INNOVATIVE ACTIVITY AND TECHNOLOGICAL CHANGE IN CHINA AND ITS REGIONS: EVIDENCE FROM CHINESE DOMESTIC PATENTS

by

Hong Yin

A dissertation submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics

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ABSTRACT

In this dissertation, I provide a detailed analysis of patenting activity in China and its regions from 1985 to 2004. Chinese domestic patents are used to analyze China's patenting activity by technological fields and by industrial sectors. Spatial distributions of China's innovative activity are also examined. I find that China's overall technological development in the past twenty years is modest and the regional disparity in technological development is severe. Technological strengths of China are mainly in the low and traditional technological fields, however, China has built up its technological strengths in some key areas, such as biotechnology and organic chemistry. The technological gap between China and industrialized countries is mainly in the hi-tech sectors. I further estimate a patent production function and a knowledge production function at the provincial level. I find that the patents-R&D relationship is well established at the Chinese provincial level and technology contributes positively to industrial growth. In addition, I examine the effects of inter-regional knowledge spillovers on both patenting activity and value added industrial output. I find that there are positive inter-regional knowledge spillovers among the Chinese provinces, but the effects of knowledge spillovers are small and weak, compared to those of more industrialized countries.

Chapter 1

INTRODUCTION

Technological progress has been regarded as the driving force for modern economic growth. In developed countries significant resources are continuously invested in research and development (R&D) by companies to increase their competitiveness. Correspondingly, there have been numerous studies of innovation and technological change in developed countries. In sharp contrast, innovations in developing countries have received little attention. Research studies on technological change in China have been rare, though the number of such studies has recently been increasing (Liu and White, 2001; Lu, 2000; Sun, 2000, 2003).

Among developing countries China is one of the few in a position to engage effectively in planned nationwide R&D efforts. Historically, China has had a large number of highly qualified scientists and engineers and has extensive experiences in some hi-tech programs which have been carried out since the 1950s, mainly for military purposes. Since the 1980s there have been tremendous endogenous changes in China's Science and Technology (S&T) system: (1) there have been extensive R&D infrastructure reforms; and (2) supporting S&T policy has been introduced to strengthen intellectual property rights (IPR) and stimulate the nation's innovation system. It is quite clear that China is committed to increasing its global competitiveness through its own innovative activity. R&D investment in China was already 1.31 per cent of GDP by 2003 and it has been rising at a double-digit rate in the most recent years (see Figure 1.1).

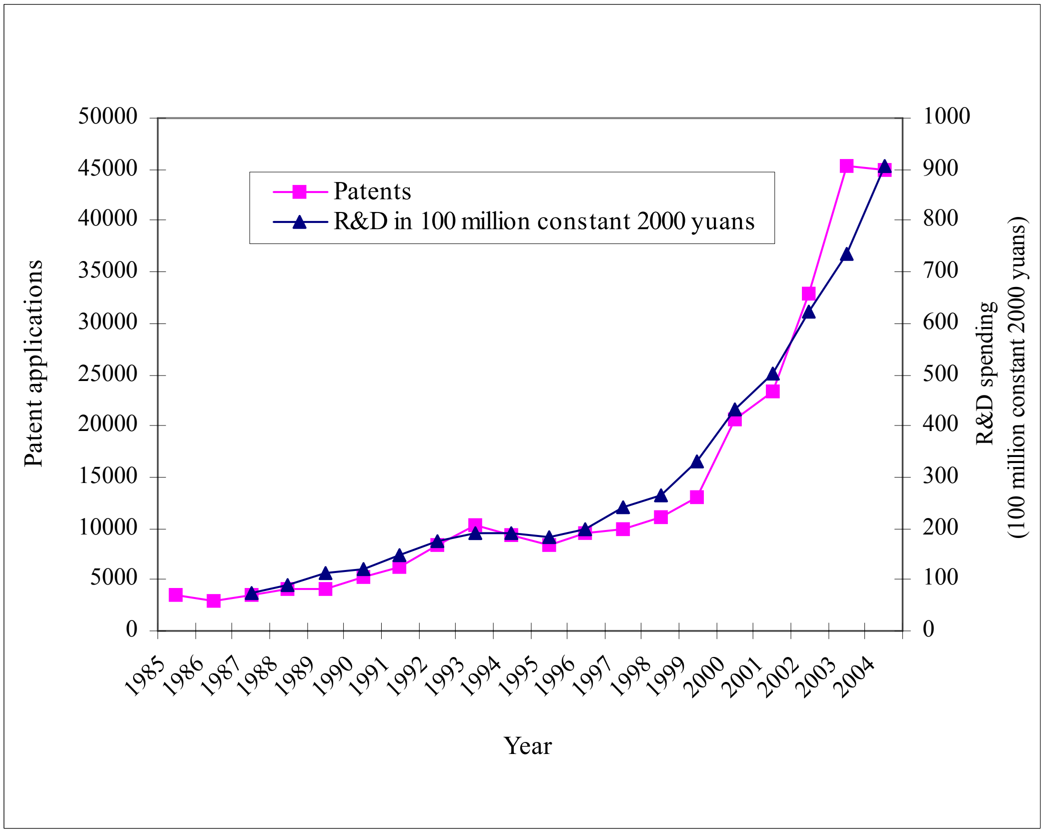

Figure 1.1 Aggregated Domestic Patent Applications and R&D Spending from 1985 to 2004.

Note: R&D data are collected from China Science & Technology Statistics (http://www.sts.org.cn). Patent data are collected from the official website of the State Intellectual Property Offices (http://www.sipo.gov.cn).

As a result, China had become the third biggest spender in R&D spending by 2004 (The State of Global R&D, 2005).

