997), as well as productivity in neighbouring regions (Fischer, Scherngell, and Reismann, 2009). For China, the evidence is ambiguous. The findings of Scherngell and Hu (2011), which are based on citation data for the year 2007, and Scherngell, Borowiecki, and Hu (2014) that use patent data for the period 1988 to 2007, suggest positive inter-regional spillover effects, while findings by Crescenzi, Rodríguez-Pose, and Storper (2012) that use patent data for the years 1994 to 2007 point to negative inter-regional spillover effects.

The identification of spillover effects from university research is difficult due to endogeneity, i.e. industry and universities might locate in economically dynamic regions. One strand of research uses data on the opening of new universities to identify causal proximity effects of universities (Kantor and Whalley, 2019; Toivanen and Väänänen, 2016; Liu, 2015). These studies, however useful, do not control for possible local shocks that might have caused universities to locate in dynamic locations.

Universities might choose to locate in economic prosperous regions due to better economic conditions or better governance. In this case, the location of universities would correlate with unobserved variables that also stimulate economic activity, such as e.g. local human capital advantages, geographical advantages, or better economic governance. For China, Glaeser and Lu (2018) try to account for endogeneity of university locations using the re-location of university departments during China's Great Leap Forward in the 1950s as a natural experiment. To date – to the author's knowledge, there is no evidence on spillover effects from university research on innovation and productivity in China. Pro-patent university reforms in 2002 provided an exogenous shock to university patent activity in China and offer a quasi-experimental setting to analyse the effects of universities on industry patent activity and innovation. This leads to the following research question:

Research question 2: *What is the effect of pro-patent university reforms on changes in industry patent numbers and TFP levels?*

The impact of university reforms on industry are analysed by means of comparing numbers of industry patents and TFP levels before and after university reforms. Impacts of university reforms may differ between newly established firms and incumbent firms. Incumbent firms have advantages due to better absorptive capacity and higher R&D investment, thus being in a better position to take advantage of increased university patent activity. On the other hand, studies point to a positive association between university research and performance of start-ups or young firms (e.g. Motohashi, 2005; Audretsch and Stephan, 1996). The impact of reforms may also differ between technology-intensive industries and less technology-intensive industries due to different needs of industry. Studies for the United States found that spillover effects from university research differ between technology-intensive industries and less technology-intensive industries due to different needs of industry (Furman and Stern, 2011; Furman and MacGarvie, 2007).

The ownership of an enterprise may affect the extent to which it benefits from university reforms to patenting. China has an important state-owned industrial sector, which leads to the question whether the state-ownership benefits or hinders its technological catch-up. State-owned enterprises (SOEs) may be in a better position to take advantage from university research, for example, through preferential access to financial resources to fund R&D, and protection from competition in selected industries, giving them a lead ahead of private firms. For China, evidence on the impact of university patents by firm ownership, technology-intensity of the industry in which the firm operates, and across entering and incumbent firms is missing. Therefore, additional analyses explore the differential effects by (i) newly established enterprises and incumbent enterprises, (ii) high technology-intensive and low technology-intensive industries, (iii) and state-owned enterprises and privately-owned enterprises. Evidence for China will provide new insights on this question.

Studies have highlighted that differences in channels linking university research to industrial innovation matter (D'Este and Perkman, 2013; Grimpe and Fier, 2010; Boardman, 2009; Bekkers and Bodas Freitas, 2008; Schartinger et al., 2002). The thesis uses data from Chinese university surveys to examine the extent to which university R&D relates to contract research and patent licensing – two channels linking university research to industry:

Research question 3: *What is the relationship between university R&D, university patent licensing and university contract research with industry?*

The evidence collected for Europe, Japan, and the United States suggest that contract research and consulting are more important channels of knowledge transfer than licensing and patenting of university patents because only a small fraction of research results can be patented. For China, the evidence is mixed. An analysis of trends in university licensing and contract research will provide new insights.

The focus on one specific channel of technology transfer might have detrimental effects on other channels of technology transfer. This debate is particularly important for China, where policy efforts have put emphasis on university patenting during the period 1998 to 2007. Firms may perceive patent-active universities as interfering in their markets as technology providers. As contract research requires trust between researchers and firms, these channels of technology transfer may be jeopardised by patent activity of universities (Wright et al., 2008). To data, there is, to the author's knowledge, little evidence on potential trade-offs between different channels of technology transfer.[2] Therefore, the analysis assesses the occurrence of trade-offs between contract research and patent licensing:

Research question 4: *Is there a trade-off between patent licence activity and contract research activity of Chinese universities?*

Methods

Methodologically, this thesis uses several empirical approaches to address the research objectives. Spatial econometric techniques are used to test for inter-regional spillovers from university patenting (*research question 1*), as measured by the relationship between university patent activity and industry performance in other prefectures. Following LeSage and Fischer (2012) and Robbins (2006), university patent stocks in other prefectures are used interacted with the distance to these prefectures to measure spillovers across prefectural borders.

To identify the effects of increased university patent activity on industry (*research question 2*), the thesis uses pro-patent university reforms as an exogenous shock to university patent activity. Using a difference-in-difference approach, it tests whether industrial patent numbers and TFP levels increased significantly following university reforms in 2002 as compared to before. A panel version of a standard difference-in-difference estimation framework is implemented that controls for industry fixed effects, prefecture fixed effects and year fixed effects. This approach follows the methodology adopted by studies of university effects on local economic performance (e.g. Valero and Van Reenen, 2019; Toivanen and Väänänen, 2016; Cantoni and Yuchtman, 2014).

The analysis of university effects addresses several concerns that might arise due to endogeneity. First, by using nation-wide university reforms that affected all Chinese prefectures, the approach addresses potential endogeneity of university locations. For instance, universities might choose to locate in economic prosperous regions due to better economic conditions. In this case, the location of universities would correlate with unobserved variables that also stimulate economic activity, such as e.g. local human capital advantages, geographical advantages, or better economic governance. The use of nation-wide reforms that affected only patent activity of universities accounts for potential local economic shocks. Second, the empirical strategy controls for unobserved industry and prefecture-level characteristics that might be responsible for increases in industrial patenting and productivity. And third, the use of a comprehensive set of observable prefecture-level variables controls for other potential drivers of industry patenting and productivity such as human capital, levels and growth of population, levels of per capita income, patent activity of foreign-owned enterprises, and the industry structure.

In order to document trends in licensing of university patents and contract research with industry (*research questions 3 and 4*), the thesis makes use of monetary measures, notably university revenues from patent licensing and university revenues from contract research with industry. The measures are expressed in RMB at 1998 prices, which allows for easier comparison of economic relevance of the channels of technology transfer for universities. Moreover, revenue-based measures are regressed on university R&D expenditures to estimate revenue elasticities regarding changes in R&D expenditures of universities.

The empirical analysis draws on data from (1) Chinese industrial census information taken from the Annual Survey of Industrial Enterprises (National Bureau of Statistics, 2008), (2) university survey information from the World Higher Education Database (WHED) (International Association of Universities, 2017), (3) technology transfer information from several University Science and Technology Annual Reports (MOE, 2010), and (4) information on patents granted to Chinese residents by the Chinese State Intellectual Property Office (SIPO) taken from the EPO Worldwide Statistical Patent Database (OECD, 2017). The data covers 261 prefectures and 28 provinces of Mainland China, and 30 industries at the 3-digit CIC Rev. 2002 level for the years 1998 to 2007. In line with established literature on Chinese productivity dynamics (e.g. Brandt et al., 2012), industrial productivity is measured by means of total factor productivity indices calculated according to the methodology developed by Caves, Christensen, and Diewert (1982) and Olley and Pakes (1996). Following studies of business innovation in China (Rong, Wu, and Böing, 2017; Hu and Jefferson, 2009), patents granted to Chinese inventors by the China's State Intellectual Property Office (SIPO) are used to construct patent stocks of industrial enterprises.

Structure

The remainder of the thesis is organised as follows. Section 2 provides a literature review. Subsection 2.1 describes China's current framework for technology transfer between universities and industry. Subsection 2.2 provides an overview of the literature on channels linking university research and industry with emphasis on patents, patent licensing, and contract research with industry. Subsection 2.3 reviews current studies on industrial patenting and productivity dynamics in China, before Subsection 2.4 discusses the literature on spillover effects of universities, including the role of geographical proximity to universities, spillover effects by industry, and reforms to university intellectual property rights (IPR) in 2002.

Section 3 presents the conceptual framework to analyse university spillover effects on innovation and productivity. Subsection 3.1 presents a conceptional model to analyse the relationship between productivity and spillovers from university patent stocks in line with theoretical contributions of Romer (1986 and 1990) and Griliches (1979). It also presents a model to investigate the relationship between industry patent stocks and university patent stocks. The two models represent augmented version of the regional knowledge production functions that account for inter-prefectural university spillovers (Scherngell et al., 2014; LeSage and Fischer 2012; Fischer et al. 2009). Following the presentation of the conceptual framework, Subsection 3.2 discusses methodological challenges to the measurement of spillover effects, including endogeneity, before Subsection 3.3 derives the hypothesis for empirical testing.

Section 4 provides the findings of the empirical analysis of university effects on innovation and productivity. Subsection 4.1 describes the data and variables used, presents the spatial area and industries under investigation, and provides descriptive statistics. Subsection 4.2 introduces to the empirical methodology to analyse the relationship between university patent stocks, industry patent stocks and industry TFP. It describes the spatial panel model to account for inter-prefectural spillover effects from university patent stocks and presents the estimation framework to identify the effects of pro-patent university reforms on industry patent activity and TFP. The analysis uses a difference-in-difference approach to estimate changes in levels of industrial TFP and patent stock numbers after pro-patent university IPR in 2002. Subsection 4.3 presents the findings of the descriptive analysis of the relationship between university patent numbers, industry patent numbers and TFP levels, and shows findings on the numbers of industry patents before and after pro-patent university reforms in 2002. Subsection 4.4 presents the findings of the empirical analysis of the relationship between university patent activity and industry performance – as measured by patents and TFP, (i) within a prefecture, and (ii) to other prefectures of the country (*research question 1*). Subsection 4.5 brings forward evidence on the impact of university reforms on increases in industrial patent stocks and TFP levels (*research question 2*). Additional findings report the differential effects of university reforms by (i) newly established enterprises and incumbent enterprises, (ii) high technology-intensive and low technology-intensive industries, (iii) and state-owned enterprises, privately-owned enterprises, and foreign-owned enterprises.

Section 5 presents results of the analysis of technology transfer channels of Chinese universities. Subsection 5.1 describes the data and empirical methodology, before Subsection 5.2 presents descriptive statistics on trends in patent licensing and contract research with industry. Subsection 5.3 provides findings of the analysis of (i) the relationship between growth in university R&D expenditures and growth in university revenues from patent licensing, as well as (ii) the relationship between growth in university R&D expenditures and growth in university revenues from contract research with industry (*research question 3*). Finally, the Subsection 5.3 brings forward findings from the analysis of trade-offs between patent licensing and contract research of Chinese universities (*research question 4*).

Section 6 discusses the main findings of the thesis and highlights the main contributions to the literature, before it concludes with limitations of the work and an outlook on future research.

2. Literature review

A growing body of empirical literature shows that universities contribute to industrial innovation and productivity through different channels of technology transfer (for a literature overview, see Perkmann et al., 2013). These consist broadly of *commercialisation* of academic research (e.g. patenting and licensing of university inventions), *science-industry collaboration* (e.g. collaborative research with industry, contract research for industry), *spillovers from university research* (e.g. networking and citations mediated through geographical proximity between universities and firms), and *spillovers from university education* (e.g. hiring of students and researchers).

This Section discusses the major issues surrounding university impacts on industry innovation and productivity in China. Subsection 2.1 provides an overview of China's policies supporting university research, and the country's framework for technology transfer that regulates university patenting, licensing and other commercialisation activities of universities. China differs significantly from developed economies in that the country has only recently established its legal framework for technology transfer. Important reforms to technology transfer are presented, including the landmark pro-patent reform of 2002 that facilitated university patenting with potential knock-on effects on industry innovation and productivity. Following the discussion of the institutional framework, Subsection 2.2 provides an overview of the literature on channels linking university research and industry with emphasis on university patents, patent licensing, and contract research with industry. Having taken stock of the current state of the debate on channels linking university research to industry, Subsection 2.3 reviews evidence collected by researchers on trends in productivity and innovation of Chinese industrial enterprises. Studies of Chinese patenting and productivity indicate an economic transition towards innovation- and productivity-led growth in China, while there is no evidence linking these trends to university research. Subsection 2.4 discusses evidence on impact of universities on innovation- and productivity-led growth in developed economies, including studies of spillover effects of universities on their local economy and differential impacts by industry.

2.1. China's institutional framework for technology transfer of university research

2.1.1. Public policies in support of university research in China

Historically, the Chinese higher education institutions gave priority to education over research (Landes, 2006; Lin 1995). The first higher education institution, known as Taixue (*tàixué*), were established during the Han Dynasty in the year 3 AD. They were part of the establishment of nationwide higher education system. Since the Sui dynasty around the year 600, institutions of higher education were called Guozijian (*guózǐjiàn*). Their core mission was to prepare students to enter the public administration. To be eligible for a position in the public administration, students had to pass imperial examinations, which tested for expertise in Chinese classics, literature, law, mathematics, and military skills (Hayhoe, 1989).

Research universities were created at the beginning of the 20th century in China with the aim to close the technological gap with the West. The first research university, Tianjin University, was established in 1895, followed by the Imperial University of Peking in 1898, later known as Peking University.[3] At the same time, the imperial examination system was abolished (Hayhoe, 1989). At research universities, Chinese scholars began to engage in scientific endeavours, conduct controlled experiments, and publish their research results in international scientific journals subject to peer-review. Chinese universities became sites of training of scientists (Lin, 1995).

Starting in the 1980s, the Chinese government devoted significant resources to university research in expectation that science should be put at the "service of industrial, agricultural and national defense" (Hayhoe, 1989, p. 68). The government launched new national R&D programmes for the development of key technologies and state-of-the-art research in which universities featured prominently (Liu and White, 2001). The newly established National Natural Science Foundation of China (NSFC) provided grants to researchers after peer-review and based on their scientific track record. University researchers had to compete for research grants based on the number of their publications in international scientific literature (OECD, 2008, p. 244). The following major R&D programmes were introduced between 1982 and 1997 with year of establishment in parenthesis:

- National Key Technologies research and Development Programme (Zhicheng) (1982)
- National High Technology Programme (863 Programme, 1986)
- Torch Programme (1988)
- National Basic Research Programme (973 Programme, 1997)
- World-Class University Projects (985 Project, 1998; 211 Project, 1999)

The Torch programme from the Ministry of Science and Technology (MOST) provided funding for university science parks and technology business incubators (TBBIs). TBBIs were physical infrastructure around universities that hosted technology-based university start-up. TBBIs provided a wide range of technology services and business services to entrepreneurs, e.g. they provide start-ups with office space, free rent, supported the drafting of their business plan, applications for tax reductions, and provided access to university technology transfer such as testing facilities for prototypes (OECD, 2008). Under the Torch Programme, 534 TBBIs were set up that supported the establishment of around 40,000 start-up companies until 2005. By technologies, TORCH support aimed mainly at information and communication technologies (ICT) with 35% of all start-ups, automation (20%), and biotechnology (18%) (Bi, 2006). Founder Electronics is an example of successful Chinese company that was established as a university start-up during that period (Zhang, 2003). Many leading businesses in China's competitive ICT sector received support from the Torch Programme in the 1980s and 1990s, including Lenovo (Legend) and Huawei.

The National Key Technologies Research and Development Programme (NKTRD) and the 863 Programme supported technology development. In terms of specific technologies, the NKTRD Programmes and the 863 Programme provided funding for advanced manufacturing and automation techniques, agricultural technologies, biotechnology, defence, environmental technologies, ICT, and marine technologies (OECD, 2008).

The National Basic Research Programme (973 Programme) supported basic research with a focus on research teams led by young and middle-aged scientists. Its aim was to build a body of highly qualified scientists. Parts of the funds under the 973 Programme were also used to attract overseas Chinese researchers to Chinese universities. In terms of disciplines, the 973 Programme gave priority to agricultural science, environmental sciences, information technologies, life sciences, and material science (OECD, 2008).

The 985 Project and 211 Project aimed at the creation of world-class universities. The 985 Project targeted 39 top universities which were selected based on research excellence using peer review and institutional evaluations between 1999 and 2004 (Zhang et al., 2013). The 211 Project increased number of eligible universities for excellence funding to 116 (Chen et al., 2016). The 985 Project and the 211 Project provided funding for the establishment of new research centres, improved existing research facilities, attracted visiting scholars, and helped Chinese researchers and students to attend conferences abroad. Zhang et al. (2013) provide case study evidence that the 985 national R&D project is associated with an increase in the growth in scientific publication by researchers at leading Chinese 24 universities.

2.1.2. Government reforms targeted at university-industry technology transfer

The formation of the institutional framework for technology transfer was a gradual process in China (for an overview, see Chen, Patton, and Kenney, 2016). The country adopted its first formal Patent Law in 1985. In 1993, amendments to the Patent Law extended the duration of patent protection from

15 to 20 years, and the scope of patent protection to include, among others, pharmaceutical products. In the same year, Scientific and Technological Progress Law granted companies established by universities the right to license their patents and commercialise their research results. In 1996, the "Decisions on Enhancing Technological Innovation, Developing High Technology, and Realising Industrialisation" advocated for universities to improve the management of their IP. In 2000, and in anticipation of China's accession to the WTO, amendments to the Patent Law strengthened de-jure enforcement of IPR by giving patent holders the right to obtain a preliminary injunction against the infringing party before bringing up a lawsuit. Moreover, SOEs and private enterprises enjoyed equal treatment in obtaining patent rights (Chen et al., 2016).

Between 2000 and 2002, the Chinese decentralised research policy, giving greater autonomy to local governments over university policy between 2000 and 2002. The reforms resulted in a drastic transformation of China's university landscape. In 2000, there were regular 2,401 higher education institutions under the responsibility of national ministries, mainly under the Ministry of Education (MOE). In 2002, the number of universities under the MOE was reduced to 71, while local governments were responsible for 896 Chinese universities, including the leading universities. The overall number of universities was reduced to 1,016 due to mergers of institutions (Boisot and Meyer, 2008). Several local governments took advantage of their newly gained powers and introduced subsidies to encourage researchers to file their inventions (Chan and Daim, 2011). Shanghai, for instance, was the first municipality to introduce cost reimbursement subsidies to decrease the costs of patent applications for inventors in 1999. After 1999, other Chinese provinces followed suit.[4] Firms, universities and public research institutes that applied for a patent received a reimbursement of parts of the application costs (Li, 2012).

However, weak enforcement of university IPR constituted a major obstacle to science-industry relations. Chinese scholars show that there were significant regional differences in the frequency of infringements of IPR. Some provinces provided greater protection than others (Li and Qian, 2013; Li, 2012). There were also considerable regional differences regarding the enforcement of university IPR (e.g. Kafouros, et al., 2015; Ang et al., 2014). The possibility of infringement of ownership rights by competitors and local authorities resulted in legal uncertainty for firms about whether they would be able to appropriate the returns on their investment in joint R&D (Peck and Zhang, 2013). On the university side, university researchers faced uncertainty whether they would benefit from the disclosure of their invention. In the absence of legal protection of university IPR, universities may have engaged in less formal channels of knowledge transfer, including contract research for universities.

2.1.3. Pro-patent university reforms in 2002 as a natural experiment to university patenting

Pro-patent university reforms in 2002 were landmark reforms created a unified legal framework for the commercialisation of university inventions in China. In 2002, the Law on the Dissemination of Science and Technology strengthened the ownership of university IPR, providing legal clarity for universities about commercialisation of university research and their engagement with industry. Since some elements of the 2002 Law reflect provisions of the U.S. Bayh-Dole Act from 1982 that allowed U.S. universities to hold and commercialise patents from publicly funded research, literature refers to it as the "Chinese Bayh-Dole Act" (e.g. Fisch et al., 2016). Patenting and licensing of university inventions became the responsibility of the university's technology transfer office (TTO). The TTO could decide to use its right or transfer the IP right to the researcher and student responsible for its creation, which could establish a spin-off enterprise for market exploitation purpose. University researchers were required to transfer their ownership rights to the university, or the TTO, against a monetary compensation. The new regulations granted the following rights to researchers (OECD, 2008):

- If the university transferred IP to a firm, the researcher-inventor can claim a share of at least 20% of revenues stemming from publicly funded IP as a compensation;
- In case the university commercialises IP or in case of industry-university joint commercialisation, the researcher-inventor can claim a share of at least 5% or revenues;
- If a university spin-off uses the IP as equity, the researcher-inventor is entitled to 20% of that equity.

Data collected by Chinese scholars show that numbers of university patents increased following the 2002 reforms (Li, 2012; Luan, Zhou, Liu, 2010; Fisch et al., 2016; OECD, 2008). This is in line with evidence for developed economies. Mowery and Sampat (2005), Sampat et al. (2003), and Mowery and Sampat (2001) document increases in university patenting in the United States following the Bayh-Dole Act in 1982, while Thursby and Kemp (2002) demonstrate that U.S. universities increased their licensing of university inventions after the Bayh-Dole Act.

Arguably, the 2002 university reforms not only affected university patent activity, but also industry innovation though increased spillover from university patent activity. The reforms represent a source of variation in university patenting which was exogenous with respect to local economic conditions. In fact, the implementation of reforms was not confined to specific innovative locations such as e.g. Beijing or Shanghai. Neither did the reforms coincide with other major political reforms that could have affected university patenting, as shown in Table 2.1. Major policy reforms that affected Chinese industry patenting and productivity predated the 2002 reforms include the following: China's first Patent Law in 1985; and amendments to the Patent Law in 1993 and 2000; the Scientific and Technological Progress Law from 1993 that granted universities the right to license their patents and commercialise their research results; and the "Decisions on Enhancing Technological Innovation, Developing High Technology, and Realising Industrialisation" from 1996 that encouraged universities to establish spin-offs and to improve the management of their IP transfer system. Based on these considerations, it is argued that the policy reforms in 2002 are a natural experiment that can be used to identify causal effects of university IPR reforms on patenting activity of industry.

Table 2.1. Major reforms to university-industry technology transfer between 1985 and 2002

Year	Reform	Description
1985	Patent Law	Adoption of China's first Patent Law
1992	1st Amendments to the Patent Law	Extension of the duration of patent protection from 15 to 20 years, and extension of the scope of patent protection to include, among others, pharmaceutical products
1993	Scientific and Technological Progress Law	Granted universities the right to commercialise research results
1996	Decisions on Enhancing Technological Innovation, Developing High Technology, and Realising Industrialisation	Support for universities to establish spin-offs and to improve the management of their IP transfer system
1998	Cost reimbursement patent subsidy for domestic patents	The municipal government of Shanghai introduced a cost reimbursement patent subsidy to support patent fillings by universities, public research institutions and industry at the SIPO; other provinces followed in the years after 1999
2000	2nd Amendments to the Patent Law	Strengthening of patent protection by giving patent holders the right to obtain a preliminary injunction against the infringing party before bringing up a lawsuit. SOEs and private enterprises were granted de-jure equal treatment in obtaining patent rights
2002	Law on the Dissemination of Science and Technology	Nationwide standardisation of protection of university IPR and extension of ownership rights of publicly funded IP at universities to researchers ("Chinese Bayh-Dole Act")
2002	Opinions on Giving Full Play to the Role of Universities' Scientific and Technological Innovation	MOST and MOE encouraged universities' third mission, i.e. innovation and technology transfer

Source: Adapted from Chen et al. (2016).

2.2. Channels of technology transfer between universities and industry

2.2.1. Patenting and licensing of university patents

Patenting and licensing of university patents are two channels of commercialisation of university research.[5] University patents include university-hold patents and researcher-hold patents. University-hold patents are patents that are created by researchers based in universities and owned by the university. Researcher-hold patents are patents created and owned by researchers based in universities. Patenting and licensing of university inventions have the objective of market exploitation, which involves royalties and fees paid to the university or its researchers by industry (Jensen and Thursby, 2001). This differentiates them from informal interactions between researchers from universities and industry, which do not involve monetary exchanges. In their seminal work, Henderson, Jaffe and Trajtenberg (1998) analyse U.S. university patents between 1965 and 1988 and show that university patents had higher quality than industry patents as measured by numbers of citations. Geuna and Rossi (2011), and Geuna and Nesta (2006) provide evidence on university patenting for Europe.

In China, universities own patents over IP stemming from publicly sponsored research (i.e. university-hold patents). Universities file for patent protection for an invention made by one of its researchers. The university's technology transfer office (TTO) is responsible for licensing of university inventions. The TTO may decide to use its right or transfer the IP right to the researcher responsible for its creation, who may establish a spin-off enterprise for market exploitation purposes.

Statistics on licensing and patenting of Chinese university at the national and provincial level is easily available which has led to numerous studies of university patenting (for an overview, see Chen et al., 2016). Studies show that numbers of Chinese university patents are on the rise since 2002 (e.g. Fisch et al., 2016; Li, 2012). Luan et al. (2010) demonstrate that patent activity of Chinese universities contributed to a global increase of academic patents. However, some authors suggest that the increase in the numbers of Chinese university patents was not matched by increases in quality as measured by citation data (e.g. Böing and Müller, 2016; Fisch et al., 2016).

There are fewer studies that analysed patent activity at the university-level. Existing evidence shows that university patent activity is concentrated among top universities in China (Fisch et al., 2016; Luan et al, 2010; Hong, 2008). Hong and Su (2013) provide evidence on joint university-industry patents using Chinese patent data for the years 1985 to 2004. They show that levels of joint patenting involving universities and industry were low. Universities and industry jointly filed 4,861 patent applications out 562,793 SIPO patents (or 0.8%) between 1995 and 2004. The authors further show that state-owned enterprises engage more frequently in university patenting but do not provide evidence on the impact of patenting with universities on economic productivity.

Patenting may be a result of scientific productivity. University researchers that tend to publish more frequently top-cited publications in scientific literature also show higher rates of patent applications (Azoulay et al., 2007). Carayol and Matt (2004) bring forward similar evidence for research laboratories. On the other hand, commercialisation of research results may stand in conflict with the research mission of universities. Research that is published cannot be patented which might restrict its broader dissemination via journals. Researchers that engage in inventions may show higher levels of secrecy about their research than researchers who focus on publishing, thereby hindering the diffusion of academic knowledge. There are studies that document negative effects of commercialisation activity on scientific publishing (Huang and Murray, 2009; Murray and Stern, 2007).

Industries may benefit from university patent activity to varying degrees. In biomedical and chemical engineering, for instance, patenting and licensing are among the most important channels of technology transfer (Bekkers and Bodas Freitas, 2008). In these technological domains, industry patents also tend to cite scientific publications more often (Van Looy et al., 2003). For China, data on university revenues from patent licensing collected by studies show the share of university revenues from commercialisation of patents is modest (Wang et al., 2013). To date, studies have not analysed the impact of university patenting across different industries.

2.2.2. Formal R&D collaboration

The previous Section discussed university patenting, which is a channels of technology transfer of university research that involves the commercialisation of university research outcomes. This Section provides an overview of existing studies of university-industry collaborative research, including contract research. Science-industry collaborations are inter-organisational collaborations that involve universities and firms and in which university researchers and industry researchers jointly conduct research, or in which university researchers conduct research that specifically addresses industry needs. Consulting services by researchers to firms, and contract research between university researchers and industry, are two types of science-industry collaborations. Contract research describes R&D activity that is outsourced by firms to the university, either because the firm lacks its own R&D capacity, or because universities can provide the research service at more competitive prices. University researchers may receive financial rewards for their research services to industry, but other non-financial forms of compensation exist, including access to data, scientific material (e.g. biological resources), and research facilities (Perkmann and Walsh, 2009).

There are several advantages to science-industry collaboration. First, university research may compensate for lacking industrial research capacities. Industrial survey data shows that many Chinese enterprises lacked their own R&D capacities, which was a serious barrier to further productivity improvements (e.g. Hu et al., 2005). In order to compensate for their limited in-house R&D, many Chinese firms pursued an innovation strategy that relied on collaborations with universities (Motohashi and Yun, 2007). Interactions with university researchers and the exchange of information about state-of-the-art research allows enterprises to lower their search costs for new technologies, get access to scientific talent, and benefit from research capacities of universities. Universities conduct basic research, which is often too expensive for enterprises. Collaboration with university researchers may improve enterprises' entry into new technological fields, by helping them to transform research results into commercially successful products (Hall et al., 2003). The engagement in joint research with universities may enhance firms' own innovation capacities (Maietta, 2015). Moreover, joint research may create synergies based on already existing research capacities of universities and industry. Product and process innovations often result from research activity (Robin and Schubert, 2013). The underlying processes of advancement of knowledge in universities and industrial R&D laboratories are similar, notably the application of the scientific method, and experiments to systematically identify viable solutions. Synergies between university research and industry research emerge when the application of research results leads to new inventions, and new inventions inform underlying scientific theory.

There are also costs attached to science-industry collaboration. Differences in the objectives and incentives between university researchers and enterprises may render transactional costs prohibitive for enterprises or make collaborations less productive. To illustrate this argument, university researchers are typically committed to stable, long-term research and the publication of their research results in accessible scientific journals. Industry, on the other hand, intends to recover its investment costs in R&D by means of trade secrecy and IP protection and is not interested in the broad dissemination of its research results. Science-industry collaboration requires trust between researchers and enterprises, which may be put under strain by legal issues surrounding ownership of IP. Science-industry collaboration needs to accommodate these two incentive systems and find ways to coordinate joint research activities. IPR rules of universities, for instance, should not be conflict with the objectives of enterprise to protect their IP.

Science-industry collaboration has been widely studied for Europe (D'Este and Perkman, 2013; Grimpe and Fier, 2010; Bekkers and Bodas Freitas, 2008; Schartinger et al., 2002) and the United States (Boardman, 2009). The studies suggest that contract research and consulting are more important channels of knowledge transfer than licensing and patenting of inventions because only a small fraction of research results can be patented. While applied research may be more suitable for direct commercialisation, research in other disciplines such as e.g. theoretical physics and mathematics may require longer periods to be translated into new technologies. Studies also show that there are differences in science-industry collaboration intensity across industries. Bekkers and Bodas

Freitas (2008) and Schartinger et al. (2002) show that consulting and contract research is important for chemical engineering, ICT, and medical industries.

In terms of economic impact, empirical research has shown that R&D collaboration with university researchers improved enterprises' innovation performance (Robin and Schubert, 2013; Maietta, 2015), entry into new technological fields (Hall et al., 2003), and productivity of high-tech start-ups (Motohashi, 2005). For China, Brehm and Lundin (2012) use industry survey data covering 20 000 enterprises across 31 Chinese provinces for the years 1998 to 2004 and show a positive association between firm performance and contract research with universities. Other authors do not confirm any positive association between contract research and industry performance. Guan, Yam, and Mok (2005) use survey data of 948 firms in Beijing in 1998 and show that although 18% of firms engage with university researchers, there is no significant correlation with innovation and productivity outcomes.

Chinese data collected by researcher points to an increase in science-industry collaboration after reforms to the institutional framework that governs university relations with industry in 2002. Motohashi and Yun (2007) use data on 22,000 large- and medium sized industrial enterprises for the period 1995 to 2001 and demonstrate the importance of university reforms for increased science-industry R&D collaborations. Li (2012) emphasize the importance of constraints of weak enforcement of university IPR on science-industry collaboration, which increased transaction costs for industry. Kafouros, et al. (2015) demonstrate that regional differences regarding the enforcement of university IPR affected science-industry collaboration, describing how they opened the door to frequent interventions of local authorities in courts' judgments over IPR.

2.2.3. The role of university R&D for technology transfer

University R&D may affect the extent to which university researchers engage with industry. Research excellence may attract joint research with industry. Firms that screen for university partnerships may favour research laboratories and research universities over teaching-oriented institutions. Evidence suggests that researchers with a high track record in scientific publications attract more contract research from industry (Crespo and Dridi, 2007; Van Looy et al., 2004). Van Looy et al. (2004) use publication and research contract data for the University KU Leuven in Belgium for the years 1992 to 2000 and show that the number of scientific publications of a researcher is positively associated with their income from contract research. For China, Wu (2010) compares the Fudan University and Shanghai Jiaotong University for the period 1996-2003 and show that research excellence as measured by the number of national Key laboratories is positively associated with contract research and patent license income. Gao et al. (2014) use province level data on R&D expenditures and patents to demonstrate that R&D funding by industry is positively associated with higher levels of university patenting.

The type of research may affect contract research activity of universities. University research is mostly government sponsored which allows researchers to address more fundamental, long-term research that is too risky for industry. In China, most basic research is conducted at universities (Zhang et al., 2011).[6] In their study of 575 Dutch university and industry researchers in 2006, Bekkers and Bodas Freitas (2008) show that basic research with a higher potential of technological breakthroughs is associated with contract research activity. Studies suggest that basic research is more relevant for science-based industries, which rely on state-of-the-art research for the development of their new products. In biomedical and chemical engineering, for instance, evidence shows that industrial patents tend to cite scientific publications more often (Van Looy et al., 2003).

On the other hand, opportunities to collaborate with universities for firms outside of science-based industries may higher in applied research such as e.g. ICT and engineering. In these disciplines, research outcomes are more tangible and easier to codify. Applied fields of research, including engineering, were found to make commercialisation more likely (Bozeman and Gaughan, 2007; Lee and Bozeman, 2005).

2.3. Existing evidence on patenting and productivity growth in China

2.3.1. Productivity growth of industrial enterprises

While the previous Subsections described channels linking university research to industry, this Subsection discusses evidence on empirical trends in productivity in China. Evidence on firm productivity provides insights on China's transition towards productivity-led growth, a widely used measure for the efficiency of production. Productivity is a crucial factor for a country's living standards as it measures the efficiency with which its firms convert production inputs (i.e. labour effort, capital) into production outputs such as e.g. goods and services. Total factor productivity (TFP) is a widely used measure for productivity. It is defined as the growth in output not explained by the growth of labour and capital inputs (e.g. Solow, 1956).[7] Following Solow's (1956) seminal work on TFP as a measure of technological change, empirical studies have made frequent use of TFP to measure the relative contributions of technological change to growth versus the mobilisation of physical capital and labour. One disadvantage of TFP is that it is a residual measure of all possible factors of growth that are not captured by labour and physical capital, including human capital and structural change.

There is agreement in literature that total factor productivity (TFP) of industry has been rising in China for over four decades since pro-market reforms in 1978. Studies that looked at China's aggregate TFP levels suggest that it grew from 3 per cent of U.S. levels in 1978, to 13 per cent of the U.S. level in 2007 (e.g. Zhu, 2012).

The empirical literature on the contributions of TFP growth to China's economic growth has provided rather mixed results (for an overview, see Tian and Yu, 2012; and Wu, 2011). Some works point to low contributions of TFP to growth of around 1.4% (see, e.g., Young, 2003), while others point to TFP as the key driver of growth with TFP explaining more than 3% of China's annual growth rate during the 1990s and 2000s (see, e.g. Zhu, 2012; Bosworth and Collins, 2008). In terms of aggregate contributions, Zhu (2012) shows that TFP growth contributed to 78% of total industrial output growth in China between 1978 and 2008.

The availability of firm-level data sets has led to an increased academic interest in productivity dynamics in China (e.g. Böing et al. 2016; Brandt et al., 2012; Park et al., 2010; Hsieh and Klenow, 2009). Empirical studies looked at industrial productivity of new firms versus incumbent firms (Brandt et al., 2012; Hsieh and Klenow, 2009). Brandt et al. (2012), for instance, use industrial survey data for the period 1998 to 2007 and show that firm entry has contributed significantly to productivity growth of manufacturing industries. These findings reflect China's economic liberalisation during the late 1990s and early 2000s. During this period, many newly established enterprises entered previously protected industries.

Other studies analysed productivity by type of ownership. Between 1998 and 2002, many SOEs were privatized, and private enterprises entered previously protected industries. Jefferson, Rawski, and Zhang (2008), for instance, use industrial survey data on 41,783 enterprises and show that TFP levels of SOEs increased by 15.6% between 1998 and 2005, while TFP levels of POEs grew on average by 6.1% during the same period. Böing et al. (2016) use a sample of 1,927 listed firms at Chinese stock markets and show that SOEs experienced higher productivity gains than POEs. In contrast, earlier studies have found higher productivity growth for private enterprises than for SOEs (Jefferson and Rawski, 1994).

2.3.2. Industrial patent activity

Inventions and innovations are important for a country's technological advances and long-term increases in living standards. The measurement of innovation is not straightforward, as by definition innovation describes novel products, production processes, and ways of organising production and marketing products. One commonly used proxy for innovation are inventions and patents, i.e. inventions that offer a potential for commercialisation. A patent is a legal right that grants the inventor a temporary monopoly right for the exclusive use and commercialisation of a technical invention. In China, a patent right for a technical invention is granted for a period of 20 years starting with the filing date of the patent application. To be eligible for patent protection, a technical invention needs to be new, industrially applicable, and involve an inventive step. The exclusive right over the invention allows the owner to claim monopoly rent, which is a price higher than the competitive price. The monopoly right serves the purpose to recover R&D and other investment costs related to the development of the invention. Without patent protection, competitors may imitate the invention and sell it at lower prices because they do not incur any R&D expenditures.

Three types of patent rights exist in China: Invention patents, utility model patents, and design patents. Invention patents resemble patents in Europe and the United States. Invention patents are substantially examined to check if they fulfil the requirements of novelty, industrial application, and inventive steps. The Chinese utility model does not exist in Europe or the United States. It requires a lower level of inventive step, e.g. incremental technical improvements with a potential commercial value. Design patents are comparable to industrial designs, which constitute the ornamental or aesthetic aspect of an article and do not involve any technical solution.

In China, the inventor files a patent application to the State Intellectual Property Office (SIPO), which is the country's patent office. The SIPO grants patents to domestic and foreign enterprises, universities, public research institutes, and individual inventors. If the inventor is a foreign resident or a foreign-owned firm without a legal headquarters in China, she or he needs to entrust a Chinese patent agency with the application. The application needs to undergo an examination process, which takes between three to five years starting with the filing date. First, the SIPO examines whether the patent fulfils the formal criteria of a patent, which takes 1.5 years. After the formal examination, the patent application is published online. The applicant has then to file the application for a substantive examination during which the novelty, inventive step, and industrial applicability of the technical invention are examined. The substantive examination takes up to 3.5 years.

China passed its first Intellectual Property Law in 1984.[8] In 1985, the country acceded to the Paris Convention for the Protection of Industrial Property, followed by the Patent Cooperation Treaty (PCT) in 1994. The PCT is an international Patent Law treaty that provides a unified procedure for filing patent applications (international patent applications) to protect inventions in each of the PCT's member states. While a Chinese patent grants protection for the territory of the People's Republic of China (PRC), a PCT patent provides protection for potentially all countries that signed the PCT treaty. However, the application for international patent protection at the World Intellectual Property Organization (WIPO) is associated with higher costs and a longer evaluation procedure.

Amendments to China's Patent Law have broadened the scope of patents rights and their length in 1992 and 2000. The scope of patent protection was extended to cover, among other things, pharmaceutical products, food, beverages, while the duration of patent protection was extended from 15 years to 20 years. In 2000, and in preparation to China's accession to the World Trade Organisation (WTO) in 2001, China amended its Patent Law to fulfil its commitment to join the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS). Joining the TRIPS agreement is mandatory for countries that want to join the WTO. It requires its signatory countries to provide copyright rights, industrial designs, patents, new plant varieties, and trademarks. It specifies enforcement procedures and dispute resolution procedures. For instance, the Amendment of the Patent Law in 2000 affirmed that state-owned and private enterprises enjoy equal treatment when they file for patent protection. Patent revocation procedures were removed, which had been often invoked by government officials to invalidate procedures of private inventors.

The number of domestic and international patents surged after 2002. Some authors relate the increase in patent numbers to growing business R&D expenditures and the changes in the legal environment for patents (Hu and Jefferson, 2009). Studies also point to the role of universities in driving overall patent numbers (Luan et al., 2010). The patent surge has led to a debate on whether China's patents are of less quality, or whether the increase is related to the county's transformation towards a knowledge-driven economy (see e.g. Dang and Motohashi, 2015; Gilboy, 2004). Studies that use citation data to measure patent quality suggest that the increase in numbers did not follow similar increases in patent quality (Böing and Müller, 2016; Fisch et al., 2016).