In response to this impressive R&D spending boom, we would expect to see a significant increases in Chinese domestic innovation. Patents are generally considered to be good indicators of innovation and many patent studies have been done in the industrialized countries. However, few empirical studies have been done on patenting activity in large developing countries like China. With respect to China, its first patent law was first established in 1984 and became effective in April 1985. Since then patent applications by both domestic and foreign firms have been growing quickly, particularly after China became a member of the World Intellectual Property Organization (WIPO) in 1995. Figure 1.1 also displays Chinese domestic patent filings from 1985 to 2004. As expected, the overall increase in patent filings is closely related to the increase in R&D investment. The growth rates of patent filings since 2000 are especially impressive.

This dissertation is mainly motivated by the remarkable improvement in China's innovation efforts, both in terms of R&D investment and patenting activity. The foremost objectives are to examine: (1) whether China's technological capabilities have substantially increased since 1980s, as a result of its rapid increase in R&D investment; (2) to what extent this rapid increase in domestic patenting activity directly links to the substantial increase in R&D spending; (3) whether this rapid growth in domestic patenting activities is related to China's economic growth over the years; and (4) whether the technological development (measured as patents) is uniform across China's regions; and (5) to what extent are regional variations in patenting activity associated with regional variations in economic growth.

The recent rapid growth in Chinese domestic patents may also be linked to a growing propensity to patent, in addition to the increase in R&D investment. It has been observed that patent filings have greatly increased worldwide in the most recent years. The WIPO reports that the growth rate of international patent applications using the Patent Cooperation Treaty (PCT) has increased significantly in recent years: applications increased by 9.4% in 2005, compared to a 4.3% increase in 2004. Most impressively, the number of applications from China rose by 212% in 2006 and China has become the 10^{th} largest PCT user (WIPO, 2006). Thus, even taking account of worldwide increasing in patent applications, the growth rates of patents in China (either filed at home or abroad) are still very high. Naturally, this leads us to ask: what are the other driving forces behind this explosion in domestic patenting activity? Apparently, the most important event in the recent years was China's joining the World Trade Organization (WTO) in 2001. Thus, this study also investigates whether the exceptional growth rates of patents in China are related to China's WTO accession in 2001.

China's WTO accession has significantly changed the economic environment for Chinese domestic firms. The impact of WTO accession on China's economy has received extensive attention. Preliminary studies tend to indicate that the results of China's accession have been positive overall, particularly in output, trade, and employment (Bhattasli, Li and Martin, 2004;Pangestu, 2004). However, with respect to China's industry, the impact on domestic firms is not uniform, depending on their industrial sectors, their degree of exposure to the foreign competition and their market shares. Most studies point out that China's industrial sectors will face immense difficulties and challenges in the global market (Broadman, 2002; Nolan, 2002). As a matter of fact, using foreign competition to stimulate the domestic economy is a major objective for China in seeking to join the WTO (Chow, 2001). Conforming to the requirements of the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS), China has made significant progress in the enforcement of intellectual property rights (IPR). This changing environment presents both opportunities and challenges for domestic firms. On the one hand, foreign firms are increasingly penetrating into those markets that were formerly monopolized by domestic firms. The increasing foreign competition will force domestic firms to cut cost and increase their own competitiveness through technological improvement. On the other hand, stronger IPRs will reduce the incentives of copying and imitation as the costs of violating IPRs increase and thus over time promote the dynamic competition through their innovation efforts (Maskus, 2004). Obviously, the challenges facing domestic firms are huge as most domestic firms lack the technological capabilities to develop their own innovations.

In anticipation of China's accession to the WTO, China's industry has been undergoing restructuring since the early 1990s. This industry reform was intended to invigorate China's industry so that it would be able to compete in the global economy. The reforms include selling or merging tens of thousands of inefficient state-owned enterprises and restructuring medium and large state-owned enterprises. A large sell-off campaign began in 1994 (Cauley, Cornes, and Sandler, 1999). In the process, many state-owned research institutes were shut down and/or merged. The impact of this enterprise reform on domestic technological development has not been addressed before, thus this study is the first to analyze the effect of China's industrial reforms on its domestic innovation activity.

Efforts to analyze innovations and technological capabilities of China have largely ignored indigenous innovative activity, focusing instead on technology transfers from foreign countries (Ho, 1997; Li, 2003; Walsh, 1999). In this context, my research constitutes one of the few attempts to identify China's technological profile, its patents-R&D relationships and their technological contributions to economic growth by means of econometric analysis of patent indicators. In this study I find that China's technological strengths have not changed much since the 1980s and are still primarily in the low and medium technology industrial sectors. I also find that China has increasingly focused its innovation activity on hi-tech sectors, especially in the most recent ten years. Hi-tech oriented technology policy has been implemented throughout China. Additional analysis indicates that nationwide hi-tech policy is not effective in stimulating high-level innovation activity in most of the provinces.

With respect to the patents-R&D relationship, I estimate a patent production function at the provincial level and find that the patents-R&D relationship is well established at the provincial level in China. The estimated elasticity of patents to R&D is in the range of those found in the literature. In addition, this study also finds that the domestic propensity to patent has greatly increased since China's WTO accession in 2001.

With respect to the relationship between technology (measured as patents) and economic growth, I find that patents contribute positively to industrial output growth at the provincial level, however, contributions from technology inputs are very small compared to those in advanced countries. In addition, in this study I also investigate the effect of knowledge spillovers on patenting activity and industrial output growth. I find that in both cases the interregional knowledge spillovers are significant but small, thus the diffusion of technology among Chinese provinces is slow.

In terms of regional variations in patents, my analysis shows that there are large variations in innovation activity across regions and they are closely related to regional variations in economic growth: innovations are increasingly concentrated in the eastern region, which has higher incomes and a higher level of economic development.

The econometric analysis conducted in this study should not be viewed as a simple application of the known models since the results of this analysis provide a useful basis for future thinking about China's economic and technology policy. The patent production equation was originally developed to analyze the patents-R&D relationship in industrialized countries. In contrast, China's economy is viewed as different from those market economies of developed countries, despite its more than twenty years market-oriented economic reform. My successful application of the patent production equation to in this study provides new evidence regarding the question of whether China's economy has been effectively transformed to a market-based economy due to its economic policies over the past twenty years. If it has, then China's economy increasingly functions like those of market-based industrialized countries. In addition, this study provides some insights for other large developing countries in terms of technology policy and technological development. On one hand, impressive increases in R&D investment and patents are directly related to China's Science and Technology policy, which is targeted to stimulate domestic innovations. On the other hand, in this study I find that technology's contribution to China's economic growth is small, compared to its contribution in the advanced countries.

Therefore, it is still an open question whether other large developing countries should follow the road China has taken in terms of technological development.

Due to the constraints of data, my analysis is confined to the provincial level. I find that multicollinearity is a problem, which is not surprising with aggregated provincial-level data. To reduce the multicollinearity, it would be better to use micro-level data, such as individual firm data. More detailed firm-level data are also needed for more sophisticated estimation techniques, such as the Poisson regression. However, reliable Chinese firm-level data are very difficult to obtain at the present and thus major research challenge in the area of R&D and patents are still the measurement issues.

Section 1.1 describes the context of this study. Section 1.2 describes the dissertation's objectives and section 1.3 describes the dissertation's contribution to the literature.

1.1 Context of the Study

1.1.1 China's Patent System

In the past twenty years, China has gradually established a complete and modern Intellectual Property (IP) legal system. Among them, the patent law was first established in March 1984 and became effective in April 1985. The 1985 version of patent laws and regulations contained the most universal requirements for patents, that is, utility, novelty and inventiveness. However, there were serious intrinsic problems. One of the major problems was that it favored foreign entities over Chinese citizens: Chinese citizens could apply for patents only if they produced the invention either totally on their own or while working for a non-state-owned enterprise. This effectively precluded all Chinese citizens from eligibility at that time. They were only eligible for utility models (which is a form of "petty" patent) and consequently monetary rewards were very modest (Allison and Lin, 1999). In 1992 the United States and China signed a Memorandum of Understanding on Mutual Protection of Intellectual Property. After that, China's patent law was substantially amended in September 1992, which rendered it similar to the patent laws of many well-developed nations. Through a series of revisions, the patent system has moved from ambiguity to relative clarity. The latest revision was made in 2000 in line with China's entry into the World Trade Organization (WTO). In addition, the Chinese government has further demonstrated its desire to improve and modernize its IPR protection regime by signing various international conventions and joining a number of international organizations, such as the World Intellectual Property Organization (WIPO) in 1995.

Today's Chinese patent system reflects European patent systems more than the US system, since both the 1985 patent act and the 1992 amendments were based primarily on the German model (Lin, 2001). There are three types of patents available: invention, utility model and design. An invention patent is comparable to a utility patent in the US. The utility model is available only for some technical improvements, i.e., a form of "petty" patent not recognized in the US. A design patent embodies mostly incremental improvement in aesthetic features rather than technical features. Thus invention patents represent the highest levels of technological capabilities. Correspondingly, the protection for invention patents is twenty years from the date of filing and the term for utility models and design patents is only 10 years, which conforms to the international norms. As in most patent systems, China's patent law provides for publication of patent applications eighteen months after filing.

It also recognizes "prior user rights" and provides compulsory licensing (Patent Law of People's Republic of China, 2000).

The adopted patent classification system is the International Classification System (IPC). The sixth edition of IPC is a hierarchical patent classification system. It divides all technological fields into eight sections designated by capital letter from A to H (see Table 1.1). Those eight sections are further subdivided into 118 classes. Each class has a title and a symbol. The symbol consists of the relevant section letter followed by a two-digit number. The classes are subdivided into 624 subclasses.

Table 1. 1 Main IPC Classes

IPC Classes	Class Titles
Section A	Human Necessities
Section B	Performing Operations; Transporting
Section C	Chemistry; Metallurgy
Section D	Textiles; Papers
Section E	Fixed Constructions
Section F	Mechanical Engineering Lighting; Heating; Weapon; Blasting
Section G	Physics
Section H	Electricity

Source: WIPO (http://www.wipo.int/classification/fulltext/new_ipc).

1.1.2 The Effect of IPR Enforcement in China

In principle, patent protection directly affects economic growth through inducement to innovations (Allred and Park, 2004; Grossman and Helpman, 1991; Taylor 1994). Most researchers agree that the social return on patents is much higher than the private return to the innovator (Machlup, 1958; Mansfield et al., 1977). Gould and Gruben (1996) conduct a cross-country study and conclude that IP protection is a significant determinant of economic growth, but their results depend on the openness of host countries. Braga and Willmore (1991) suggest that, in a closed regime, protection of IP may not increase domestic innovation because inadequate competitiveness fails to stimulate innovations. Few studies have addressed the impact of IPR enforcement on domestic innovation in developing countries. Mansfield (1994) presents some evidence that IPR protection has a positive impact on R&D investment in developing countries. Bosworth and Yang (2000) argue that IPR laws and enforcement play a vital role in the process of economic development. Their study shows that the introduction of numerous IPR laws has significantly increased flows of patents, trademarks and other intellectual properties to China by industrialized countries.

Although most scholars and businesses in the west are still very suspicious about IPR protection in China, it should be noticed that remarkable progress has been made in a relatively short period. In fact, foreign companies are the main beneficiaries of China's patent system. O'Keefe (2005) compares the US, EU, Japanese and Korean companies' patenting activity in Japan and in China. He finds that major Korean and EU companies are now filing as many patent applications in China as the numbers of the US granted patents they are obtaining. And for most Japanese companies, Chinese filings are now about half that of their US grants.