Empirical evidence shows that patenting propensities are much lower in state-owned firms than in private firms (e.g. Rong et al., 2017; Hu and Jefferson, 2009). Hu and Jefferson (2009) use data on 20,000 large- and medium sized industrial enterprises for the period 1995 to 2001 and demonstrate that the propensity to patent is higher in privately owned and foreign-owned enterprises than in state-owned enterprises. Rong et al. (2017) bring forward similar evidence for a sample of 8,412 Chinese firms listed at the Shanghai and Shenzhen Stock Exchanges between 2002 and 2011. The authors show that private ownership enhances patent activity. A possible explanation is that pro-patent reforms resulted in stronger property right protection, which may have led private firms to engage more frequently in patenting without facing the risk of invalidation of their intellectual property rights (IPR) by the government.

2.4. Existing evidence on spillovers from university research

2.4.1. University spillovers and economic performance

Beyond universities' direct contributions to innovation (e.g. licensing of university patents, joint research with industry), universities increase innovation and productivity in the private sector via through knowledge spillovers. Knowledge spillovers from university research denote the benefits of university research to firms not responsible for the original investment in the creation of this research (e.g. Scherngell, Borowiecki, and Hu, 2014). Knowledge spillovers include codified knowledge flows, and direct interactions between university faculty and business establishments where knowledge flows between the two sides, and which do not involve any financial or non-financial rewards. Examples of codified knowledge flows are citations to scientific publications and patents of university researchers. Examples of direct interactions include networking between researchers, conferences, and hiring of PhDs. The potential scope of spillover effects is not confined to direct contributions of university researchers, such as their patents and scientific publications. They include knock-on effects of university research on industry due to the dissemination and industrial application of knowledge contained in research outcomes, including, among other things, the use of scientific methods and tools described in scientific publications and patents, and imitation of technical inventions.

According to modern economic understanding, research spillovers are drivers of long-term productivity (Aghion and Howitt, 1992; Grossman and Helpman, 1991; Romer 1990, and 1986). Following this theoretical view, one line of inquiry analysed patent data to provide evidence on spillovers. Empirical studies have found positive evidence for spillover effects on industrial patent activity using information on citations from industry patents to university patents (Fischer and Varga, 2003; Jaffe, Trajtenberg, and Henderson, 1993; Jaffe, 1989). In their seminal studies, Jaffe (1989) and Jaffe, Trajtenberg, and Henderson (1993) use U.S. patent data at the state-level for the years 1972 to 1981 to show that industry patents cite university patents more frequently if the university is located within the same state as compared to cross-state citations. This evidence points to geographical spillover effects of universities. Fischer and Varga (2003) provide similar evidence for Europe using Austrian patent data for the year 1991.

Another stream of work analysed information on new university establishments and provided evidence on the effects of these newly established universities on patenting and productivity (Toivanen and Väänänen, 2016; Cantoni and Yuchtman, 2014; Andersson et al., 2009). For Sweden, Andersson et al. (2009) show that the establishment of new universities increased annual productivity growth of localities in which the universities were established by 1.6%. For Finland, Toivanen and Väänänen (2016) show that the establishment of technical universities increased the number of industry patents in Finland over the period 1988 to 1996. The establishment of three new technical universities resulted in a 20% increase in the number of USPTO patents by Finnish inventors. In a historical study of Germany, Cantoni and Yuchtman (2014) use data on universities and provide evidence of causal effects of new universities on the establishment of new market towns between 1386 and 1400. On the other hand, Bonander et al. (2016) does not find evidence of economic impacts of university establishments on patent applications or start-ups in Sweden. The authors differ from the other studies that report positive effect in that they use the synthetic control method (Abadie, Diamond, and Hainmüller, 2015 and 2010) to compare the effects of three new universities (i.e. former university colleges) versus a control group of Swedish regions.

Research has also linked university research, or university spending, to local economic development. In a global study using data on 15,000 universities in about 1,500 regions across 78 countries spanning over the years 1950 to 2010, Valero and Van Reenen (2019) show that increases in the number of universities are positively associated with growth of regional GDP per capita. Similarly, studies by Kantor and Whalley (2014) and Aghion et al. (2009) point to positive impacts of university expenditures on regional growth and productivity. Kantor and Whalley (2014) use U.S university survey data for the years 1981 to 1996 and stock market shocks to university endowment values to report that university R&D expenditures have a positive impact on regional growth. They further show that research universities exhibit larger spillover effects on regional growth than teaching colleges. Other studies show that universities may affect growth by stimulating patenting in their region (Toivanen and Väänänen 2016; Belenzon and Schankerman 2013; Jaffe 1989).

For China, Hu and Mathews (2008) use data on university R&D expenditures and demonstrate that university research expenditure is positively associated with increases in industry patent activity for the years 1990 to 2005. However, they study do not provide estimates for causal effects, and they do not differentiate between effects across regions and industries. Chen and Kenney (2007) provide case study evidence on the role of universities and public research institutions for regional innovation outcomes in Beijing and Shenzhen. Their study, however, is not comparable to other regions in China with less developed innovation ecosystems.

2.4.2. Spillover effects by industry characteristics

Spillover effects from university research might differ between technology-intensive industries and less technology-intensive industries due to different needs of industry. Science-based industries, such as e.g. pharmaceutical industries, biotechnology, and chemical industries may require state-of-the art research for their product development. Other, less science-based industries such as e.g. machinery and equipment industry may use more applied technologies that universities cannot provide. In fact, studies report positive spillover effects from university research on private R&D activity in science-based industries, including pharmaceutical industries (Furman and MacGarvie, 2007) and biotechnology (Furman and Stern, 2011). For pharmaceutical industries, Furman and MacGarvie (2007) use data on industrial research laboratories in the U.S. pharmaceutical industry from 1927 to 1946 to demonstrate that there was a significant positive effect of university research on the growth of industrial pharmaceutical laboratories. For Europe, Lomas (2007) provides anecdotal evidence for engagement between university researchers and the German chemical industry in the 19th century.

Studies of Chinese industry dynamics show that industry R&D and patenting propensities differ across ownership type of firms (e.g. Rong et al., 2017; Hu and Jefferson, 2009). Using data on 1,927 firms listed at the Chinese stock exchange (Shanghai and Shenzhen) between 2002 and 2011, Rong, Wu, and Böing, (2017) show that POEs have larger returns on their R&D investment than SOEs. Hu and Jefferson (2009) use information on 22,000 large- and medium-sized Chinese enterprise and show that POEs were responsible for the increase in patent activity in China between 1995 and 2001. As for science-industry collaboration, Hong and Su (2013) use patent information on jointly hold patent between universities and industry and show that SOEs benefit from better access to university research. Institutional proximity, measured as belonging to the same Ministry or local government, is positively associated with science-industry collaboration. Related evidence suggests that SOEs may be in a better position to take advantage from university research, for example, through preferential access to financial resources to fund R&D (Zhu, 2012; Branstetter and Feenstra, 2002), and protection from competition in selected industries, giving them a lead ahead of private firms (Amiti and Javorcik, 2008). Ownership may also play out through managerial practice. State agencies manage SOEs, such as e.g. the State-Owned Asset Supervision and Administration Commission (SASAC), which have exclusive rights to appoint SOE managers (Naughton, 2007). SOE managers are selected through a political process from a pool of managers and government officials. Their promotion depends on the achievement of financial performance targets that are set by the government. With political control of their appointments, SOE managers may tend to give priority to achieving political goals such as e.g. employment over pursuing profitability and innovation. In contrast, the selection of executives in private firms is not subject to political considerations.[9]

Further, spillover effects from university research may differ between newly established firms and incumbent firms. Incumbent firms have advantages due to better absorptive capacity and higher R&D investment. Leading businesses invest to a higher degree in R&D (OECD, 2015). Using U.S. manufacturing data for the period 1981-2001, Bloom. Schankerman, and Van Reenen (2013) show that smaller firms generate lower spillovers from their R&D activities because they occupy mainly technological niches. Incumbents, on the other hand, are in a better position to appropriate their returns on investment in R&D. Research shows that in R&D intensive sectors the use of patents favours incumbents at the expense of young firms (Cockburn, MacGarvie, and Müller, 2010). Another strand of literature points to positive association between university research and performance of start-ups or young firms (e.g. Motohashi, 2005; Audretsch and Stephan, 1996). For Japan, Motohashi (2005) uses information from a survey on science-industry collaboration and shows that newly established technology-based firms achieve higher productivity through collaboration with industry than large enterprises. R&D collaboration with universities might provide new enterprises with less financial assets with access to research, tools, and talent – e.g. advanced machinery and skilled scientists – that typically require large upfront costs.

2.4.3. The role of geographical proximity to universities

Innovation is localised, more so than other economic activities. Studies have shown that knowledge spillovers – an important driver of innovation, are more localised than other economic activities that give rise to agglomeration economies, including local labour markets, sharing of supplier chains, and local demand (Ellison, Glaeser, and Kerr, 2010; Arzaghi and Henderson, 2008; Rosenthal and Strange, 2003 and 2001). Arzaghi and Henderson (2008), for instance, use data on the location of advertisement agencies in Manhattan, New York, and show that knowledge spillovers between agencies are confined to a radius of half a mile. Ellison et al. (2010) analyse the relative importance of sharing of labour, goods, and knowledge for industry co-location and provide evidence that knowledge spillovers are the most localised mechanism of these three.

Geographical proximity also mediates knowledge spillovers from university research on innovation and productivity. The diffusion of codified knowledge produced by universities is constrained by geographic distance, as shown for industry citations to university patents and scientific publications

(Belenzon and Schankerman, 2013). Direct face-to-face interaction and networking between researchers, another channels of knowledge spillover, become increasingly costly with growing distances (Rosenthal and Strange, 2008).

There is an established body of literature that provides important evidence on the positive role of geographical proximity to universities for industrial innovation and productivity (Helmers and Overman, 2017; Belenzon and Schankerman, 2013; Andersson et al., 2009; Branstetter, 2005). Belenzon and Schankerman (2013) study data on U.S. citations from corporate patents to university patents and show that proximity effects decline sharply with distances up to about 100 miles between university patent holder and industry patent holder. For Europe, Andersson et al. (2009) show that the establishment of new universities increased local productivity growth in Sweden between 1985 and 2001, with roughly 40% of the cumulative productivity gains within 10 km of the newly established university. Helmers and Overman (2017) show that the opening of new research stations in the United Kingdom between 2000 and 2010 increased scientific publication numbers that made use of data produced at the new research stations, with larger increases in locations within 25 km distance of the research station. In an older study, Branstetter (2005) uses data on patent citations to scientific publications of Californian universities for the years 1986 to 1998 and finds a positive relationship between geographical proximity to universities and industry patent activity. For China, Hong and Su (2013) use Chinese patent data for the years 1984 to 2004 and show that universities and industry file joint patent more frequently if the university is located within the same city as the industry partner.

The identification of proximity effects from university research is difficult due to endogeneity, i.e. industry and universities might locate in economically dynamic regions. One strand of research uses data on the opening of new universities to identify causal proximity effects of universities. Kantor and Whalley (2014) use U.S university survey data for the years 1981 to 1996 and stock market shocks to university endowment values to show that university R&D expenditures have a positive impact on regional growth. Kantor and Whalley (2019) use U.S. agricultural census data to show that improvements to agricultural productivity can been traced to the establishment of new agricultural research stations as measured by improvements crop revenue per farm acre. Between 1860 and 1990, agricultural productivity in locations surrounding research stations increased by 24% or 0.6% on an annual basis. Similarly, the openings of land-grant universities enhanced levels of manufacturing productivity in surrounding localities by 57% in the United States between 1860 and 1940, which corresponds to an annual increase of 0.7% per cent (Liu, 2015). Studies that use recent data point to even higher magnitudes of proximity effects. For Europe, Andersson et al. (2009) show that the establishment of new universities increased annual productivity growth of localities in which the universities were established by 1.6% in Sweden between 1985 and 1998.

These studies, however useful, do not control for possible local shocks that might have caused universities to locate in dynamic locations. Universities might choose to locate in economic prosperous regions due to better economic conditions or better governance. In this case, the location of universities would correlate with unobserved variables that also stimulate economic activity, such as e.g. local human capital advantages, geographical advantages, or better economic governance. For China, Glaeser and Lu (2018) try to account for endogeneity of university locations using the re-location of university departments during China's Great Leap Forward in the 1950s as a natural experiment. The authors use Chinese population census data between 2002 and 2013 and show that there are spillovers from university education activities on individual earnings across Chinese cities. To identify causality, the authors instrument city-level education using the number of relocated university departments across cities in the 1950s[10] and document that one year more city-level education increases individual hourly wage by 22.0 per cent. However, their study does not provide evidence on spillover effects from university research on innovation and productivity.

3. Conceptual framework

Endogenous growth theory has given rise to an established body of empirical literature on the relationship between productivity and spillovers from R&D (e.g. Romer, 1990; Griliches, 1979). This Section departs from the literature's core analytical model, the knowledge production function, and adapts it to the context of university spillovers, productivity and innovation in China. Subsection 3.1 derives a conceptional model of university spillover effects on TFP in a region, and on TFP in other regions. It also derives a conceptional model of the effects of university spillovers on industry patent stocks in a region, and on industry patents stocks in other regions. Subsection 3.2 discusses challenges that arise to the empirical implementation of the model, including the measurement of university spillovers in China. Having derived the conceptional model of university spillovers and discussed empirical challenges, Subsection 3.3 derives the hypothesis to be tested in the following Sections.

3.1. A model of university spillovers, innovation and productivity

3.1.1. The relationship between university spillover and industrial productivity

Following endogenous growth theory, the thesis uses the knowledge production function (KPF) framework to analyse the relationship between productivity and spillovers from university R&D (e.g. Romer, 1990; Griliches, 1979). The KPF includes university knowledge capital as additional input to labour and physical capital (Griliches 1979, Mairesse and Sassenou 1991). The KPF model is implemented at the level of Chinese prefectures and includes a variable to capture cross-prefectural spillovers from university research. According to LeSage and Fischer (2012) and Fischer et al. (2009), the regional KPF is suited to capture the economic effects of inter-prefectural university research spillovers. For China, Scherngell et al (2014) use the KPF framework to analyse intra-provincial spillover effects of patent activity on TFP.

Assuming a *M*-prefectures setting with c = 1, ..., *M* prefectures and *t* = 1, ..., *T* time periods, the relationship between industrial value added and university research may be written as

$$Q_{ct} = Q(X_{ct}, A_{ct}) \tag{1}$$

with

$$X_{ct} = g(L_{ct}, C_{ct}) \tag{2}$$

$$A_{ct} = A(K_{ct}, K^*_{ct}) \tag{3}$$

where Q_{ct} denotes industrial value added, and X_{ct} captures the conventional production inputs labour (L_{ct}) and the physical capital stock (C_{ct}). $g(.,.)$ exhibits diminishing marginal returns to the accumulation of L_{ct} and C_{ct}. A_{ct} denotes prefectural productivity, with K_{ct} and K^*_{ct} denoting the stocks of prefectural university knowledge capital stocks and university knowledge capital stocks in other prefectures, respectively.

Assuming a Cobb-Douglas production technology for prefecture c at time t gives

$$Q_{ct} = L^{\alpha}_{ct} \; C^{1-\alpha}_{ct} \; K^{\beta_1}_{ct} \; K^{*\beta_2}_{ct} \; \exp(\phi_c + \tau_t + \varepsilon_{ct}) \tag{4}$$

that connects industrial value to industrial labour and physical capital augmented with knowledge capital produced by universities. The terms ϕ_c and τ_t capture unobserved differences across prefectures and annual time trends, respectively. ε_{ct} is the error term which reflects unobserved determinants of industrial value added. α and α-1 are the output elasticities with respect to labour and physical capital. Constant returns to scale are assumed. The interest is on the parameters β_1 and β_2, which represent value-added elasticities of prefectural university knowledge capital, and value-added elasticities of university knowledge capital in neighbouring and other prefectures, respectively.

If total factor productivity TFP_{ct} for prefecture c = 1, ..., M, and year t = 1, ..., T is defined as

$$TFP_{ct} = Q_{ct} \,/\, L^{\alpha}_{ct} \; C^{1-\alpha}_{ct} \tag{5}$$

then Equation (4) leads to

$$TFP_{ct} = K^{\beta_1}_{ct} \; K^{*\beta_2}_{ct} \; \exp(\phi_c + \tau_t + \varepsilon_{ct}) \tag{6}$$

which relates university knowledge capital to productivity in a reduced-form framework. β_1 is the elasticity of TFP with respect to changes in prefectural university knowledge capital, while β_2 is the elasticity of TFP with respect to changes in university knowledge capital in other prefectures. The empirical estimate of β_2 gives the magnitude of the spillover effect from university knowledge capital in other prefectures on prefectural TFP. A positive and significant β_2 points to inter-prefectural knowledge spillovers (see Mairesse and Sassenou 1991).

3.1.2. The relationship between university spillover and industrial knowledge capital

At the regional level, assuming a M-prefecture setting with c = 1, ..., M prefectures, and denoting time periods by t = 1, ..., T, the relationship between industrial knowledge capital and university knowledge capital may be written as

$$P_{ct} = f(K_{ct}, K^{*}_{ct}) \tag{7}$$

where P_{ct} denotes industrial knowledge capital. $f(.,.)$ is a function assumed to exhibit diminishing marginal returns to the accumulation of each factor alone. K_{ct} and K^{*}_{ct} denoting the stocks of prefectural university knowledge capital and university knowledge capital in other prefectures.

Assuming a Hicks-neutral knowledge production for prefecture c at time t gives

$$P_{ct} = K_{ct}^{\gamma_1}\ K_{ct}^{*\gamma_2}\ \exp(\phi_c + \tau_t + u_{ct}) \tag{8}$$

which relates university knowledge capital to industrial knowledge capital in a reduced-form framework. γ_1 is the elasticity of industrial knowledge capital with respect to changes in prefectural university knowledge capital, while γ_2 is the elasticity of industrial knowledge capital with respect to changes in university knowledge capital in other prefectures. The terms ϕ_c and τ_t represent unobserved differences across prefectures and annual time trends, respectively. u_{ct} is the error term reflecting unobserved determinants of industrial knowledge capital.

3.2. Methodological challenges to the measurement of university spillover effects

Several methodological issues arise when analysing the effects of university spillover on industry. This includes the measurement of spillovers, endogeneity, sampling issues, heterogeneous effects across different industries (so-called parameter heterogeneity), and inter-region spillover effects.

The first issue relates to the measurement of spillovers from university research. Studies have used input measures based on R&D expenditures (e.g. Kantor and Whalley 2014; Aghion et al., 2009). An advantage of R&D-based measures are their comparability in terms of economic value. Data on R&D expenditures is comparable across industries, and using appropriate exchange rates, across countries. Moreover, time series of R&D expenditures can be easily constructed using price deflators. One disadvantage of R&D data is that it does not capture research outcomes. Another serious limitation concerns Chinese industrial enterprise data, for which R&D data is limited. In the Chinese industrial census (National Bureau of Statistics, 2008), information on R&D expenditures of enterprises is only available for the years 2005-2007 and contains many missing values.

Another stream of literature uses output measures based on patent data to analyse spillover effects of university research (e.g. Belenzon and Schankerman, 2013; Fischer and Varga, 2003; Jaffe, Trajtenberg, and Henderson, 1993; Jaffe, 1989). One advantage of patent data is that it is more directly related to research outcomes. Patent data provides a rich source of technology, citation, and geographical information about inventive activity. Patents protect state-of-the-art technologies that have the potential for commercialisation, which makes patents potentially more interesting for industry than scientific papers. Although the inventor acquire a monopoly right over the technology by means of patent protection, some portion of the knowledge may diffuse to other firms through various transfer channels such as citations (e.g. Belenzon and Schankerman, 2013). Patent data, however useful, do not necessarily capture innovation as only a small share of patents is commercialised. Another disadvantage of patent data relates to their economic value, which is difficult to measure. Moreover, patent propensities vary across industries and technologies.

A second issue is endogeneity, which arises due to omitted variables or reverse causality. Omitted, unobserved factors may drive changes in university research and industry performance. Universities might choose to locate in economic prosperous regions due to better economic conditions. In this case, the location of universities would correlate with unobserved variables that also stimulate economic activity, such as local advantages due to geography, history or better governance.

Reverse causality from industry innovation to university research is another source of endogeneity. The central challenge to the empirical approach is to establish that university research caused increased industry performance. One commonly used approach to establish causality is difference-in-difference estimation. It consists of comparisons of industry performance before and after an exogenous event that affected university research but not industry. Kantor and Whalley (2014), for instance, use data on stock market shocks that affect university endowment values to identify causal proximity effects of universities. For China, Glaeser and Lu (2018) try to account for endogeneity of university locations using the re-location of university departments during China's Great Leap Forward in the 1950s as a natural experiment. Another approach consists in using instrumental variables estimation frameworks. A valid instrument induces changes in university research outcomes but has no independent effect on industry performance.

Another concern for the measurement of spillover effects relates to sample issues. Patenting and R&D activity are concentrated among a few universities and enterprises (Chen et al., 2016; Zhang et al., 2013). This means that few enterprises and top university researchers produce most of R&D and patents. A random sample of universities and firms can easily miss those firms and universities, leading to a downward bias in estimates of spillover effects from university research. Comprehensive country-wide census data provide a better coverage of universities and industrial firms.

Studies of spillover effects that use industry- and firm-level data report average effects within their sample. Average effects do not reveal differential effects across industries. Cross-industry differences can be informative because they might show that only a subset of firms and industries benefits from spillovers. One approach to provide evidence on differential impacts across industries is to use sub-samples of industries and of certain firm characteristics, such as e.g. newly established firms. Studies that use subsamples have provided important insights into differential patent propensities of industries and differential effects of science-industry collaboration by new enterprises and incumbent enterprises. Motohashi (2005), for instance, shows that newly established technology-based firms achieve higher productivity through collaboration with industry than large firms in Japan. Studies of Chinese industry dynamics show that industry R&D and patenting differ across firm ownership (e.g. Rong et al., 2017; Hu and Jefferson, 2009). One disadvantage of smaller samples is that they reduce the precision of estimates of spillover effects due to lower degrees of freedom.

Finally, country- and regional-level data may miss inter-regional spillover effects. Research that accounts for inter-regional spillovers from university research includes measures of research outcomes of neighbouring and other regions in a country. One commonly used approach is to construct spatially weighted university patent stocks that are calculated based on patent data (e.g. Valero and Van Reenen, 2019; Scherngell et al., 2014; Fischer et al., 2009). A related issue is distance decay. Studies have shown that near innovation activities are more related to research than distant activities (e.g. Andersson et al., 2009; Helmers and Overman, 2017). These studies use the geographical distance between firms and universities to account for diminishing effects in distance (e.g. Valero and Van Reenen, 2019; Fischer et al., 2009)

3.3. Derivation of hypotheses

Section 2 reviewed the existing evidence on the impact of universities on economic performance (e.g. Glaeser and Lu, 2018; Maietta, 2015; Toivanen and Väänänen, 2016; Kantor and Whalley; 2014; Robin and Schubert, 2013; Motohashi, 2005; Hall et al., 2003). Following this literature, several hypotheses are advanced in this Section to test them empirically for Chinese universities and industrial enterprises. The hypotheses apply to the relationship between university patent activity and industry patenting and productivity; the impact of university IPR reforms on increases in industry patenting and productivity; and channels linking university research to industry innovation.

3.3.1. The relationship between university spillovers, industrial patenting and productivity

The following Section derives hypotheses related to *research question 1*: What is the relationship between university patent activity and industry TFP and patent activity (i) within a prefecture, and (ii) in neighbouring and other prefectures in China?

Much of the available empirical evidence on the link between university research and industrial performance concerns spillover effects of universities on the local economy (Glaeser and Lu, 2018; Toivanen and Väänänen, 2016; Kantor and Whalley; 2014). Geographical proximity between universities and enterprises may mediate spillover effects from university research on innovation and productivity. The rationale is that the maintenance of face-to-face interaction and networking between researchers – the underlying mechanisms of knowledge spillovers - becomes increasingly costly with growing distances. There are other potential direct interactions between university faculty and firms where knowledge flows between the two sides in close geographical proximity. Examples of such direct interactions includes hiring of researchers and PhDs.

Empirical evidence shows that the presence of spillover effects from university research can be partly explained by citations of industry research to academic research (Belenzon and Schankerman 2013; Jaffe, Trajtenberg, and Henderson, 1993; Jaffe, 1989). While industry research aims to be commercially applicable, both types of research activity share the objective of advancing state-of-the-art knowledge and technologies. Spillover effects may arise due to the dissemination and industrial application of knowledge contained in academic research outcomes, including, among other things, use of scientific methods and tools described therein, and imitation of technical inventions. This would imply that the underlying knowledge creation activities are similar so that industry can benefit from academic research.

Research that linked university R&D spending to regional growth provided additional evidence on statistically significant local spillover effects from university R&D (Kantor and Whalley, 2014; Aghion et al., 2009). Using U.S university R&D data for the years 1981 to 1996, Kantor and Whalley (2014) apply stock markets shocks to university endowment values as an instrument for university R&D spending and report that university R&D expenditures have a positive impact on regional growth. Empirical studies that used information on new university establishments show that newly established universities are associated with increased patent activity and productivity of localities surrounding the new universities (Toivanen and Väänänen, 2016; Valero and Van Reenen, 2019; Andersson et al., 2009). Andersson et al. (2009) use Swedish firm data for the for the period 1985 and 2001 and provide an estimate for increased annual productivity growth of 1.6% for firms within 10 kilometres distance to a new university. Toivanen and Väänänen (2016) provide evidence that the establishment of three new technical universities resulted in a 20% increase in the number of USPTO patents by Finnish inventors that had previously studied at these universities and remained in their geographical vicinity over the period 1988 to 1996.

Government sponsored research at universities is often more basic in nature, which suggests that research outcomes of universities might take longer to affect industrial activity. Industry needs to translate fundamental research into new techniques and products such as e.g. new drugs, which requires time. Kantor and Whalley (2019) analysed the time lag and persistence of spillover effects using U.S. data on public agricultural research stations between 1870 and 2000 and show a considerable time lag of eight years for new crop varieties to produce an impact on agricultural productivity. The authors went on to show that the effects lasted on average 20 to 40 years after an agricultural discovery had been made.[11] Adams (1990) uses scientific publication data between 1911 and 1980 and shows a positive association between scientific publications and productivity growth of industries that cite the publications 20 years after the scientific papers were published. These findings are in line with evidence on hybrid corn adoption rates among U.S. farmers between 1932 and 1953 brought forward by Griliches (1957). New agricultural crop varieties had been first adopted by innovative farmers and needed an additional 10 to 20 years to diffuse to latecomers. Other studies point to a longer time span for university effects to materialise. Liu (2015) uses data on the openings of land-grant universities in the United States in 1860s and demonstrates that new universities enhanced levels of local manufacturing productivity by 57% up to 80 years after their establishment. A similar positive relationship is proposed for university patent activity, industrial patent activity and industrial productivity for China:

Hypothesis 1a: *The higher level of university patent stocks in a prefecture, the higher the level of industrial TFP.*

Hypothesis 1b: *The higher the level of university patent stocks in a prefecture, the higher the level of industrial patent stocks.*

Studies suggest that lagging regions without the presence of strong local R&D-intensive firms can draw from R&D conducted at universities in neighbouring regions. University collaborations with industry, for instance, can span regional boundaries (Bathelt et al., 2004). For the United States and Europe, studies report that the presence of research universities is positively associated with patent activity in neighbouring regions (Fischer and Varga, 2003; Anselin, Varga, and Acs, 1997), as well as productivity in neighbouring regions (Fischer et al., 2009). Similarly, negative effects arise if knowledge spillovers from public research do not reach lagging regions. For China, the evidence is ambiguous. The findings of Scherngell and Hu (2011), which are based on citation data for the year 2007, and Scherngell et al. (2014) that use patent data for the period 1988 to 2007, suggest positive inter-regional spillover effects, while findings by Crescenzi et al. (2012) that use patent data for the years 1994 to 2007 point to negative inter-regional spillover effects. Evidence on the relationship between university research and industrial patenting and productivity in neighbouring or other prefectures is absent for China, which leads to the following testable hypotheses:

Hypothesis 1c: *The higher the level of university patent stocks in neighbouring prefectures, the higher the level of industrial TFP in a prefecture.*

Hypothesis 1d: *The higher the level of university patent stocks in neighbouring prefectures, the higher the level of industrial patent stocks in a prefecture.*

3.3.2. The impact of reforms to university IPR on industrial innovation and productivity

The following hypotheses relate to *research question 2*: What is the effect of pro-patent university reforms on changes in industry patent numbers and TFP levels?

The available literature on the relation between the institutional framework governing science-industry relations concerns intellectual property rights. Existing studies provide evidence on the positive association between pro-patent reforms and university patenting. The introduction of university ownership of publicly sponsored research (Bayh-Dole Act) was followed by a surge in university patent activity after 1982 in the United State (Mowery and Sampat, 2005; Sampat et al., 2003; Mowery and Sampat, 2001). Similar evidence exists for increases in commercialisation of university patents for the United States (Thursby and Kemp, 2002)

In the context of China, weak enforcement of university IPR may constitute a major obstacle to science-industry relations. The possibility of infringement of ownership rights over IPR may result in legal uncertainty for firms about whether they would be able to appropriate the returns on their investment in joint R&D (Peck and Zhang, 2013). Chinese researchers show that there were significant regional differences in the enforcement of IPR (Ang et al., 2014; Li and Qian, 2013; Li, 2012), and that these differences in IPR enforcement affected science-industry collaboration (Kafouros, et al., 2015).

The Law on the Dissemination of Science and Technology from 2002 strengthened the enforcement of university IPR and created a unified institutional framework for technology transfer in China. Some elements of the 2002 Law reflect provisions of the U.S. Bayh-Dole Act from 1982 that allowed U.S. universities to hold and commercialise patents from publicly funded research. For China, studies relate increases in university patent activity to reforms to the legal framework of IPR (e.g. Fisch et al., 2016). To date, there is, to the author's knowledge, no evidence on the impact of the 2002 reforms of university IPR on industry patenting and productivity, which leads to the following hypotheses:

Hypothesis 2a: *Industrial TFP levels increased significantly following reforms to university IPR in 2002.*

Hypothesis 2b: *Industrial patent numbers increased significantly following reforms to university IPR in 2002.*

The channels that link increased university patent activity – the target of university reforms, to industry performance may differ according to industry characteristics. Previous research has identified that industry R&D and patenting propensities differ across ownership type of firms in China (e.g. Rong et al., 2017; Hu and Jefferson, 2009). SOEs may benefit from preferential access to financial resources to fund in-house R&D (Zhu, 2012; Branstetter and Feenstra, 2002), giving them a lead ahead of private firms in the exploitation of publicly-funded research (Amiti and Javorcik, 2008). In the Chinese context, access to university research may be easier for state-owned enterprises that benefit from previous collaborations with science and institutional proximity between Ministries and universities (Hong and Su, 2013). Conversely, managerial practice of SOEs may be detrimental to innovation. SOE managers are selected through a political process and their promotion depends on the achievement of financial performance targets that are set by the government. With political control of their appointments, SOE managers may tend to give priority to achieving political goals such as e.g. employment over pursuing innovation. In contrast, the selection of executives in private firms is not subject to political considerations. While evidence shows that corporate funding may be positively related to university patent activity in China (Gao et al., 2014), there is no evidence on the impact of university IPR reforms on patent activity and productivity by state-owned and private firms. The following testable hypotheses arise:

Hypothesis 2c: *The levels of industrial TFP of privately-owned enterprises increased more compared to that of state-owned enterprises following university IPR-reforms in 2002.*

Hypothesis 2d: *The numbers of industrial patent stocks of privately-owned enterprises increased more compared to that of state-owned enterprises following university IPR-reforms in 2002.*

The effects of increased numbers of university patents due to pro-IPR university reforms might differ between technology-intensive industries and less technology-intensive industries. University research results may benefit especially high technology-intensive industries, such as e.g. pharmaceutical industries and chemical industries. In biomedical and chemical engineering, for instance, patenting with universities and licensing of university IP are among the most important channels of technology transfer (Bekkers and Bodas Freitas, 2008). In these technological domains industry patents also tend to cite scientific publications more often (Van Looy et al., 2003). Empirical evidence reports positive spillover effects from university research on private R&D activity in science-based industries, including pharmaceutical industries (Furman and MacGarvie, 2007) and biotechnology (Furman and Stern, 2011). Evidence on the impact of university patenting on patent activity and productivity of high technology-intensive industries and low technology-intensive industries for China does not exist, leading to the following hypotheses for empirical analysis:

Hypothesis 2e: *The levels of industrial TFP of high technology-intensive industries increased more compared to that of low technology-intensive industries following university IPR-reforms in 2002.*

Hypothesis 2f: *The numbers of industrial patent stocks of high technology-intensive industries increased more compared to that of low technology-intensive industries following university IPR-reforms in 2002.*

Further, the impact of university IPR reforms may differ between newly established firms and incumbent firms. Studies that use firm data show that incumbent firms have advantages due to better absorptive capacity (Bloom et al., 2013). Other authors bring forward evidence on the positive association between university research and increased performance of start-ups or young firms (e.g. Motohashi, 2005; Audretsch and Stephan, 1996). For Japan, Motohashi (2005) uses information from a survey on science-industry collaboration activity and shows that newly established technology-based firms achieved higher productivity through collaboration with industry than large enterprises. The underlying rationale may be that newly established enterprises benefit from R&D collaboration with universities due to access to advanced scientific machinery and skilled scientists that typically require large upfront costs. Considering the existing evidence, the following hypotheses are tested concerning impacts of university IPR reforms on patent activity and productivity of newly established firms and incumbent firms for China:

Hypothesis 2g: *The levels of industrial TFP of newly established enterprises increased more compared to that of incumbent enterprises following university IPR-reforms in 2002.*

Hypothesis 2h: *The numbers of industrial patent stocks of newly established enterprises increased more compared to that of incumbent enterprises following university IPR-reforms in 2002.*

3.3.3. Technology transfer channels linking university research and industry

The following hypotheses concern *research question 3*: What is the relationship between university R&D, university patent licensing and university contract research with industry?

Previous research has shown that many Chinese enterprises lacked their own R&D capacities, which was a serious barrier to further productivity improvements (e.g. Hu et al., 2005). In order to compensate for their limited in-house R&D, many Chinese firms pursued an innovation strategy that relied on collaborations with universities (Motohashi and Yun, 2007). Interactions with university researchers and the exchange of information about state-of-the-art research allows enterprises to lower their search costs for new technologies, get access to scientific talent, and benefit from research capacities of universities. For Europe, Japan and the United States, there is evidence that engagement in joint research with universities enhanced firms' innovation performance (Robin and Schubert, 2013; Maietta, 2015), spurred enterprises' entry into new technological fields (Hall et al., 2003), and increased productivity of high-tech start-ups (Motohashi, 2005). Joint research may also create synergies based on already existing research capacities of universities and industry. The underlying processes of research in universities and industrial R&D laboratories are similar, notably the application of the scientific method, and experiments to systematically identify viable solutions. Synergies between university research and industry research emerge, for instance, when the application of research results leads to new technologies, and new technologies inform underlying scientific theory.

Studies have highlighted that differences in channels linking university research to industrial innovation matter (D'Este and Perkman, 2013; Grimpe and Fier, 2010; Boardman, 2009; Bekkers and Bodas Freitas, 2008; Schartinger et al., 2002). The evidence collected for Europe, Japan, and the United States suggest that contract research and consulting are more important channels of knowledge transfer than licensing and patenting of university inventions because only a small fraction of research results can be patented. For China, the evidence is mixed. Regarding contract research, Brehm and Lundin (2012) use industry survey data covering 20,000 enterprises across 31 Chinese provinces for the years 1998 to 2004 and show a positive association between firm performance and contract research with universities. Conversely, Guan et al. (2005) use survey data of 948 firms in Beijing in 1998 and show that there was no significant association between R&D collaboration with universities and firms' innovation and productivity outcomes.

University income from patent licensing and contract research with industry may be a result of increased university R&D activity. Studies that analysed individual researchers provide evidence that researchers with a high track record in scientific publications attract more contract research from industry (Crespo and Dridi, 2007; Van Looy et al., 2004). Van Looy et al. (2004) use publication and research contract data for the University KU Leuven in Belgium for the years 1992 to 2000 and show that the number of scientific publications of researchers is positively associated with their income from contract research. These findings suggest that firms that screen for university partnerships may favour researchers and universities that engage in state-of-the-art research over teaching-oriented institutions. For China, Wu (2010) compare the Fudan University and Shanghai Jiaotong University for the period 1996-2003 and show that research excellence as measured by the number of national Key laboratories is positively associated with contract research and patent license income. On the other hand, commercialisation of research results may stand in conflict with the research mission of universities. Researchers that engage in patenting may show higher levels of secrecy about their research than researchers who focus on publishing, thereby hindering the diffusion of academic knowledge (Huang and Murray, 2009; Murray and Stern, 2007).

The type of research may affect science-industry R&D collaboration. In their study of 575 Dutch university and industry researchers in 2006, Bekkers and Bodas Freitas (2008) show that engagement in basic research is associated with universities' contract research activity with industry. Basic research seems to be more relevant for science-based industries, which rely on state-of-the-art research for the development of their new products (Van Looy et al., 2003). On the other hand, firms' opportunities to collaborate with universities may be higher in applied research such as e.g. engineering. In these disciplines, research outcomes are more tangible and easier to codify. In fact, applied fields of research, including engineering, were found to make commercialisation more likely (Bozeman and Gaughan, 2007; Lee and Bozeman, 2005). To investigate the link between type of university R&D and university revenues from patent licensing and contract research for China, the following hypotheses are proposed:

Hypothesis 3a: *The higher the growth rate of university R&D expenditures on basic research in the same province, the higher (i) the growth rate of university revenues from patent licensing, and the higher (ii) the growth rate of university revenues from contract research.*

Hypothesis 3b: *The higher the growth rate of university R&D expenditures on applied research in the same province, the higher (i) the growth rate of university revenues from patent licensing, and the higher (ii) the growth rate of university revenues from contract research.*

The focus on one specific channel of technology transfer might have detrimental effects on other channels of technology transfer. This debate is particularly important for China, where policy efforts have put emphasis on university IPR and patenting during the period 1998 to 2007. Universities that engage in commercialisation of their IP may be regarded as competitors by industry. For instance, firms may perceive universities as interfering in their markets as technology providers. As contract research and other forms of science-industry collaboration require trust between researchers and firms, these channels of technology transfer may be jeopardised by patent activity of universities (Wright et al., 2008).

To data, there is, to the author’s knowledge, little evidence on potential trade-offs between different channels of technology transfer. One notable exemption is the study by van Looy et al. (2011) that uses survey data for 105 European universities in the year 2003 and shows that there is no trade-off between patenting and contract research. The evidence suggests that, on the one hand, contract research is an input factor for patenting and licensing activities of universities. On the other hand, patenting activity of universities may be a follow-up activity of joint research with industry. University researchers’ engagement with industry may provide them with insights into commercial research areas. To test for potential trade-offs and synergies between university patent licensing and contract research with industry for China (*research question 4*), the following hypotheses is tested:

Hypothesis 4: *The higher the growth rate of university revenues from patent licensing in the same province, the higher the growth rate of university revenues from contract research.*

4. Empirical analysis of the effects of universities on innovation and productivity

This Section provides results from an empirical analysis of spillover effects from university patents on industry TFP and industry patents – as measured by means of geographical distance between industry and patent-active universities. It presents results on university spillovers within a prefecture, and to other prefectures in China (so-called cross-regional spillovers). Section 4.1 describes the data, while Section 4.2 presents the empirical methodology. Section 4.3 describes trends in university patenting and industrial patenting in China for the period 1998 to 2007, during which China's innovation system underwent a transformation towards industry-led innovation. Section 4.4 provides evidence on the relationship between university patent activity and industry TFP and patent activity (i) within a prefecture, and (ii) in neighbouring and other prefectures in China (*research question 1*). The findings provide insights on the potential effects of universities on their local economy, and on the crucial question whether universities generate spillovers to other prefectures in China. Section 4.5 brings forward evidence on the effect of pro-patent university reforms in 2002 on changes in industry patent numbers and TFP levels (*research question 2*). Pro-patent university reforms targeted university patenting, while they had a potential impact on industry patent activity only through university patents. Therefore, this Section argues that pro-patent university reforms provide an exogenous shock to university patent activity in China and offer a quasi-experimental setting to analyse the causal effects of university patent activity on industry. Additional analyses provide evidence on the differential impact of reforms by (i) newly established enterprises and incumbent enterprises, (ii) high technology-intensive and low technology-intensive industries, (iii) and state-owned enterprises and privately-owned enterprises.

4.1. Data and variables

4.1.1. Data

The data used for analysis consists of (1) Chinese industrial census information taken from the Annual Survey of Industrial Enterprises (National Bureau of Statistics, 2008), (2) university survey information from the World Higher Education Database (International Association of Universities, 2017), (3) information on patents granted to Chinese residents by the Chinese State Intellectual Property Office (SIPO) taken from the EPO Worldwide Statistical Patent database (PATSTAT) (European Patent Office, 2017), and (4) information on Chinese patents granted to industrial enterprises taken from the patent-industrial census linked dataset of He et al. (2017).

Enterprise data is the product of the annual industrial census conducted by the Chinese National Bureau of Statistics (NBS). The industrial census collects information on enterprises in the industrial sector, which comprises mining industries, manufacturing industries, and utilities. The census covers 165,118 industrial enterprises in 1998, which increases to 325,297 industrial enterprises in 2007 after accounting for privatisations and firm restructuring (see Brandt et al., 2012). The broad coverage makes the ASIE the most comprehensive database of Chinese industrial enterprises. A comparison with statistical information from the Chinese Statistical Yearbook reveals that the industrial census covered 91.1% of industry output and 72.2% of the industrial workforce in China in 2004. The survey covers state-owned enterprises (SOEs) and non-SOEs with sales above USD 700 000 (RMB 5 million), including privately-owned enterprises (POEs). Among the 325,297 enterprises contained in the 2007 sample, 2,927 were classified as large firms (0.9%), 32,529 as medium-size firms (10.0%), and 290,164 as small firms (89.2%).[12]

The industrial census collects detailed data on enterprise name, employment, total production output, value added, fixed capital stocks, 4-digit CIC Rev. 2002 industry classification, ownership status, year of establishment, and address including postal code of the enterprise. Moreover, the industrial census provides information on single plants and multi-plants expansions. This study uses only single plant observations. One advantage of the industrial census over statistical information is that the data is reliable in terms of consistency. Firms are required by law to respond to the survey conducted by the NBS. The data is used by the NBS for economic analysis, while the information provided cannot be used by other government authorities, including tax offices. Enterprises arguably have no incentive to provide false information. There is an established literature that draws on industrial census data to analyse determinants of firm productivity in China (e.g. Böing et al., 2016; Brandt et al., 2012; Song, Storesletten, and Zilibotti, 2011; Hsieh, and Klenow, 2009; Hu et al., 2005).

University data is taken from the World Higher Education Database (International Association of Universities, 2017). WHED collects information on Chinese 681 universities, including their name, number of students, disciplines offered, year of establishment, and geographical information on the university's main campus (i.e. its address and postal code). The data is based a survey conducted by the International Association of Universities under the United Nations Educational, Scientific and Cultural Organisation (UNESCO). It includes all degree-granting institutions of higher education that offer a post-graduate degree (or higher) and/or a professional diploma that requires four years or more of study. The list of institutions was provided to the UNESCO by Chinese authorities. WHED data has been used by Valero and Van Reenen (2019) to study the relationship between number of universities and regional economic growth in a systematic cross-country comparison.

Chinese patent data is used to construct measures of university research outcomes and industry innovation. Patent information is drawn from the EPO Worldwide Statistical Patent database (PATSTAT), which is the biggest freely available source for Chinese patent information. For the years 1998 to 2007, PATSTAT collects data on 218,156 invention patents granted[13] to Chinese inventors by the China's State Intellectual Property Office (SIPO) (hereafter referred to as SIPO patents). PATSTAT provides detailed information on characteristics of patents, including year of filing at the SIPO, information about the technology class at 4-digit IPC 8 level, name of applicants and inventors, as well as number of applicants and inventors of a patent. Chinese patent data has been widely used to study business innovation (Böing and Müller, 2016; Dang and Motohashi, 2015) and science-industry linkages (Hong and Su, 2013) in China.

To construct the dataset for the empirical analysis, all SIPO patents from Chinese universities were matched to their respective university using a text-matching algorithm. To link SIPO patents from industrial enterprises to their respective industrial enterprise, Patent and industrial enterprise information was drawn from the patent-industrial census linked dataset of He et al. (2017 and 2018). He et al. (2017 and 2018) provide Chinese patent data linked to China's industrial census data for the years 1998 to 2007.[14] The patent-census linked dataset contains information on IDs and patent publication numbers of industrial enterprises, which was linked to the patent data and industrial enterprise data using publication number and enterprise ID, respectively. A total of 127,840 out of 218,156 (or 58.6%) SIPO patents could be matched to industrial census and university survey data. Finally, the enterprise and university-level data were aggregated to the level of industries and prefectures.

While industry information is readily available in the industrial census, the regionalisation of industrial enterprises and universities depends on the geographical information available. The industrial census and the university survey include information on postal code of enterprise plants and the main campus of the university, which is matched to prefecture data using a lookup table for Chinese postal codes and prefectures. Details regarding the construction of the database, including accounting for privatisation after 1998 and industrial reclassification in 2002, the matching of enterprise and university data to patent data, and their regionalisation are provided in the Annex.

The dataset for empirical analysis covers 62,670 observations at the prefecture-industry level from 261 prefectures of Mainland China and 30 industries at the 3-digit CIC Rev. 2002 level for the years 1998 to 2007. Following Chinese studies (e.g. OECD, 2008), the focus is on the period 1998 to 2007 that saw a radical restructuring of China's innovation system that was characterised by the emergence of leading research universities and the emergence of private R&D.

Given the importance of the manufacturing sector for Chinese innovation and productivity growth, the study focuses on manufacturing industries as defined by the 1-digit class C of the Industrial Classification for National Economic Activities (hereafter referred to as Chinese Industry Classification or CIC) (Rev. 2002). The industry coverage is balanced with most observations in the beverage industry and the non-metallic mineral products industry and the fewest number of observations in the recycling and disposal of waste industry.

By prefecture, Guangdong has the highest number of observations with 5,690, while the Beijing, Chongqing, Shanghai, Tianjin[15], and Zhejiang have the lowest. While the sample is representative for the most Chinese province, it underrepresents Zhejiang province, which is a prosperous province bordering Shanghai at the East Coast. The coverage of industry by ownership is tilted towards privately owned enterprises (POEs) with 24,269 of prefecture-industry observations of POEs out of total 62,670 (or 39%), against 17,284 prefecture-industry observations of state-owned enterprises (SOEs) (or 28%).[16] Interestingly, the data shows that foreign-owned enterprises are present in 16,663 prefecture-industries (or 27%). The coverage of incumbent enterprises versus entrant enterprises is balanced, with 27,430 observations of entrants against 21,109 observations of incumbents. This shows a high share of newly established enterprises in the sample which is also confirmed in other studies of Chinese business dynamics (e.g. Brandt et al., 2012). By technology intensity, the sample consists mostly of low technology-intense and medium-low technology-intense industries, which reflects China's stage of economic development during the period 1998 to 2007. Table 4.1 describes the sample.

Table 4.1. Sample characteristics

	Number of Observations
Province	
Anhui	4,040
Beijing	270
Chongqing	10
Fujian	2,280
Gansu	2,180
Guangdong	5,690
Guangxi	3,150
Guizhou	830
Hebei	2,870
Heilongjiang	2,475
Henan	4,740
Hubei	3,400
Hunan	3,640
Jiangsu	3,770
Jiangxi	2,865
Jilin	2,040
Liaoning	3,390
Nei Mongol	1,880
Ningxia Hui	710
Shaanxi	1,940
Shandong	4,860
Shanghai	250
Shanxi	2,360
Sichuan	1,230
Tianjin	290
Yunnan	1,412
Zhejiang	90
Manufacturing industry	
Non-metallic mineral products	2,470
Articles for culture and education	1,570
Artwork	1,810
Beverages	2,440
Chemical fibers	1,340
Chemical raw materials	2,460
Communication equipment	1,890
Electrical machinery and equipment	2,220
Foods	2,390
Furniture	1,930
General purpose machinery	2,350
Leather, fur, and feather	1,930
Measuring instruments	1,700
Medicines	2,320
Metal products	2,320
Paper and paper products	2,340
Plastics	2,340
Rubber	2,000
Special purpose machinery	2,310
Textile wearing apparel	2,080
Textiles	2,310
Tobacco	770
Transport equipment	2,230

Printing, and reproduction of recording	2,080
Processing of food from agricultural products	2,460
Processing of petroleum and coking	1,980
Processing of timber	2,120
Recycling and disposal of waste	30
Smelting and processing of ferrous metals	2,320
Smelting and processing of non-ferrous metals	2,250
Ownership	
State-owned	17,284
Privately-owned	24,269
Foreign-owned	16,663
Age	
Incumbent (established before 1996)	21,109
Entrant (est. 1996 or after)	27,430
Technology intensity	
High-tech	2,839
Medium-high tech	6,213
Medium-low tech	7,492
Low-tech	12,592
Full sample	62,670
Number of years	10
Number of industries	30
Number of prefectures	261

Note: The unit of observation are prefecture-industries. The second row, second column shows that there are 4,040 prefecture-industry level observations in the province of Anhui, i.e. 30 industries, 16 prefectures, and 10 years. A prefecture does not necessarily have all 30 industries present. Industry information is based on the 3-digit CIC Rev. 2002.
Source: National Bureau of Statistics (2008), He et al. (2017), European Patent Office (2017), and International Association of Universities (2017).

To estimate differential impacts of university IPR reforms across industries, the sample of industrial enterprises is split according to (i) ownership type, (ii) technology-intensity of industry, and (iii) new entrants and incumbent enterprises. Information on ownership type of the enterprise is readily available in the industrial census. To construct the sample of state-owned enterprises (SOEs), state-owned and collectively owned enterprises are included. Privately owned enterprises (POEs) are selected based on the category private ownership, whereas limited liability corporations are excluded due to their mixed state-private ownership. Foreign-owned enterprises (FOEs) include Hong Kong-, Macao-, and Taiwan-owned enterprises (so-called HMT-owned enterprises), and other foreign ownership. Information on technology intensity of industries was taken from the OECD classification for technology intensity of industries (Hatzichronoglou, 1997). The 30 three-digit CIC Rev. 2002 level manufacturing industries are classified according to four categories: High-technology intensive, medium-high technology-intensive, medium-low technology intensive, and low technology-intensive (see Table 4.2 in Section 4.1.5). And finally, information on the year of establishment of the enterprise is used to differentiate between new entering enterprises and incumbent enterprises. New entering enterprises are defined as being founded in 1996 or later, while incumbent enterprises are established before 1996.

Industrial census, university survey, and patent data are complemented with official statistical information on prefecture-level characteristics, including population, GDP per capita, investment in machinery and equipment, foreign direct investment, labour force, and enrolment in secondary and tertiary education taken from Statistical Yearbooks of the NBS for the years 1999 to 2008. Information on technology intensity of industries was taken from the OECD classification for technology intensity of industries (Hatzichronoglou, 1997). Geographic information to construct geographical distance measures was taken from the spatial database DIVA-GIS (DIVA-GIS, 2018). Geodata includes the precise geographical latitude and longitude coordinates of the prefecture centre where the industrial enterprises and universities are located.

There are several caveats when using industrial census and patent data for China. Regarding enterprise coverage, the industrial census provides a very detailed picture of state-owned industrial enterprises and medium-sized to large private industrial enterprises. It does not cover smaller private firms with sales below USD 600 000 at 1998 prices (RMB 5 million). Although this fixed threshold is less of a restriction towards the end of the period of observation, business dynamics of small enterprises is not captured by the data. Still, the industrial census is the largest available micro-dataset for studies of Chinese industrial dynamics. Regarding university coverage, the WHED university survey covers only leading institutions of higher education, excluding, for example, teaching-oriented colleges and further education institutions (e.g. institutions for training of nurses and specialised technicians).

Several caveats exist when using patent data, including the fact that not all inventions are patented and not all patents lead to innovations. Patent statistics are not perfect measures of innovations as not all innovations are necessarily patented. Differences across industries and their propensity to patent are controlled for using industry fixed effects. For instance, patents are more effective in protecting pharmaceutical, chemical, and electronics technology. The main drawback of working with Chinese patent data relates to measures of patent quality. Several studies suggest that while the number of Chinese patents surged after 1998, their quality remained low which might impede innovation dynamics in China (Böing and Müller, 2016; Dang and Motohashi, 2015). SIPO patent data in PATSTAT contains only inadequate citation information — a widely used patent quality indicator. Another limitation is that Chinese patent data does not provide information on the address of the inventor. The inventor’s address is required for the regionalisation of patent data according to the location where knowledge production took place. Instead, the address of the enterprise and university that holds the patent are used for regionalisation, which might introduce a bias towards locations where these enterprises and universities are located.

4.1.2. Outcome variables

The first dependent variable is the logarithm of annual levels of total factor productivity (TFP) (hereafter referred to as industrial TFP growth) at the level of prefecture-industries for the period 1998 to 2007. Following Caves et al. (1982), the industrial TFP index tfp_{ict} of industry i, prefecture c and time period t is calculated using the logarithm of real value added q_{itc}, the logarithm of employment l_{ict}, the logarithm of gross fixed capital stocks c_{ict}, as well as labour compensation shares s_{it} for each prefecture c and time-period t. Formally, the index is defined by

$$tfp_{ict} = (q_{ict} - \overline{q}_t) - s_{ict}\left(l_{ict} - \overline{l}_{it}\right) - (1 - s_{ict})(c_{ict} - \overline{c}_t) \tag{9}$$

where an upper bar above a variable denotes a geometric mean. A labour compensation share s of 34.2% is used following Brandt et al. (2012). Value added data is in RMB at constant prices of 1998. Nominal value-added values are deflated using the output deflator provided by Brandt et al. (2012). Labour is measured in terms of the number of employed persons in industrial enterprises. Information on gross fixed capital stocks is measured in RMB at constant prices of 1998.

One caveat of Chinese industrial census data is that data on investment is not available. To proxy for investment, which is needed to construct TFP indices, this work follows Brandt et al. (2012) and uses gross fixed capital stock data that is provided in the industrial census. As firms report the value of their fixed capital stock at original purchasing prices, these nominal values are converted into real values as follows:

- Combined with information on firm age, the initial nominal fixed capital stock values for the year in which the firm appears in the data set are used to calculate the initial capital stocks of a firm for the year in which it was established.
- The nominal fixed capital stocks in the following years are constructed by multiplying the initial nominal fixed capital stock by $(1+r)^n$ where n is the number of years that the firm is operative, and r is the estimated rate of growth in the nominal fixed capital stock at the three-digit industry-level by province.

- The growth rate r is calculated using information on nominal fixed capital stocks at the three-digit industry-level by province taken from Statistical yearbooks of the National Bureau of Statistics.

Gross fixed capital stocks are constructed for each prefecture-industry by using the perpetual inventory method, $C_{ict} = (1 - d)\ C_{ict-1} + I_{ict-1}$, where C_{ict} is the stock of nominal fixed capital stock of industry i and prefecture c at time t, I_{ict-1} is the flow of gross investment in period $t-1$ that becomes productive in period t, and d is the constant depreciation rate of 9%. Fixed investment deflator of Perkins and Rawski (2008) is used to deflate annual flows of fixed investments. The deflator of Perkins and Rawski (2008) is a chain-linked price deflator based on separate price indices for equipment, machinery and buildings.

To test the robustness of results, productivity is also measured by labour productivity and TFP indices constructed according to the methodology proposed by Olley and Pakes (1996). Prefecture-level labour productivity is measured by dividing prefecture-level value added in RMB at 1998 prices by number of employees in the prefecture. Olley-Pakes TFP indices account for firm entry and exit. To construct the Olley-Pakes TFP indices, first, gross fixed capital formation equations are used to account for unobserved productivity. In a second step, differences in productivity of entering and exiting firms are controlled for, which might bias overall productivity estimates.

The second dependent variable is annual numbers of industry SIPO patent stocks of prefecture-industries. Following literature on innovation dynamics of Chinese business (e.g. Rong et al., 2017; Hu and Jefferson, 2009), industrial innovation dynamics is proxied using patent activity of industry. The second dependent variable is thus the logarithm of annual numbers of SIPO patent stocks held by industrial enterprises (hereafter referred to as industrial SIPO patent stock) for the period 1998 to 2007. To identify industrial patents, SIPO patents granted to universities are distinguished from SIPO patents granted to industrial enterprises. In order to do so, information from patent documents on patent holders (i.e. applicant names) is matched to the patent-industrial census database of He et el. (2017). He et al. (2017) provide a dataset of Chinese patents linked to industrial enterprises of the ASIE industrial census. For further details, see Annex.

I calculate the industrial patent stocks p_{ict} of industry i, prefecture c, and time period t using the logarithm of SIPO patent numbers. The industrial patent stock accumulates over time and depreciates from period to period at a constant rate r_p according the perpetual inventory method so that

$$p_{ict} = (1 - r_p) p_{ict-1} + s_{ict-1} \tag{10}$$

which states that the patent stock p of period $t - 1$ consists of the depreciated patent stock of $t - 1$ added by patents s produced in period $t - 1$. Patents produced in period $t - 1$ refer to the sum of SIPO patents granted to industrial enterprises in the year $t - 1$, while the patent stock in $t - 1$ refers to the depreciated sum of SIPO patents granted in the periods before t – 1, which is $t - 2$, $t - 3$, …, $t - (t - 1)$. A constant 12% depreciation rate is applied for each year to the stock of patents created in earlier years, in line with existing empirical studies (see, among others, Robbins 2006). Prefecture-industry-level patent stocks are constructed for the period 1998-2007 by transforming the patents, first, by the year of filing of the patent, and second, by the industry and the prefecture where the industrial enterprise (i.e. plant) is located. The plant's postal code is used for regionalisation.

4.1.3. Explanatory variables

For the analysis of university effects on industry, the main explanatory variable of interest is regional patent stock of universities that is used as a measure of university research outcomes. Patents protect, by definition, state-of-the-art technologies that have the potential for commercialisation, which makes patents interesting for industry. The technology produced and patented by a university researcher may spill over to other researchers and firms through various transfer channels such as face-to-face interactions and citations (e.g. Belenzon and Schankerman, 2013). This way, industry may benefit from improved processes, scientific instruments, and core technologies developed at universities and sponsored by public funding.

I calculate university patent stocks k_{ct} of prefecture c at time period t using the logarithm of SIPO patent numbers of universities. As in the case of industrial patent stocks, the university patent stock accumulates over time and depreciates from period to period at a constant rate r_k according to the perpetual inventory method so that

$$k_{ct} = (1 - r_k) k_{ct-1} + v_{ct-1} \tag{11}$$

which states that the patent stock k of period $t - 1$ consists of the depreciated patent stock of $t - 1$ added by university patents v produced in period $t - 1$. A constant 12% depreciation rate is applied. To create prefecture-level university patent stocks for the period 1998-2007, the patents are transformed, first, by sorting based on the year when a patent was filed at the SIPO, and, second, by the prefecture where the university resides. Information on applicant name and university name are used as they appear in the university surveys and matched using a text-based algorithm (for details, see Annex). To trace the prefecture of the university, the postal code of the university's main campus was used.

To account for geographical spillovers from university research, this work follows Scherngell et al. (2014) and Fischer et al. (2009) and defines a geographical spillover variable k^*_{ct}. as spatially weighted university patent stock as follows

$$k^*_{ct} = \sum_{c \neq d}^{M} w_{cd} k_{dt-q} \tag{12}$$

where w_{cd} is the spatial weight as measured by the geographical distance between region c and region d. It represents region's c capacity to access external patent stocks of region d at time t. Geographical distance between prefectures M is measured in terms of distance in kilometres, d_{cd}, between the centre of prefecture c and prefecture d (centroid distances). The distances in kilometres of prefecture c to all other prefectures d are captured in the spatial weight matrix W_{cd} whose elements, w_{cd} reflect the access that industry in prefecture c have to university research in prefecture d. Following standard convention, proximity of a prefecture c to itself is excluded, i.e. $w_{cc} = 0$ for all $c = 1, \ldots, M$.

Studies have shown that the effects of research are subject to distance decay, i.e. near innovation activities are more related to research than distant activities (e.g. Andersson et al., 2009; Helmers and Overman, 2017). To account for diminishing effects in distance, the negative exponential function of distance in kilometres is used, which has the form $w_{cd} = \exp(-\alpha^* distance_{cd})$ where α is any positive exponent. It is convenient to normalize the spatial weights w_{cd} to avoid dependence of the weights on the scaling factor α. Let the c^{th} row of W_{cd} contain all spatial weights w_{cd} related to prefectures $d \neq c$. To produce a normalised spatial weight matrix W_{cd}, each row c is normalised to have the unit sum 1, i.e.

$$\sum_{d=1}^{M} w_{cd} = 1, \; c = 1, \; \ldots, \; M \tag{13}$$

where w_{cd} is the fraction of the distance in kilometres between prefecture c and prefecture d of the total sum of distances in kilometres between prefecture c and prefectures $d = 1, \ldots, M$.

Finally, prefecture-level characteristics are controlled for, including population numbers, numbers of students enrolled in secondary education (i.e. high school and vocational education) and tertiary education (i.e. higher education), levels of GDP per capita, investment in physical capital, foreign direct investment, as well as controls for industry structures as measured by the share of employees in services, manufacturing, and self-employed in total employment. Numbers of patent stocks of foreign-owned enterprises are routinely controlled for to account for possible technology transfer from foreign enterprises. Studies highlight the important role of technology transfer between foreign and domestic enterprises in China (Jiang et al., 2018). Foreign-owned enterprises are required to enter joint ventures with domestic enterprises in return for market access in China.

To assess the impacts of university reforms on industry, the main explanatory variables of interest are a post university-reform dummy variable, $POST_t$, which equals 1 for all years after 2002, and the proximity to university dummy variable, $PROXIMITY_{ic}$, which equals 1 for all prefecture-industry observations outside of 20 km distance from the nearest university. Following Cantoni and Yuchtman (2014), locations outside of 20 kilometres are used to account for endogeneity of university locations. Universities may locate in economic prosperous and more innovative regions, which renders the identification of university effects difficult. The restriction of the sample to industry locations outside of the immediate neighbourhood of universities should account for endogenous university locations. Geographical proximity between prefectures is measured in terms of log distance in kilometres, d_{cd}, between the centre of prefecture c and prefecture d (centroid distances).

I further construct alternative proximity measures for robustness, including $PROXIMITY^{50KM}_{ic}$, which equals 1 for all prefecture-industry observations outside of 50 km from a university; $PROXIMITY^{MEAN}_{ic}$, which equals 1 for all prefecture-industry observations outside of the mean distance of 62 km from a university; $PROXIMITY^{MEDIAN}_{ic}$, which equals 1 for all prefecture-industry observations outside of the median distance of 46 km from a university; and $PROXIMITY^{NEIGHBOUR}_{ic}$, which equals 1 for all prefecture-industry observations in prefectures that (i) do not have universities themselves, and that (ii) share a border with a prefecture that houses a university.

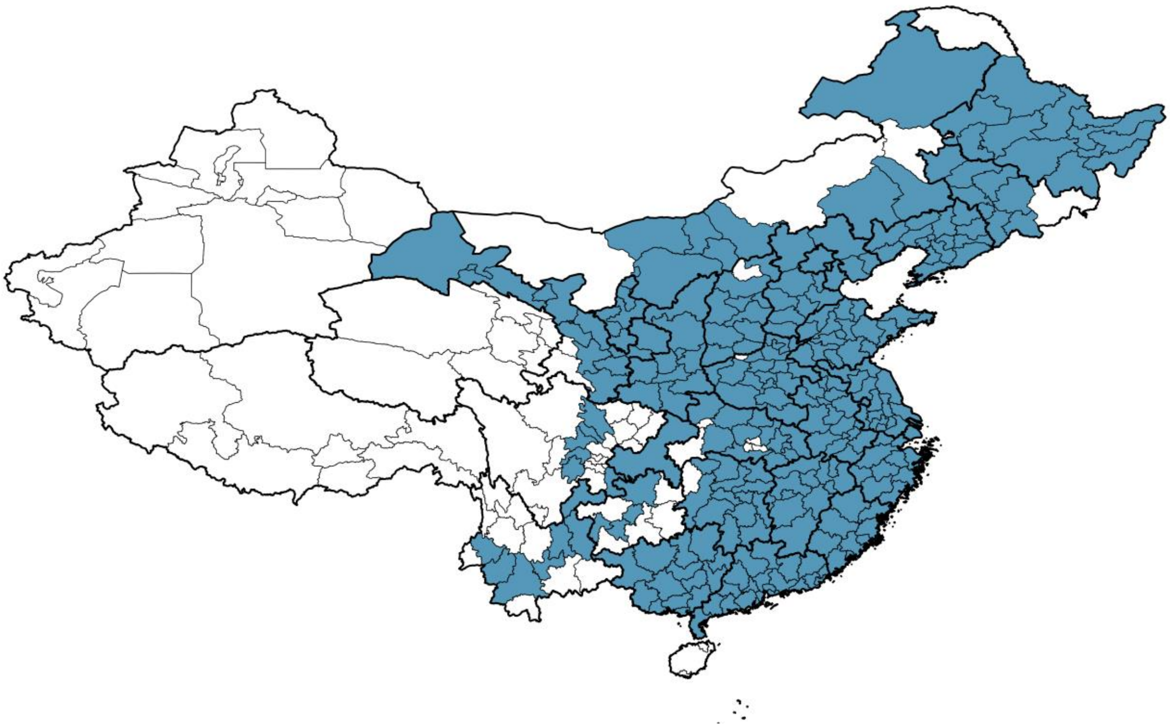
4.1.4. Spatial area under investigation

This thesis takes a geographical perspective and uses Chinese prefectures as level of analysis. The prefectural-level constitutes the second level of administrative divisions of the PRC. From the top to lower levels of division, China's administration is divided in provinces[17], prefectures, counties, townships, and villages. The prefectural level consists of 293 prefecture-level cities (dìjíshì), 8 prefectures (dìqū), 30 Autonomous prefectures (zìzhìzhōu), and 3 leagues (méng). Most provinces are divided into prefecture-level cities are municipalities that were given the right to govern surrounding counties.

In 2018, there were 334 prefectural level divisions in the PRC (Figure 4.8). In practice, prefecture-level cities contain urban and rural counties and do not represent cities in the traditional sense. Only the provinces of Yunnan, Guizhou, and Qinghai and the autonomous regions Tibet and Xinjiang have autonomous prefectures, leagues and prefectures as additional second-level divisions. There are criteria that a prefecture must meet to become a prefecture-level city:

- An urban centre with a population over 250,000;
- Value of gross industry output of RMB 200 million (USD 56 million in 2016 purchasing power parities);
- Industry share of GDP of at least 35%.

Figure 4.1. Area under investigation and its regional division



Note: Darker areas show geographical areas under investigation. Borders in bold represent boundaries of provinces while thin border show boundaries of prefectures.
Source: DIVA-GIS (Geodata)

There are several advantages of prefecture-level data over country and province-level data that have been used in analysis of patent activity in China so far. First, prefecture-level data provides a detailed picture of the distribution of patenting activity in China. Patent activity is concentrated in selected cities across China's geography (e.g. Crescenzi et al., 2012), which more aggregate statistics at the country-level do capture. There is also considerable within-province variation of patenting activity in China. This is related to the fact that Chinese provinces are comparable in size to European countries where the biggest Chinese province in terms of population, Guangdong, had a population of 104 million in 2018. Second, statistics on region and industry characteristics is readily available at the prefecture-level for the period under study as the NBS has collected data on GDP and other economic aggregates since the early 1990s. And third, the geographical information on prefectures including geographical latitude and longitude coordinates is readily available for spatial modelling and analysis.

Data on lower levels of geographical aggregation would be preferable to prefecture-level data to account for the localised nature of patent activity. However, county-level information on region and industry characteristics is not available for the period under study.

4.1.5. Industries under investigation and delineation of technology-intensity of industries

I use 30 three digit-level industries according to the Industrial Classification for National Economic Activities (hereafter called Chinese Industry Classification or CIC Rev. 2002) for the empirical analysis. The CIC is a standard classification of economic activity in China that is comparable to the Standard International Industrial Classification (SITC). The 2002 re-classification is accounted for following the concordance scheme developed by Brandt et al. (2012) (see Table A2 in the appendix). The industrial census provides information on secondary industries that consist of mining (class B), manufacturing industries (class C), and utilities. For the purpose of the empirical analysis, my thesis focuses on manufacturing industries as defined by the 1-digit CIC Rev. 2002 class C, which results in a sample of 30 three-digit CIC Rev. 2002 level industries. Mining and utilities are excluded because they are dominated by state-owned enterprises and have not seen the same level of market-driven reforms as manufacturing industries, which might influence my results for impacts of university research on business innovation and productivity.

In line with Hatzichronoglou (1997), CIC industries are classified according to their technology intensity. This is an internationally comparable classification developed by the OECD that classifies technology intensity of industries using data on their R&D-intensity. R&D-intensity is defined as the share of R&D expenditures in value added of the industry. The classification distinguishes between high technology-intensive industries, medium-high technology-intensive industries, medium-low technology intensive industries, and low technology-intensive industries. Figure 4.9 shows the three-digit CIC Rev. 2002 level industries used for my analysis and their classification according to technology-intensity.

Table 4.2. List of analysed manufacturing industries and their technology-intensity

CIC 3-digit code	Name	Technology intensity
C13	Processing of food from agricultural products	Low-tech
C14	Foods	Low-tech
C15	Beverages	Low-tech
C16	Tobacco	Low-tech
C17	Textiles	Low-tech
C18	Textile wearing apparel	Low-tech
C19	Leather, fur, and feather	Low-tech
C20	Processing of timber	Low-tech
C21	Furniture	Low-tech
C22	Paper and paper products	Low-tech
C23	Printing, and reproduction of recording	Low-tech
C24	Articles for culture and education	Low-tech
C25	Processing of petroleum and coking	Medium-low-tech
C26	Chemical raw materials	Medium-high-tech
C27	Medicines	High-tech
C28	Chemical fibres	Medium-high-tech
C29	Rubber	Medium-low-tech
C30	Plastics	Medium-low-tech
C31	Non-metallic mineral products	Medium-low-tech
C32	Smelting and processing of ferrous metals	Medium-low-tech
C33	Smelting and processing of non-ferrous metals	Medium-low-tech
C34	Metal products	Medium-low-tech
C35	General purpose machinery	Medium-high-tech
C36	Special purpose machinery	Medium-high-tech
C37	Transport equipment	Medium-high-tech
C39	Electrical machinery and equipment	Medium-high-tech
C40	Communication equipment	High-tech
C41	Measuring instruments	High-tech
C42	Artwork	Low-tech
C43	Recycling and disposal of waste	Low-tech

Note: Industry information is based on the 3-digit CIC Rev. 2002. Technology intensity corresponds to the OECD classification for technology intensity of industries (Hatzichronoglou, 1997).
Source: National Bureau of Statistics of China (2018).

4.1.6. Descriptive statistics

The descriptive statistics, reported in Table 4.3, reveals that the mean annual level of the total factor productivity (TFP) index across prefecture-industries was 0.09. The standard deviation of 0.46 reveals a high variation in TFP levels across prefectures and industries in China during the period 1998 to 2007. A more intuitive metric to quantify productivity differences is labour productivity, or value added per worker. The mean level of labour productivity stood at 200 RMB per worker (in 1998 prices) per year in the sample of industrial enterprises under study. The lowest labour productivity observed was -440 RMB in the industry “Manufacturing of chemical fibres” in Kunming, Yunnan province, in 1998. The highest level stood was 4,072,130 RMB per worker in the industry “Processing of petroleum, coking, and processing of nuclear fuel” in Zhaoqing, Guangdong province, in 2006. Among the ten most productive prefecture-industries during the period 1998 to 2007 is the pharmaceutical industry in Suzhou, Jiangsu province. The mean annual number of industry SIPO patents across prefectures and industries was 1.24. The mean annual number of industry patent stocks is somehow higher with 3.12, reflecting the number of accumulated patent stocks over time. There was substantial variation in patent numbers across prefectures and industries in China. While 5,744 prefecture industries recorded no patent activity, the manufacturing industry "Communication equipment, computers and other electronic equipment" in Shenzhen in the year 2007 had the highest number of SIPO patents observed (8,255 patents).

The average prefecture had 14.96 patents during the period 1998 to 2007. As with industry patents, there was considerable variation in numbers of university patents across prefectures. The prefecture with highest number of university patents was Beijing with 2,575 patents in 2007. The mean distance to the nearest university, as measured in kilometres (km) from industry location to the prefecture centre where the university is located, was 62 km. The median distance to the nearest university was 46 kilometres. The sample also shows considerable differences across prefectures in terms of population size. The highest annual population size reported is 32.35 million inhabitants for Chongqing in 2007, against the lowest level of 0.14 million inhabitants for Jiayuguan, Gansu province, in 1998. Similarly, Chinese prefectures differed with regard to number of students enrolled in higher education, GDP per capita, investment, shares of employment in manufacturing, and shares of self-employed, as shown in Table 4.3.

Table 4.3. Descriptive statistics

	Number of observations	Mean	Standard deviation	Min.	Max.
Prefecture-industry level variables					
Total factor productivity index (according to Caves et el., 1982)	20,866	0.09	0.46	-5.24	7.25
Total factor productivity index (according to Olley and Pakes, 1996)	27,100	7.10	1.53	-1.85	14.26
Labour productivity in 1,000 RMB	27,911	0.20	22.78	-0.44	3,806.18
Number of industry SIPO patents	62,670	1.24	51.34	0.00	8,255.00
Number of industry SIPO patent stocks	62,670	3.12	119.52	0.00	21,859.56
Number of university SIPO patents	62,670	14.96	94.54	0.00	2,575.00
Number of university SIPO patent stocks	62,670	32.88	213.79	0.00	5476.17
Number of SIPO patents of foreign-owned enterprises	62,670	0.30	11.66	0.00	1,617.00
Number of SIPO patent stocks of foreign-owned enterprises	62,670	0.74	26.80	0.00	4,174.84
Distance to nearest university in kilometres	62,662	62.60	84.22	0.00	788.60
Prefecture-level variables					
Number of population in 1,000 inhabitants	62,662	4,175.42	2,461.99	142.90	32,353.20
Number of students in secondary education in 1,000 students	62,662	269.09	174.97	7.70	2,305.10
Number of students in tertiary education in 1,000 students	62,662	40.70	88.71	0.09	778.37
Gross domestic product per capita in 1,000 RMB at 1998 prices	62,662	13,258.40	18,651.10	1,473.80	29,388.50
Investment in machinery and equipment in RMB million at 1998 prices	62,662	10,219.92	15,258.10	209.39	186,878.00
Foreign direct investment in RMB million at 1998 prices	62,653	273.34	690.55	0.00	7,020.57
Share of employees in manufacturing industries in prefectural workforce	62,662	0.25	0.14	0.01	0.86
Share of employees in service industries in prefectural workforce	62,662	0.42	0.17	0.01	0.87
Share of self-employed in prefectural workforce	62,662	0.08	0.07	0.00	0.10
Full sample	62,670				
Number of years	10				
Number of industries	30				
Number of prefectures	261				

Note: The unit of observation is prefecture-industry. Industry information is based on the 3-digit CIC Rev. 2002.
Source: National Bureau of Statistics (2008), He et al. (2017), European Patent Office (2017), and International Association of Universities (2017).

4.2. Empirical methodology

The following Subsection presents the empirical methodology to estimate the effects of university spillover on industrial TFP and patent activity. For a general overview of the methodology and its theoretical underpinning, see Section 3.1.

4.2.1. Assessing the relationship between university research and industry performance

A first approach to empirically test the long-run relationship between university research and industrial innovation and productivity is to regress (i) the logarithm of annual industrial TFP levels and (ii) the logarithm of industrial SIPO patent stock numbers on the 5-year lagged logarithm of university SIPO patent stock numbers as follows:

$$\ln\left(tfp_{ict}\right) = \alpha_1 + \beta_1 \ln\left(k_{ct-5}\right) + X_{ct-5}\gamma_1 + \eta_{1i} + \tau_{1ct} + \varepsilon_{1ict} \tag{14}$$

and

$$\ln\left(p_{ict}\right) = \alpha_2 + \beta_2 \ln\left(k_{ct-5}\right) + X_{ct-5}\gamma_2 + \eta_{2i} + \tau_{2ct} + \varepsilon_{2ict} \tag{15}$$

where ln(tfp_{ict}) in Eq. (14) corresponds to the logarithm of industrial TFP levels of industry i and prefecture c at time t, and ln(k_{ct-5}) stands for the lagged logarithm of university patent stocks in prefecture c at time t-5 plus 1 to include observations where there are no university patents. Following Valero and Van Reenen (2019), the model uses the 5-year lag to account for the effect that university research is unlikely to have an immediate impact on productivity.[18]

I control for several prefecture-level characteristics X_{ct-5} that may be related to TFP growth and the growth in university patenting, in particular the lagged log level of population because increases in university patenting may simply reflect greater demand due to population levels (Valero and Van Reenen, 2019). Two measures of human capital are included, notably the lagged log number of students enrolled in secondary education, and the lagged log number of students enrolled in tertiary education in order to control for the effects that university education may have on prefectural productivity. Further, the lagged log level of prefectural GDP per capita is controlled for because changes in productivity and university patenting may reflect changes in levels of economic development. To account for investment dynamics, which might drive investment in R&D and productivity, the lagged log of investment and the lagged log of foreign direct investment (FDI) are included. Differences in economic structure of prefectures are accounted for by including the lagged share of employees in manufacturing in total prefectural workforce, and the lagged share of employees in services in total prefectural workforce. To account for differences in entrepreneurship, which might be related to productivity and innovation, the lagged share of self-employed in total prefectural workforce is included. Finally, the lagged log of SIPO patent stocks of foreign-owned enterprises is regularly controlled for. Studies have shown that technology transfer from foreign-owned enterprises to the domestic economy, and joint ventures between Chinese enterprises and foreign-owned enterprises are important channels of knowledge transfer in China (e.g. Jiang, 2018).

The other variables in Eq. (14) are as follows: μ_{1i} describes industry fixed effects that capture time-invariant differences across industries whose omission could bias the estimates, and τ_{1ct} stands for prefecture-year fixed effects that capture differences across prefectures and annual trends that affect all prefectures. The inclusion of fixed effects controls for industry, prefecture and time variation that is exogenous to my model. Finally, ε_{1ict} captures the residual terms that vary across industries *i,* prefectures *c* and years *t* with zero mean and variance σ .

Eq. (15) uses $\ln(p_{ict})$ as the outcome variable, which corresponds to the log of annual numbers of patent stocks of industry *i* and prefecture *c* at time *t*. As in Eq. (14), $\ln(k_{ct-5})$ stands for the lagged log of university patent stocks in prefecture *c* at time *t*-5 plus 1 to include observations where there are no university patents. Further, a host of prefecture-level characteristics X_{ct-5} is controlled for. As before, prefecture fixed effects μ_{2i} capture differences across industries, and prefecture-year fixed effects τ_{2ct} capture differences across prefectures and annual trends. As before, ε_{2ict} is the residual term that vary across industries *i,* prefectures *c* and years *t* with zero mean and variance σ .

4.2.2. Accounting for geographical spillovers

My baseline estimation strategy, shown in Eq. (14) and (15), does not account for geographical spillover from university research across prefectural borders. From a methodological point of view, the estimation of productivity and innovation effects using ordinary least square (OLS) regression analysis depends on the critical assumption that observations of productivity and innovation are randomly distributed across space. If they are not randomly distributed, we speak of spatial autocorrelation, i.e. observations of productivity and innovation in prefecture *c* depend on observations of productivity and innovation in prefectures *d*. If left unaccounted for in the model, spatial autocorrelation will enter the error terms and bias my regression estimates (Cliff and Ord, 1969; LeSage and Pace 2009). As empirical studies have shown, productivity growth and industrial patent growth in a given prefecture depend on productivity and innovation in surrounding prefectures via cross-regional knowledge spillovers (e.g. Scherngell et al., 2014; Fischer et al., 2009; Fischer and Varga, 2003; Anselin, Varga, and Acs, 1997).