Encouragingly, the patent system has become an increasingly important factor in China's economic and technological development. According to the statistics of the State Intellectual Property Offices (SIPO), 1,931,118 patent applications have been received by SIPO from 1985 to 2003, of which 82.6% were domestic and 17.4% were foreign (SIPO, 2003). In addition, domestic applications for invention patents increased at an average annual growth rate of 13.3% for the sixteen years following the introduction of the patent law (SIPO, 2002). However, most domestic applications are for utility model and design patents, while most of the foreign ones are invention patents. Encouragingly, patent statistics also show that domestic applications for invention patents are growing faster than other two types of patents (SIPO, 2003). Year 2003 is viewed as an important year with respect to the effectiveness of patent enforcement. There were two significant features regarding patent applications in 2003: (1) the number of domestic invention applications caught up with that of utility models for the first time in sixteen years and accounted for one third of total applications; and (2) domestic invention patents applied exceeded foreign ones for the first time in eight years (SIPO, 2003).

Although statistics show that domestic applications for invention patents have caught up with foreign applications, foreign patents still occupy most of the hi-tech fields. This reflects the fact that there is a large gap in terms of R&D capacities between developed countries and China. The benefits of a modern patent system rely largely on a nation's own innovative capacities. In particularly, internal R&D capabilities are essential and necessary for the patent system to play a positive role in the nation's economic development. In this context, there are sharp differences between developing countries like China and industrialized countries like the US. In the next section I briefly discuss China's internal R&D capacities, its Science and Technology system, and its strategic reform.

1.1.3 China's Science and Technology (S&T) System

In the US and other developed countries, major R&D is increasingly carried out by large private corporations and has become progressively more market-driven, though direct and indirect roles for the state are still important (OECD 1998). In China the core of R&D efforts is heavily concentrated in various state-owned research organizations and universities. This situation is largely due to an S&T system copied from the former USSR. In China S&T activity refer to the organized activity which are closely related to creation, development, dissemination and application of scientific and technological knowledge. S&T activities are classified into R&D activities, applications of R&D results and related S&T services (NBS, 2002). S&T research bodies in China consist of the Chinese Academy of Sciences (CAS) and research organizations under various government branches, universities and industrial enterprises. Among those organizations, the most important one is the Chinese Academy of Sciences. It alone has 108 research institutes and over 200 S&T enterprises and employs 39,000 scientific and technical personnel across the country (CAS, 2005). Currently, there are almost 3 millions scientists, engineers and other personnel engaged in S&T activities in China (NBS, 2001).

S&T policy in China has gone through a dramatic strategic change and major progress has been made to establish a new system beneficial to economic development. Since March 1986, China has taken steps to implement the State Hi-Tech Research and Development Plan,[1] an intermediate and long term plan which aims to integrate military and civilian productions in China (CERNET, 2005a). Since the implementation of this plan, China has gradually improved its R&D strategy in conformity with its economic conditions. The main S&T policy targets are : (1) to attract R&D funding from various resources, (2) to encourage innovative activity, and

[1] The plan is referred to as the "863" plan, since it was created in March 1986.

(3) to develop scientific and technological capabilities primarily through Chinese indigenous efforts (CERNET, 2005b).

Admittedly, there is still a large gap between China's internal R&D capabilities and those of industrialized countries. One of the main challenges is R&D spending. China's investment in non-military R&D was virtually zero about twenty years ago, but it has steadily increased since the 1980s. R&D spending averaged on 0.6% of its GNP between 1981 and 1995, and the figure was 1.23 % of GDP in 2002 (NBS 2003). As a result, before being able to generate substantial internal growth and technological advances on its own, China has followed the typical pattern of a developing nation by depending heavily on foreign investment and imported technology.

Another main problem of China's old S&T system is that its technology is totally disengaged from its economy. After more than twenty years of reform, this situation has been remedied, but only to some extent. Some scholars view the current Chinese R&D system as totally inadequate to support its internal technological development. They suggest that the current R&D system lacks sufficient sophistication to work hand in hand with the new patent system in achieving the technological advancement necessary for sustained economic growth (Lin and Allison, 1999). But they also recognize that China's commitment to R&D efforts is new by any measures and spending on R&D as a percentage of GDP is steadily growing.

Gabriel (2002) conducts an extensive study on S&T policy and technological progress in China. He concludes that the efficiency of China's R&D has increased, but there is still a large gap in terms of resources between goals set up by

S&T policy and actual R&D activity. He argues that a true knowledge-based revolution, in terms of a substantial increase in R&D intensity, has yet to take place in China. Much scientific and technological training and investment in R&D are necessary to improve China's patent system and to achieve technology worth patenting. We should expect that, with continuing commitment to the growth of R&D spending, the patent system will play an increasingly positive role in China's economic future.

State-planned R&D and strategic technology programs are obviously very important in promoting a nation's innovative activity, but it is crucial that the generation of technological progress reaches to the level of productive enterprises. In the theoretic framework of an evolutionary approach, productive enterprises should be considered as an integral part of national innovation system (Lundvall, 1992). In China as elsewhere, enterprises are responsible for the application of internally and externally generated knowledge to production. In the next section, I briefly discuss China's industry and its technological progress.

1.1.4 China' s Industry

China's industry consists of nearly eight million enterprises. A relatively small number of these enterprises, approximately 22,000, are classified as large- and medium-sized (LME).[2] The small number of LME enterprises accounts for approximately one third of China's industrial output and nearly two thirds of total industrial assets (NBS, 2001). Reconstruction of China's industrial system has been taking place since the 1980s, but complete reforms in state-owned enterprises (SOE)

[2] Each industrial sector has its own standards to classify the enterprises into large, medium or small sized.

started only in 1994.[3] The most visible change during the mid and later 1990s has been a rapid decline in the number of state-owned enterprises. More resources are redirected and concentrated on a few large and strategic firms, according to the "grasping the big and enlivening the small" principle laid out in China's S&T policy (CERNET, 2005b).

Core state-owned enterprises (SOE) are mainly concentrated in high technology sectors, while collective-owned enterprises tend to operate in low and medium technology sectors. Many large and medium-sized enterprises (including SOEs) have been performing well, both in economic and technological terms (Jefferson, Rawski, and Zheng, 1997; Lo, 1999). These records seem to support China's industrial strategy, which aims at concentrating the most advanced S&T potential on a small number of elite SOEs along with sufficient human capital and financial resources in order to spearhead technological progress in the most advanced fields and to maximize its economy-wide benefits. However, other state-owned enterprises, most of them small, have improved little in terms of efficiency and have increased their financial losses. In contrast, collective-owned enterprises tend to improve their total factor productivity faster than most SOEs (Jefferson et al., 1997).

There is another important phenomenon in China's industrial evolution: emerging hi-tech and R&D-intensive enterprises. As part of strategic S&T reform, the "Torch" program was implemented in 1988. This program was intended to link the R&D in new and advanced technologies to production. Within this program, numerous hi-tech development zones have been established across the country to

[3] National-wide industrial reform was carried out in 1994, in terms of large-scale shutdown, merge and/or sell-off state-owned enterprises (Cauley et al., 1999).

foster new and advanced technology enterprises. These new and advanced technology enterprises are viewed as crucial in the development, dissemination and application of technology in China. By regulations, it is required that scientists and technical personnel with college education shall account for 30% or more of all the personnel in the companies, with R&D personnel accounting for 10% or more. In addition, R&D spending must be at least 3% of gross revenues. In 2001, there were 24,293 enterprises, which employ 2.7 million people in these development zones (NBS, 2002).

However, over the years, only hi-tech development zones in Beijing, Shanghai and Guangdong have developed into hi-tech industrial parks. In general, hi-tech sectors in China have been heavily dependent on oversea technology to further their own innovations, so in many key IT sectors companies are mainly dependent on imported components and simply perform processing production. As a result, processing trade accounts for about 90% of total trade in hi-tech products (Chen and Shih, 2005). In short, the innovation capabilities of China's hi-tech enterprises are very low and it will take some time for China's hi-tech companies to develop their own technology and become competitive.

1.2 Dissertation Objectives

In this study, the basic assertion is that patent applications filed domestically provide valuable information about China's innovation capabilities. Through detailed analysis of domestic patent data in different dimensions, my dissertation addresses the following important questions:

1. Are internal R&D activities closely related to domestic patent growths in China?

2. Are there any links between strong economic growth in China and returns to domestic R&D efforts?

3. Are inter-regional differences in economic development in China closely related to inter-regional differences in innovation activities? If so, is regional technological progress towards convergence or divergence?

4. Are there any leading industries or industrial branches in innovation activity?

5. Is S&T policy conducive to the development and growth of China's innovation activity, particularly in the these industries?

Related to these questions, I define my objectives of the study in the followings.

First, I identify general characteristics of Chinese domestic patent data in terms of the patent intensity, propensity to patent, growth rate of patents, and the distribution of patents both by technological fields and by industrial sectors. The patent intensity can be computed as patents per 10,000 persons. The propensity to patent is usually measured as the ratio of patents to the number of inventions; however, a direct count of inventions is not available, so I use the ratio of patents to volume of R&D spending as a proxy. The average growth rates of patents between 1985 and 2004 are computed at the national and regional levels. The distributions of patents (measured as share of total) by technological fields and by industrial sectors reflect the relative importance of innovation activities in a given technological field and sector.

Second, I compute the Revealed Technology Advantage (RTA) index by both technological fields and industrial sectors to identify the relative technological strengths and weaknesses at the national and regional levels. RTA indexes at the national level reveal China's technological strengths to the world average. An index larger than 1 indicates that China has a relative advantage in a given technological field or industrial sector compared to the world average. Regional RTA indexes reveal the spatial distributions of technological strengths in China. Based on computed patent indicators, i.e., patent intensities, patent growth rates, and RTA indexes, the evolution of geographic distributions of patenting activities over time are mapped by technological fields and by industrial sectors, respectively.

Third, I identify the main determinants of patenting activities at the provincial level. A patent production function is estimated as:

$$\begin{aligned}\log(P_{it}) = a(t) + \alpha_i + \beta_1 \log(RD_{it}) + \beta_2 \log(GDP_{it}) + \beta_3 \log(EMPLOY_{it}) + \\ \beta_4 \log(POP_{it}) + \beta_5 \log(UNIV_{it}) + \beta_6 \log(HITECH_{it}) + \varepsilon_{it}\,,\end{aligned} \qquad (1.1)$$

where P_{it} is patent applications of region i at time t; a is a measure of changing in propensity to patent economic-wide; α_i is region-specific fixed effect; RD_{it} is R&D spending in the region i at time t,. To control for the other effects of each region, a set of variables are included, such as income (GDP_{it}), manufacturing employment ($EMPLOY_{it}$), population (POP_{it}), the number of universities ($UNIV_{it}$), and hi-tech output ($HITECH_{it}$).