I also explore the extent to which (i) changes in industrial TFP and (ii) changes in industrial patent stocks in prefecture *c* may be affected by changes of university patent stocks in other prefectures in China. The estimating equations (14) and (15) are extended to include the growth of the log of university patent stocks in other prefectures, which may be all other prefectures or the nearest prefectures. In doing so, the equation includes the log of prefecture *c*'s own lagged university patent stock $\ln(k_{ct-5})$, as well as spillovers from the lagged log of university patent stocks $\ln(k_{dt-5})$ in neighbouring prefectures d=1, ..., M-1. Drawing on the conceptual reduced-form relationship between firm productivity and university knowledge capital as derived in Eq. (6), annual TFP levels are regressed on the logarithm of annual university patent stocks in year t for c, d = 1, ..., M = 261 prefectures and t = 1, ..., T = 10 years as follows:

$$\ln\left(tfp_{ct}\right)=\rho_3 W_{cd}\ln\left(tfp_{dt-5}\right)+\beta_3\ln\left(k_{ct-5}\right)+\delta_3 W_{cd}\ln\left(k_{dt-5}\right)+X_{ct}\gamma_3+\phi_{3c}+\tau_{3t}+\varepsilon_{3ct} \tag{16}$$

where ln(tfp_{ct}) corresponds to annual TFP levels of prefecture c at time t, while ln(k_{ct-5}) stands for the 5-year lagged log of university patent stocks of prefecture c at time t-5. W is the non-stochastic, time-invariant spatial weights matrix with weights w_{cd} that reflect the geographical proximity between prefectures $c = 1, \ldots, M$ and $d = 1, \ldots, M-1$. Wln(k_{dt-5}) is the average of the spatially lagged log of university patent stocks in all other prefectures $d = 1, \ldots, M-1$ at time t-5. According to spatial econometrics literature (e.g. LeSage and Pace 2009), spatially autocorrelated productivity growth across prefectures is controlled for: Wln(tfp_{dt-5}) is the average of the spatially lagged TFP levels in all other prefectures $d = 1, \ldots, M-1$, and ρ_3 is the spatial autoregressive coefficient that measures the strength of the spatial autoregressive relationship between prefectural productivity levels. ϕ_{3c} describes prefecture fixed effects that capture differences across prefectures, and τ_{3t} captures year fixed effects that capture time-specific shocks that affect all prefectures. The inclusion of fixed effects controls for prefecture and time variation that is exogenous to the model. Finally, ε_{3ct} captures the residual terms that vary across prefectures c and years t with zero mean and variance σ .

The relationship of interest is captured by the coefficient β_3 that denotes how changes in industrial TFP levels relate to changes in levels of university patent stocks in the same prefecture, once fixed effects and prefecture-level characteristics are considered. Another coefficient of interest is δ_3 that denotes how changes in the log of university patent stocks of other prefectures d relate to changes in TFP of prefecture c. Eq. (16) accounts for spatial dependence in patenting by including spatial lags of industrial TFP levels and university patent stocks.

For estimating the relationship between industrial patent activity and university patent activity, this chapter draws on the conceptual reduced-form relationship between industrial knowledge capital and university knowledge capital as derived in Eq. (8). The logarithm of annual industrial patent stocks is regressed on the logarithm of annual university patent stocks for c, $d = 1, ..., M = 261$ prefectures and $t = 1, ..., T = 9$ years as follows:

$$\ln\left(p_{ct}\right)=\rho_4 W_{cd}\ln\left(p_{dt-5}\right)+\beta_4\ln\left(k_{ct-5}\right)+\delta_4 W_{cd}\ln\left(k_{dt-5}\right)+X_{ct-5}\gamma_4+\phi_{4c}+\tau_{4t}+\varepsilon_{4ct} \tag{17}$$

where ln(p_{ct}) corresponds to the logarithm industrial patent stocks of prefecture c at time t, while – as above, ln(k_{ct-5}) stands for the log of university patent stocks of prefecture c at time t-5. Following the notation above, W is the spatial weights matrix with weights w_{cd} that reflect the geographical proximity between prefectures $c = 1, \ldots, M$ and $d = 1, \ldots, M-1$. Wln(k_{dt-5}) is the average of the spatially lagged log of university patent stocks in all other prefectures $d = 1, \ldots, M-1$ at time t-5, and $W\ln(p_{dt-5})$ is the average of the spatially lagged industrial patent stocks in all other prefectures $d = 1, \ldots, M-1$. ϕ_{4c} describes prefecture fixed effects, and τ_{4t} captures year fixed effects. ε_{4ct} is the residual term. The augmented model in Eq. (17) accounts for spatial dependence in patenting by including spatial lags of industrial patent stocks and university patent stocks.

4.2.3. Assessing impacts of university reforms

As a result of university IPR reforms in 2002, patent activity of universities increased significantly. To identify potential effects of university IPR reforms on industry innovation and productivity, the analysis uses a difference-in-difference approach to estimate changes in levels of industrial TFP and patent stock numbers after policy reforms in 2002. Increased university patenting is assumed to be the channel linking university reforms to increased industry patenting and productivity.

One important issue for the identification of effects of university reforms, however, is endogeneity of university locations. Endogeneity issues arise if the location of universities is correlated with good local economic conditions that also stimulate productivity and innovation. For instance, a positive local economic shock, leading to increased industrial innovation and productivity, might have increased the demand for university research at the time of university reforms. To account for possible endogeneity of university locations, the sample of industry is restricted to locations outside of 20 kilometres distance from a university. Therefore, the identification strategy rests on the assumption that reforms to the policy framework for university IPR affected locations outside of university cities.

I define a proximity to university dummy variable, $PROXIMITY_{ic}$, which equals 1 for all prefecture-industry observations outside of 20 km distance to the nearest university. A post university-reform dummy variable is also defined, $POST_t$, which equals 1 for all years after 2002, the year of introduction of the reforms. The difference-in-difference estimation model for TFP regresses annual levels of TFP, tfp_{ict}, on the interaction of the post university-reform dummy with the proximity to university dummy $POST_t$ x $PROXIMITY_{ic}$ for $i = 1, \ldots, N = 30$ *industries,* $c = 1, \ldots, M = 261$ prefectures, and $t = 1, \ldots, T = 10$ years as follows:

$$\ln\left(tfp_{ict}\right) = \alpha_1 + \beta_1 POST_t \times PROXIMITY_{ct} + X_{ct}\gamma_1 + \eta_{1i} + \tau_{1ct} + \varepsilon_{1ict} \tag{18}$$

where the dependent variable $\ln(tfp_{ict})$ captures the logarithm of annual levels of industrial TFP. Several terms on the right-hand side are of special interest. The coefficient β_1 of the term $POST_t$ x $PROXIMITY_{ic}$ will indicate whether TFP levels outside of 20-kilometre distance from a university experienced a significant increase after 2002, the year of the policy reforms. If the reforms led to stronger university patenting over time, and these patents supported industrial productivity via geographical spillovers, one would expect this coefficient to be positive and significant. Further, X_{ct} captures control variables that describes prefecture-level characteristics and economic conditions that prevail in a given prefecture c at time t, that if omitted might bias the estimates on the effects of university reforms. First, a control for the population size of the prefecture is included, i.e. the log of population of the prefecture in thousand inhabitants. control variables to capture human capital in the prefecture are also included, notably the number of students enrolled in secondary education, and the number of students enrolled in tertiary education. In addition, the log level of investment in machinery in equipment, and log levels of FDI are controlled for. This is in line with research that studied firm growth in the developing country (Ghani, Kerr, and O'Connell, 2014). To control for demand side conditions that drive productivity levels, the log levels of prefectural GDP per capita is included. Finally, differences in the economic structure of the prefecture are controlled for, including the share of employment in manufacturing industries in prefectural employment, the share of employment in service industries in prefectural employment, and the share of self-employed in the prefectural labour force to control for entrepreneurial drive of the prefecture. η_{1i} denotes industry fixed effects that measure unobserved differences across industries, and τ_{1ct} denote prefecture-year fixed effects that control for unobserved differences across prefectures and annual time trends. ε_{1ict} captures the residual terms that vary across prefectures and time periods with zero mean and variance σ^2.

Similarly, a difference-in-difference estimation model is used for industry patent stocks and regress annual levels of industrial patent stocks, p_{ict}, on the interaction of the post university-reform dummy with the proximity to university dummy $POST_t$ x $PROXIMITY_{ic}$ for $i = 1, ..., N = 30$ industries, $c = 1, ..., M = 261$ prefectures, and $t = 1, ..., T = 10$ years as follows:

$$\ln\left(p_{ict}\right) = \alpha_2 + \beta_2 POST_t \times PROXIMITY_{ct} + X_{ct}\gamma_2 + \eta_{2i} + \tau_{2ct} + \varepsilon_{2ict} \tag{19}$$

where the dependent variable p_{ict} denotes the logarithm annual levels of industrial patent stocks. As in Eq. (18), the main interest for the hypothesis is the term $POST_t$ x $PROXIMITY_{ic}$. The corresponding coefficient β_2 indicates whether industry patent stocks outside of 20-kilometre distance from a university experienced an increase after policy reforms in 2002. X_{ct} captures control variables for prefecture-level characteristics. η_{2i} denote industry fixed effects that measure unobserved differences across industries, and τ_{2ct} denote prefecture-year fixed effects that control for unobserved differences across prefectures and annual time trends. ε_{2ict} captures the residual terms that vary across prefectures and time periods with zero mean and variance σ^2.

Additional analysis tests for differential impacts of university reforms across industries by estimating the difference-in-difference estimation models in Eq. (18) and Eq. (19) separately by (i) ownership type, (ii) technology-intensity of industry, and (iii) new entrants and incumbent enterprises. Studies that use proximity-based identification approaches include Becker and Wössmann (2009), Cantoni and Yuchtman (2014), and Toivanen and Väänänen (2016).

4.3. Descriptive analysis

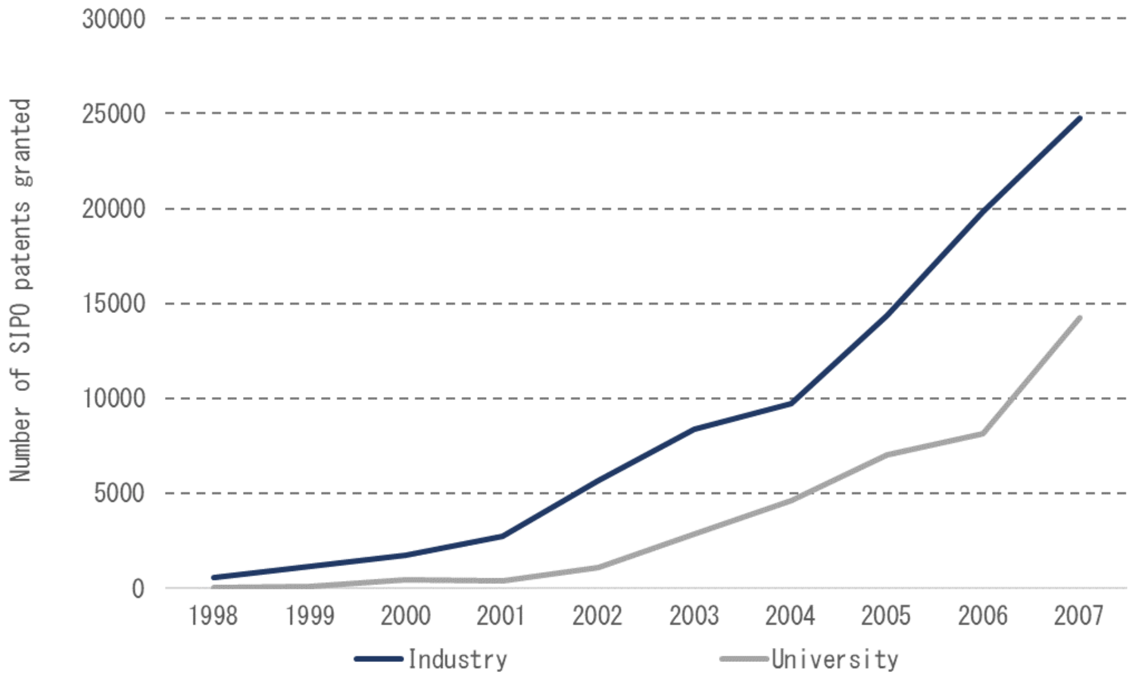
4.3.1. University patenting and industry performance

Figure 4.9 illustrates the evolution of industry and university SIPO patent counts between 1998 and 2007. It shows that the numbers of industrial patents and those of university patents increased significantly since 1998. The sample reports 527 industry patents in 1998, which increased to 24,757 industry patents in 2007. The number of university patents increased from 52 in 1998 to 14,255 in 2007. One finding that strikes out is that universities contributed significantly to increases in total patent numbers in China. The sample shows that between 1998 and 2007, Chinese universities produced 38,930 patents out of a total of 127,840 patents (or 30%) in the sample, against 88,910 patents in the industrial sector (or 70%).

These findings support existing studies that reported similar increases in the number of industry and university patents for China (He et al. 2018; Fisch et el., 2016; Dang and Motohashi, 2005). He et al. (2018) use Chinese patent-industrial census linked data and document 170,420 patents of industrial enterprises between 1998 and 2007, against 127,840 reported in the sample used for this study. The difference stems from the different sample size of industrial enterprises. In this study, the sample accounts for enterprise restructuring and firm exit, which leads to a smaller sample, whereas He et al. (2018) do not account for firm restructuring and firm exit. In a related study, Dang and Motohashi (2015) match industrial census data to SIPO patent data and report 126,386 patent applications of industrial enterprises for the same period, which is similar to the number reported in this study. However, the authors report 12,208 patent holding enterprises, which is higher than the 11.388 enterprises reported in this study. As for university patents, Fisch et al. (2016) report 41,064 patents from 1991 until 2009, compared to 38,930 university patents from 1998 to 2007 reported here. Their sample consists of 155 universities, against a sample of 406 patent active universities in this study.

Figure 4.2. Number of industry and university SIPO patents

1998-2007

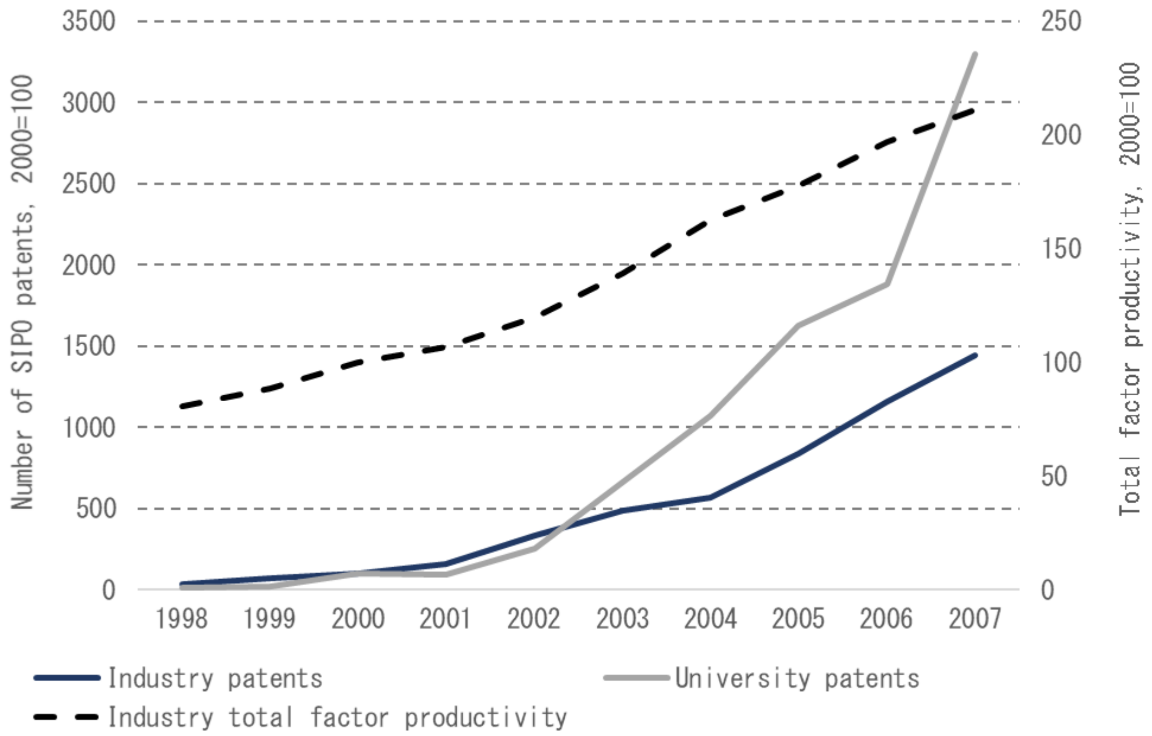


Note: The figure illustrates the number of SIPO patents granted to industrial enterprises (darker line) and universities (lighter line) between 1998 and 2007.
Source: Author's calculations based on National Bureau of Statistics (2008), He et al. (2017), European Patent Office (2017), and International Association of Universities (2017).

Figure 4.3 compares trends in patent numbers and total factor productivity levels between 1998 and 2007. 2000 is taken as the reference year with patent numbers and TFP levels set to 100 for easier comparison of trends over time. On the left vertical axis, we see that the numbers of industry patents increased 15-fold between 2000 and 2007, albeit from low initial levels. The increase in university patent numbers was even higher. Numbers of university patents grew more than 30-fold between 1998 and 2007. The positive trends in patent numbers are associated with a positive trend in TFP levels between 1998 and 2007. The right vertical axis shows that TFP levels of industrial enterprises doubled during this period, suggesting a potential association between patent activity and productivity.

Figure 4.3. Trends in TFP levels and SIPO patent numbers, 1998-2007

2000=100



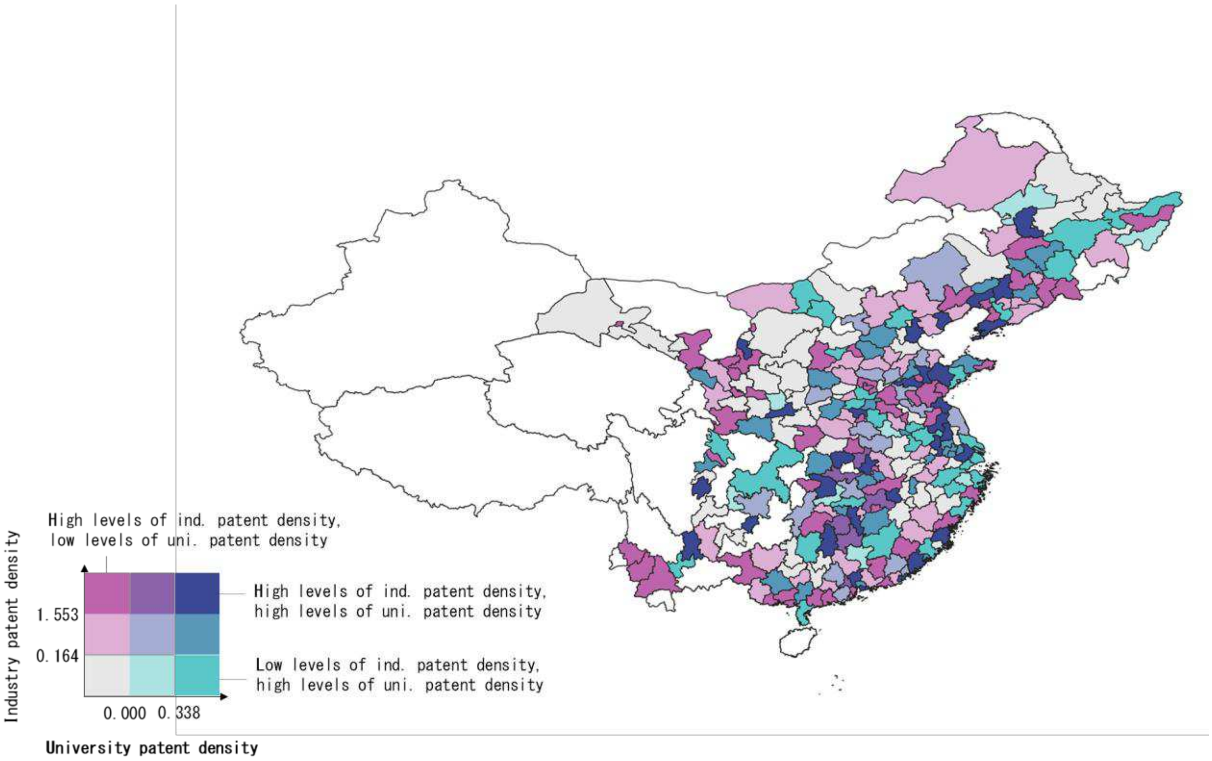
Note: The figure illustrates trends in levels of total factor productivity (calculated according to Caves et al., 1982) (black dashed line), numbers of SIPO patents of industrial enterprises (darker line), and numbers of SIPO patents of universities (lighter line) for the period 1998 to 2007. The left vertical axis shows the number of SIPO patents relative to the year 2000 (i.e. 2000=100), while the right vertical axis shows the level of total factor productivity relative to the year 2000 (i.e. 2000=100).
Source: Author's calculations based on National Bureau of Statistics (2008), He et al. (2017), European Patent Office (2017), and International Association of Universities (2017).

Figure 4.4 illustrates the relationship between the average number of university SIPO patents per million inhabitants (university patent density) and the average number of industry SIPO patents per million inhabitants (industry patent density) across Chinese prefectures for the period 1998 to 2007. While the area covered might seem small compared to the entire territory of China, the sample of prefectures analysed in this study represents 84.5% of the population of the PRC in 2007.[19] Darker shaded areas show prefectures with higher mean university patent density and higher mean industry patent density for the period 1998 to 2007. The top tercile of prefectures in terms of industry patent density and university patent density (dark blue) consist of 31 prefectures, with 17 prefectures being in five coastal provinces: Guangdong, Jiangsu, Liaoning, Shandong, and Tianjin. Another feature of China's geography of innovation – as measured by patent density, is that prefectures with higher values of patent density are bordering each other, including Dalian (Liaoning), Fuzhou (Fujian), Jinzhou (Liaoning), Shenzhen (Guandong), Guangzhou (Guandong), Huai'an (Jiangsu), Lianyungang

(Jiangsu), Nanjing (Jiangsu), Shantou (Guangdong), Shenyang (Liaoning), Suzhou (Jiangsu), Tai'an (Shandong), Tianjin, Weifang (Shandong), Yangzhou (Jiangsu), Zhangzhou (Fujian), and Zibo (Shandong). These prefectures form clusters of high patent density.

Figure 4.4. Industry patent density and university patent density by prefecture

1998-2007

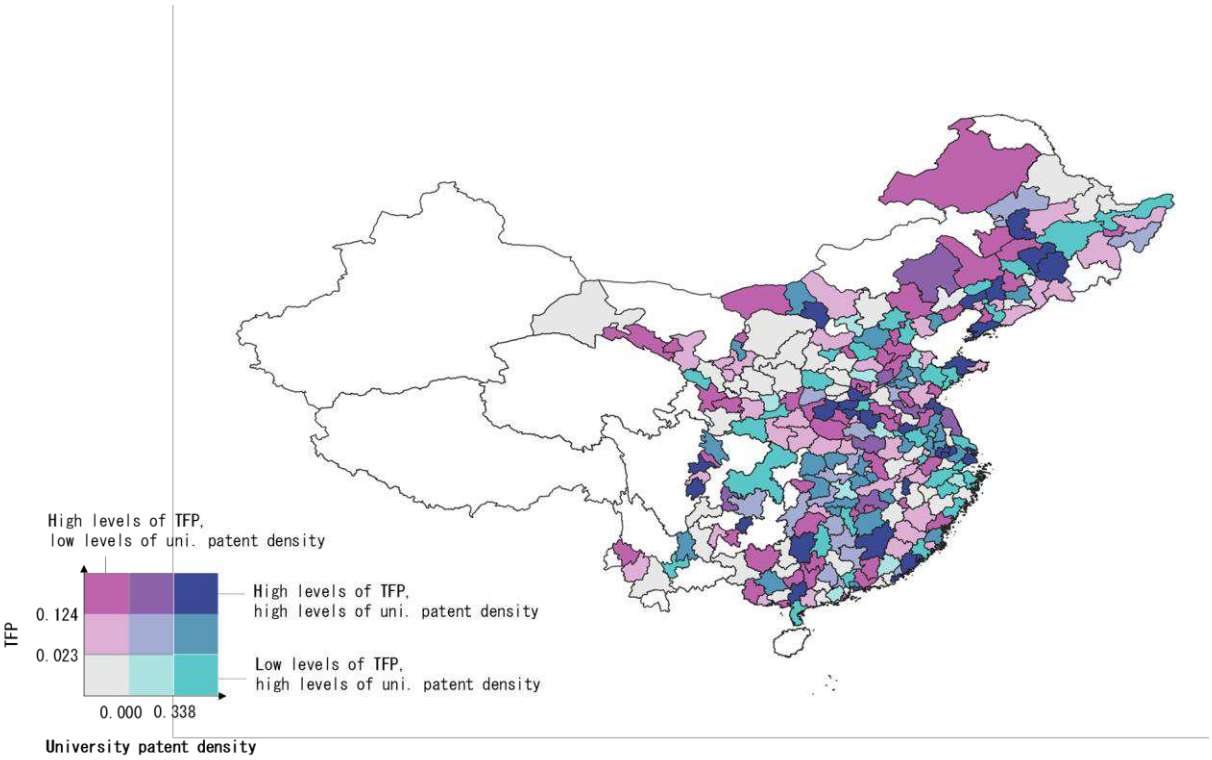


Note: The figure illustrates the relationship between numbers of SIPO patent stocks of industrial enterprises per million inhabitants (industry patent density) and numbers of SIPO patents of universities per million inhabitants (university patent density) by prefecture for the period 1998 to 2007. Darker areas show prefectures with higher industry patent density and higher levels of university patent density.
Source: Author's calculations based on National Bureau of Statistics (2008), DIVA-GIS (Geodata), He et al. (2017), European Patent Office (2017) and International Association of Universities (2017).

Figure 4.5 shows the relationship between average university patent intensities and average levels of industrial TFP by prefectures for the period 1998 to 2007. The data shows that the top tercile of prefectures in terms of TFP and university patent density (dark blue) consist of 29 prefectures, with 12 prefectures being in five provinces: Guangdong, Jiangsu, Liaoning, Shanghai, and Shandong. The top 12 prefectures are located along the coast. Another feature of China's geography of innovation is that prefectures with higher levels of TFP and higher values of patent density are bordering each other, including Changzhou (Jiangsu), Dalian (Liaoning), Jinzhou (Liaoning), Shenzhen (Guandong), Lianyungang (Jiangsu), Shanghai, Shantou (Guangdong), Shenyang (Liaoning), Wuxi (Jiangsu), Xiamen (Fujian), Yantai (Shandong), and Zhangzhou (Fujian). These prefectures form clusters of high patent density.

Figure 4.5. TFP levels and university patent density by prefecture

1998-2007

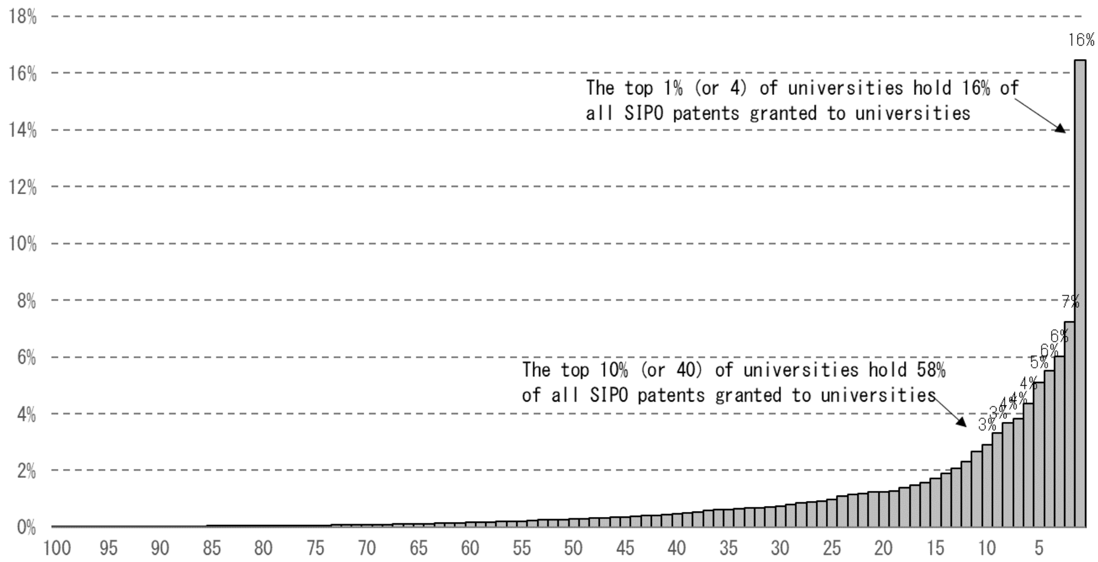


Note: The figure illustrates the relationship between levels of the total factor productivity (calculated according to Caves et al. 1982) and numbers of SIPO patent stocks of universities per million inhabitants (university patent density) by prefectures for the period 1998 to 2007. Darker areas show prefectures with higher levels of total factor productivity and higher levels of university patent density.
Source: Author's calculations based on National Bureau of Statistics (2008), DIVA-GIS (Geodata), He et al. (2017), European Patent Office (2017) and International Association of Universities (2017).

University patents were concentrated among a few leading universities between 1998 and 2007, as shown in Figure 4.6. The sample of universities that held universities during this period consists of 406 institutions. The first decile, or the leading 40 institutions, accounted for 58% of all SIPO patent granted to Chinese universities between 1998 and 2007, while the first percentile, or the 4 leading institutions, held 16% of all SIPO patents granted to universities during that period.

Figure 4.6. Shares of SIPO patents by university percentiles

1998-2007



Note: The figure illustrates the share of patents held by the university percentile or below. For instance, the top percentile of universities (i.e. 4 universities) held 16% of all SIPO patents granted to universities, while universities in the lower 99 percentiles held 84% of all university SIPO patents.
Source: Author's calculations based on European Patent Office (2017) and International Association of Universities (2017).

Table 4.4 lists the leading 10 universities in terms of SIPO patent number between 1998 and 2007. The data suggest that a few leading universities account for the increase in total numbers of university patents in China, including prestigious universities such as e.g. Tsinghua University and the Shanghai Jiao Tong University. Together, the ten leading institutions held 10,348 patents with application years between 1998 and 2007, which corresponded to 27% of all university patents in the sample during this period. This finding confirms evidence brought forward by Fisch et el. (2016) that suggests that Chinese policy efforts to create "world-class" universities during this period have strengthened the concentration of patent activity among leading institutions.

Table 4.4. Top ten universities by number of SIPO patents, 1998-2007

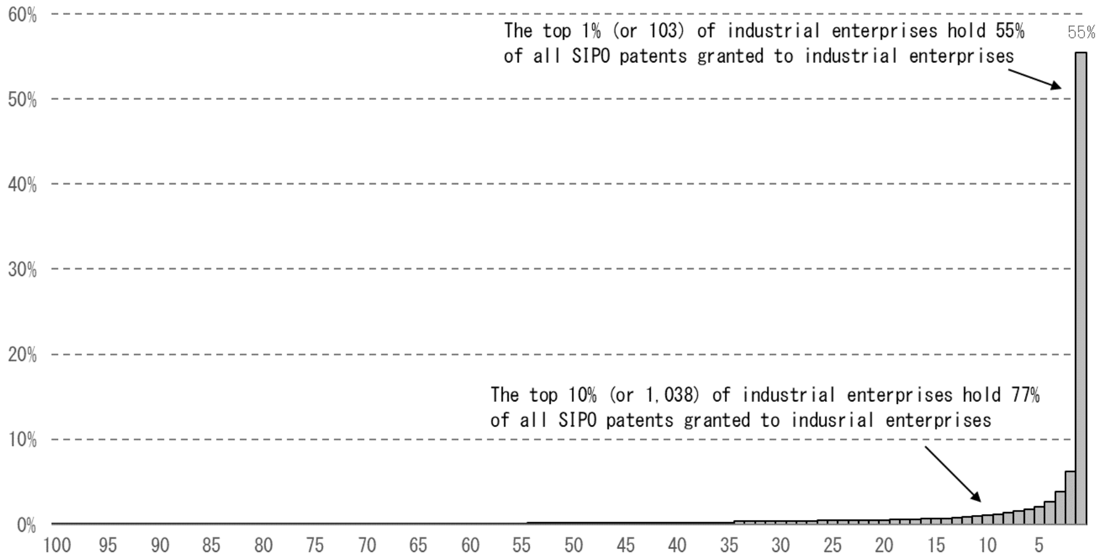
Rank	Number of SIPO patents granted	Name of university
1	1,963	Zhejiang University
2	1,949	Tsinghua University
3	1,433	Shanghai Jiao Tong University
4	1,010	Harbin Institute of Technology
5	894	South China University of Technology
6	653	Fudan University
7	633	Tianjin University
8	616	Kunming University of Science and Technology
9	611	Southeast University
10	586	University of Electronic Science and Technology of China

Source: Author's calculations based on European Patent Office (2017) and International Association of Universities (2017).

In Figure 4.7, we see high levels of concentration of patent counts among industrial enterprises. In total, the sample contains 10,388 enterprises that could be matched to patents (patent holding enterprises). Out of 10,388 enterprises, the leading 103 industrial enterprises in terms of SIPO patent numbers, or the top 1% of enterprises, accounted for 55% of all SIPO patents granted to industrial enterprises in China between 1998 and 2007. The top 10% of industrial enterprises (or 1,038 enterprises) held 77% of all industrial SIPO.

Figure 4.7. Shares of SIPO patents by enterprise percentiles

1998-2007



Note: The figure illustrates the share of patents held by the enterprise percentile or below. For instance, the top percentile of enterprises (i.e. 103 enterprises) held 55% of all SIPO patents granted to industrial enterprises, while enterprises in the lower 99 percentiles held 45% of all SIPO patents.
Source: Author's calculations based on National Bureau of Statistics (2008), He et al. (2017), and European Patent Office (2017).

Table 4.5 provides a list of the leading ten industrial enterprises, which includes known names such as e.g. Huawei, ZTE and Lenovo. These leading firms were the main drivers behind China's patent surge during the period 1998 to 2007. This data sheds light on the underlying distribution of patent activity, adding to a growing body of empirical evidence on Chinese innovation dynamics (e.g. Rong et al., 2017; Hu and Jefferson, 2009). Interestingly, 8 out of 10 leading enterprises belong to the communication equipment and computers industry. The two other enterprises are active in the automotive industry (BYD Company) and in the steel industry (Baoshan Iron and Steel).

Table 4.5. Top ten industrial enterprises by number of SIPO patents, 1998-2007

Rank	Number of SIPO patents granted	Name of industrial enterprise
1	14,524	Huawei Technologies
2	7,776	ZTE
3	2,602	LG Electronics (China)
4	3,475	Hongfujin Precision Industry
5	1,153	BYD Company
6	1,131	Lenovo
7	1,116	Semiconductor Manufacturing International
8	977	Shanghai Bell
9	823	Hangzhou Huasan Communication Technology
10	797	Baoshan Iron and Steel

Source: Author's calculations based on National Bureau of Statistics (2008), He et al. (2017), and European Patent Office (2017).

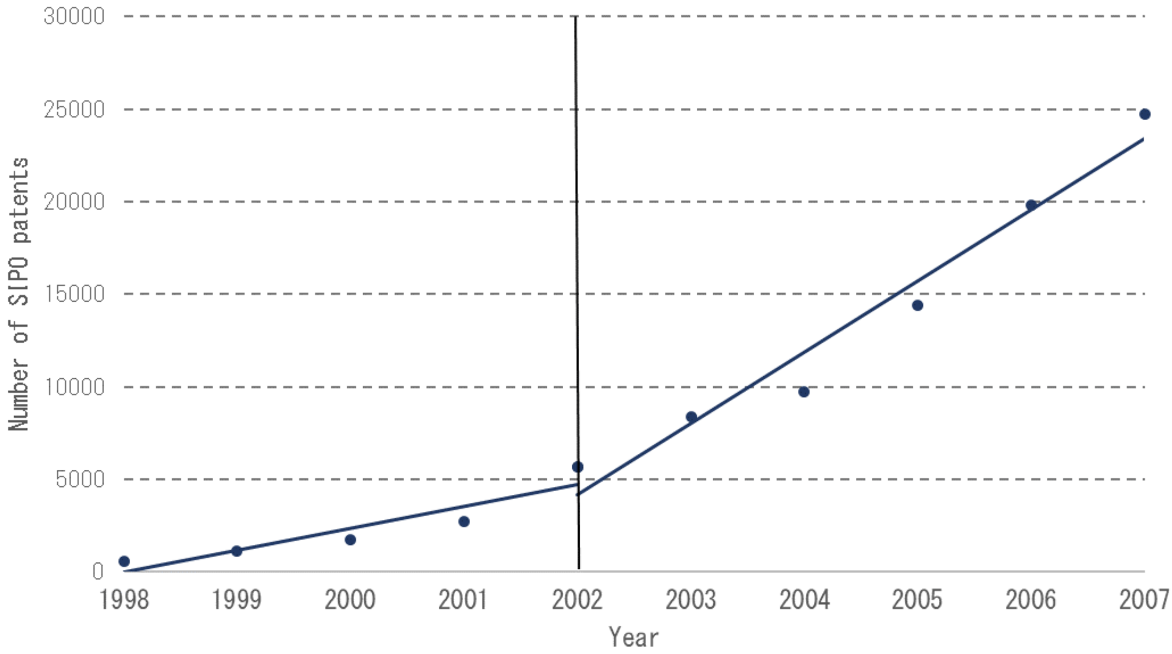
4.3.2. Numbers of industrial patents after university reforms

University IPR reforms introduced a unified institutional setting for ownership of university IPR across China's territory, with the aim to support licensing and patenting of university inventions and joint science-industry R&D collaboration. This Section documents changes in the numbers of industrial patents and university patents after university IPR reforms in 2002.

Table 4.8 presents data on the number of SIPO patents granted to industrial enterprises in the period 1998 to 2007. It shows a marked trend break in the number industry patents after 2002. Between 1998 and 2002, the number of SIPO patents held by industrial enterprises averaged 2,367 per year. The annual numbers of SIPO patents of industrial enterprises increased considerably after pro-technology transfer reforms in 2002: In the first five years after reforms, the average number of industry SIPO patents stood already at 15,415 per year.

Figure 4.8. Number of industry SIPO patents

1998-2007



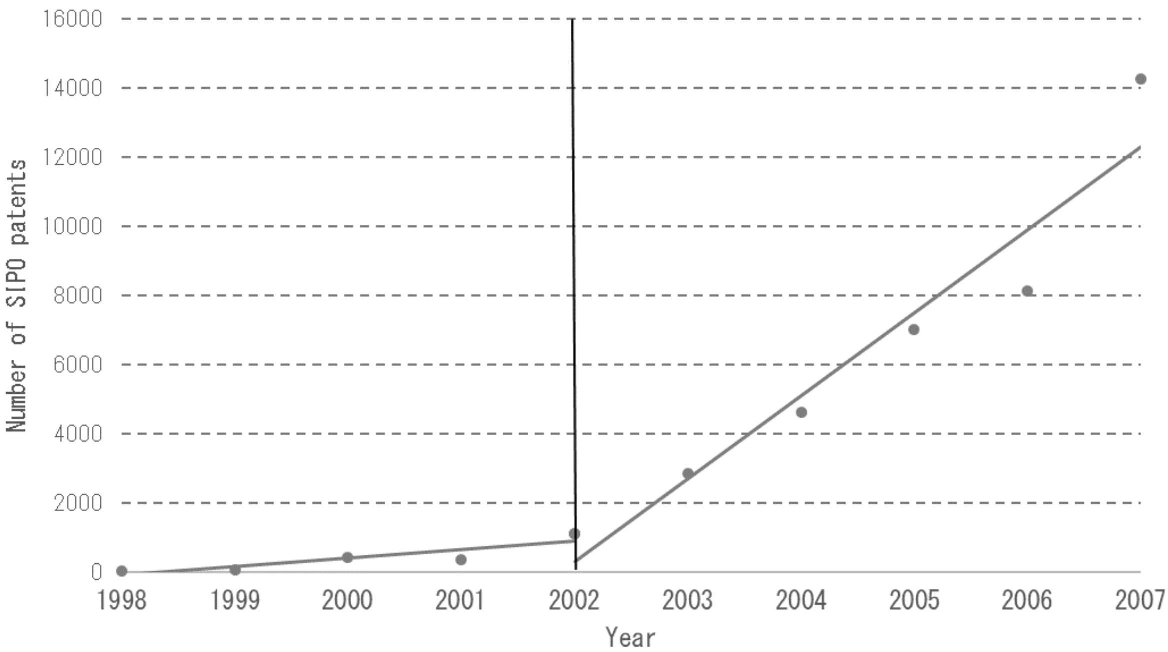
Note: The figure illustrates annual numbers of SIPO patents of industrial enterprises for the period 1998 to 2007. The trend lines compare the linear trend of annual patent numbers before and after reforms in 2002. The vertical line shows the year of university IPR reforms in 2002.
Source: Author's calculations based on National Bureau of Statistics (2008), He et al. (2017), and European Patent Office (2017).

There are several possible explanations other than the 2002 reform for the increase in patent numbers after 2002. One of them is that industrial patenting might have benefitted from earlier pro-IPR reforms in China. China adopted its first formal Patent Law in 1985 and reformed it in 1993 and 2000. In 1993, amendments to the Patent Law extended the scope of patent protection to include, among others, pharmaceutical products. In the same year, the Scientific and Technological Progress Law granted universities the right to license their patents and in 1996, the "Decisions on Enhancing Technological Innovation, Developing High Technology, and Realising Industrialisation" encouraged universities to improve the management of their IP transfer system with view to strengthen university patenting. In 2000, and in anticipation of China's accession to the WTO, amendments to the Patent Law strengthened the enforcement of IPR. Given these policy efforts, one would expect any effects on industrial patenting to materialise before 2002. As shown in Figure 4.8, the marked increase in the numbers of industrial patents happened only after 2002, suggesting that the 2002 reforms coincided with the patent surge.

An alternative explanation is that the increase in industrial patent activity might have been related to China's opening-up to world trade after the country's accession to WTO in 2001. During this period, previously protected industries faced a sudden increase in international competition. Studies show that increased import competition can lead to higher R&D, patenting, and TFP (e.g. Bloom, Draca and Van Reenen, 2016). This thesis brings forward evidence that increases in Chinese patent counts after 2002 were not confined to industry – the main beneficiary of China's WTO accession. In Figure 4.9, we see that the number of university SIPO patents increased considerably after university IPR reforms in 2002. In fact, the increase in the average annual number of Chinese patents was higher for universities than for industry. Between 1998 and 2002, the annual numbers of SIPO patents held by universities averaged 410 per year. In the period 2003 to 2007, the average number of university SIPO patents stood already at 7,376 per year.

Figure 4.9. Number of university SIPO patents

1998-2007

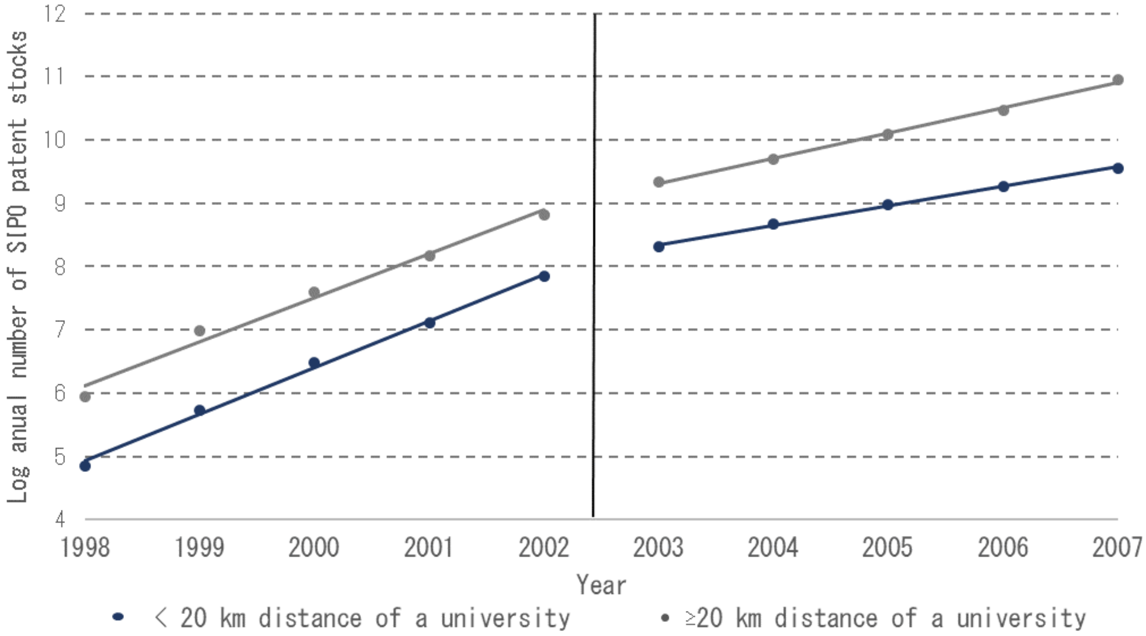


Note: The figure illustrates the annual numbers of SIPO patents of universities for the period 1998 to 2007. The trend lines compare the linear trend of annual patent numbers before and after reforms in 2002. The vertical line shows the year of university IPR reforms in 2002.
Source: Author's calculations based on European Patent Office (2017) and International Association of Universities (2017).

Figure 4.10 shows the trend in log mean numbers of industrial SIPO patent stocks before and after university IPR reforms by distance to university. It compares industrial patent activity in locations with less than 20 kilometres distance to the nearest university and patent activity in locations with 20 kilometres or more distance to the nearest university. While the two groups of locations show a similar positive trend in log numbers of industrial SIPO patent stocks before university reforms, their trends of patent numbers diverge after reforms in 2002. The parallel trend before reforms and the divergence in trends after reforms points to a potential role of university reforms for increases in industrial patent activity.

Figure 4.10. Trends in industry patent stock numbers by distance to university

1998-2007



Note: The figure illustrates the log annual numbers of SIPO patent stocks of 62,670 prefecture-industries (261 prefectures and 30 industries at the 3-digit CIC Rev. 2002 level) by their distance to nearest university for the period 1998 to 2007. Darker dots show observations of log annual numbers of industrial SIPO patent stocks within 20 kilometres distance of a university, while lighter dots show observations of log mean annual numbers of industrial SIPO patent stocks in 20 kilometres or more distance of a university. The trend line depicts the trend in log mean numbers of industrial SIPO patent stocks before and after university IPR reforms in 2002 by distance to university. The vertical line shows the year of university IPR reforms in 2002.
Source: Author's calculations based on National Bureau of Statistics (2008), He et al. (2017), European Patent Office (2017), and International Association of Universities (2017).

4.4. Empirical analysis of university patent activity and industry performance

4.4.1. The relationship between university patent stocks and industry performance

Table 4.6 summarises baseline estimation results of the reduced-form relationship between industrial TFP and 5-year lagged university patent stocks at the level of prefecture-industries as derived in Eq. 14. The findings in column (1) show the simple correlation between the logarithm of TFP and the lagged logarithm of university SIPO patent stocks. The results show that lagged university patent stocks are negatively associated with TFP, taking into consideration log levels of prefectural population. One source for the negative association might lie in annual trends which are not accounted for in column (1). Therefore, column (2) adds prefecture-year fixed effects and industry fixed effects. The inclusion of fixed effects changes the coefficient for university patent stocks, which becomes positive and significant. Column (3) includes additional controls for prefecture-level characteristics, which does not affect the main result: The coefficient of lagged university patent stocks remains positive and significant. The estimate suggests that a 1% increase in 5-year lagged university patent stocks is associated with a 2.5% increase in industrial TFP levels, irrespective of differences across prefectures, industries, and annual time trends.

The controls for prefecture-level characteristics turn out to be insignificant. Two things stand out. First, the number of students enrolled in secondary education and tertiary education turn out to be insignificant, suggesting that supply of human capital does not directly relate to industrial TFP growth at the prefecture-industry level. And second, the results reveal that lagged industry patent stocks and lagged patent stocks of foreign-owned industrial enterprises turn out to be insignificant as well. In other words, the evidence for the link between industry patent activity and productivity is weak, once university patenting is taken into consideration. Controlling for these additional factors, *hypothesis 1a* is confirmed: Higher industrial TFP levels coincide with higher 5-year lagged levels university SIPO patent stocks in the same prefecture.

Table 4.6. TFP on lagged university patent stock regression, 1998-2007

Dependent variable	ln(TFP)		
	(1)	(2)	(3)
Lagged ln(1+university SIPO patent stock)	-0.010* (0.004)	0.026** (0.009)	0.025** (0.009)
Lagged ln(population)	-0.008 (0.006)	0.017 (0.217)	0.053 (0.229)
Lagged ln(students in secondary education)			0.074 (0.069)
Lagged ln(students in tertiary education)			0.021 (0.018)
Lagged ln(GDP per capita)			0.005 (0.033)
Lagged ln(investment)			-0.005 (0.015)
Lagged ln(foreign direct investment)			-0.007 (0.007)
Lagged share of employment in manufacturing			-0.108 (0.059)
Lagged share of employment in services			-0.023 (0.035)
Lagged share of self-employed			0.007 (0.015)
Lagged ln(1+industry SIPO patent stock)			0.019 (0.021)
Lagged ln(1+SIPO patent stock of foreign-owned enterprises)			-0.009 (0.045)
Prefecture-year fixed effects	No	Yes	Yes
Industry fixed effects	No	Yes	Yes
Observations	17,370	17,370	17,260
σ-squared	0.001	0.005	0.005
R-squared	0.463	0.425	0.425
Adjusted R-squared	0.000	0.488	0.490
Log-likelihood	-11,263.040	-6,286.088	-6,252.689
Akaike information criterion (AIC)	22,532.079	12,584.176	12,537.379
Bayesian information criterion (BIC)	22,555.367	12,630.751	12,661.477
F-statistics	4.429	10.563	4.093
Degrees of freedom (df)	17,367	11,619	11,524

Note: OLS estimates for 261 prefectures, 30 industries at the 3-digit CIC Rev. 2002 level, and 10 years (1998-2007). Column (1) regresses the logarithm of TFP on the 5-year lagged logarithm of university SIPO patent stocks and controls for the 5-year lagged log level of population. Column (2) includes industry fixed effects and prefecture-year fixed effects. Column (3) adds controls for prefecture-level characteristics, the 5-year lagged logarithm of industry patent stocks (plus 1), and the 5-year lagged logarithm of SIPO patent stocks of foreign-owned industrial enterprises (plus 1). Standard errors are clustered at the prefecture level. Standard errors in parentheses. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels, respectively.
Source: Author's calculations based on National Bureau of Statistics (2008), He et al. (2017), European Patent Office (2017), and International Association of Universities (2017).

Table 4.7 summarises the results of the industry patent stock on lagged university patent stock regression at the level of prefecture-industries as derived in Eq. 15. Column (1) shows that industry patent stocks are positively associated with university SIPO patent stocks across prefecture-industries, irrespective of the level of population of the prefecture. Column (2) includes prefecture-year fixed effects and industry fixed effects to control for differences across prefectures, differences across industries and annual time trends. The coefficient for university SIPO patent stocks of remains positive and significant, although its magnitude reduces from 0.027 to 0.012. Column (3) adds a host of prefecture-level controls, which does not affect the positive and significant coefficient of university patent stocks. In terms of economic magnitude, a 1% increase in university patent stocks is associated with a 1% increase in industrial patent stocks between 1998 and 2007.

Regarding the controls for prefecture-level characteristics, the 5-year lagged log level of foreign direct investment is positive and significant. The results also show that the 5-year lagged log level SIPO patent stock of foreign-owned enterprises is positive and significant. This suggests that access to foreign technology and foreign investment matter for Chinese enterprises' patent activity, as expected. A downside to introducing the foreign-owned enterprises' patent stock variable is endogeneity because enterprise patent activity is explained with another variable of enterprise patent activity. The number of students in tertiary education (i.e. higher education), the number of students in secondary education, prefectural GDP per capita, investment in machinery and equipment, and the share of self-employed in the prefectural workforce turn out to be insignificant. Controlling for observable prefecture-level characteristics, and irrespective of differences across prefectures, industries, and annual trends, *hypothesis 1b* is clearly confirmed: Higher levels of industry SIPO patent stocks coincide with higher 5-year lagged university SIPO patent stocks in the same prefecture.

Table 4.7. Industry patent stock on lagged university patent stock regression, 1998-2007

Dependent variable	ln(1+industry SIPO patent stock)		
	(1)	(2)	(3)
Lagged ln(1+university SIPO patent stock)	0.027*** (0.006)	0.012*** (0.004)	0.010** (0.004)
Lagged ln(population)	-0.049*** (0.008)	0.345*** (0.081)	0.425*** (0.085)
Lagged ln(students in secondary education)			-0.046 (0.025)
Lagged ln(students in tertiary education)			0.004 (0.006)
Lagged ln(GDP per capita)			0.021 (0.011)
Lagged ln(investment)			-0.009 (0.006)
Lagged ln(foreign direct investment)			0.009** (0.003)
Lagged share of employment in manufacturing			-0.053* (0.022)
Lagged share of employment in services			-0.082*** (0.014)
Lagged share of self-employed			-0.004 (0.006)
Lagged ln(1+SIPO patent stock of foreign-owned enterprises)			0.211*** (0.018)
Prefecture-year fixed effects	No	Yes	Yes
Industry fixed effects	No	Yes	Yes
Observations	31,331	31,331	31,094
σ-squared	0.001	0.127	0.135
R-squared	0.894	0.280	0.280
Adjusted R-squared	0.001	0.092	0.083
Log-likelihood	-40,942.533	-1,115.838	-1,030.088
Akaike information criterion (AIC)	81,891.066	2,245.676	2,092.177
Bayesian information criterion (BIC)	81,916.123	2,304.143	2,225.693
F-statistics	23.184	606.752	258.213
Degrees of freedom (df)	31,328	25,058	24,837

Note: OLS estimates for 261 prefectures, 30 industries at the 3-digit CIC Rev. 2002 level, and 10 years (1998-2007). Column (1) regresses the logarithm of industry patent stocks (plus 1) on the 5-year lagged logarithm of university SIPO patent stocks and controls for the 5-year lagged log level of population. Column (2) includes industry fixed effects and prefecture-year fixed effects. Column (3) adds controls for prefecture-level characteristics and the 5-year lagged logarithm of SIPO patent stocks of foreign-owned industrial enterprises. Standard errors are clustered at the prefecture level. Standard errors in parentheses. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels, respectively.
Source: Author's calculations based on National Bureau of Statistics (2008), He et al. (2017), European Patent Office (2017), and International Association of Universities (2017).

In Table 4.8, different distributed lag structures are analysed in order to gain insights about the time lag of potential university effects. The results suggest that for industry patent stocks, the 5-year lag is a good approximation of the data. The data also suggests that effects of university patent stocks may be persistent over time. The relationship between industry patent numbers and university patent numbers remains positive over several lags, from the 2-year lag to the 7-year lag. For TFP, on the other hand, the distributed lags structure does not provide evidence on a significant relationship with university patent stocks over time.

Table 4.8. Distributed lag specifications

Panel A: Industry patent stock								
Dependent variable	ln(1+industry SIPO patent stock)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(1+university SIPO patent stock)	-0.006***	-0.015***	-0.016***	-0.003	-0.001	-0.009	0.004	-0.008
	(0.002)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
1-year lagged ln(1+university SIPO patent stock)		0.011*	0.000	-0.011	0.003	0.010	-0.008	0.001
		(0.004)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
2-year lagged ln(1+university SIPO patent stock)			0.013**	0.005	-0.009	0.006	0.014*	0.001
			(0.004)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
3-year lagged ln(1+university SIPO patent stock)				0.011*	-0.001	-0.020***	-0.007	-0.004
				(0.005)	(0.006)	(0.006)	(0.006)	(0.007)
4-year lagged ln(1+university SIPO patent stock)					0.017***	0.014*	-0.009	0.003
					(0.005)	(0.006)	(0.006)	(0.007)
5-year lagged ln(1+university SIPO patent stock)						0.018***	0.004	-0.012
						(0.005)	(0.006)	(0.008)
6-year lagged ln(1+university SIPO patent stock)							0.014**	0.015**
							(0.005)	(0.006)
7-year lagged ln(1+university SIPO patent stock)								0.012*
								(0.006)
Lagged ln(population)	-0.071*	-0.055	-0.033	0.041	0.121*	0.348***	0.212*	0.046
	(0.032)	(0.032)	(0.033)	(0.046)	(0.055)	(0.082)	(0.089)	(0.096)
Prefecture-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	62,662	56,396	50,130	43,864	37,598	31,331	25,064	18,797
σ-squared	0.385	0.368	0.348	0.328	0.305	0.280	0.255	0.224
R-squared	0.133	0.134	0.135	0.134	0.131	0.127	0.121	0.110
Adjusted R-squared	0.037	0.026	0.011	0.011	0.043	0.091	0.173	0.336
Log-likelihood	-25,868.9	-20,266.2	-14,898.7	-9,895.0	-5,270.1	-1,106.0	2,315.8	5,281.3
Akaike information criterion (AIC)	51,761.9	40,556.5	29,821.4	19,814.1	10,564.2	2,236.0	-4,607.7	-10,538.7
Bayesian information criterion (BIC)	51,870.4	40,663.8	29,927.3	19,918.4	10,666.6	2,336.2	-4,510.1	-10,444.6
F-statistics	788.7	707.3	620.9	528.3	429.6	332.5	234.8	140.5
Degrees of freedom (df)	56,384	50,118	43,852	37,586	31,320	25,053	18,786	12,519
Panel B: Industry TFP								
Dependent variable	ln(TFP)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(1+university SIPO patent stock)	-0.013	-0.024*	-0.026*	-0.028*	-0.026*	-0.013	-0.015	-0.020
	(0.008)	(0.010)	(0.011)	(0.011)	(0.012)	(0.013)	(0.013)	(0.021)
1-year lagged ln(1+university SIPO patent stock)		0.016	0.008	0.013	0.006	0.006	0.004	0.001
		(0.010)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.016)
2-year lagged ln(1+university SIPO patent stock)			0.009	0.012	0.013	0.001	0.003	-0.013
			(0.010)	(0.013)	(0.013)	(0.013)	(0.013)	(0.017)
3-year lagged ln(1+university SIPO patent stock)				0.002	0.005	0.012	0.007	0.006
				(0.011)	(0.014)	(0.014)	(0.014)	(0.017)
4-year lagged ln(1+university SIPO patent stock)					0.005	0.013	0.015	0.010
					(0.013)	(0.015)	(0.015)	(0.021)
5-year lagged ln(1+university SIPO patent stock)						0.017	0.015	0.005
						(0.011)	(0.012)	(0.022)
6-year lagged ln(1+university SIPO patent stock)							0.008	-0.001
							(0.011)	(0.012)
7-year lagged ln(1+university SIPO patent stock)								0.040

								(0.026)
Lagged ln(population)	-0.019 (0.079)	-0.035 (0.076)	0.161 (0.116)	0.161 (0.116)	-0.276 (0.309)	0.002 (0.218)	-0.076 (0.188)	-0.626 (0.385)
Prefecture-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,861	20,861	20,861	19,603	18,461	17,370	16,216	11,097
σ-squared	0.434	0.434	0.434	0.428	0.434	0.425	0.401	0.362
R-squared	0.005	0.006	0.006	0.005	0.004	0.005	0.002	0.003
Adjusted R-squared	0.374	0.374	0.374	0.409	0.447	0.488	0.546	1.061
Log-likelihood	-8,798.1	-8,796.2	-8,794.5	-7,772.6	-7,342.8	-6,282.4	-4,654.2	-441.6
Akaike information criterion (AIC)	17,614.3	17,612.5	17,611.1	15,567.2	14,707.7	12,586.8	9,330.4	905.3
Bayesian information criterion (BIC)	17,685.8	17,691.9	17,698.5	15,654.0	14,793.7	12,672.2	9,415.0	985.8
F-statistics	10.3	9.4	8.7	7.2	5.2	5.7	2.0	1.5
Degrees of freedom (df)	15,096	15,095	15,094	13,841	12,703	11,614	10,470	5,368

Note: Panel A, column (1) replicates column (2) from Table 4.7. Columns (2) to (8) in Panel A add contemporaneous and further lagged logs of university SIPO patent stocks. Panel B, column (1) replicates column (2) from Table 4.6. Columns (2) to (8) in Panel B add contemporaneous and further lagged logs of university SIPO patent stocks. Results control for corresponding lagged log levels of population. Standard errors are clustered at the prefecture level. Standard errors in parentheses. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels respectively.

Source: Author's calculations based on National Bureau of Statistics (2008), He et al. (2017), European Patent Office (2017), and International Association of Universities (2017).

4.4.2. Geographical spillover from university patent activity

University patent activity will not only have an effect on the prefecture in which they are located, but also in other prefectures. In addition to the 5-year lagged university patent stocks of the own prefecture, an interaction term of 5-year lagged university patent stocks of all other prefectures with the distance to these prefectures is included in a Spatial Durbin Model (SDM) estimation framework as derived in Eq. 6 and Eq. 8. Distance is measured in kilometres and based on the distance between centre points of prefectures (so-called distance between centroids). The interaction with distance allows to account for distance decay, i.e. university effects will become weaker with growing geographical distance. In a second step, the sample of potential spillovers is reduced to the nearest prefectures, which are prefectures that share a border with the home prefecture.[20]

Table 4.9 shows the results for the SDM model for industrial patent stocks (Eq. 17) in columns (1) and (2), and for industrial TFP in columns (3) and (4) using data on 261 prefectures for the period 1998 to 2007.[21] Column (1) includes spatially lagged university patent stocks, i.e. the interaction term of 5-year lagged university patent stocks in all other regions with distance to these regions. It also controls for the spatially lagged industrial patent stock, a host of prefecture-level characteristics, and prefecture fixed effects and year fixed effects. The findings show that the coefficient for university patent stocks in the home prefecture is positive and significant. In other words, a 1% increase university patent stocks in the home prefecture is associated with a 6.4% increase in industrial patent stocks in the home prefecture. This estimate is higher in magnitude than the estimate of the nonspatial model. Conversely, the spatially lagged university patent stock turns out to be insignificant, which means that there is weak evidence for inter-regional university spillovers on industry patent activity in China. As in the model without spillovers, the logarithm of SIPO patent stocks of foreign-owned enterprises is positive and significant. Interestingly, the spatially lagged industry SIPO patent stock turns out positive and significant, which points to spillover effects from industrial patent activity in neighbouring prefectures on industrial patent activity in the home prefecture.

In column (2), university patent stocks in the nearest prefectures are shown. The result shows that university patent stocks in the five nearest prefectures is not significant, pointing to no spillovers from university patenting. The spatially lagged industry patent stock is positive and significant, which suggests that industry patent activity in neighbouring prefectures affects industry patenting in the home prefecture. Considering these findings, *hypothesis 1d* about university spillovers on industrial patent stocks cannot be confirmed: Higher 5-year lagged levels of university patent stocks do not coincide with higher levels of industrial patent stocks in neighbouring prefectures or other prefectures in China.

Table 4.9. University spillovers from other prefectures, 1998-2007

Dependent variable	ln(1+industry patent stock)		ln(TFP)	
	(1)	(2)	(3)	(4)
Lagged ln(1+university SIPO patent stock)	0.064*** 0.019	0.055*** 0.020	0.000 0.003	0.000 0.003
Lagged ln(population)	0.392* 0.195	0.457* 0.201	-0.008 0.028	-0.007 0.028
Lagged ln(students in secondary education)	-0.258*** 0.033	-0.265*** 0.034	-0.007 0.005	-0.007 0.005
Lagged ln(students in tertiary education)	-0.073 0.193	-0.145 0.199	0.016 0.028	0.015 0.028
Lagged ln(GDP per capita)	0.352*** 0.056	0.380*** 0.058	0.019* 0.008	0.019* 0.008
Lagged ln(investment)	0.022 0.066	0.041 0.068	-0.003 0.010	-0.004 0.010
Lagged ln(foreign direct investment)	0.040 0.021	0.033 0.022	-0.001 0.003	-0.001 0.003
Lagged share of employment in manufacturing	-0.650* 0.262	-0.697*** 0.270	-0.031 0.038	-0.030 0.038
Lagged share of employment in services	0.348 0.194	0.410* 0.200	0.004 0.028	0.004 0.028
Lagged share of self-employed	0.044 0.068	0.052 0.070	-0.014 0.010	-0.014 0.010
Lagged ln(1+SIPO patent stock of foreign-owned enterprises)	1.199*** 0.043	1.274*** 0.044	0.005 0.006	0.005 0.006
Spatially lagged university SIPO patent stock x distance to home region	-0.007 0.031		0.000 0.005	
Spatially lagged university SIPO patent stock, nearest prefectures		0.035 0.038		0.000 0.005
Spatially lagged industry SIPO patent stock x distance to	0.522***			

home region	0.021			
Spatially lagged industry SIPO patent stock, nearest prefectures		0.548*** 0.025		
Spatially lagged TFP x distance to home region			0.149*** (0.015)	
Spatially lagged TFP, nearest prefectures				-0.046 0.050
Prefecture fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	2,600	2,600	2,600	2,600
σ-squared	1.258	1.334	0.026	0.026
R-squared	0.624	0.602	0.153	0.145
Adjusted R-squared	0.355	0.354	0.014	0.006
Log-likelihood	-4,045.829	-4,101.242	1,045.036	1,033.423
Akaike information criterion (AIC)	2,692.900	2,692.100	-4,711.600	-4,711.700
Bayesian information criterion (BIC)	2,779.600	2,778.800	-4,619.100	-4,619.200
Degrees of freedom (df)	281	281	282	281
Lagrange Multiplier test (spatial error model)	0.288	0.373	0.000	0.019
Lagrange Multiplier test (spatial lag model)	0.150	1.783	0.001	0.023

Note: ML estimates for 261 prefectures and 10 years (1998-2007). Column (1) regresses industrial SIPO patent stocks (plus 1) on the 5-year lagged university SIPO patent stock (plus 1) and adds an interaction term of the spatially lagged university SIPO patent stock in all other regions with distance to that region (in km). It also includes the spatially lagged industry SIPO patent stock in all other regions interacted with the distance to the region (in km), the log level of population, prefecture fixed effects and year fixed effects, and controls for prefecture-level characteristics. Column (2) adds an interaction term of the spatially lagged university SIPO patent stock in neighbouring regions. It also includes the spatially lagged industry SIPO patent stock in neighbouring regions, the log level of population, prefecture fixed effects and year fixed effects, and controls for prefecture-level characteristics. Column (3) regresses industry TFP levels on the 5-year lagged university SIPO patent stock (plus 1) and adds an interaction term of the spatially lagged university SIPO patent stock in all other regions with distance to that region (in km). It also includes spatially lagged industry TFP levels in all other regions interacted with the distance to the region (in km), the log level of population, prefecture fixed effects and year fixed effects, and controls for prefecture-level characteristics. Column (4) adds an interaction term of the spatially lagged university SIPO patent stock in neighbouring regions. It also includes spatially lagged industry TFP levels in neighbouring regions, the log level of population, prefecture fixed effects and year fixed effects, and controls for prefecture-level characteristics. Standard errors in parentheses. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels, respectively.
Source: Author's calculations based on National Bureau of Statistics (2008), He et al. (2017), European Patent Office (2017), and International Association of Universities (2017).

For TFP (Eq. 16), the results in column (3) show that university SIPO patent stocks in other prefectures are not significantly associated with industrial TFP levels in the home prefecture, after controlling for the spatial lag of industrial patent stocks, a host of prefecture-level characteristics, as well as prefecture fixed effects and year fixed effects. However, another finding stands out. The interaction between TFP levels in other prefectures with distance in kilometres to the other prefectures is positive and significant. This suggests that TFP levels in other prefectures affect industry TFP levels in the home prefectures.

Column (4) includes the logarithm of university patent stocks in the five nearest prefectures. The coefficient for the spatial lag of university patent stock turns out insignificant, as in the other models. Interestingly, TFP levels in the five nearest prefectures turn out to be positive and significant. This points to productivity benefits that arise from spatial proximity of prefectures. Taking into consideration these findings, *hypothesis 1c* is rejected: Higher 5-year lagged levels of university patent stocks do not coincide with higher levels of industrial TFP in neighbouring prefectures or other prefectures in China.

4.5. Empirical analysis of TFP and industrial patent stocks following university reforms

4.5.1. The impact of university IPR reforms on increases in industry patent stocks and TFP

Table 4.10 provides findings from the difference-in-difference estimation of the impacts of university reforms on changes in industry patent stocks. It estimates the empirical model in Eq. (19) for the sample of industries with locations outside 20 kilometres distance from the nearest university. The results in column (1) and show that there was a significant increase in the number of industrial SIPO patent stocks outside of 20 kilometres distance from a university in the period 2003-2007 as compared to the period 1998-2002 ($POST_t$x$PROXIMITY_{ic}$). The interaction term $POST_t$x$PROXIMITY_{ic}$ is positive and significant after controlling for the log level of population, industry fixed effects and prefecture-year fixed effects.

Column (2) includes control variables for prefecture-level characteristics, which does not affect the significance interaction term $POST_t$x$PROXIMITY_{ic}$. In terms of magnitude, the coefficient of the term $POST_t$x$PROXIMITY_{ic}$ has a value of 0.070. This can be interpreted as an increase of 7% in patent stocks after 2002 for the period 2003 to 2007, or an annual increase of 1.4%. As for the controls for prefecture-level characteristics, the logarithm of number of students enrolled in tertiary education, the log level of GDP per capita, the share of employees in manufacturing industries (in the prefectural labour force), and the share of self-employed (in the prefectural labour force) are positive and significant. The logarithm of investment in machinery and equipment is negative and significant, while the other control variables turn out to be insignificant. Considering these factors, *hypothesis 2b* is confirmed: The number of industrial SIPO patent stocks increased significantly following university IPR-reforms in 2002.

Table 4.10. Changes in industry patent stocks and TFP levels following university reforms

Dependent variable	ln(1+industry patent stock)		ln(TFP)	
	(1)	(2)	(3)	(4)
POST x PROXIMITY	0.050***	0.070***	0.081***	0.080***
	(0.009)	(0.010)	(0.020)	(0.021)
ln(population)	-0.067	0.002***	-0.006	0.020
	(0.046)	(0.000)	(0.081)	(0.087)
ln(students in secondary education)		-0.000		-0.026*
		(0.000)		(0.012)
ln(students in tertiary education)		0.002***		-0.045
		(0.000)		(0.031)
ln(GDP per capita)		0.004		0.021
		(0.014)		(0.045)
ln(investment)		-0.047***		0.013
		(0.008)		(0.018)
ln(foreign direct investment)		0.003		-0.003
		(0.003)		(0.006)
Share of employment in manufacturing		0.094**		-0.078
		(0.030)		(0.059)
Share of employment in services		-0.050*		-0.007
		(0.019)		(0.037)
Share of self-employed		0.022***		-0.012
		(0.005)		(0.012)
Prefecture-year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	60,752	60,320	20,861	20,765
σ-squared	0.543	0.545	0.454	0.454
R-squared	0.435	0.436	0.047	0.048
Adjusted R-squared	0.433	0.434	0.036	0.036
Log-likelihood	-49,015.610	-48,802.009	-12,996.805	-12,942.116
Akaike information criterion (AIC)	98,055.220	97,644.018	25,999.610	25,906.232
Bayesian information criterion (BIC)	98,163.395	97,824.166	26,023.446	25,993.583
F-statistics	409.204	241.057	8.019	2.688
Degrees of freedom (df)	60,464	60,024	20,605	20,504

Note: Difference-in-difference estimates for 261 prefectures, 30 industries at the 3-digit CIC Rev. 2002 level, and 10 years (1998-2007). Column (1) regresses log annual numbers of industrial SIPO patent stocks on the interaction $POST_t$x$PROXIMITY_{ic}$ of the post-university reform dummy variable, $POST_t$, which equals 1 for all years after 2002, with the proximity dummy variable, $PROXIMITY_{ic}$, which equals 1 for all industries with 20 km or more distance to a university, and adds controls for the log level of population as well as prefecture-year fixed effects and industry fixed effects. Column (2) adds controls for prefecture-level characteristics. Columns (3) regresses log annual TFP levels on the interaction term $POST_t$x$PROXIMITY_{ic}$ and adds controls for the log level of population as well as prefecture-year fixed effects and industry fixed effects. Column (4) adds controls for prefecture-level characteristics. Standard errors are clustered at the prefecture level. Standard errors in parentheses. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels, respectively.
Source: Author's calculations based on National Bureau of Statistics (2008), He et al. (2017), European Patent Office (2017), and International Association of Universities (2017).

Turning to TFP, the results in column (3) show a significant increase in the level of industrial TFP outside 20 kilometres distance from a university after reforms in 2002. The estimates provided refer to the difference-in-difference model specification shown in Eq. (18). Column (4) adds controls for prefecture-level characteristics, prefecture-year fixed effects and industry fixed, which does not change the result: TFP levels increased significantly in locations outside of 20 kilometres distance to the nearest university following university reforms relative to before the reforms. This finding leads to the confirmation of *hypothesis 2a:* The level of industrial TFP increased significantly following university IPR-reforms in 2002.

4.5.2. The impact of university IPR reforms by technology-intensity and across types of ownership

I next turn to the impacts of 2002 reforms on industry across different ownership types of industry and by technology-intensity of the industry. One would expect the impacts of reforms to be heterogeneous across these industry characteristics. High-tech intensive industry might be in a better position to take advantage of university research due to its higher absorptive capacity, while private enterprises might be more inclined to look for university partners to improve their innovativeness.

Table 4.11 shows the results of the estimation of the difference-in-difference model in Eq. (19) for separate samples of privately-owned industrial enterprises (POEs), state-owned industrial enterprises (SOEs), and foreign-owned industrial enterprises (FOEs). the estimation shown in column (2) of Table 4.10 is replicated for these samples. Column (1) shows the results for the sample of POEs. It reveals a significant increase in the number of SIPO patent stocks of POEs outside 20 kilometres distance from a university in the period 2003-2007 as compared to the period 1998-2002 ($POST_t$x$PROXIMITY_{ic}$), after controlling for difference across prefectures, industries and annual time trends. In terms of magnitude, private industry experienced a 3.7% increase in levels of patent stocks following university reforms. The findings also control for prefecture-level characteristics and show that the log number of students in tertiary education, the log level of foreign direct investment, the share of employment in manufacturing in prefectural labour force, and the share of self-employed in prefectural labour force are positive and significant for the POEs sample.

Column (2) displays the results for the sample of SOEs. We see that the interaction term $POST_t$x$PROXIMITY_{ic}$ is significant after controlling for differences across prefectures, industries and annual time trends. One finding stands out: The increase of industry patent activity was smaller for the sample of SOEs than for POEs. In terms of magnitude, SOEs experienced a 1.9% increase in levels of patent stocks after reforms in 2002, against an increase of 3.7% for the sample of privately-owned enterprises. Considering these factors, *hypothesis 2d* is confirmed that the number of industrial patent stocks of privately-owned enterprises increased more compared to that of state-owned enterprises following university IPR-reforms in 2002.

As for FOEs, the results in column (3) show a significant increase in the number of SIPO patent stocks for FOEs outside of 20 kilometres distance from a university in the period 2003-2007 as compared to the period 1998-2002. As in the case of the POE sample, the log number of students in tertiary education, the log level of foreign direct investment, the share of employment in manufacturing industries, and the share of self-employed turn out to be positive and significant.

Table 4.11. Ownership status, technology intensity and changes in industry patent stocks

Dependent variable	ln(1+industry patent stock)				
	Privately-owned enterprises	State-owned enterprises	Foreign-owned enterprises	High-tech industries	Low-tech industries
	(1)	(2)	(3)	(4)	(5)
POST x PROXIMITY	0.037***	0.019***	0.049***	0.016*	0.024***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.004)
ln(population)	-0.055*	-0.017	-0.094***	-0.034	-0.007
	(0.022)	(0.023)	(0.027)	(0.032)	(0.022)
ln(students in secondary education)	0.000	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(students in tertiary education)	0.000*	-0.000	0.001***	0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(GDP per capita)	-0.005	-0.009	-0.018*	0.002	-0.004
	(0.007)	(0.007)	(0.008)	(0.009)	(0.006)
ln(investment)	-0.018***	-0.014***	-0.027***	-0.012*	-0.009*
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
ln(foreign direct investment)	0.007***	0.002	0.005**	0.000	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Share of employment in manufacturing	0.067***	0.026	0.057***	0.015	0.024
	(0.014)	(0.014)	(0.017)	(0.020)	(0.014)
Share of employment in services	-0.004	0.001	-0.022	-0.015	-0.006
	(0.009)	(0.009)	(0.011)	(0.013)	(0.009)
Share of self-employed	0.009**	-0.002	0.010**	0.006	0.003
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Prefecture-year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	59,703	60,320	60,320	60,320	60,320
σ-squared	0.258	0.264	0.313	0.366	0.252
R-squared	0.234	0.264	0.269	0.203	0.191
Adjusted R-squared	0.230	0.260	0.265	0.199	0.187
Log-likelihood	-3,573.208	-5,196.114	-15,287.984	-24,893.102	-2,278.952
Akaike information criterion (AIC)	7,186.415	10,432.229	30,615.968	49,826.205	4,597.904
Bayesian information criterion (BIC)	7,366.358	10,612.377	30,796.116	50,006.353	4,778.052
F-statistics	154.049	34.757	92.506	23.690	50.435
Degrees of freedom (df)	59,408	60,024	60,024	60,024	60,024

Note: Difference-in-difference estimates for 261 prefectures, 30 industries at the 3-digit CIC Rev. 2002 level, and 10 years (1998-2007). Samples examined in the table are: Privately-owned enterprises (or POEs, column (1)); state-owned enterprises (or SOEs, column (2)); foreign-owned enterprises (or FOEs, column (3)); high technology-intensive industries (column (4)); and low technology-intensive industries (column (5)). Standard errors are clustered at the prefecture level. Standard errors in parentheses. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels, respectively.

Source: Author's calculations based on National Bureau of Statistics (2008), He et al. (2017), European Patent Office (2017), and International Association of Universities (2017).

Table 4.11 further shows the results for the samples of high-tech intensive industries and low-tech intensive industries. Columns (4) and (5) provide evidence for significant increases in patent stocks for the sample of high-tech industries and for the sample of low-tech industries after university reforms in 2002. The interaction term $POST_t$x$PROXIMITY_{ic}$ is positive and significant for both samples after controlling for observable prefecture-level characteristics, unobservable differences across prefectures and industries, and annual time trends. For the high-tech sample, the coefficient of the term $POST_t$x$PROXIMITY_{ic}$ shown in column (4) has a value of 0.016. For the low-tech sample, the value is 0.024, as shown in column (5). This can be interpreted as an increase of 1.6% in patent stocks of high-tech industries after 2002, against a somewhat higher increase of 2.4% in patent stocks of low-tech industries after 2002. Considering these findings, *hypothesis 2f* cannot be confirmed: The number of industrial patent stocks of high-tech industry did not increase more compared to that of low-tech industry following university IPR-reforms in 2002.

Turning to TFP, Table 4.12 shows the results of the estimation of the difference-in-difference model in Eq. (18) for separate samples of privately-owned industrial enterprises (POEs), state-owned industrial enterprises (SOEs), and foreign-owned industrial enterprises (FOEs). The estimation shown column (4) of Table 4.10 is conducted separately for these samples to obtain the results. Contrary to the findings for industry patent stocks, columns (1) to (3) do not provide evidence for any significant increase in patent stocks following university reforms in 2002 for the samples POEs, SOEs, and POEs. Contrary to expectations, privately-owned industry outside of 20 kilometres distance to the closest university experienced a decrease in TFP levels following university reforms in 2002 (column 1). TFP levels of SOEs and FOEs seem unaffected by reforms in 2002 (column 2 and 3, respectively). Based on these results, *hypothesis 2c* is rejected: The level of industrial TFP of privately-owned enterprises did not increase more compared to that of state-owned enterprises following university IPR-reforms in 2002.