Further, I analyze the contribution of technology (patenting activity) to value-added industrial output at the provincial level by estimating a standard knowledge production function. The technology input is proxied by the contemporaneous patent applications and patent stocks. The basic knowledge production function equation is specified as :

$$\log(Y_{it}) = a(t) + \alpha_i + \beta_1 \log(C_{it}) + \beta_2 \log(L)_{it} + \beta_3 \log(P)_{it} + \varepsilon_{it} \qquad (1.2)$$

where Y_{it} is value added industrial output in the region i at time t; a is a measure of exogenous change in the technological progress over the time; and C_{it} and L_{it} are the capital and labor inputs in the region i at time t.

Finally, I examine the effects of knowledge spillovers at the provincial level. The inter-regional knowledge spillovers are examined in two ways. First, I estimate the effects of inter-regional knowledge spillovers on the patenting activity by estimating a modified patent production equation with an additional spillover variable. The knowledge spillover variable is proxied by the R&D activity and patent activity performed in the other regions. Next, I further examine the effect of inter-regional spillovers on industrial growth. Patenting activities performed in the other regions are used as the source of knowledge spillovers. The knowledge production function of equation 1.2 is modified to include the spillover variable and the effect of inter-regional spillovers on value-added industrial output is estimated directly.

1.3 Contribution to the Literature

The contributions of this dissertation are mainly in the areas of patent literature and economic studies of China: (1) The positive relationships between R&D, patents, and output growth are well-established in the US and other industrialized countries. This study verifies these relationships at the Chinese provincial level by using Chinese domestic patent data. The results provide valuable information about properties of Chinese domestic patents versus those of industrialized countries. (2) This study is the first to compute China's Relative Technological Advantage Index by industrial sectors and by technological fields at the national and provincial levels. Through detailed analysis of domestic patent data by technological fields and by industrial sectors for the years 1985-2004, my study identifies China's comparative technological advantages/weaknesses in the world. (3) This study investigates the effects of knowledge spillovers at the provincial level and is the first to use Chinese patent data to analyze the effects of inter-regional spillovers in China. It contributes to both regional economic study of China and the literature on knowledge spillovers. (4) One of the central issues facing S&T policy is how to maintain sufficient incentives for innovations while minimize the distortion created by patent grants. Giving the current emphasis of China's S&T policy on domestic innovative activity, this study provides some valuable evidence of the impact and effectiveness of hi-tech oriented S&T policy in promoting domestic technological capabilities.

1.4 Organization of the Dissertation

Chapter 2 first reviews the literature on innovation, technological change, and patenting activity, then discusses the empirical studies of patenting activity in China.

Chapter 3 provides an interpretative analysis of China's patenting activity. The strengths and weaknesses of China's technological capabilities are examined and spatial distributions of innovation activity at the provincial level are analyzed and mapped.

Chapter 4 analyzes the determinants of patent production equation at the provincial level. The patent production equation is first estimated with a panel data of 30 provinces for the years 1998-2004. Next, basic specifications of patent production equations are modified to estimate the effects of locations and China's WTO accession on domestic patenting activity. Finally, the model is further modified to examine the effects of inter-regional knowledge spillovers on patenting activity.

Chapter 5 estimates the contribution of technology (patenting activity) to value-added industrial output. A value-added Cobb-Douglas knowledge production function is estimated at the provincial level. Further, the effects of inter-regional technology spillovers on value-added output are estimated and compared to those of own technology.

Chapter 6 summarizes the empirical findings of this study in terms of China's overall technological development, its regional variations in technological activity, the patents-R&D relationships, and the effects of inter-regional knowledge spillovers.

Chapter 2

LITERATURE REVIEW

2.1 Innovation and Technological Change

The innovation process has drawn substantial attention among economists. Economists generally agree that innovation plays a crucial role in economic growth. It is not only the primary source of national economic growth but also stimulates regional and local economic development.

Innovation is generally defined as the activity of developing and commercializing something new (e.g., see Edwards and Gordon, 1984). As a form of advancing technology, innovation is a principle source of change for firms, industries, regions or nations. Successful innovation relies on both internal organizational factors as well as external factors, such as technological characteristics, market forces, and appropriability conditions.

So, what is technology? According to Mansfield et al. (1982), technology consists of a pool of knowledge; hence, it is knowledge that ultimately drives innovation. There are two types of knowledge that lead to innovation: technological knowledge and market knowledge. Technological knowledge is the knowledge of processes methods and techniques (Rosenberg, 1982). In contrast, market knowledge is that of customers, their preferences, local customs and other environments. Further, there are two parts of knowledge, codified knowledge and tacit knowledge.

In the past, such as in the 1950s and 1960s, the analysis of innovation and technological change was dominated by linear models, such as demand-pull and technology-push theories (Schmookler, 1966). Demand-pull theory focuses on the capability of the market to generate the needs for new products and on the ability of firms to convey them. The technology-push theory instead considers firms as the promoters of technological innovation.

Current thinking on innovation process emphasize the tacit part of knowledge and thus the complex and cumulative nature of technology. Dosi (1988) characterizes the innovation process by five stylized facts: (1) the uncertainty of the innovation process, (2) the reliance on university research, (3) the complexity of the innovation process, (4) learning by doing, and (5) the cumulative nature of innovative activity. At present, interactive models of the innovation process, which emphasize the feedback, the timely exchange of information, and the accumulation of knowledge have replaced linear models (Fischer, 1999).

2.1.1 The Nature of Technological Change

Technological change can be defined in many ways. The concept encompasses product, production processes, management, and intermediate inputs in the economic system (Stoneman, 1983). In the Schumpeterian view, technological change involves three stages: invention, innovation, and diffusion (Schumpeter, 1942). Invention is the generation of a new idea; innovation is the development of a new idea into marketable products; and diffusion is the new product and new process spreading across the potential markets. Thus the impacts of new technology generally occur at the third stage, e.g., diffusion. However, innovation is commonly used to describe the whole technological change, which represents doing something new.