Columns (4) and (5) provide evidence on impacts of university reforms on changes in TFP levels of high-tech industries and low-tech industries. According to the results in column (4), TFP levels of high-tech industry outside of 20 kilometres distance to the closest university remained unaffected following university reforms. For the sample of low-tech industries, as shown in column (5), the interaction term $POST_t$x$PROXIMITY_{ic}$ is positive and significant after controlling for observable prefecture-level characteristics, unobservable differences across prefectures and industries, and annual time trends. In other words, low-tech industry outside of 20 kilometres distance to the closest university experienced a significant increase in TFP levels following university reforms. In terms of magnitude, the coefficient of the term $POST_t$x$PROXIMITY_{ic}$ shown in column (5) has a value of

0.121, which can be interpreted as an increase of 12.1% in TFP levels of low-tech industries after 2002. Considering these findings, *hypothesis 2e* cannot be confirmed: The level of industrial TFP of high-tech industry did not increase more compared to that of low-tech industry following university IPR-reforms in 2002.

Table 4.12. Ownership status, technology intensity and changes in TFP levels

Dependent variable	ln(TFP)				
	Privately-owned enterprises	State-owned enterprises	Foreign-owned enterprises	High-tech industries	Low-tech industries
	(1)	(2)	(3)	(4)	(5)
POST x PROXIMITY	-0.068** (0.025)	-0.015 (0.029)	0.014 (0.031)	0.055 (0.068)	0.121*** (0.030)
ln(population)	-0.080 (0.109)	0.094 (0.209)	0.077 (0.147)	0.408 (0.268)	-0.105 (0.127)
ln(students in secondary education)	-0.027 (0.036)	-0.015 (0.058)	0.024 (0.060)	0.025 (0.117)	-0.039 (0.048)
ln(students in tertiary education)	0.008 (0.014)	0.007 (0.017)	0.007 (0.020)	-0.003 (0.040)	-0.028 (0.018)
ln(GDP per capita)	0.029 (0.053)	0.125 (0.076)	-0.005 (0.079)	0.225 (0.155)	-0.028 (0.069)
ln(investment)	0.028 (0.021)	0.007 (0.027)	-0.029 (0.028)	0.054 (0.061)	0.007 (0.027)
ln(foreign direct investment)	-0.004 (0.007)	-0.010 (0.010)	-0.002 (0.011)	-0.036 (0.022)	0.013 (0.010)
Share of employment in manufacturing	-0.109 (0.068)	-0.008 (0.096)	-0.174 (0.094)	-0.137 (0.200)	-0.140 (0.090)
Share of employment in services	0.012 (0.042)	-0.028 (0.058)	-0.050 (0.059)	0.009 (0.129)	-0.002 (0.056)
Share of self-employed	0.006 (0.014)	-0.000 (0.021)	-0.022 (0.020)	-0.085* (0.041)	-0.029 (0.018)
Prefecture-year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	17,330	12,553	11,264	1,971	9,029
σ-squared	0.472	0.593	0.553	0.489	0.453
R-squared	0.041	0.036	0.036	0.204	0.066
Adjusted R-squared	0.026	0.016	0.015	0.095	0.038
Log-likelihood	-11,458.132	-11,116.771	-9,179.322	-1,261.976	-5,536.736
Akaike information criterion (AIC)	22,938.263	22,255.541	18,380.644	2,545.952	11,095.472
Bayesian information criterion (BIC)	23,023.625	22,337.356	18,461.267	2,607.402	11,173.663
F-statistics	1.575	0.490	0.801	1.150	2.906
Degrees of freedom (df)	17,069	12,296	11,016	1,734	8,768

Note: Difference-in-difference estimates for 261 prefectures, 30 industries at the 3-digit CIC Rev. 2002 level, and 10 years (1998-2007). Samples examined in the table are: Privately-owned enterprises (or POEs, column (1)); state-owned enterprises (or SOEs, column (2)); foreign-owned enterprises (or FOEs, column (3)); high technology-intensive industries (column (4)); and low technology-intensive industries (column (5)). Standard errors are clustered at the prefecture level. Standard errors in parentheses. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels, respectively.

Source: Author's calculations based on National Bureau of Statistics (2008), He et al. (2017), European Patent Office (2017), and International Association of Universities (2017).

4.5.3. Entrants versus incumbents and the impact of university IPR reforms

The effects of university IPR reforms may differ across newly established enterprises (entrants) and incumbent firms due to different levels of R&D experience and absorptive capacity. The estimation results for the separate samples of entering firms and incumbent firms are shown in Table 4.13. Column (1) reports results for changes in industry patent stocks following university reforms for the sample of entrants, i.e. industrial enterprises that were established in 1996 of later. It controls for prefecture-level characteristics, prefecture-year fixed effects and industry fixed effects. The results reveal that the interaction term $POST_t \mathrm{x} PROXIMITY_{ic}$ is positive and significant and has a value of 0.064. This means that newly established industrial enterprises outside 20 kilometres distance to a university experienced an increase of 6.4% in patent stock numbers following the 2002 reforms. This corresponds to an annual increase of 1.3% for the period 2003 to 2007. As for the controls for prefecture-level characteristics, the log number of students enrolled in tertiary education, the share of employees in manufacturing industries, and the share of self-employed are positive and significant. It is worth noting that compared to the results for the total sample of industrial enterprises, the log level of foreign direct investment turns out to be insignificant. This suggests that patent activity of newly established Chinese enterprises relies to a lesser extent on foreign investment than the average industrial enterprise in China.

Turning to the results for the sample of incumbent enterprises, as shown in column (2), the findings reveal a positive and significant coefficient for the interaction term $POST_t \mathrm{x} PROXIMITY_{ic}$. Incumbent enterprises outside of 20 kilometres distance to a university experienced an increase of 5.1% in patent stock numbers after 2002. Notably, the increase in patent stocks for incumbent enterprises is lower than the increase reported for newly established enterprises. This finding is important as it suggests that entrants benefited to a higher extent from university reforms than incumbents. Considering these factors, *hypothesis 2h* can be confirmed: The number of patent stocks of newly established enterprises increased more compared to that of incumbent enterprises following university IPR-reforms in 2002.

As for TFP, the results reported in columns (3) and (4) do not show any significant increase in TFP levels following university reforms for the samples of entrants and incumbents. The results account for differences across prefectures, differences across industries, annual time trends, as well as controls for prefecture-level characteristics. Therefore, *hypothesis 2g* is rejected: TFP levels of newly established enterprises did not increase more compared to that of incumbent enterprises following university IPR-reforms in 2002.

Table 4.13. Entrants, incumbents and changes in industry patent stocks and TFP levels

Dependent variable	ln(1+industry patent stock)		ln(TFP)	
	Newly established enterprises	Incumbent enterprises	Newly established enterprises	Incumbent enterprises
	(1)	(2)	(3)	(4)
POST x PROXIMITY	0.064***	0.051***	0.034	0.015
	(0.007)	(0.007)	(0.023)	(0.022)
ln(population)	-0.087*	-0.084*	-0.004	0.091
	(0.035)	(0.036)	(0.094)	(0.116)
ln(students in secondary education)	-0.000	-0.000	-0.048	-0.004
	(0.000)	(0.000)	(0.034)	(0.042)
ln(students in tertiary education)	0.001***	0.000	0.002	0.009
	(0.000)	(0.000)	(0.013)	(0.013)
ln(GDP per capita)	-0.004	-0.021*	-0.040	0.091
	(0.010)	(0.011)	(0.049)	(0.054)
ln(investment)	-0.036***	-0.032***	-0.005	-0.018
	(0.006)	(0.006)	(0.020)	(0.020)
ln(foreign direct investment)	0.004	0.006*	0.003	-0.002
	(0.002)	(0.003)	(0.007)	(0.007)
Share of employment in manufacturing	0.092***	0.051*	-0.180**	0.012
	(0.022)	(0.023)	(0.065)	(0.069)
Share of employment in services	-0.020	-0.014	-0.024	-0.023
	(0.014)	(0.015)	(0.040)	(0.043)
Share of self-employed	0.015***	0.001	-0.013	-0.004
	(0.004)	(0.004)	(0.013)	(0.015)
Prefecture-year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	60,320	60,320	19,566	15,091
σ-squared	0.400	0.413	0.481	0.470
R-squared	0.287	0.386	0.038	0.040
Adjusted R-squared	0.283	0.383	0.025	0.023
Log-likelihood	-30,192.732	-32,049.741	-13,292.442	-9,891.211
Akaike information criterion (AIC)	60,425.463	64,139.482	26,606.884	19,804.423
Bayesian information criterion (BIC)	60,605.612	64,319.631	26,693.581	19,888.263
F-statistics	226.577	92.918	1.461	0.480
Degrees of freedom (df)	60,024	60,024	19,305	14,831

Note: Difference-in-difference estimates for 261 prefectures, 30 industries at the 3-digit CIC Rev. 2002 level, and 10 years (1998-2007). Samples examined in the table are: Newly established enterprises, i.e. enterprises established in 1996 or after (columns (1) and (3)); incumbent enterprises, i.e. enterprises established before 1996 (columns (2) and (4)). Standard errors are clustered at the prefecture level. Standard errors in parentheses. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels, respectively.

Source: Author's calculations based on National Bureau of Statistics (2008), He et al. (2017), European Patent Office (2017), and International Association of Universities (2017).

4.5.4. Accounting for endogeneity of university locations

I examine the possibility that my results in Table 4.10 to Table 4.13 were the result of endogenous location decisions of universities around the time of university reforms. In that case, unobserved local economic shocks would explain increases in university patent activity, industrial patent activity, and TFP levels. If local economic shocks affected industry and universities, one would expect that industrial patenting and TFP levels increased in locations closer to universities but not so in locations further away. Therefore, the sample of industry that might benefit from impacts of university reforms is restricted to industry in locations outside of (i) 50 kilometres distance to the nearest university, (ii) outside of the median distance of 46 kilometres distance to the nearest university, (iii) outside of the mean distance of 62 kilometres distance to the nearest university, (iv) outside of 20 kilometres distance to Beijing, the dominant research hubs in China, (v) outside of 20 kilometres distance to Shanghai, the biggest economic centre in China, and (vi) in prefectures without universities that border prefectures with universities.

In Table 4.14, column (1) shows a significant increase in the number of industry patent stocks in the sample of prefectures with 50 kilometres or more distance to a university following 2002 reforms. Similarly, as shown in column (2), the results support the view that there was a significant increase in patent numbers of industrial enterprises in locations outside of the median distance (≥46 km) from a university following 2002 reforms. Column (3) uses the sample of locations outside of the mean distance of 62 kilometres to the closest university, which does not affect the results. Beijing and Shanghai are the two main research and economic hubs in China, and they might be responsible for increases in overall patent numbers during the period 2003 to 2007 following university IPR reform. The results in columns (4) and (5) reject this argument. They show that industrial patent stocks increased significantly in locations outside of 20 kilometres distance to Beijing, as well as in locations outside of 20 kilometres distance to Shanghai. And finally, in column (6), the results can confirm a significant increase in industry patent stocks for the sample of prefectures that share a border with a university prefecture following university reforms. Based on these findings, it is concluded that university reforms were associated with increases in industrial patent stocks, irrespective of local economic shocks occurring at the time of university reforms in 2002.

To account for local economic shocks that might drive the TFP results, the difference-in-difference estimation in Eq. (18) is estimated using samples of industry located outside their potential geographical impact. As above, industry within 50 kilometres distance to a university is excluded. Then, the sample is, first, restricted to industry in locations outside the median distance of 46 kilometres to the nearest university, and then to the sample of industry in locations outside of the mean distance of 62 kilometres distance to the nearest university. And finally, the study analyses the sample of industries located in prefectures without research universities that share a border with a prefecture that houses a university (bordering prefectures).

Table 4.14. Changes to industry patent stocks in samples with higher distance to university

Dependent variable	ln(1+industry patent stock)					
	≥ 50 km distance (1)	≥ Median distance (46 km) (2)	≥ Mean distance (62 km) (3)	≥ 20 km distance to Beijing (4)	≥ 20 km distance to Shanghai (5)	Bordering prefectures (6)
POST x PROXIMITY	0.089***	0.085***	0.045***	0.163*	0.301***	0.069***
	(0.010)	(0.010)	(0.010)	(0.070)	(0.073)	(0.015)
ln(population)	-0.084	-0.085	-0.090	-0.095*	-0.096*	-0.192
	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.115)
ln(students in secondary education)	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(students in tertiary education)	0.002***	0.002***	0.001**	0.001	0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
ln(GDP per capita)	0.006	0.004	0.002	0.007	0.007	-0.003
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.018)
ln(investment)	-0.045***	-0.046***	-0.043***	-0.045***	-0.048***	-0.090***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.013)
ln(foreign direct investment)	0.003	0.003	0.004	0.004	0.004	0.010*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
Share of employment in manufacturing	0.090**	0.089**	0.086**	0.086**	0.089**	0.037
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.056)
Share of employment in services	-0.047*	-0.047*	-0.045*	-0.038	-0.041*	-0.031
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.030)
Share of self-employed	0.022***	0.022***	0.020***	0.018**	0.020***	0.004
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)
Prefecture-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	62,230	62,230	62,230	62,230	62,230	31,445
σ-squared	0.569	0.569	0.569	0.569	0.569	0.613
R-squared	0.369	0.369	0.368	0.368	0.368	0.410
Adjusted R-squared	0.366	0.366	0.365	0.365	0.365	0.407
Log-likelihood	-53,025.458	-53,029.801	-53,056.474	-53,064.362	-53,058.476	-29,136.063
Akaike information criterion (AIC)	106,072.916	106,081.602	106,134.948	106,150.725	106,138.952	58,294.126
Bayesian information criterion (BIC)	106,172.341	106,181.027	106,234.373	106,250.149	106,238.376	58,386.042
F-statistics	13.751	12.885	7.565	5.993	7.166	7.335
Degrees of freedom (df)	61,951	61,951	61,951	61,951	61,951	31,294

Note: Difference-in-difference estimates for 261 prefectures, 30 industries at the 3-digit CIC Rev. 2002 level, and 10 years (1998-2007). Samples examined in the table are: Industries with 50 km or more distance to a university (column (1)); industries with median distance of 46 km or more to a university (column (2)); industries with mean distance of 62 km or more to a university (column (3)); industries with 20 or more distance to Beijing (column (4)); industries with 20 km or more distance to Shanghai (column (5)); industries in prefectures that share a border with a prefecture with university presence, i.e. they do not have a university themselves (column (6)). Standard errors are clustered at the prefecture level. Standard errors in parentheses. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels, respectively.
Source: Author's calculations based on National Bureau of Statistics (2008), He et al. (2017), European Patent Office (2017), and International Association of Universities (2017).

The results provided in Table 4.15, column (1), show a significant increase in levels of industry TFP in the sample of prefectures with 50 kilometres or more distance to a university following 2002 reforms. Column (2) confirms that there was a significant increase in industrial TFP levels in locations outside of the median distance (≥46 km) from a university following 2002 reforms. Column

(3) uses the sample of locations outside of the mean distance of 62 kilometres to the closest university and provides evidence for a significant increase in TFP levels. Results reported in column (4) do not support that there was a significant increase in industry TFP levels for the sample of prefectures that share a border with a university prefecture following university reforms.

Table 4.15. Changes to TFP levels in samples with higher distance to university

Dependent variable	ln(TFP)			
	≥ 50 km distance (1)	≥ Median distance (46 km) (2)	≥ Mean distance (62 km) (3)	Bordering prefectures (4)
POST x PROXIMITY	0.080*** (0.021)	0.080*** (0.021)	0.095*** (0.020)	-0.073* (0.030)
ln(population)	0.022 (0.087)	0.020 (0.087)	0.023 (0.087)	0.752 (0.534)
ln(students in secondary education)	-0.045 (0.031)	-0.045 (0.031)	-0.045 (0.031)	-0.042 (0.036)
ln(students in tertiary education)	-0.026* (0.012)	-0.026* (0.012)	-0.026* (0.012)	-0.001 (0.015)
ln(GDP per capita)	0.023 (0.045)	0.021 (0.045)	0.022 (0.045)	0.016 (0.061)
ln(investment)	0.014 (0.018)	0.013 (0.018)	0.009 (0.018)	0.017 (0.027)
ln(foreign direct investment)	-0.003 (0.006)	-0.003 (0.006)	-0.004 (0.006)	-0.000 (0.008)
Share of employment in manufacturing	-0.078 (0.059)	-0.078 (0.059)	-0.081 (0.059)	-0.080 (0.096)
Share of employment in services	-0.007 (0.037)	-0.007 (0.037)	-0.006 (0.037)	0.006 (0.051)
Share of self-employed	-0.012 (0.012)	-0.012 (0.012)	-0.012 (0.012)	-0.025 (0.020)
Prefecture-year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	20,765	20,765	20,765	10,803
σ-squared	0.454	0.454	0.454	0.471
R-squared	0.048	0.048	0.048	0.049
Adjusted R-squared	0.036	0.036	0.036	0.036
Log-likelihood	-12,942.008	-12,942.116	-12,938.487	-7,130.929
Akaike information criterion (AIC)	25,906.016	25,906.232	25,898.974	14,283.859
Bayesian information criterion (BIC)	25,993.367	25,993.583	25,986.325	14,364.022
F-statistics	2.709	2.688	3.406	1.208
Degrees of freedom (df)	20,504	20,504	20,504	10,660

Note: Difference-in-difference estimates for 261 prefectures, 30 industries at the 3-digit CIC Rev. 2002 level, and 10 years (1998-2007). Samples examined in the table are: Industries with 50 km or more distance to a university (column (1)); industries with median distance of 46 km or more to a university (column (2)); industries with mean distance of 62 km or more to a university (column (3)); industries in prefectures that share a border with a prefecture with university presence, i.e. they do not have a university themselves (column (4)). Standard errors are clustered at the prefecture level. Standard errors in parentheses. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels, respectively.
Source: Author's calculations based on National Bureau of Statistics (2008), He et al. (2017), European Patent Office (2017), and International Association of Universities (2017).

5. Empirical analysis of technology transfer activities of Chinese universities

This Section provides results from an empirical analysis of two selected channels linking university research to industry, i.e. university patent licensing and university contract research. Section 5.1 describes the data and methods used. Section 5.2 brings forward evidence on trends in university patent licensing and contract research in China for the period 1998 to 2007. Section 5.3 provides evidence on the extent to which university R&D relates to contract research and patent licensing (*research question 3*). Additional analysis provides evidence on the question whether universities' licensing activity – as measured by growth in university revenues from patent licensing, had detrimental effects on the growth of their revenues from contract research with industry. Evidence in this regard is important to understand potential trade-offs between university's patent licensing and contract research with industry (*research question 4*).

5.1. Methodology and data

5.1.1. Data

The empirical analysis draws on secondary data taken from University Science and Technology (US&T) Annual Reports published by the Chinese Ministry of Education (MOE, 2010). US&T annual reports are the result of annual surveys that are sent out to universities. The university survey collects information about 1,016 higher education institutions, including detailed data on their expenditures on R&D, type of R&D activity, patents, patent licenses, contract research, and revenues from licenses and contract research. Several empirical studies have made use of the data provided in the US&T annual reports to analyse trends in university-industry technology transfer (e.g. Wu and Zhou, 2012).

The dataset that used for empirical analysis covers 252 province-level observations from 28 provinces of Mainland China for the years 1998 to 2007.[22] Growth rates are the available for the period 1999 to 2007. Information from the US&T annual reports is complemented with official statistical information on business R&D expenditures, technology market turnover, and technology imports taken from various Statistical Yearbooks of the NBS for the years 1998 to 2007.

One caveat of the US&T annual reports is that the data is not available at the level of individual universities. The lowest available level reported is the level of Chinese provinces. University-level data could be easily matched to the university-firm database to study dynamics of technology transfer at micro-levels. This would reveal important insights about the distribution of technology transfer activities across the universe of Chinese higher education institutions. Another shortcoming of the data is the limited number of channels of technology transfer covered. The university survey captures information on formal channels, including licensing of university patents, patenting, as well as contract research and academic consulting (hereafter referred to as contract research with industry). Informal channels such as e.g. student mobility and student entrepreneurship are not covered. Nonetheless, the university survey is the most comprehensive dataset available for studies of Chinese technology transfer dynamics.

5.1.2. Variables

The analysis of the university research-technology transfer relationship makes use of two outcome variables of technology transfer activity of universities, notably annual growth in patent license revenues of universities and annual growth in contract research revenues of universities. Revenue data provides important insights on the economic value of technology transfer activities for universities and can be easily compared to university expenditures on R&D.

The explanatory variables are as follows: The annual growth rate of university R&D expenditures is used to test for the relationship between university research and technology transfer activity. The analysis also tests for the role of type of university R&D activity using the variables annual growth rate of R&D expenditures performed by universities on basic research, and annual growth rate of R&D expenditures performed by universities on applied research and experimental development (hereafter referred to as applied research only). R&D expenditures are measured in RMB at 1998 prices. The correlation coefficients between the three R&D variables are all below 0.7, which suggests that their combined use will not lead to issues of multicollinearity. To test for trade-offs between patent licensing revenues and contract research revenues, the analysis uses annual growth rate of university revenues from patent licensing as explanatory variable in the model for contract research, and the growth of university revenues from contract research in the model for patent licensing.

The logarithm of numbers of university R&D personnel (in fill-time equivalents), and the growth rate of the logarithm of numbers of university R&D personnel are used to control for different sizes of provincial university systems. To account for province-level characteristics, the analysis makes use of several control variables. First, it includes the annual growth rate of provincial business R&D expenditures. R&D expenditures are measured in terms of RMB at constant 1998 prices. Growth in university licensing of patents and contract research might be driven by the presence of R&D performing enterprises in the province and not university research. Second, the annual growth rate of provincial technology market turnover controls for the size of the provincial technology market, another channels of technology transfer between universities and industry. The turnover of technology markets is measured in RMB at 1998 prices. Technology markets are technology fairs where representatives of universities, research institutions and firms meet face-to-face to establish contractual relations. Universities established legal entities to sell their IP and technical services at technology market. And third, the share of technology imports in provincial technology market turnover is used to control for technology imports. The volume of technology imports and technology transfer turnover is measured in RBM at 1998 prices. Chinese enterprises may use foreign technology as main channel of technology transfer (e.g. Keller, 2004). Finally, the growth rate of population is included to control for possible increases in aggregate demand that could have influenced demand for university research.

5.1.3. Empirical methodology

The empirical analysis is based on two models. Each of the two models considers one of the two technology transfer activities as outcome variables: (1) growth in revenues from patent licensing and (2) growth in revenues from R&D collaboration. The first model regresses annual growth in university revenues from patent licensing, $\Delta\ln(license_{ct})$, on the annual growth rate of total university R&D expenditures $\Delta\ln(R\&D^{total}{}_{ct})$, for c = 1, ..., M = 28 provinces, and t = 1, ..., T = 9 years as follows:

$$\ln\left(license_{ct}\right)=\alpha_1+\beta_1\ln\left(RD_{ct}^{total}\right)+\gamma_1\ln\left(RD_{ct}^{basic}\right)+\delta_1\ln\left(RD_{ct}^{applied}\right)+\phi_1\ln\left(contract_{ct}\right)+X_{ct}\chi_1+\eta_{1c}+\tau_{1t}+\varepsilon_{1ct} \quad (20)$$

where $\Delta\ln(R\&D^{basic}{}_{ct})$ denotes the annual growth rate of the logarithm of university R&D expenditures on basic research, and $\Delta\ln(R\&D^{applied}{}_{ct})$ captures the annual growth rate of the logarithm of university R&D expenditures on applied research and experimental development. These two variables test for the role of the type of R&D expenditure (basic versus applied R&D). $\Delta\ln(contract_{ct})$ denotes annual growth in university revenues from contract research with industry and tests for trade-offs between patent licensing and contract research with industry. Further, X_{ct} captures control variables that describes province-level characteristics that may affect science-industry technology transfer. These include the level and growth rate of university R&D personnel, growth of business R&D expenditures, growth of technology market transactions, the value of technology imports as a share of turnover at technology markets, and growth in population in a given province c at time t. η_{1c} denotes province fixed effects that measure unobserved differences across provinces, and τ_{1t} denote year fixed effects that control for annual time trends. ε_{1ct} captures the residual terms that vary across provinces and time periods with zero mean and variance σ^2.

Similarly, the second model regresses annual growth in university revenues from contract research, $\Delta\ln(contract_{ct})$, on the annual growth rate of total university R&D expenditures $\Delta\ln(R\&D^{total}{}_{ct})$, for c = 1, ..., M = 28 provinces, and t = 1, ..., T = 9 years as follows:

$$\ln\left(contract_{ct}\right) = \alpha_2 + \beta_2 \ln\left(RD_{ct}^{total}\right) + \gamma_2 \ln\left(RD_{ct}^{basic}\right) + \delta_2 \ln\left(RD_{ct}^{applied}\right) + \varphi_2 \ln\left(license_{ct}\right) + X_{ct}\chi_2 + \eta_{2c} + \tau_{2t} + \varepsilon_{2ct} \quad (21)$$

where, as above, $\Delta\ln(R\&D^{basic}{}_{ct})$ denotes the annual growth rate of the logarithm of university R&D expenditures on basic research, and $\Delta\ln(R\&D^{applied}{}_{ct})$ captures the annual growth rate of the logarithm of university R&D expenditures on applied research and experimental development. $\Delta\ln(license_{ct})$ denotes annual growth in university revenues from patent licensing and tests for trade-offs between patent licensing and contract research with industry. X_{ct} captures control variables that describes province-level characteristics, including level and growth in university R&D personnel, growth of business R&D expenditures, growth of technology market transactions, the value of technology imports as a share of turnover at technology markets, and growth in population. η_{2c} denotes province fixed effects and τ_{2t} stands for year fixed effects, while ε_{2ct} captures the residual terms with zero mean and variance σ^2.

5.2. Descriptive analysis of technology transfer activities of Chinese universities

The descriptive statistics, reported in Table 5.1, reveals that university revenues from patent licensing grew on average stronger than university revenues from contract research with industry during the years 1999 to 2007. The mean growth rate of university revenues from patent licensing across provinces was 22% per year in the period 1999 to 2007, against a mean annual growth rate of university revenues from contract research of 13% for the same period. The data further shows that there was substantial variation in growth rates of patent license revenues and contract research revenues across provinces in China. As for university R&D expenditures, three findings stand out. First, R&D expenditures grew on average stronger than university revenues from patent licensing and contract research. The mean annual growth rate of R&D expenditures reported across provinces was 23% between 1999 and 2007, against the mean annual growth rate of 22% of patent licence revenues and the mean annual growth rate of contract research revenues of 13%. Second, there was considerable variation across provinces in terms of annual growth rates of university R&D expenditures. And third, university R&D expenditures on basic research grew stronger than university R&D expenditures on applied research during the years 1999 to 2007. The sample also shows considerable differences across provinces in terms of business R&D expenditures, technology market turnover, and technology imports as a share of technology market turnover. If omitted, the differences across provinces might bias the estimates of my models.

Table 5.1. Descriptive statistics

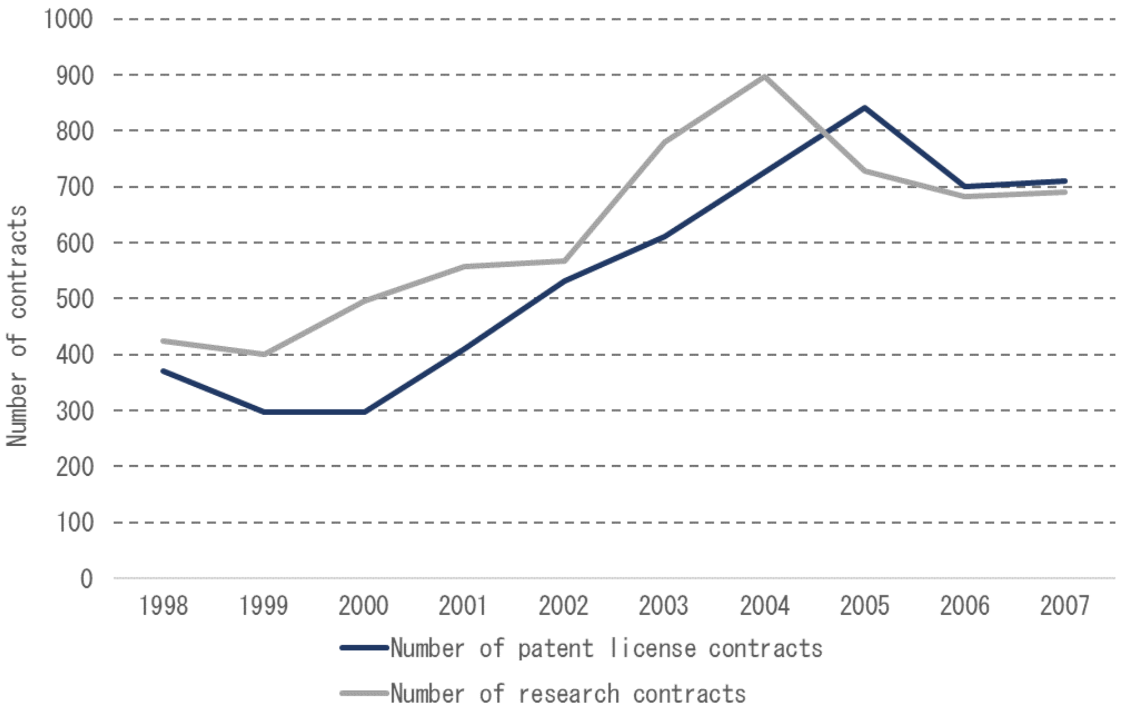
	Number of observations	Mean	Standard deviation	Min.	Max.
Growth of patent license revenues	162	0.22	1.63	-5.30	4.38
Growth of contract research revenues	219	0.13	1.15	-4.43	4.80
Growth of university R&D expenditures	225	0.23	0.29	-0.64	1.31
Growth of university expenditures for basic research	225	0.26	0.42	-0.97	1.86
Growth of university expenditures for applied research	225	0.20	0.30	-0.89	1.50
Number of university R&D personnel in thousand full-time equivalents	252	166.37	177.58	0.00	837.39
Growth of university R&D personnel	225	0.05	0.13	-0.41	0.44
Growth of business R&D expenditures	175	0.24	0.16	-0.28	0.82
Growth of technology market transactions	225	0.11	0.44	-2.92	3.11
Value of technology imports (as a share of turnover at technology markets)	250	0.08	0.14	0.00	1.43
Growth in population	243	0.01	0.02	-0.12	0.11
Full sample	252				
Number of years	9				
Number of provinces	28				

Note: The unit of observation is the province for the years 1998 to 2007. Growth rates are the available for the period 1999 to 2007.
Source: Author's calculations based on data from the MOE University Science and Technology Annual Report (2010).

Information on the number of patent license contracts and research contracts with industry, shown in Figure 5.1, points to the presence of joint university-industry research, as measured by research contracts with industry, already in 1998. The data also illustrates the growing importance of licensing of university patenting for the period 1998 to 2007. The number of university research contracts with industry increased from 425 in the year 1998 to 690 in the year 2007, against an increase of patent license contracts from 371 to 711 during the same period. While the number of patent licence contracts was initially lower than the number of R&D contracts, the number of licenses overtook the number of research contract with industry in 2005. Interestingly, the increase in number of patent license contracts lags the increase of R&D contracts, which suggests that contract research might attract follow-up demand for university intellectual property.

Figure 5.1. Number of university patent licenses and research contracts with industry

1998-2007

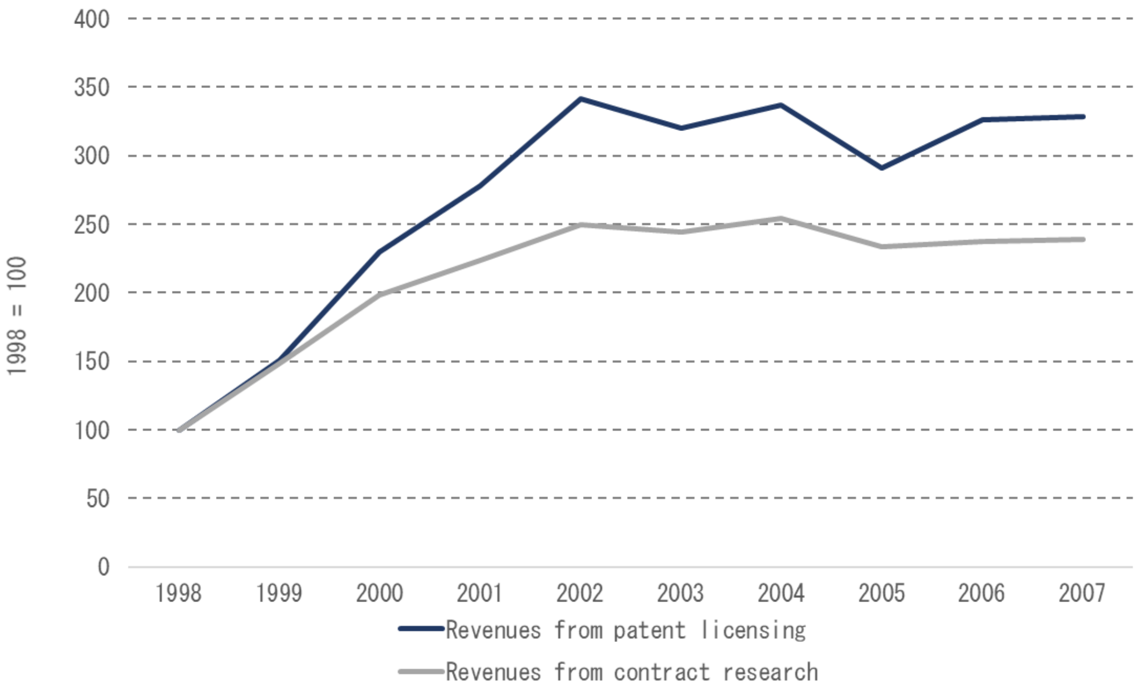


Note: The figure illustrates the annual number of patent license contracts (darker line) and research contracts (lighter line) between universities and industrial enterprises for the period 1998 to 2007.
Source: Author's calculations based on data from the MOE's University Science and Technology Annual Report (2010).

Figure 5.2 is based on information on university revenues and illustrates positive trends of university revenues from patent licensing and revenues from contract research with industry between 1998 and 2007. It shows trends in revenues using 1998 as reference year (i.e. 1998 = 100) for easier comparison. The data reveals that revenues from contract research grew by around 200% between 1998 and 2007, while revenues from patent licensing increased by more than 300%. Two things stand out. First, revenues from licensing of university patents increased more compared to revenues from contract research with industry. This finding points towards increased efforts of universities to commercialise their patents, which is in line with evidence on policy efforts that targeted university patenting in China (e.g. Fisch et al., 2016). And second, the positive trend in revenues from patent licensing and contract research stalled around the year 2002. Considering evidence brought forward on the increase in university patents after 2002 (see Section 4), this finding suggests a shift in the strategy of universities away from contract research and licensing of university intellectual property (IP) towards the protection of intellectual property generated from university research.

Figure 5.2. Trends in university revenues from licensing and contract research, 1998-2007

1998=100



Note: The figure illustrates the trend in annual university revenues from patent licenses (darker line) and contract research (lighter line) for the years 1998 to 2007 relative to 1998 (i.e. 1998=100).
Source: Author's calculations based on data from the MOE's University Science and Technology Annual Report (2010).

I expect that the shift in universities technology transfer strategies becomes visible regarding their industry partner. The analysis uses information on trends in university revenues from contract research with industry by ownership type for the period 1998 to 2007, as shown in Figure 5.3. The data reveals that increases in university revenues from contract research came primarily from collaboration with private enterprises. University revenues from privately owned enterprises (POEs) increased by 500% between 1998 and 2007, against an increase in revenues from contract research with state-owned enterprises (SOEs) of nearly 200% during the same period. The source for this shift may have been an increased innovation effort of private firms, which looked for strategic partnerships with universities to conduct risky research.

Figure 5.3. Trends in university revenues from contract research by source of funds

1998=100

Note: The figure illustrates the trend in annual university revenues from contract research with state-owned enterprises (dashed line) and with privately-owned enterprises (lighter line) for the years 1998 to 2007 relative to 1998 (i.e. 1998=100).
Source: Author's calculations based on data from the MOE's University Science and Technology Annual Report (2010).

5.3. Empirical analysis of technology transfer activities of Chinese universities

5.3.1. Technology transfer and university R&D

Table 5.2 summarises the findings from the estimation of the relationship between growth in university R&D expenditures and growth in revenues from technology transfer. the reported estimation coefficient are obtained after controlling for differences across provinces and annual time trends. Column (1) uses annual growth in university revenues from patent licensing as outcome variable. The results reveal that the annual growth rate of university R&D expenditures turns out to be insignificant. By type of research, growth in university R&D expenditures on basic research is positive and significant. In terms of magnitude, the coefficient of 1.330 tells us that a 1% increase in the growth rate of university R&D expenditures on basic research is associated with a 133% increase in the growth rate of university revenues from patent licensing. Conversely, the findings do not show any significant association between patent license revenues of universities and university R&D

expenditures on applied research. Regarding controls for province-level characteristics, growth in business R&D expenditures and the share of imported technology in technology market turnover turn out to be insignificant. Controlling for the factors, *hypotheses 3a*(*i*) is clearly confirmed (for patent licensing): Higher growth rates of university revenues from patent licensing coincide with higher growth rates of university R&D expenditures on basic research. *Hypothesis 3b*(*i*), on the other hand, is rejected (for patent licensing): Higher growth rates of university revenues from patent licensing do not coincide with higher growth in university R&D expenditures on applied research.

Column (2) shows the results for annual growth in university revenues from contract research with industry as outcome variable. As in the case of the patent license model, growth in total university R&D expenditures turns out to be insignificant. However, opposed to the findings for growth in patent license revenues, the growth rate of university R&D expenditures on basic research is not significant, while the growth rate of university R&D expenditures on applied research is negative and significant. This finding points to a lesser role of university R&D expenditures on basic research for contract research than for licensing of university patents. Regarding the control variables for province-level characteristics, growth in business R&D expenditures and the share of imported technology in technology market turnover are negative and significant. Based on these results, *hypotheses 3a*(*ii*) *and 3b*(*ii*) is rejected for contract research: Higher growth rates of university revenues from contract research with industry do not coincide with (a) higher growth rates of university R&D expenditures on basic research or (b) higher growth rates of university R&D expenditures on applied research.

Table 5.2. Growth in university revenues on growth in university R&D regression, 1999-2007

Dependent variable	Growth of patent license revenues (1)	Growth of contract research revenues (2)
Growth of university R&D expenditures	-0.284 (0.727)	0.438 (0.592)
Growth of university expenditures for basic research	1.330* (0.534)	0.652 (0.446)
Growth of university expenditures for applied research	-0.432 (0.670)	-1.428** (0.527)
ln(university R&D personnel)	-0.371 (1.682)	-0.419 (1.374)
Growth in university R&D personnel	-0.413 (1.666)	-0.533 (1.360)
Growth of contract research revenues	0.210 (0.128)	
Growth of patent license revenues		0.140 (0.085)
Growth of business R&D expenditures	-0.064 (1.033)	-2.587** (0.798)
Growth of technology market transactions	-0.850* (0.388)	-0.503 (0.321)

Value of technology imports (as a share of turnover at technology markets)	-2.007 (1.892)	-3.781* (1.503)
ln(population)	7.887 (13.415)	8.799 (10.941)
Growth in population	-13.486 (15.276)	9.596 (12.493)
Province fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	130	130
σ-squared	1.522	1.243
R-squared	0.293	0.346
Adjusted R-squared	-0.024	0.052
Log-likelihood	-214.425	-188.146
Akaike information criterion (AIC)	452.850	400.293
Bayesian information criterion (BIC)	487.260	434.703
F-statistics	1.963	3.182
Degrees of freedom (df)	89	89

Note: OLS estimates for 28 provinces and 9 years (1999-2007). Column (1) regresses annual growth in university revenues from patent licensing on annual growth in total university R&D expenditures, annual growth in university R&D expenditures on basic research, annual growth in university R&D expenditures on applied research and development, annual growth in university revenues from contract research with industry, and controls for level and growth in university R&D personnel, annual growth in business R&D expenditures, annual growth in technology market transaction turnover, the value of technology imports as a share of technology market turnover, and level and growth in population. It also controls for province fixed effects and year fixed effects. Column (2) regresses annual growth in university revenues from contract research with industry on annual growth in university R&D expenditures, annual growth in university R&D expenditures on basic research, annual growth in university R&D expenditures on applied research and development, annual growth in university revenues from patent licensing, and controls for level and growth in university R&D personnel, annual growth in business R&D expenditures, annual growth in technology market transaction turnover, the value of technology imports as a share of technology market turnover, and level and growth in population. It also controls province fixed effects and year fixed effects. Standard errors are clustered at the province level. *, **, and *** indicate significance at 5%, 1%, and 0.1% levels, respectively.
Source: Author's calculations based on data from the MOE University Science and Technology Annual Report (2010).

5.3.2. Trade-offs between technology transfer channels

There may be potential trade-offs between university licensing and contract research with industry. On the one hand, patent licensing might have detrimental effects on university's engagement with industry. Firms may perceive patent-active universities as interfering in their markets as technology providers. As contract research requires trust between researchers and firms, these channels of technology transfer may be jeopardised by patent activity of universities. On the other hand, there might be synergies between these two channels of technology transfer. Contract research is an input factor for patenting and licensing activities of universities. Patenting activity of universities may be a follow-up activity of joint research with industry. University researchers' engagement with industry may provide them with insights into commercial research areas.

Table 5.2 summarises the findings from the estimation of trade-offs between patent licensing and R&D collaboration. Column (1) suggests that there is no significant trade-off between the growth rate of university revenues from patent licensing and the growth rate of revenues from contract research with industry. The coefficient is positive, which might point towards potential synergies, albeit not significant. Based on this finding, *hypothesis 4* is not confirmed: Higher growth rates of university revenues from contract research with industry do not coincide with higher growth rates of university revenues from patent licensing.

6. Conclusion

Summary

This thesis investigates the effects of universities on innovation and productivity between 1998 and 2007, thereby providing insights on the role of university research in driving China's transition towards innovation- and productivity-based growth. It does so by means of a dataset that links Chinese patents to China's industrial enterprises and universities. *First*, it provides evidence on the relationship between university patent activity and industry patent activity and TFP (i) within a prefecture, and (ii) in other prefectures of the country. To better identify the effects of university patent activity on industry, the thesis analyses the impact of pro-patent reforms – an exogenous shock that led to increased university patent activity, on increases in patent numbers and TFP levels of industrial enterprises. Additional analysis explores the differential effects of university reforms on patent activity and productivity by (i) entering and incumbent firms, (ii) high technology-intensive and low technology-intensive firms, (iii) and state-owned and private firms. *Second*, the thesis uses data from Chinese university surveys to examine the extent to which university R&D relates to contract research and patent licensing – two channels linking university research to industry, considering R&D expenditures of the regional business environment. Additional analyses assess the occurrence of trade-offs between contract research and patent licensing.

The findings show that increases in university patents are positively associated with increases in industrial patents and industrial total factor productivity (TFP) in the same prefecture, while evidence for spillover effects from university patent activity to other prefectures is weak (*research question 1*). The findings further show that pro-patent university reforms had a positive impact on industrial patent numbers and TFP levels (*research question 2*). Additional analysis reveals that the impacts of reforms were larger for newly established enterprises and for privately-owned enterprises. Regarding channels linking university research to industry, the results reveal that growth in university revenues from patent licensing is associated with growth in university R&D expenditures on basic research, while evidence for the role of R&D expenditures on applied is weaker (*research question 3*). Trade-offs between patent licensing and contract research do not reveal themselves (*research question 4*). Table 6.1 provides a summary of the findings according to research question and hypothesis to which they refer.

Table 6.1. Summary of findings

Research question	Hypothesis	Finding
1. What is the relationship between university patent activity and industry TFP and patent activity (i) within a prefecture, and (ii) in neighbouring and other prefectures in China?	1a. The higher level of university patent stocks in a prefecture, the higher the level of industrial TFP.	Confirmed
	1b. The higher the level of university patent stocks in a prefecture, the higher the level of industrial patent stocks.	Confirmed
	1c. The higher the level of university patent stocks in neighbouring prefectures, the higher the level of industrial TFP in a prefecture.	Rejected
	1d. The higher the level of university patent stocks in neighbouring prefectures, the higher the level of industrial patent stocks in a prefecture.	Rejected
2. What is the effect of pro-patent university reforms on changes in industry patent numbers and TFP levels?	2a. Industrial TFP levels increased significantly following reforms to university IPR in 2002.	Confirmed
	2b. Industrial patent numbers increased significantly following reforms to university IPR in 2002.	Confirmed
	2c. The levels of industrial TFP of privately-owned enterprises increased more compared to that of state-owned enterprises following university IPR-reforms in 2002.	Rejected
	2d. The numbers of industrial patent stocks of privately-owned enterprises increased more compared to that of state-owned enterprises following university IPR-reforms in 2002.	Confirmed
	2e. The levels of industrial TFP of high technology-intensive industries increased more compared to that of low technology-intensive industries following university IPR-reforms in 2002.	Rejected
	2f. The numbers of industrial patent stocks of high technology-intensive industries increased more compared to that of low technology-intensive industries following university IPR-reforms in 2002.	Rejected
	2g. The levels of industrial TFP of newly established enterprises increased more compared to that of incumbent enterprises following university IPR-reforms in 2002.	Rejected
	2h. The numbers of industrial patent stocks of newly established enterprises increased more compared to that of incumbent enterprises following university IPR-reforms in 2002.	Confirmed
3. What is the relationship between university R&D, university patent licensing and university contract research with industry?	3a(i). The higher the growth rate of university R&D expenditures on basic research in the same province, the higher the growth rate of university revenues from patent licensing.	(i) Confirmed
	3a(ii). The higher the growth rate of university R&D expenditures on basic research in the same province, the higher the growth rate of university revenues from contract research.	(ii) Rejected
	3b(i). The higher the growth rate of university R&D expenditures on applied research in the same province, the higher the growth rate of university revenues from patent licensing.	(i) Rejected
	3b(ii). The higher the growth rate of university R&D expenditures on applied research in the same province, the higher the growth rate of university revenues from contract research.	(ii) Rejected
4. Is there a trade-off between patent licence activity and contract research activity of Chinese universities?	4. The higher the growth rate of university revenues from patent licensing in the same province, the higher the growth rate of university revenues from contract research.	Rejected

Discussion of the findings

The findings report evidence that increases in university patent stocks are associated with increases in TFP levels and patent stocks of industrial enterprises in the same prefecture, thereby providing new evidence on the potential contributions of universities to innovation and productivity of their local economies. The estimates imply that a 1% increase in 5-year lagged university patent stocks is associated with (i) a 1% increase in industrial patent stocks in the same prefecture, and a 2.5% increase in industrial TFP levels in the same prefecture between 1998 and 2007. The results hold after controlling for prefecture fixed effects, industry fixed effects, year fixed effects, and a host of controls for observable prefectural characteristics. Conversely, the evidence for inter-regional spillover effects is weak. Considering these findings, China's investment in university research seemed to have paid off in terms of increased innovation and productivity. However, considering the findings on spillover effects on neighbouring prefectures, policies aimed at increasing the impact of university research on innovation and productivity should help create equal conditions for enterprises in remote regions in China. Creating a level playing field matters as emerging economies are characterised by very few innovative regions surrounded by regions with weaker innovation capacities (e.g. Crescenzi et al., 2012).

Further, the thesis provides empirical evidence on the effect of pro-patent university reforms on increases in industrial patent numbers and TFP levels. The data shows that industry experienced an increase in patent numbers of 7% after the reforms in 2002 (for the period 2003-2007) relative to before (1998-2002). This corresponds to an annual increase of 1.4% in patent numbers following reforms. The findings further report an increase of 8% in TFP levels after the reforms in 2002 (for the period 2003-2007) relative to before (1998-2002), which corresponds to an annual increase of 1.6%. Additional analysis reveal that impacts of university reforms differed across enterprises and industries. The effects of reforms were larger for newly established enterprises than for incumbent enterprises, and larger for privately-owned enterprises compared to state-owned enterprises, while they affected high technology-intensive enterprises and low technology-intensive enterprises to the same extent. The results hold for the sample of industrial enterprises outside of 46 kilometres, 50 kilometres, and 62 kilometres distance to the closest university to account for potential endogeneity of university locations.

Data on the distribution of Chinese patents of industrial enterprises and universities reveals that a few leading industrial enterprises and universities were responsible for increases in China's overall patent numbers between 1998 and 2007. The leading 103 industrial enterprises in terms of patent numbers, or the top 1% of enterprises in the sample, accounted for 55% of all Chinese patents. This number includes well-known enterprises such as e.g. Huawei, ZTE and Lenovo. As for universities, the leading 40 universities accounted for 58% of all Chinese patents granted to Chinese universities between 1998 and 2007. These findings suggest that Chinese policy efforts to create “world-class” universities might have led to the concentration of patent activity among leading institutions (Chen et al., 2016; Zhang et al., 2013). The findings also show that China’s leading tech firms were responsible for China’s patent surge during the period 1998 to 2007, providing new evidence to our understanding of Chinese innovation dynamics (e.g. Rong et al., 2017; Hu and Jefferson, 2009).

Understanding the channels that link university research and industry is an important field of study. The thesis uses information on patent licensing and contract research activity of Chinese universities in 28 provinces for the years 1998 to 2007 and reveals several interesting findings about the economic relevance of these channels of technology transfer for Chinese universities. University revenues from licensing of patents increased more compared to revenues from contract research with industry between 1998 and 2007. This positive trend coincides with increased policy efforts supporting the commercialisation of university IPR during the same period (Li, 2012; Hu and Jefferson, 2009). However, increases in university revenues from patent licensing halted around the year 2002, which suggests that universities might have shifted their technology transfer strategies away from commercialisation of IP and contract research with industry towards university patenting. Understanding the extent to which university strategies for technology transfer affects industry innovation in China is an important area to investigate further.

Finally, the data show that there were no trade-offs between university licensing activity and contract research with industry in the period 1998 to 2007. This suggests that universities that engaged to a stronger degree in commercialisation of their IP did not enter in competition with industry but seemed to have attracted contract research with industry. As for the relationship between university R&D expenditures and university revenues from technology transfer, the data shows that increases in university R&D expenditures on basic research were associated with increases in university revenues from patent licensing, while the evidence on the effects of R&D expenditures for applied research is weak. This finding points to the importance of basic research for the patent activity.

Contribution to the literature

This thesis stands out from the existing literature in that it uses a comprehensive firm- and university-level dataset and links it to Chinese patent data for the empirical analysis. The new dataset is an important contribution to recent research that matched Chinese industrial census data to patent data (He et al., 2018 and 2017), by providing additional information on patent activity of universities. The dataset combines information on 127.840 patents from 10.388 Chinese industrial enterprises and 406 universities. The data also includes information on the precise location of enterprises and universities, which allows constructing measures of geographical distance between enterprises and universities in order to analyse spillover effects of universities. The final data also accounted for industrial privatisation after 1998 and industrial reclassification in 2002 following established literature for China (e.g. Brandt et al., 2012).

This is the first study, to the author's knowledge, that reports evidence for university spillover effects on patenting and productivity for a sample of industrial firms in an emerging economy. In doing so, the thesis contributes to the growing empirical body of literature on the link between universities and economic development. In a historical study of Germany, Cantoni and Yuchtman (2014) provide evidence that the establishment universities played a causal role in the formation of new market towns in 14th century Germany. In a global study using of 15,000 universities across 78 countries, Valero and Van Reenen (2019) show that increases in the number of universities were related to growth of GDP per capita over the period 1950 to 2010. For the United States, Kantor and Whalley (2014) demonstrate that university R&D expenditures had a causal impact on regional growth for the years 1981 to 1996. The authors use market shocks to university endowment values as an instrument for university spending. For Finland, Toivanen and Väänänen (2016) show that the establishment of technical universities increased the number of industry patents in Finland over the period 1988 to 1996. For China, Glaeser and Lu (2018) use population census data between 2002 and 2013 and show that there were spillovers from university education activities on individual earnings across Chinese cities. To identify causality, the authors instrumented city-level education using the number of relocated university departments across cities in the 1950s.

To date, there are only few studies that have considered differential impacts of universities by industry characteristics. Motohashi (2005) investigates the effects of science-industry R&D collaboration on productivity of newly established enterprises and incumbent enterprises in Japan. For China, studies show differences between state-owned enterprises and private enterprises in their patent propensity (Rong et al., 2017; Hu and Jefferson, 2009), and productivity (Böing et al., 2016;

Brandt et al., 2012). Hong and Su (2013) provide additional insights on differences in joint patenting with universities across ownership type of enterprises. However, they do not analyse the link between university research and industrial performance.

The thesis also contributes to a growing empirical literature on the role of geographical proximity to universities for innovation. Belenzon and Schankerman (2013) study data on U.S. citations from corporate patents to university patents and show that proximity effects declined sharply with distances between university patent holder and industry patent holder. Andersson et al. (2009) demonstrate that the establishment of new universities increased local productivity growth in Sweden between 1985 and 2001. Helmers and Overman (2017) use data on the opening of new research stations in the United Kingdom and report increases scientific publications within 25 km distance of the new research station in the first ten years after its opening. The evidence on inter-region geographical spillovers is ambiguous. For China, Scherngell and Hu (2011) use data on scientific co-publications and provide evidence for positive inter-regional spillover effects, while the findings of Crescenzi et al. (2012) that are based on patent data point to negative spillover effects across Chinese provinces.

The evidence reported in this thesis suggests that policy can provide the necessary framework conditions to facilitate spillovers from university research, thus increasing the effectiveness of public investment in university research. IPR is one core dimension of the policy framework for science-industry technology transfer. Scholars have highlighted the importance of reforms to the legal framework for IPR for China's surge in patenting. Hu and Jefferson (2009) use data on 22,000 large- and medium sized industrial enterprises for the period 1995 to 2001 and demonstrate that increases in industrial patent activity were associated with pro-patent reforms. Motohashi and Yun (2007), building on the same dataset of 22,000 manufacturing firms for the period 1996 to 2002, point to the importance of university reforms for increased science-industry R&D collaborations. Li and Qian (2013) and Li (2012) argue that weak enforcement of IPR represented was a constraint for science-industry collaboration. Kafouros, et al. (2015) provide evidence that regional differences in the enforcement of university IPR affected science-industry collaboration in China. Li (2012) argues that administrative reforms that established a unified institutional framework for university IPR were important in increasing patent activity of universities and industry in 2002. Other studies analysed the impacts of national R&D programmes in China. Zhang, Patton, and Kenney (2013) provide case study evidence that university reforms, specifically the 985 national R&D project, were associated with an increase in the rate of publication in international journals by researchers at leading Chinese 24 universities.

Finally, the findings contribute to empirical evidence on distinct channels linking university research and industry innovation. Case studies for China so far have looked separately at, among others, co-patent activity involving universities and industry (Hong and Su, 2013), and formal R&D collaboration (Motohashi and Yun, 2007). Studies that analysed the associations between R&D collaboration with universities and industry patenting outside China include, among others, Hall et al. (2003) for the United States, Robin and Schubert (2013) for France and Germany, and Maietta (2015) for Italy. This thesis provides evidence on the separate effects of distinct channels linking university research and industry patent activity, including university patenting, patent licensing, and contract research with industry.

Limitations and future research

There are several limitations to the work. While this thesis provides evidence the effects of spillover from university research on industry innovation and productivity, it does not track actual knowledge flows from universities to industry, which is a serious limitation of the available Chinese patent data. Rather, the analysis made use of geographic proximity to assess the role of university spillovers for local industrial patent activity and TFP.

There are several caveats related to Chinese industrial census and patent data. First, the industrial census, however useful in providing a comprehensive picture of industrial activity, does not cover smaller private firms with sales below USD 600 000 at 1998 prices (RMB 5 million). This means that the data does not reveal any insights about the potential impact of universities on spin-off creation in China, which is another important channel of impact. Second, the WHED university survey covers only leading institutions of higher education, excluding, for example, teaching-oriented colleges and further education institutions. These institutions are responsible for teaching and engage with local business, which is not captured in the data used in this thesis. And finally, studies suggest that while the number of Chinese patents surged after 1998, their quality remained low which might impede innovation dynamics in China (Böing and Müller, 2016; Dang and Motohashi, 2015). Unfortunately, SIPO patent data in PATSTAT contains only inadequate citation information — a widely used patent quality indicator.

Future research needs to address these limitations. Better data is needed to unravel mechanisms linking university research to industry in China, as well as new forms of science-industry interactions. This includes citation data, data on the movement of students, university spin-offs, and new forms of strategic joint research between universities and enterprises (e.g. public-private collaborative platforms for enabling technologies). Additional research that analyses the causal impacts of university research on firm innovation and productivity using better causal designs would be also a valuable extension.

Annex. Construction of the dataset for empirical analysis

This thesis contributes to the empirical literature with a new firm- and university-level dataset for economic analysis. This annex describes the steps involved in the construction of the database, including matching of observations of industrial enterprises and universities with patent information, regionalisation of the enterprise and university data using postal code-prefecture concordance tables, construction of productivity indexes, patent stock measures, distance measures, the appropriate use of deflators for nominal variables, industrial concordance tables, and technology intensity concordance tables.

A.1. Creation of an industry panel

Each enterprise in the industrial census database has a unique numerical identifier (ID). Annual observations of enterprises in the industrial census are matched using their unique IDs to create a ten-year firm panel. In line with Brandt et al. (2012), the fraction of enterprises that can be linked over time increases from 85% in the first two years (1998-1999) to 92% in the last two years (2006-2007). In line with Brandt et al. (2012), 95.9% of all matches are constructed using enterprise IDs, and 4.1% are constructed using the information on the enterprise name. This provides an unbalanced panel that increases in size from 165,118 firms in 1998 to 325,297 in 2007 (see Table A1). On average, 14% of enterprises exit the sample. Entry rates outnumber exit rates with the average enterprise entry at 20% a year. 99.9% of enterprises have information on postal code, which is required for the regionalisation of the data (see Section A.6). Information on the year of establishment of an enterprise is available for 99.9% of the enterprise sample. This information is needed to construct samples of new entering enterprises (established in 1996 or after), and of incumbent enterprises (established before 1996).

Table A1. Sample of industrial enterprises

	Number of enterprises
1998	165,118
1999	150,562
2000	162,882
2001	159,785
2002	181,557
2003	196,220
2004	279,092
2005	271,835
2006	301,961
2007	325,297
Full sample	2,194,309

Source: Author's calculations using National Bureau of Statistics (2008).

A.2. Accounting for enterprise restructuring and privatisation of enterprises

During the period 1998 to 2007, many Chinese enterprises were restructured. The restructuring took the form of privatisations of state-owned enterprises, joint ventures, mergers or acquisitions. It is not unusual that an enterprise with the same name acquired a different ID due to the ownership change. To account for the restructuring of enterprises and to avoid treating them falsely as newly established enterprises, enterprises are tracked as their ownership changes over time using information on their names. Privatised enterprises, which received a new ID but remained under the same name, are treated as one enterprise and their first observed ID is used throughout the period of observation. If an enterprise changes ownership, the latest observed ownership type (e.g. private) is applied to the entire period of observation.

A.3. Accounting for the industry reclassification in 2002

I use the three digit-level industry Chinese Industry Classification Rev. 2002 for the empirical analysis of industry differences in impacts of university research. The industrial census contains information on the four-digit level industry class. The CIC is a standard classification of economic activity in China that is comparable to the Standard International Industrial Classification (SITC). CIC was developed by the NBS and underwent a reform in 2002. The 2002 re-classification is accounted for following the concordance scheme developed by Brandt et al. (2012) (see Table A2). The CIC classification distinguishes between different levels of classes from the first level (1-digit level) to the fourth level (4-digit level). The 1-digit level provides information on broad industry classes including primary industries (class A), secondary industries that consist of mining (class B), manufacturing industries (class C), utilities (class D), construction industries (classes E) and tertiary industry that includes service industries (class F to T). The lowest 4-digit level contains detailed information on products.

Table A2. Industry concordance, pre- and after 2002 CIC reform

2002 CIC	pre-2002 CIC	2002 CIC	pre-2002 CIC	2002 CIC	pre-2002 CIC	2002 CIC	pre-2002 CIC	2002 CIC	pre-2002 CIC	2002 CIC	pre-2002 CIC
1310	1312	1756	1725	2631	2631	3220	3220	3622	3624	3931	4041
1310	1311	1756	1725	2631	2633	3230	3240	3623	3625	3931	4041
1320	1314	1756	1726	2631	2633	3240	3260	3624	3643	3933	4043
1320	1315	1757	1890	2641	2652	3311	3311	3624	3626	3939	4049
1320	1319	1757	1790	2642	2653	3312	3312	3624	3626	3940	4045
1331	1321	1757	1790	2643	2654	3313	3314	3625	3434	3939	4049
1332	1322	1761	1781	2644	2655	3314	3316	3631	3631	3940	4045
1340	1332	1762	1782	2645	2659	3315	3317	3632	3632	3940	4046
1340	1334	1763	1783	2651	2664	3316	3321	3633	3633	3951	4063
1340	1331	1769	1789	2651	2662	3317	3322	3641	3638	3952	4065
1351	1341	1810	1810	2651	2665	3319	3319	3642	3627	3953	4064
1352	1342	1820	1830	2651	2663	3319	3329	3643	3639	3954	4066
1352	1343	1830	1820	2651	2661	3319	3318	3644	3628	3955	4062
1361	1351	1910	1919	2652	2666	3319	3323	3645	3636	3955	4061
1362	1353	1910	1912	2653	2667	3321	3331	3646	3637	3956	4069
1362	1354	1910	1911	2659	2669	3322	3332	3649	3679	3956	4069
1362	1352	1921	1921	2661	2671	3329	3339	3649	3679	3956	4069
1363	1317	1922	1923	2662	2672	3331	3341	3651	3635	3961	3487
1364	1359	1923	1924	2662	2683	3340	3360	3651	3635	3969	3486
1364	1359	1923	1925	2662	2682	3351	3381	3651	3635	3971	4071
1370	1390	1924	1929	2664	2674	3351	3383	3653	3674	3972	4073
1370	1390	1924	1929	2665	2675	3352	3385	3661	3615	3979	4072
1391	1492	1931	1931	2667	2688	3411	3410	3662	3617	3979	4074
1391	1497	1932	1932	2671	2681	3412	3465	3663	3900	3979	4079
1392	1491	1939	1939	2672	2685	3421	3431	3669	3619	3991	4099
1393	1344	1941	1951	2673	2686	3422	3435	3671	3641	3991	4080
1411	1412	1942	1952	2674	2684	3423	3491	3672	3642	3991	4099
1419	1413	2011	2011	2679	2687	3424	3484	3674	3644	4011	4111
1421	1411	2012	2012	2679	2689	3424	3488	3675	3645	4012	4112
1422	1419	2021	2021	2710	2710	3429	3439	3676	3647	4013	4113
1422	1415	2022	2022	2720	2720	3431	3441	3679	3683	4013	4113
1431	1313	2023	2023	2730	2730	3432	3442	3679	3649	4019	4119
1432	1414	2029	2029	2730	2730	3432	3442	3681	3652	4019	4181
1432	1414	2031	2673	2750	2740	3440	3450	3681	3652	4020	4122
1440	1420	2031	2031	2760	2750	3451	3461	3681	3652	4020	4121
1451	1431	2031	2031	2770	3654	3451	3485	3681	3652	4031	4130
1451	1432	2031	2033	2811	2811	3452	3463	3684	3651	4031	4130
1452	1433	2031	2031	2812	2812	3453	3499	3684	3653	4039	4182
1453	1434	2031	2673	2812	2819	3453	3499	3684	3673	4041	4141
1453	1435	2040	2040	2821	2821	3453	3495	3686	3655	4042	4143
1459	1439	2110	2110	2822	2822	3453	3499	3689	3685	4042	4143
1461	1442	2120	2120	2823	2823	3459	3469	3691	3677	4051	4151
1462	1451	2130	2130	2824	2824	3460	3470	3692	3672	4052	4153
1462	1452	2140	2140	2829	2829	3471	3481	3693	3676	4052	4153
1469	1445	2190	2190	2911	2910	3471	3481	3694	3675	4053	4155
1469	1454	2210	2210	2912	2920	3471	3481	3695	3678	4061	4160
1469	1444	2221	2221	2913	2981	3481	3483	3695	3678	4061	4160
1469	1453	2222	2223	2920	2930	3481	3483	3697	3646	4071	4171
1469	1441	2223	2224	2930	2940	3481	3482	3711	3712	4072	4172
1469	1443	2231	2230	2940	2950	3489	3489	3711	3713	4090	4190
1469	1449	2231	2230	2950	2970	3511	3511	3711	3711	4090	4189

1469	1459	2311	2311	2960	2960	3512	3512	3712	3532	4111	4211
1491	1493	2312	2413	2990	2990	3512	3515	3713	3714	4112	4212
1492	1498	2319	2312	2990	2989	3513	3513	3714	3717	4113	4242
1492	1495	2320	2319	3010	3010	3514	3514	3714	3716	4113	4241
1493	1360	2330	2320	3020	3020	3519	3519	3714	3715	4114	4215
1494	2677	2411	2411	3030	3030	3521	3521	3719	3781	4114	4217
1499	1499	2411	2411	3040	3040	3522	3523	3719	3719	4115	4216
1510	1511	2412	2415	3040	3040	3523	3525	3721	3722	4119	4219
1521	1512	2413	2417	3060	3050	3524	4091	3721	3723	4119	4218
1522	1513	2419	2419	3070	3080	3525	3526	3721	3724	4121	4221
1523	1514	2421	2421	3081	3060	3529	3529	3721	3721	4122	4222
1524	1515	2422	2423	3082	3070	3530	3531	3722	3725	4123	4226
1529	1516	2422	2423	3090	3090	3541	3533	3723	3784	4123	4223
1531	1521	2423	2859	3111	3110	3542	3535	3723	3750	4124	4224
1532	1522	2423	2429	3112	3132	3542	3535	3724	3726	4125	4225
1533	1523	2423	2429	3121	3121	3543	3542	3725	3727	4126	4227
1534	1529	2423	2429	3122	3123	3544	3561	3726	3782	4127	4228
1534	1590	2431	2431	3123	3124	3544	3562	3731	3731	4128	4230
1534	1529	2432	2433	3124	3134	3551	3541	3732	3732	4129	4229
1535	1524	2433	2435	3129	3129	3552	3568	3741	3740	4130	4214
1540	1550	2439	2439	3131	3131	3552	3567	3741	3740	4130	4260
1610	1610	2440	2440	3132	3151	3560	4092	3751	3763	4141	4213
1620	1620	2451	2450	3132	3151	3571	3534	3751	3762	4142	4353
1690	1690	2452	2490	3133	3133	3573	3536	3751	3761	4151	4251
1711	1729	2511	2520	3134	3135	3574	3537	3752	4392	4152	4252
1711	1721	2511	2530	3135	3136	3574	3538	3752	4391	4153	4254
1711	1722	2512	2510	3139	3139	3575	3539	3752	3785	4154	4257
1712	1723	2520	2570	3141	3141	3575	3539	3752	4391	4154	4256
1721	1741	2530	3387	3142	3142	3575	3590	3752	4391	4155	4173
1722	1742	2530	3349	3143	3143	3576	3634	3752	4392	4159	4259
1722	1749	2530	3387	3144	3145	3577	4243	3752	4391	4190	4290
1722	1743	2530	3349	3145	3147	3581	3563	3754	3764	4211	4311
1723	1744	2530	3349	3146	3148	3582	3565	3759	3791	4212	4312
1730	1769	2530	2676	3147	3181	3582	3566	3761	3786	4213	4313
1730	1761	2611	2611	3148	3182	3583	3580	3761	3771	4214	4314
1730	1762	2612	2615	3149	3189	3583	3681	3762	3779	4215	4315
1741	1771	2612	2613	3149	3149	3583	3689	3762	3779	4216	4316
1742	1773	2613	2617	3152	3153	3589	3569	3791	3792	4217	4317
1742	1779	2614	2651	3153	3155	3591	3571	3792	3793	4218	4318
1742	1772	2619	2619	3159	3159	3592	3564	3799	3789	4219	4319
1743	1774	2619	2619	3161	3161	3592	3572	3911	4011	4221	4351
1751	1724	2619	2619	3162	3163	3611	3611	3912	4012	4222	4357
1752	1745	2621	2621	3169	3169	3612	3621	3919	4013	4229	4355
1753	1763	2622	2622	3191	3171	3613	3671	3921	4022	4310	6290
1754	1775	2623	2623	3191	3172	3614	3629	3921	4021	4310	6290
1755	2851	2624	2624	3199	3190	3614	3629	3922	4023		
1755	2852	2625	2629	3199	3179	3615	3613	3923	4024		
1755	2853	2625	2625	3210	3420	3621	3622	3924	4027		
1755	2854	2625	2629	3210	3210	3621	3623	3929	4029		

Source: Brandt et al. (2012), available at https://feb.kuleuven.be/public/n07057/China/ (accessed 4 February 2019).

A.4. Creation of a university panel

University survey information contains only the latest available year of observation, which is mostly the year 2014. To construct a university panel from 1998 to 2007, data from the World Higher Education database (WHED) (International Association of Universities, 2017) on the latest available year was taken and expanded to cover the years 1998 to 2007. Data expansion is possible because WHED data provides time-invariable characteristics of universities including name, age, public or private status, location (address and postal code), and year of establishment. In the case that a university was established after 1998, data was expanded up to the year of establishment. This resulted in a university panel that increases in size from 627 universities in 1998 to 680 in 2007. The university data is matched to the enterprise data by linking year and prefecture information (see section A.5).

A.5. Matching of enterprise and university information with patent data

To match university data with patent data, information on university names is used as it appears in the university surveys and match them to names of patent holders (or assignees) as they appear on the patent document as follows:

- In a first step, exact matches of patent holder names and university names were identified. In order to do so, the names of patent holders and universities are transformed to lowercases and common appellations of patent holder names are dropped to reduce computing time, such as e.g. “co” and “ltd”. The cleaned patent holder names are then matched to cleaned university names using the matching algorithm “match” in the software package STATA. 2,206 patent holder names can be linked to university names using exact matches, i.e. where the name in the patent document corresponds 1:1 to the name of the university as they appear in the survey.

- In a second step, patent holder name and university name are matched using approximate matching that allows linking cases for which names differ slightly due to e.g. spelling mistakes. Similarity scores are calculated between two names and a match is defined between names when the score is above a certain threshold. It is assumed that when there is a high overlap between the names, then the patent holder name and the university name are identical, e.g. “University of Beijing” and “University Beijing”. The textual information contained in the names is partitioned into bigrams or parts of two letters, e.g. "University" is partitioned into “Un”, “ni”, “iv”, “ve”, “er”, “rs”, “si”, “it”, and “ty”. Using the bigrams, Jaccard similarity coefficients are calculated to measure similarity between the set of bigrams A of patent holder names and the set of bigrams B of university names to see which partitions are shared and which are distinct. Similarity between set A and set B is measured using the Jaccard coefficient J, which is a commonly used measure of similarity that ranges from 0% to 100%, where 100% is the maximum value for similarity, and is defined as follows:

$$J(A,B)=\frac{|A\cap B|}{|A\cup B|}=\frac{|A\cap B|}{|A|+|B|-|A\cap B|} \tag{22}$$

where $A \cap B$ represents the intersection of sets A and B, i.e. the total number of attributes where A and B both have identical bigrams. A U B denotes the union sets A and B, i.e. the total number of attributes where A and B both have different bigrams. similar matches are defined as matches with Jaccard similarity coefficients of 0.90 (90%) or higher.

I could not apply the text-matching algorithm for industrial enterprise data and PATSTAT data directly because PATSTAT provides information on patent holder names in English, while the industrial census provides the information in Chinese. SIPO provides information on patent holder names in Chines, but the data is not freely available in PATSTAT. To link ASIE industrial enterprise data with PATSTAT patent data, patent-industrial census linked dataset of He et al. (2017 and 2018) is used. Their dataset provides Chinese patent data linked to China's industrial census data for the years 1998 to 2007 and contains information on enterprise IDs and patent publication numbers. The authors use approximate matching to link university patents to their respective universities (for details of the matching process, see He et al., 2018). The dataset provides information on names and IDs of industrial enterprises, as well as the publication numbers of their Chinese patents.[23] Publication numbers in the SIPO patent database used by He et al. (2017 and 2018) and in the EPO Worldwide Statistical Patent database are identical, which allows me to link patent numbers of Chinese industrial enterprises to the EPO Worldwide Statistical Patent database. As He et al. (2017 and 2018) use the same industrial data, Chinese patents can be easily matched to the dataset of this thesis using enterprise IDs in the industrial census.

The text-based matching process resulted in 127,840 SIPO patents out of a total of 218,156 (or 59%) SIPO patents with Chinese patent holders[24] that could be matched to enterprises and universities. This includes 88,910 SIPO patents of enterprises (or 41%), and 38,930 SIPO patents of universities (18%) for the period 1998 to 2007 (see Table A3). Out of the 127,840 linked patents, 70% are industry patents and 30% represent university patents.

Table A3. Sample of Chinese patents

	Number of patents in PATSTAT	No. of patents matched to industrial enterprises	No. of patents matched to universities
1998	5,765	572	52
1999	7,096	1,144	78
2000	10,075	1,718	432
2001	13,579	2,746	383
2002	21,226	5,656	1,106
2003	29,358	8,362	2,850
2004	32,751	9,738	4,635
2005	39,481	14,379	7,017
2006	36,690	19,838	8,122
2007	22,135	24,757	14,255
Full sample	218,156	88,910	38,930

Source: Author's calculations, using National Bureau of Statistics (2008), He et al. (2017), European Patent Office (2017) and International Association of Universities (2017).

A.6. Regionalisation

Regions are defined as Chinese prefectures. The prefectural-level constitutes the second level of administrative divisions of PRC. The prefectural level consists of 293 prefecture-level cities (dìjíshì), 8 prefectures (dìqū), 30 Autonomous prefectures (zìzhìzhōu), and 3 leagues (méng). In 2018, there were 334 prefectural level divisions in the PRC. In practice, prefecture-level cities contain urban and rural counties and do not represent cities in the traditional sense. Only the provinces of Yunnan, Guizhou, and Qinghai and the autonomous regions Tibet and Xinjiang have autonomous prefectures, leagues and prefectures as additional second-level divisions. Most provinces are divided into prefecture-level cities are municipalities that were given the right to govern surrounding counties. Beijing, Chongqing, Shanghai, and Tianjin are municipalities with the status of a province and that correspond to single prefecture observations. The sample for empirical analysis consists of 261 prefectures level observations (in short prefectures).

Information provided in the industry survey and the university survey includes the address of the enterprise and the main campus of the university. This information, which includes city, province and postal code, makes it possible to link enterprises and universities to their respective prefectures with the use of concordance tables. postal code information was matched to prefectures using a concordance table (Table A4). Information on location codes was applied that is used by survey data collectors to replace missing values for postal codes. In a final step, the enterprise, university, and patent data are aggregated to the level of three-digit level CIC Rev. 2002 industries and the level of prefectures to obtain prefecture-industry-level observations.

Table A4. Postal code-prefecture concordance

Postal codes	Prefecture	Postal codes	Prefecture	Postal codes	Prefecture
10000 – 11999	Hohhot	238000 - 238999	Chaohu	462000 - 462999	Luohe
12000 – 12599	Ulaan Chab	239000 - 240999	Chuzhou	463000 - 463999	Zhumadian
14000 – 14999	Baotou	241000 - 241999	Wuhu	464000 - 465999	Xinyang
15000 – 15999	Baynnur	242000 - 242999	Xuancheng	466000 - 466999	Zhoukou
16000 – 16999	Wuhai	243000 - 243999	Ma'anshan	467000 - 470999	Pingdingshan
17000 – 20999	Ordos	244000 - 244999	Tongling	471000 - 471999	Luoyang
21000 – 23999	Hulunbuir	245000 - 245999	Huangshan	472000 - 472999	Sanmenxia
24000 – 27999	Chifeng	246000 - 247099	Anqing	473000 - 474999	Nanyang
28000 – 29999	Tongliao	247100 - 249999	Chizhou	475000 - 475999	Kaifeng
30000 – 32999	Taiyuan	250000 - 251999	Jinan	476000 - 479999	Shangqiu
33000 – 33999	Luliang	252000 - 252999	Liaocheng	510000 - 511499	Guangzhou
34000 – 36999	Xinzhou	253000 - 254999	Dezhou	511500 - 511999	Qingyuan
37000 – 37999	Datong	255000 - 256599	Zibo	512000 - 513999	Shaoguan
38000 – 38499	Jinzhong	256600 - 256999	Binzhou	514000 - 514999	Meizhou
41000 – 43999	Linfen	257000 - 260999	Dongying	515000 - 515999	Shantou
44000 – 44999	Yuncheng	261000 - 263999	Weifang	516000 - 516599	Huizhou
45000 – 45999	Yangquan	264000 - 264199	Yantai	516600 - 516999	Shanwei
46000 – 47999	Changzhi	264200 - 265999	Weihai	517000 - 517999	Heyuan
48000 – 49999	Jincheng	266000 - 270999	Qingdao	518000 - 518999	Shenzhen
50000 – 52999	Shijiazhuang	271000 - 271099	Tai'an	519000 - 520999	Zhuhai
53000 – 53999	Hengshui	271100 - 271999	Laiwu	521000 - 521999	Chaozhou
54000 – 55999	Xingtai	272000 - 273999	Jining	522000 - 522999	Jieyang
56000 – 60999	Handan	274000 - 275999	Heze	523000 - 523999	Dongguan
61000 – 62999	Cangzhou	276000 - 276799	Linyi	524000 - 524999	Zhanjiang
63000 – 64999	Tangshan	276800 - 276999	Rizhao	525000 - 525999	Maoming
65000 – 65999	Langfang	277000 - 279999	Zaozhuang	526000 - 527299	Zhaoqing
66000 – 66999	Qinhuangdao	300000 - 309999	Tianjin	527300 - 527999	Yunfu
67000 – 70999	Chengde	310000 - 311999	Hangzhou	528000 - 528399	Foshan
71000 – 74999	Baoding	312000 - 312999	Shaoxing	528400 - 528999	Zhongshan
75000 – 79999	Zhangjiakou	313000 - 313999	Huzhou	529000 - 529499	Jiangmen
100000 - 109999	Beijing	314000 - 314999	Jiaxing	529500 - 529999	Yangjiang
110000 - 110999	Shenyang	315000 - 315999	Ningbo	530000 - 532199	Nanning
111000 - 111999	Liaoyang	316000 - 317999	Zhoushan	532200 - 532999	Chongzuo
112000 - 112999	Tieling	318000 - 320999	Taizhou	533000 - 534999	Baise
113000 - 113999	Fushun	321000 - 322999	Jinhua	535000 - 535999	Qinzhou
114000 - 114999	Anshan	323000 - 323999	Lishui	536000 - 536999	Beihai
116000 - 116999	Dalian	324000 - 324999	Quzhou	537000 - 537099	Yulin
117000 - 117999	Benxi	325000 - 329999	Wenzhou	537100 - 537599	Guigang
118000 - 120999	Dandong	330000 - 331999	Nanchang	537600 - 537999	Yulin
121000 - 121999	Jinzhou	332000 - 332999	Jiujiang	538000 - 540999	Fangchenggang
122000 - 122999	Chaoyang	333000 - 333999	Jingdezhen	541000 - 542799	Guilin
123000 - 123999	Fuxin	334000 - 334999	Shangrao	542800 - 542999	Hezhou
124000 - 124999	Panjin	335000 - 335999	Yingtan	543000 - 544999	Wuzhou
125000 - 129999	Huludao	336000 - 336499	Yichun	545000 - 546099	Liuzhou
130000 - 131999	Changchun	336500 - 336999	Xinyu	546100 - 546999	Laibin
132000 - 132999	Jilin	337000 - 340999	Pingxiang	547000 - 549999	Hechi
134000 - 134299	Tonghua	341000 - 342999	Ganzhou	550000 - 551699	Guiyang
134300 - 135999	Baishan	343000 - 343999	Ji'an	553000 - 554299	Liupanshui
136000 - 136199	Siping	344000 - 349999	Fuzhou	561000 - 562399	Anshun
136200 - 136999	Liaoyuan	350000 - 351099	Fuzhou	563000 - 569999	Zunyi
137000 - 137399	Baicheng	351100 - 351999	Putian	610000 - 613999	Chengdu
138000 - 139999	Songyuan	352000 - 352999	Ningde	614000 - 614999	Leshan
150000 - 151999	Harbin	353000 - 360999	Nanping	618000 - 619999	Deyang

152000 - 152999	Suihua	361000 - 361999	Xiamen	620000 - 620999	Meishan
153000 - 153999	Yichun	362000 - 362999	Quanzhou	621000 - 623999	Mianyang
154000 - 154099	Jiamusi	363000 - 363999	Zhangzhou	646000 - 649999	Luzhou
154100 - 154599	Hegang	364000 - 364999	Longyan	650000 - 653099	Kunming
154600 - 155099	Qitaihe	365000 - 369999	Sanming	653100 - 654999	Yuxi
155100 - 156999	Shuangyashan	400000 - 409999	Chongqing	655000 - 656999	Qujing
157000 - 158099	Mudanjiang	410000 - 411099	Changsha	657000 - 660999	Zhaotong
158100 - 160999	Jixi	411100 - 411999	Xiangtan	665000 - 666099	Pu'er
161000 - 162599	Qiqihar	412000 - 412999	Zhuzhou	677000 - 677999	Lincang
162600 - 162999	Hulunbuir	413000 - 413999	Yiyang	678000 - 678599	Baoshan
163000 - 164299	Daqing	414000 - 414999	Yueyang	710000 - 711999	Xi'an
164300 - 164999	Heihe	415000 - 415999	Changde	712000 - 713999	Xianyang
200000 - 202449	Shanghai	417000 - 417999	Loudi	714000 - 715999	Weinan
202450 - 202500	Zhoushan	418000 - 420999	Huaihua	716000 - 718999	Yan'an
202500 - 209999	Shanghai	421000 - 421999	Hengyang	719000 - 720999	Yulin
210000 - 211999	Nanjing	422000 - 422999	Shaoyang	721000 - 722999	Baoji
212000 - 212999	Zhenjiang	423000 - 424999	Chenzhou	723000 - 724999	Hanzhong
213000 - 213999	Changzhou	425000 - 426999	Yongzhou	725000 - 725999	Ankang
214000 - 214999	Wuxi	427000 - 429999	Zhangjiajie	726000 - 726999	Shangluo
215000 - 220999	Suzhou	430000 - 431699	Wuhan	727000 - 729999	Tongchuan
221000 - 221999	Xuzhou	432000 - 432999	Xiaogan	730000 - 730899	Lanzhou
222000 - 223000	Lianyungang	434000 - 434999	Jingzhou	730900 - 731099	Baiyin
223001 - 223799	Huai'an	435000 - 435999	Huangshi	733000 - 733999	Wuwei
223800 - 223999	Suqian	436000 - 436999	Ezhou	734000 - 734999	Zhangye
224000 - 224999	Yancheng	437000 - 437999	Xianning	735000 - 735099	Jiuquan
225000 - 225299	Yangzhou	438000 - 440999	Huanggang	735100 - 735199	Jiayuguan
225300 - 225999	Taizhou	441000 - 441299	Xiangfan	735200 - 737099	Jiuquan
226000 - 229999	Nantong	441300 - 441999	Suizhou Shi	737100 - 740999	Jinchang
230000 - 231999	Hefei	442000 - 442999	Shiyan	741000 - 742499	Tianshui
232000 - 232999	Huainan	443000 - 444999	Yichang	742500 - 742999	Longnan
233000 - 233499	Bengbu	448000 - 449999	Jingmen	743000 - 743999	Dingxi
233500 - 233699	Bozhou	450000 - 452999	Zhengzhou	744000 - 744999	Pingliang
233700 - 233999	Bengbu	453000 - 454149	Xinxiang	745000 - 746999	Qingyang
234000 - 234999	Suzhou	454150 - 454999	Jiaozuo	750000 - 750299	Yinchuan
235000 - 235999	Huaibei	455000 - 456999	Anyang	751100 - 751699	Wuzhong
236000 - 236699	Fuyang	457000 - 457999	Puyang	751700 - 752999	Zhongwei
236700 - 236999	Bozhou	458000 - 460999	Hebi	753000 - 755999	Shizuishan
237000 - 237999	Lu'an	461000 - 461999	Xuchang	756000 - 759999	Guyuan

Source: Author’s compilation using National Bureau of Statistics (2008) and the China Area Code and Zip Code database https://www.travelchinaguide.com/essential/area_zip/ (accessed 4 February 2019).