Clearly, technological change occurs over time: there is generally a lag between invention, innovation and diffusion. It also involves risk and uncertainty. The risk is related to both technological risk and commercial risk (Stoneman, 1995). The increasing complexity of technology and research has led to a significant growth of organizational R&D activity in the US and other developed countries. Mowery (1983) finds that industry-performed R&D grows at a much higher rate than industrial output or employment and also tends to be internalized within firms. As a whole, in-house R&D has become the dominant form of corporate technological research (Rosenberg, 1985).

Different approaches have been developed to model technological change: (1) the neo-classical approach centers on the production function (e.g., Griliches 1979); (2) structure-conduct-performance paradigm relates to the technology market and its performance (e.g. Geroski, 1995); (3) the evolutionary approach; and (4) the game-theoretic approach. In the following review, I focus on the neo-classic approach and its empirical findings.

2.1.2 Propensity for Innovation

Technological knowledge is cumulative, specific and partially tacit. This nature of technology has considerable implications for understanding the perceived differences in innovation activity among firms, industries, regions or nations. The cross-sectional distributions of technological opportunities are far from homogenous (Pavitt, 1984; Scherer, 1982, 1984). Rosenberg (1976) argues that differentiated technological opportunities determine the different cost structures of technological advances. Thus innovation opportunity is to some extent both firm specific and local, and it is also constrained by specific characteristics of each technological area and the knowledge pool that can be drawn upon.

The relationship between firm size and innovation is the subject of a long-standing debate and findings are sometimes conflicting (Griliches 1984; Pavitt, Robson, and Townsend, 1987; Soete, 1979). Schumpeter (1942) was the first to claim that firm size matters in innovation activity. He claims that the large-scale establishment has come to be the most powerful engine of progress. But R&D itself is a function of specialization and size, thus R&D data tend to considerably overestimate the contribution of large firms to the production of new technology (Cohen, 1995).

Studies generally find that larger firms tend to conduct relatively more incremental R&D (Mansfield, 1981; Wilson, Ashton, and Eagan, 1980) and relatively more process R&D than smaller firms (Link, 1981; Pivot et al., 1987; Scherer, 1991). However, this is actually industry-specific: large firms may be more conducive to innovation in some industries, while in other industries small firms are more likely to innovate. Some of the conclusions from this line of research are: (1) large firms have a greater propensity to patent than small firms; (2) small firms are just as innovative as large firms; and (3) small firms and large firms' innovative activities are complementary (Cohen, 1995).

Since small firms can be as innovative as their large counterparts, at least in certain industries, it casts doubts on the proposition that scale economies exist for R&D and consequently innovation activity. So, why may small firms tend to, in fact, have an innovation advantage over large firms? Link and Rees (1990) explain that diseconomies of scale in the production of innovation are due to the inherent bureaucratization process within big corporations, which inhibits both innovation activity and the speed with which new inventions move through the corporate system towards markets.

Another important reason for observed inter-industry differences in R&D is related to different methods of innovative research. In some industries, e.g., electronics, drug, and aerospace, innovation involves complex and formal R&D labs, while in other industries innovation is much more informal.

Certainly, the market-determined inducement mechanism is not irrelevant to the propensity for innovation. The observed sectoral patterns of technological change are the results of the interplay between various sorts of market inducements, technological opportunities, and appropriability conditions.

2.1.3 The Knowledge Production Function

There are roughly three approaches to the contribution of R&D: (1) historical case studies, (2) the analysis of innovation counts and patent statistics, and (3) econometric studies relating productivity to R&D or similar variables (Griliches, 1998). The most widely used knowledge production function in the literature was first introduced by Griliches (1979). The basic framework tries to capture the contribution of R&D to output growth, holding the contribution of other inputs constant. In the simplest form, it can be expressed as:

$$Y=F\ (X, K, u), \tag{2.1}$$

where Y is the output at the micro or macro level; X is an index of conventional inputs, such as labor and capital; K is the current state of knowledge capital, which is determined in part by current and past R&D expenditure; and u stands for all other unmeasured determinants.

Assuming a conventional Cobb-Douglas form, the model (in the logarithms) can be expressed as:

$$\log (Y) = a(t) + \beta\log(X) + \gamma\log(K) + \mu, \qquad (2.2)$$

where a (t) represents other forces which affect the output and change systematically over the time and μ reflects all other random and unsystematic fluctuations in the output. Alternatively, the equation can be expressed in the growth rate version. Most studies use Total Factor Productivity (TFP) as an output measure. However, the TFP measure presents some aggregation problems, such as choosing the weights to be used in order to obtain a single output to single input ratio (Griliches, 1979).

The main issue of using such an equation is the measurement of R&D capital, i.e., the depreciation rate, the deflator, and the specific lag structure of R&D variable. Griliches suggests that the R&D depreciation rate of knowledge capital is probably high. Knowledge capital K is usually constructed as a weighted sum of current and past R&D expenditures with the weights reflecting both the potential delays in the impact of R&D on output and its possible eventual depreciation, that is:

$$K = G\,(W(B)\,R,\, v), \qquad (2.3)$$

where W (B)R is an index of current and past levels of R&D expenditures; W(B) is a lag polynomial describing the relative contribution of past and current R&D to K; B is the lag operator; and v is another set of unmeasured influences on the accumulated level of knowledge (Griliches, 1979). However this lag structure is difficult to identify and most of the weights appear to fall on the contemporaneous R&D (Griliches, Pakes, and Hall, 1986).

In estimating this knowledge production function, there are other serious econometric problems, such as multicollinearity and simultaneity. Griliches (1979) suggests that micro-time-series data at the firm level is probably the best way to reduce the multicollinearity. Simultaneity refers to the possible problem of reverse causality: future output and its profitability depend on the past R&D, while R&D in turn depends on both past output and the expectation about its future.