Notes

[1] A notable exception is the recent study by Glaeser and Lu (2018) on human capital spillovers from universities.

[2] One notable exemption is the study by van Looy et al. (2011) that uses survey data for 105 European universities in the year 2003 and shows that there is no trade-off between patenting and contract research.

[3] In the years that followed, research universities were established in China, including Jiao Tong University in Shanghai (1896), Zhejiang University (1897), Peking University (1898), Nanjing University (1902), Fudan University (1905), and Tsinghua University (1911).

[4] The Chinese central government introduced a similar subsidy programme for patents filed under the Patent Cooperation Treaty (PCT) or international patents in 2009.

[5] For a literature overview of university spin-offs, see Chen, Patton and Kenny (2016).

[6] However, there are marked differences in basic research investment between China and developed countries. In 1995, the share of spending on basic research stood at 5% in China as opposed to 16% in the U.S., 15% in Japan and in 21% Germany. The share has remained steady at 5% since then in China while it has increased e.g. to 17% in the US (National Bureau of Statistics, 2012).

[7] Another widely used measure of productivity is labour productivity. Labour productivity is defined as the share of value added in the number of hours worked or the number of workers.

[8] The Republic of China (ROC), during 1912-1949, and the People's Republic of China (PRC), after 1949, did not have patent systems in place. In imperial China, the government did not support the broader use of new techniques inventions beyond military applications, which constrained potential applications of new technologies (Landes, 2006). In those cases when protection was granted to individual inventors, it was incomplete because the emperor could rescind those rights at any time.

[9] Since 2006, government criteria for promotion of SOE managers include number of patents (Chen and Naughton, 2016).

[10] The authors argue that the relocation of university departments in the 1950s was a political decision to strengthen industrialisation and did not reflect local economic conditions at that time.

[11] The authors use location decisions of agricultural research stations as exogenous instruments to identify research effects. Stations were established at pre-determined sites of federal public land grant colleges and not influenced by local productivity of already existing agriculture.

[12] There is no uniform classifications of enterprise size. The NBS uses different criteria based annual production and fixed assets. Within the machinery industry, for example, the size class of industrial enterprises is defined based on annual production in 10,000 tons and the value of fixed production assets in RMB (Jefferson et al., 2003).

[13] Using application years of the patent at the SIPO.

[14] The text-matching algorithm for industrial enterprise data and PATSTAT data could not be applied directly because PATSTAT provides information on patent holder names in English, while the industrial census provides the information in Chinese. A better approach would be to directly use information on Chinese patents from SIPO, which provides information on patent holder names in Chinese. However, SIPO data is not freely available.

[15] Beijing, Chongqing, Shanghai, and Tianjin are municipalities and are not further divided into prefectures.

[16] Observations different from zero.

[17] The province-level division includes 22 provinces, 5 autonomous regions (Guangxi, Inner Mongolia, Ningxia, Tibet, and Xinjiang), 4 municipalities (Beijing, Chongqing, Tianjin, and Shanghai), and 2 special administrative regions (Hong Kong and Macau). PRC refers to Taiwan as a claimed province.

[18] The study also estimates shorter and longer distributed lag specifications.

[19] In total numbers, the prefectures covered in this thesis had 1,117,774,800 inhabitants in 2007, against a total number of 1,321,290,000 inhabitants in the PRC in 2007.

[20] The number of neighbouring prefectures is restricted to five, which is the average number of bordering neighbours of a prefecture in China. Unreported results show that the results are not sensitive to 2-nearest neighbours, 3-nearest neighbours, 4-nearest neighbours, 6-nearest neighbours and so on up to 10-nearest neighbours.

[21] Information on industries cannot be used due to the unbalanced industry panel for my period of observation. The use of the spatial weight matrix to construct spatial lags requires a balanced panel.

[22] Data for the autonomous provinces Tibet and Xinjiang is not available.

[23] The patent-industrial census linked dataset is freely available. For access, see He et al. (2017).

[24] There is a total of 723,912 SIPO patents including patent holders from outside China.

List of Tables

List of Figures

List of Abbreviations

ASIE	Annual surveys of industrial enterprises (industrial census)
CIC	Industrial Classification for National Economic Activities
CNIPA	China National Intellectual Property Administration
EPO	European Patent Office
FOEs	Foreign-owned enterprises
GDP	Gross domestic product
ICT	Information and communication technologies
IPR	Intellectual property right
MOE	Ministry of Education
MOST	Ministry of Science and Technology
MNEs	Multinational enterprises
NBS	National Bureau of Statistics of China
NSFC	Natural Science Foundation of China
OECD	Organisation for Economic Cooperation and Development
PATSTAT	Worldwide Patent Statistical Database of the European Patent Office
PCT	Patent Cooperation Treaty
POEs	Private-owned enterprises
PRC	People's Republic of China
RMB	Renminbi (also referred to as "yuan"), Chinese currency
R&D	Research and development
SASAC	State-Owned Asset Supervision and Administration Commission
SEZ	Special Economic Zones
SIPO	State Intellectual Property Office (renamed in China National Intellectual Property Administration or CNIPA in 2018)
SITC	Standard International Industrial Classification
SOEs	State-owned enterprises
STI	Science, technology and innovation
TFP	Total factor productivity
TRIPS	Agreement on Trade-Related Aspects of Intellectual Property Rights
TTO	Technology transfer office

UNESCO	United Nations Educational, Scientific and Cultural Organisation
U.S.	United States
USD	United States Dollar
US&T	University Science and Technology
WIPO	World Intellectual Property Organization
WHED	World Higher Education Database
WTO	World Trade Organization
211 Project	National Key Universities and Colleges Programme
863 Programme	National High Technology Programme
973 Programme	National Basic Research Programme
985 Project	National Key Construction Project

Bibliography

Adams, J. (1990). Fundamental stocks of knowledge and productivity growth. *Journal of Political Economy*, 98(4), 673-702.

Aghion, P., Boustan, L., Hoxby, C. and Vandenbussche, J. (2009). The causal impact of education on economic growth: Evidence from the United States. Brooking Papers on Economic Activity, Spring Conference 2009.

Aghion, P. and Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, 60(2), 323-351.

Amiti, M. and Javorcik, B. (2008). Trade cost and location of foreign firms in China. *Journal of Development Economics*, 85(1-2), 129-149.

Andersson, R., Quigley, J.M. and Wilhelmsson, M. (2009). Urbanization, productivity, and innovation: Evidence from investment in higher education. *Journal of Urban Economics*, 66(1), 2-15.

Ang, J.S., Wu, C. and Cheng, Y. (2014). Does enforcement of intellectual property rights matter in China? Evidence from financing and investment choices in the high-tech industry. *Review of Economics and Statistics*, 96(2), 332-348.

Anselin, L., Varga, A. and Acs, Z. (1997). Local geographic spillovers between university research and high technology innovations. *Journal of Urban Economics*, 42(3), 422-448.

Arzaghi, M. and Henderson, J.V. (2008). Networking off Madison Avenue. *Review of Economic Studies*, 75(4), 1011-1038.

Audretsch, D. and Stephan, P. (1996). Company scientist locational links: The case of biotechnology. *American Economic Review*, 86(3), 641-652.

Azoulay, P., Zivin, J.S.G., Li, D. and Sampat, B.N. (2014). Public R&D Investments and Private-sector Patenting: Evidence from NIH Funding Rules. NBER Working Paper, No. 20889.

Bathelt, H., Malmberg, A. and Maskell, P. (2004). Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation. *Progress in Human Geography*, 28(1), 31-56.

Becker, S.O. and Wössmann, L. (2009). Was Weber wrong? A human capital theory of protestant economic history. *Quarterly Journal of Economics*, 124(2), 531-596.

Bekkers, R. and Bodas Freitas, I.M. (2008). Analysing knowledge transfer channels between universities and industry: To what degree do sectors also matter? *Research Policy*, 37(10), 1837-1853.

Belenzon, S. and Schankerman, M. (2013). Spreading the word: Geography, policy and knowledge spillovers. *Review of Economics and Statistics*, 95(3), 884-903.

Bi, H. (2006). The role of the government in university technology transfer. *Science and Technology Management Research*, 1(23), 17-20. (Translation from Chinese)

Bloom, N., Draca, M. and Van Reenen, J. (2016). Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity. *Review of Economic Studies*, 83(1), 87-117.

Bloom, N., Schankerman, M. and Van Reenen, J. (2013). Identifying technology spillovers and product market rivalry. *Econometrica*, 81(4), 1347-1393.

Boardman, P.G. (2009). Government centrality to university-industry interactions: University research centers and the industry involvement of academic researchers. *Research Policy*, 38(10), 1505-1516.

Böing, F. and Müller, E. (2016), Measuring patent quality in cross-country comparison. *Economic Letters*, 149(2016), 145-147.

Böing, F., Müller, E. and Sandner, P. (2016). China's R&D explosion: Analyzing productivity effects across ownership types and over time. *Research Policy*, 45(1), 159-176.

Boisot, M. and Meyer, M.W. (2018). Which Way through the Open Door? Reflections on the Internationalization of Chinese Firms. *Management and Organization Review*, 4(3), 349-365.

Bonander, C., Jakobssona, N., Podestà, F. and Svensson, M. (2016). Universities as engines for regional growth? Using the synthetic control method to analyze the effects of research universities. *Regional Science and Urban Economics*, 60(198), 198-207.

Bosworth, B. and Collins, S.M. (2008). Accounting for growth: Comparing China and India. *Journal of Economic Perspectives*, 22(1), 45-66.

Bozeman, B. and Gaughan, M. (2007). Impacts of grants and contracts on academic researchers' interactions with industry. *Research Policy*, 36(5), 694-707.

Brandt, L., Van Biesebroeck, J. and Zhang, Y. (2012). Creative accounting or creative destruction? Firm-level productivity growth in Chinese manufacturing. *Journal of Development Economics*, 97(2), 339-351.

Branstetter, L. (2005). Exploring the link between academic science and industrial innovation. *Annales D'Économie et de Statistique*, 79(80), 119-142.

Branstetter, L. and Feenstra, R. (2002). Trade and foreign direct investment in China: A political economy approach. *Journal of International Economics*, 58(2), 335-358.

Brehm, S. and Lundin, N. (2012). University-industry linkages and absorptive capacity: An empirical analysis of China's manufacturing industry. *Economics of Innovation and New Technology*, 21(8), 837-852.

Cantoni, D. and Yuchtman, N. (2014). Medieval universities, legal institutions, and the Commercial Revolution. *The Quarterly Journal of Economics*, 129(2), 823-887.

Carayol, N. and Matt, M. (2004). Does research organization influence academic production? Laboratory level evidence from a large European university. *Research Policy*, 33(8), 1081-1102.

Caves, D.W., Christensen, L.R. and Diewert, W.E. (1982). Multilateral comparisons of output, input and productivity using superlative index numbers. *Economic Journal*, 92(365), 73-86.

Chan, L. and Daim, T.U. (2011). Technology transfer in China: Literature review and policy implications. *Journal of Science and Technology Policy in China*, 2(2), 122-145.

Chen, L. and Naughton, B. (2016). An institutional policy-making mechanism: China's return to techno-industrial policy. *Research Policy*, 45(10), 2138-2151.

Chen, A., Patton, D. and Kenny, M. (2016). University technology transfer in China: A literature review and taxonomy. *Journal of Technology Transfer*, 41(5), 891-929.

Chen, A. and Kenney, M. (2007). Universities, research institutes and regional innovation systems: The cases of Beijing and Shenzhen. *World Development*, 35(6), 1056-1074.

Cliff, A.D. and Ord, J.K. (1969). The problem of spatial autocorrelation. In Scott, A.J. (ed.) *Studies in Regional Science*, pp. 25-55. London: Pion.

Cockburn, I.M., MacGarvie, M.J. and Müller, E. (2010). Patent thickets, licensing and innovative performance. *Industrial and Corporate Change*, 19(3), 899-925.

Crescenzi, R., Rodríguez-Pose, A. and Storper, M. (2012). The territorial dynamics of innovation in China and India. *Journal of Economic Geography*, 12(1), 1055-1085.

Crespo, M. and Dridi, H. (2007). Intensification of university-industry relationships and its impact on academic research. *Higher Education*, 54(1), 61-84.

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

D'Este, P. and Perkmann, M. (2013). Why do academics engage with industry? The entrepreneurial university and individual motivations. *Journal of Technology Transfer*, 36(3), 316-339.

DIVA-GIS (2018). *Free Spatial Data*. Webpage. Available at: http://www.diva-gis.org/Data (Accessed on 30 December 2018).

Ellison, G., Glaeser, E. and Kerr, W. (2010). What causes industry agglomeration? Evidence from coagglomeration patterns. *American Economic Review*, 100(3), 1195-1213.

European Patent Office (2017). *EPO Worldwide Statistical Patent Database (PATSTAT)* (database).

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

Fischer, M.M., Scherngell, T. and Reismann, M. (2009). Knowledge spillovers and total factor productivity: Evidence using a spatial panel data model. *Geographical Analysis*, 41(2), 204-220.

Fischer, M. and Varga, A. (2003). Spatial knowledge spillovers and university research: Evidence from Austria. *Annals of Regional Science*, 37(2), 303-322.

Furman, J.L. and Stern, S. (2011). Climbing atop the shoulders of giants: The impact of institutions on cumulative research. *American Economic Review*, 101(5), 1933-1963.

Furman, J.L., and MacGarvie, M. (2007). Academic science and the birth of industrial research laboratories in the U.S. pharmaceutical industry. *Journal of Economic Behaviour and Organization*, 63(4), 756-776.

Gao, X., Song, W., Peng, X. and Song, X. (2014). Technology transferring performance of Chinese universities: Insights from patent licensing data. *Advances in Applied Sociology*, 4(12), 289-300.

Geuna, A. and Rossi, F. (2011). Changes to university IPR regulations in Europe and the impact on academic patenting. *Research Policy*, 40(8), 1068-1076.

Geuna, A. and Nesta, L.J.J. (2006). University patenting and its effects on academic research: The emerging European evidence. *Research Policy*, 35(6), 790-807.

Ghani, E., Kerr, W.R. and O'Connell, S. (2014). Spatial determinants of entrepreneurship in India. *Regional Studies*, 48(6), 1071-1089.

Gilboy, G.J. (2004). The myth behind China's miracle. *Foreign Affairs*, 83(4), 33-48.

Glaeser, E.L. and Lu, M. (2018). Human-Capital Externalities in China. NBER Working Paper No. 24925. Cambridge (MA): National Bureau of Economic Research.

Griliches, Z. (1979). Issues in assessing the contribution of research and development to productivity growth. *The Bell Journal of Economics*, 10(1), 92-116.

Griliches. Z. (1957). Hybrid corn: An exploration in the economics of technological change. *Econometrica*, 25(4), 501-522.

Grimpe, C. and Fier, H. (2010). Informal university technology transfer: a comparison between the United States and Germany. *Journal of Technology Transfer*, 35(6), 637-650.

Grossman, G.M. and Helpman, E. (1991). Quality ladders in the theory of growth. *Review of Economic Studies*, 58(1), 43-61.

Guan, J.C., Yam, R.C.M. and Mok, C.K. (2005). Collaboration between industry and research institutes/universities on industrial innovation in Beijing. *Technology Analysis and Strategic Management*, 17(3), 339-353.

Hall, B.H., Link, A. and Scott, J.T. (2003). Universities as research partners. *Review of Economics and Statistics*, 85(2), 485-491.

Hatzichronoglou, T. (1998). *Revision of the High-Technology-Sector and Product Classification*. Paris: OECD Publishing.

Hayhoe, R. (1989). *China's Universities and the Open Door*. Abingdon-on-Thames: Routledge.

He, Z.-L., Tong, T.W., Zhang, Y. and He, W. (2018). A database linking Chinese patents to China's census firms. *Scientific data*, 5(180042). DOI: 10.1038/sdata.2018.42.

He, Z.L., Tong, T., Zhang, Y. and He, W. (2017). Matching SIPO patents to firms in the Annual Survey of Industrial Enterprises (ASIE) of China's National Bureau of Statistics. Harvard Dataverse. DOI: 10.7910/DVN/QUH8KT.

Helmers, C. and Overman, H. (2017). My precious! The location and diffusion of scientific research: Evidence from the Synchrotron Diamond Light Source. *Economic Journal*, 127(604), 2006-2040.

Henderson, R., Jaffe, A. and Trajtenberg, M. (1998). Universities as a source of commercial technology: A detailed analysis of university patenting, 1965-1988. *Review of Economics and Statistics*, 80(1), 119-127.

Hong, W. (2008). Decline of the center: The decentralization process of knowledge transfer of Chinese universities from 1985 to 2004. *Research Policy*, 37(4), 580-595.

Hong, W. and Su, Y.-S. (2013). The effect of institutional proximity in non-local university-industry collaborations: An analysis based on Chinese patent data. *Research policy*, 42(2), 454-464.

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

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

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

Hu, A.G, Jefferson, G.H. and Jinchang, Q. (2005). R&D and technology transfer: Firm-level evidence from Chinese industry. *Review of Economics and Statistics*, 87(4), 780-786.

Huang, K.G. and Murray, F.E. (2009). Does patent strategy shape the long-run supply of public knowledge? Evidence from human genetics. *The Academy of Management Journal*, 52(6), 1193-1221.

International Association of Universities (2018). *World Higher Education Database (WHED)* (database). Available at: http://whed.net/home.php (Accessed 1 December 2017).

Jaffe, A. (1989). Real effects of academic research. *American Economic Review*, 79(5), 957-970.

Jaffe, A., Trajtenberg, M. and Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, 108(3), 577-598.

Jefferson, G., Rawski, T. and Zhang, Y. (2008). Productivity growth and convergence across China's industrial economy. *Journal of Chinese Economic and Business Studies*, 6(2), 121-140.

Jefferson, G.H., Hu, A.G., Guan, X. and Yu, X. (2003). Ownership, performance, and innovation in China's large- and medium-size industrial enterprise sector. *China Economic Review*, 14(1), 89-113.

Jefferson, G. and Rawski, T.G. (1994). Enterprise reform in Chinese industry. *The Journal of Economic Perspectives*, 8(2), 47-70.

Jensen, R. and Thursby, M. (2001). Proofs and prototypes for sale: The licensing of university inventions. *American Economic Review*, 91(1), 240-259.

Jiang, K., Keller, W., Qiu, L.D. and Ridley, W. (2018). International Joint Ventures and Internal vs. External Technology Transfer: Evidence from China. National Bureau of Economic Research Working Paper, No. 24455, Cambridge (MA): National Bureau of Economic Research.

Kafouros, M., Wang, C., Piperopoulos, P. and Zhang, M. (2015). Academic collaborations and firm innovation performance in China: The role of region-specific institutions. *Research Policy*, 44(3), 803-817.

Kantor, S. and A. Whalley (2019). Research proximity and productivity: Long-term evidence from agriculture. *Journal of Political Economy* (forthcoming).

Kantor, S. and Whalley, A. (2014). Knowledge spillovers from research universities: Evidence from endowment value shocks. *Review of Economics and Statistics*, 96(1), 171-188.

Keller, W. (2004). International technology diffusion. *Journal of Economic Literature*, 42(3), 752-782.

Landes, D.S. (2006). Why Europe and the West? Why Not China? *Journal of Economic Perspectives*, 20(2), 3-22.

Lee, S. and Bozeman, B. (2005). The impact of research collaboration on scientific productivity. *Social Studies of Science*, 35(5), 673-702.

LeSage, J. and Fischer, M.M. (2012). Estimates of the impact of static and dynamic knowledge spillovers on regional factor productivity. *International Regional Science Review*, *35*(1), 103-127.

LeSage, J.P. and Pace, R.K. (2009). *Introduction to Spatial Econometrics.* Boca Raton, London and New York: CRC Press.

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

Li, J. and Qian, C. (2013). Principal-principal conflicts under weak institutions: a study of corporate takeovers in China. *Strategic Management Journal*, 34(4), 498-508.

Lin, J.Y. (1995). The Needham Puzzle: Why the Industrial Revolution did not originate in China. *Economic Development and Cultural Change*, 43(2), 269-292.

Liu, S. (2015). Spillovers from universities: Evidence from the land-grant program. *Journal of Urban Economics*, 87(C), 25-41.

Liu, X. and White, S. (2001). Comparing innovation systems: A framework and application to China's transitional context. *Research Policy*, 30(7), 1091-1114.

Lomas, J. (2007). The in-between world of knowledge brokering. *British Medical Journal*, 334(7585), 129-32.

Luan, C., Zhou, C. and Liu, A. (2010). Patent surge in Chinese universities: A comparative perspective. *Scientometrics*, 84(1), 53-63.

Maietta, O.W. (2015). Determinants of university-firm R&D collaboration and its impact on innovation: A perspective from a low-tech industry. *Research Policy*, 44(7), 1341-1359.

Mairesse, J. and Sassenou, M. (1991). R&D Productivity: A Survey of Econometric Studies at the Firm Level. NBER Working Paper No. 3666, Cambridge (MA): National Bureau of Economic Research.

Ministry of Education (MOE) (Various years). *China University Science and Technology Annual Report*. Beijing: Higher Education Press.

Moretti, E. (2004). Estimating the social return to higher education: Evidence from longitudinal and repeated cross-sectional data. *Journal of Econometrics*, 121(1-2), 175-212.

Motohashi, K. (2005). University-industry collaborations in Japan: The role of new technology-based firms in transforming the National Innovation System. *Research Policy*, 34(5), 585-594.

Motohashi, K. and Yun, X. (2007). China's innovation system reform and growing industry and science linkages. *Research Policy*, 36(8),1251-1260.

Mowery, D.C. and Sampat, B.H. (2005). Universities in national innovation systems, in Fagerberg, J. and Mowery, D.C. (eds.) *The Oxford Handbook of Innovation*, pp. 209-239. Oxford: Oxford University Press.

Mowery, D.C. and Sampat, B.H. (2001). University patents and patent policy debates in the USA, 1925–1980. *Industrial and Corporate Change*, 10(3), 781-814.

Murray, F.E. and Stern, S. (2007). Do formal intellectual property rights hinder the free flow of scientific knowledge? An empirical test of the anti-commons hypothesis. *Journal of Economic Behavior and Organization*, 63(4), 648-687.

National Bureau of Statistics of China (Various Years). *China Statistical Yearbook*. Beijing: China Statistics Press.

National Bureau of Statistics of China (2018). *National Data* (database). Available at: http://data.stats.gov.cn/english/easyquery.htm?cn=C01 (Accessed 04 January 2016).

National Bureau of Statistics of China (2008). *Annual Survey of Industrial Enterprises (ASIE)* (database).

Naughton, B. (2007). *The Chinese Economy: Transitions and Growth*. Cambridge, MA: MIT Press.

OECD (2015). *The Future of Productivity*. Paris: OECD Publishing. DOI: http://dx.doi.org/10.1787/9789264248533-en (Accessed 08 April 2017).

OECD (2008). *OECD Reviews of Innovation Policy China*. Paris: OECD Publishing. DOI: http://dx.doi.org/10.1787/9789264039827-en (Accessed 08 April 2017).

Olley, G.S. and Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6), 1263-1297.

Park, A., Yang, D., Shi, X. and Jiang, Y. (2010). Exporting and firm performance: Chinese exporters and the Asian financial crisis. *The Review of Economics and Statistics*, 92(4), 833-842.

Peck, J. and Zhang, J. (2013). A variety of capitalism … with Chinese characteristics? *Journal of Economic Geography*, 13(3), 357-396.

Perkmann, M. and Walsh, K. (2009). The two faces of collaboration: impacts of university-industry relations on public research. *Industrial and Corporate Change*, 18(6), 1033-1065.

Perkmann, M., Tartiari, V., McKelvey, M., Autio, E., Broström, A., D'Este, P., Fini, R., Geuna, A., Grimaldi, R., Hughes, R., Krabel, S., Kitson, M., Llerena, P., Lissoni, P., Salter, A. and Sobrero, M. (2013). Academic engagement and commercialisation: A review of the literature on university-industry relations. *Research Policy*, 42(2), 423-442.

Robbins, C. (2006). The impact of gravity-weighted knowledge spillovers on productivity in manufacturing. *The Journal of Technology Transfer*, 31(1), 45-60.

Robin, S. and Schubert, T. (2013). Cooperation with public research institutions and success in innovation: Evidence from France and Germany. *Research Policy*, 42(1), 149-166.

Romer, P.M. (1990). Endogenous technological change. *Journal of Political Economy*, 98(5), S71-S102.

Romer, P.M. (1986). Increasing returns and long-run growth. *Journal of Political Economy*, 94(5), 1002-1037.

Rong, Z., Wu, X. and Böing, P. (2017). The effect of institutional ownership on firm innovation: Evidence from Chinese listed firms. *Research Policy*, 46(9), 1533-1551.

Rosenthal, S. and Strange, W. (2003). Geography, industrial organization, and agglomeration. *Review of Economics and Statistics*, 85(2), 377-93.

Rosenthal, S. and Strange, W. (2001). The determinants of agglomeration. *Journal of Urban Economics*, 50(2), 191-229.

Sampat, B.N., Mowery, D.C. and Ziedonis, A.A. (2003). Changes in university patent quality after the Bayh–Dole act: A re-examination. *International Journal of Industrial Organization*, 21(9), 1371-1390.

Schartinger, D., Rammer, C., Fischer, M. and Fröhlich, J. (2002). Knowledge interactions between universities and industry in Austria: Sectoral patterns and determinants. *Research Policy*, 31(3), 303-328.

Scherngell, T., Borowiecki, M. and Hu, Y. (2014). Effects of knowledge capital on total factor productivity in China: A spatial econometric perspective. *China Economic Review*, 29(2014), 82-94.

Scherngell, T. and Hu, Y. (2011). Collaborative knowledge production in China: Regional evidence from a gravity model approach. *Regional Studies*, 45(6), 755-772.

Song, Z., Storesletten, K. and Zilibotti, F. (2011). Growing like China. *American Economic Review*, 101(1), 202-241.

Tian, X. and Yu, X. (2012). The Enigmas of TFP in China: A meta-analysis. *China Economic Review*, 23(2), 396-414.

Toivanen, O. and Väänänen, L. (2016). Education and invention. *The Review of Economics and Statistics*, 98(2), 382-39.

Thursby, J.G. and Kemp, S. (2002). Growth and productive efficiency of university intellectual property licensing. *Research Policy*, 31(1), 109-124.

Valero, A. and Van Reenen, J. (2019). "The Economic Impact of Universities: Evidence from Across the Globe", *Economics of Education Review*, 68(2019), 53-67.

Van Looy, B., Landoni, P., Callaert, J., van Pottelsberghe, B., Sapsalis, E. and Debackere, K. (2011). Entrepreneurial effectiveness of European universities: An empirical assessment of antecedents and trade-offs. *Research Policy*, 40(4), 553-564.

Van Looy, B., Ranga, M., Callaert, J., Debackere, K. and Zimmermann, E. (2004). Combining entrepreneurial and scientific performance in academia: Towards a compounded and reciprocal Matthew-effect? *Research Policy*, 33(3), 425-441.

Van Looy, B., Debackere, K. and Andries, P. (2003). Policies to stimulate regional innovation capabilities via university–industry collaboration: an analysis and an assessment. *R&D Management*, 33(2), 209-229.

Wang, Y., Huang, J., Chen, Y., Pan, X. and Chen, J. (2013). Have universities embraced their third mission? New insights from a business perspective. *Scientometrics*, 97(2), 207-222.

Wu, W. (2010). Managing and incentivizing research commercialization in Chinese universities. *Journal of Technology Transfer*, 35(2), 203-224.

Wu, W. and Zhou, Y (2012). The third mission stalled? Universities in China's technological progress. *The Journal of Technology Transfer*, 37(6), 812-827.

Wu, Y. (2011). Total factor productivity growth in China: A review. *Journal of Chinese Economic and Business Studies*, 9(2), 111-126.

Young, A. (2003). Gold into base metals: Productivity growth in the People's Republic of China during the reform period. *Journal of Political Economy*, 111(6), 1220-1261.

Zhang, D., Banker, R.D., Li, X. and Liu, W. (2011). Performance impact of research policy at the Chinese Academy of Sciences. *Research Policy*, 40(6), 875-885.

Zhang, H., Patton, D. and Kenney, M. (2013). Building global-class universities: Assessing the impact of the 985 Project. *Research Policy*, 42(3), 765-775.

Zhou, Y. (2015). The rapid rise of a research nation. *Nature*, 528(7582), S170-SS173.

Zhu, X. (2012). Understanding China's growth: Past, present, and future. *Journal of Economic Perspectives*, 26(4), 103-24.

Martin Borowiecki

CONTACT INFORMATION

Economist
Directorate for Science, Technology and Innovation
OECD
2, rue André Pascal
75775 Paris Cedex 16

M: +33 (768) 798925
T: +33 (1) 4524-1801
martin.borowiecki@oecd.org

DOCTORAL STUDIES

Vienna University of Technology
Doctoral studies in Economics, Start October 2012
DISSERTATION: The effects of universities on innovation and productivity in China: An empirical analysis

PhD SUPERVISOR

Karl-Heinz Leitner
Vienna University of Technology
Institute of Management Science
Theresianumgasse 27
A-1040 Vienna AUSTRIA
+43 (0) 50550-4567
karl-heinz.leitner@tuwien.ac.at

PRIOR EDUCATION

Master in Economics with outstanding results, under the supervision of Prof. Manfred M. Fischer
Vienna University of Economics and Business — August 2011

CITIZENSHIP

Austria

LANGUAGES

German:	Mother Tongue
Polish:	Mother Tongue
English:	Fluent (written and spoken – Cambridge Certificate of Proficiency in English, level C2)
Spanish:	Fluent (written and spoken – Diploma de Español como Lengua Extranjera, level B2)
Italian:	Intermediate Level (written and spoken, 6 years)
French:	Intermediate level (written, 6 years)

RESEARCH INTERESTS

Innovation Studies, STI Policy, Economic Geography

REFEREED JOURNAL PUBLICATIONS

[1] Dachs, B., Biege, S., Borowiecki, M., Lay, G., Jr, A. and D. Schartinger. The servitisation of European manufacturing industries: Empirical evidence from a large scale database. *The Service Industries Journal*, 34(1), 5–23, 2014.

[2] Scherngell, T., Borowiecki, M. and Y. Hu. Effects of knowledge capital on total factor productivity in China: A spatial econometric perspective. *China Economic Review*, 28(2014), 82–94.

Monographs

[1] OECD, University-Industry Collaboration: New Evidence and Policy Options, OECD Publishing, Paris, 2019.

Submitted Publications

[2] Borowiecki, M., Paunov, C, and J. Guimon. How is research policy across the OECD organised? Insights from a new policy database. Research Policy.

Submitted Conference Publications

[3] Borowiecki, M. and K.H. Leitner. Determinants of new business formation in China: Prefecture-level evidence from a panel data model. In: *Proceedings of the 55th European Regional Science Association Congress on World Renaissance: Changing Roles for People and Places (ERSA 2015)*, August 28–30, 2015. Submitted.

[4] Scherngell, T., Borowiecki, M. and Y. Hu. Effects of knowledge production and knowledge spillovers on total factor productivity in China: A spatial econometric perspective. In: *Geography of Innovation Conference*, January 23–25, 2014. Submitted.

[5] Scherngell, T., Borowiecki, M. and Y. Hu. Effects of knowledge production and knowledge spillovers on total factor productivity in China: A spatial econometric perspective. In: *Proceedings of the 53rd European Regional Science Association Congress on Regional Integration: Europe, the Mediterranean and the World Economy (ERSA 2013)*, August 27–31, 2013. Submitted.

Conference Talks

[6] Borowiecki, M. Determinants of new business formation in China: Prefecture-level evidence from a panel data model. In: *55th European Regional Science Association Congress (ERSA 2015) in Lisbon, Portugal*, August 28–30, 2015.

[7] Borowiecki, M. The Austrian STI-Strategy: An Indicator-Based View. In: *2011 ST Global 11th Annual Conference on Science and Technology in Society at the AAAS in Washington*, April 15–16, 2011.

Other Publications

[8] Borowiecki, M., El-Mallakh, N., and Paunov, C. Assessing the impacts of public research institutions on industry inventions. OECD Science, Technology and Industry Policy Papers, OECD Publishing, Paris, 2019.

[9] Borowiecki, M. and Paunov, C. How is research policy across the OECD organised? Insights from a new policy database. OECD Science, Technology and Industry Policy Papers, No. 55, OECD Publishing, Paris, 2018.

[10] Borowiecki, M., Dachs, B., Schartinger, D., Biege, S., Lay, G. and A. Jäger. The Service Output of Manufacturing Industries. AIT-F&PD-Report Vol. 57, AIT Austrian Institute of Technology GmbH, 2012.

[11] Dachs, B., Biege, S., Borowiecki, M., Lay, G., Jäger, A. and D. Schartinger. The Servitization of European Manufacturing Industries. MPRA Paper 38995, MPRA - Munich Personal RePEc Archive, 2012.

[12] Schibany, A., Borowiecki, M., Dachs, B., Dinges, M., Gassler, H., Heller-Schuh, B., Leitner, K.-H., Rammer, C., Streicher, G., Weber, K.M. and G. Zahradnik. Österreichischer Forschungs- und Technologiebericht 2012. Techreport for the Austrian Federal Ministries of Science and Research, Transport, Innovation and Technology, and Economy, Family and Youth, 2012.

[13] Stehrer, R., Borowiecki, M., Dachs, B., Hanzl-Weiss, D., Kinkel, S., Pöschl, J., Sass, M., Schmall, T.C. and A. Szalavetz. Global value chains and the EU

industry. wiiw Research Reports No. 383, The Vienna Institute for International Economic Studies, 2012.

[14] Biege, S., Borowiecki, M., Dachs, B., Francois, J., Hanzl, D., Hauknes, J., Jäger, A., Knell, M., Lay, G., Pindyuk, O., Schartinger, D. and R. Stehrer. Convergence of knowledge intensive sectors and the EU's external competitiveness. Techreport for DG Enterprise carried out for the European Competitiveness Report 2011, 2011.

[15] Borowiecki, M., Budde, B., Dachs, B., Rhomberg, W. and D. Schartinger, D. Dienstleistungslandschaft in terreich II. AIT-F&PD-Report Vol. 45, AIT Austrian Institute of Technology GmbH, 2011.

[16] Leitner, K.-H., Rhomberg, W. and M. Borowiecki. Produktbegleitende Dienstleistungen und Serviceinnovationen als Chance fr die niedersterreichische Industrie. AIT-F&PD-Report Vol. 39, AIT Austrian Institute of Technology GmbH, 2011.

[17] Borowiecki, M. The Austrian STI Strategy: An Indicator Based View. PhD- & Master-Theses Series Vol. 11, AIT Austrian Institute of Technology GmbH, Vienna University of Economics and Business, 2011.

GRANTS AND AWARDS

Runner up for Best Paper Award at the 26th European Regional Science Association (ERSA) Summer School, Karlskrona, Sweden, July 2013.

Fellowship Programme of Eurasia-Pacific Uninet for a Research Visit in Macau, China, 2013.

PhD Fellowship of the Innovation & Sustainability - Knowledge & Talent Development Programme, 2012-2015.

Best Talk Award at the ST Global Science and Technology in Society Conference at the American Association for the Advancement of Science (AAAS), Washington, USA, April 2011.

Innovation Economics Vienna Fellowship, 2009-2010.

Erasmus Fellowship at the University of Pontificia Comillas, Madrid, Spain, 2010.

Scholarship by the Vienna University of Economics and Business for Outstanding Results, 2007-2009.

PROFESSIONAL EXPERIENCE

OECD, Paris FRANCE — 2016-present

Junior Economist

- Scientific research, policy consulting on innovation policy

AIT Austrian Institute of Technology GmbH, Vienna AUSTRIA — 2011-2016

Research Fellow

- Scientific research, policy consulting (European Commission, Austrian ministries) and acquisition of funding; PhD Thesis

Industriewissenschaftliches Institut, Vienna AUSTRIA — 2008-2009

Research Assistant

- Scientific research

	Austrian Foreign Trade Office, Madrid SPAIN	2008
	Analyst • Consulting	
SOFTWARE SKILLS	ArcGIS, MATLAB, Python, R, Stata	