Despite various reservations, a number of researchers have estimated such equations with rather interesting results. At the firm level, it is found that the estimated elasticity of output with respect to R&D capital lies between 0.06 and 0.1 (Cuneo and Mairesse, 1984; Griliches, 1980, 1984, 1990). With the growth rate version, it is found that the elasticity of the growth rate to R&D capital is about 0.2-0.5, both at the firm and industry levels (Griliches and Lichtenberg, 1984; Griliches, 1998; Mansfield, 1965; Scherer, 1982, 1984). The econometric estimates do not show that coefficients estimated at the industry level are higher than those estimated at the firm level, though spillover effects would make such an expectation reasonable.

2.1.4 Knowledge Spillovers

There are generally two kinds of knowledge, codified knowledge and tacit knowledge. Codified knowledge is in some way tangible, like scientific papers and patent applications, and thus publicly accessible. In contrast, much of essential knowledge resides in tacit form, that is, in the minds of experienced engineers and researchers. The tacit form of knowledge is difficult to transfer and is only diffused through personal contacts and networking. In this sense, knowledge spillovers play a key role in the technological change.

2.1.4.1 Inter- and Intra-industry Spillovers

A fundamental issue in the technological change is to identify and measure knowledge spillovers and the extent of firm's ability to exploit them economically. It should be noted that there are actually two distinct notions of R&D spillovers confused in the literature. Some consider that R&D input purchased from other industries is a form of knowledge spillovers, but this is not a real knowledge spillover. Real knowledge spillovers are ideas borrowed by research teams in industry i from industry *j* (Griliches, 1991; Jaffe, 1986), though it is not clear if they are related to input purchase flows. The underlying assumption is that the level of productivity of a firm or industry depends not only on its own R&D efforts but also on the level of the knowledge pool to which it has accessed. The size of the knowledge pool is different for different industries or technological fields.

There are several approaches to studying within- and between-industry knowledge spillovers. Some studies have used the cost function framework to estimate the effects of spillovers (Bernstein and Nadiri, 1988, 1989). The advantages of the cost function approach are that it is often more flexible in the functional form and it benefits from imposing more structures, which consider the impact of R&D spillovers not only on the total cost but also on the amount of labor and intermediate products demanded. However, it requires the use of prices for all the intermediate inputs which are not easily accessible (Griliches, 1991).

In contrast, most of the studies follow the knowledge production framework proposed by Griliches (1979). The basic knowledge production model can be modified to investigate within-industry spillover effects. A modified knowledge production function can be expressed as:

$$Y_i = B(X_i)^{1-\gamma}(K_i)^{\gamma}(K_a)^{\mu}, \tag{2.4}$$

where Y_i is the output of firm, which depends on the level of conventional inputs X_i, its specific knowledge capital K_i, and the aggregate knowledge in the industry K_a. A constant return is assumed in the firm's own inputs, X_i and K_i. The aggregate knowledge input, K_a, is computed as:

$$K_a = \Sigma K_i, \tag{2.5}$$

which is the sum of all specific firms' R&D capitals. In addition, assuming that own resources are allocated optimally within the firms and all firms face the same relative factor prices, then the ratio of K to X is:

$$(K/X)_I = (\gamma/(1-\gamma))\,(P_x / P_k) = r, \tag{2.6}$$

where P_x and P_k are the prices of X and K, respectively. Since r, the ratio of K/X, does not depend on i, we can aggregate individual production functions together to yield:

$$\Sigma Y_i = \Sigma B(K_i/X_i)^{\gamma}(K_a)^{\mu} = Br^{\gamma}(K_a)^{\mu}\Sigma X_i = B(X_a)^{1-\gamma}(K_a)^{\gamma+\mu}. \tag{2.7}$$

The last equality follows from the assumption that all the K_i/X_i ratios are equal to r and hence K_a/X_a, where $X_a = \Sigma X_i$.

The coefficient of aggregate knowledge is $\gamma+\mu$, reflecting not only private returns but also social returns to R&D. In reality, firms borrow different amounts of knowledge from different industries according to their relative economic and technological distances. More precisely, we should redefine K_a as:

$$K_{ai} = \Sigma w_{ij} K_j, \tag{2.8}$$

where K_{ai} is the amount of knowledge borrowed by the i-th industry from available sources; K_j measures the knowledge level available in these sources; and w_{ij} is the weight which can be interpreted as the effective fraction of knowledge in industry j borrowed by industry i. Presumably, w_{ij} becomes smaller as the "distance" between i and j increases, but it is difficult to define and measure this "distance" empirically (Griliches, 1979).

Robbins (2003) estimates the effects of actual distances on intra-industry and inter-industry spillovers at the state level. She finds that there are powerful spillovers within the industry and between the industries, but distance lessens the benefit of spillovers.

2.1.4.2 Geographical Proximity and Knowledge Spillovers

Geography plays a key role in innovation and in economic growth. At the regional level, innovation activity is largely constrained by local technological infrastructures which create the capacity for innovation. Due to the cumulative and self-reinforcing nature of knowledge, this capacity becomes specialized to particular technologies and industrial sectors and results in place-specific concentrations of knowledge, technological advance and competitiveness (Lundvall, 1988; Thomas, 1985).

An important issue in the study of knowledge spillovers is the role of local versus non-local knowledge spillovers. One view asserts that technological progress is a public good; therefore knowledge spillovers are not locally bounded but can move freely across borders (Coe and Helpman, 1995). For example, the codified part of patented ideas is likely to be perfectly available to anyone and therefore can be considered as a fully public good. Nevertheless, the tacit part of knowledge is not easily accessible. A growing literature emphasizes the local nature of knowledge which is still costly and difficult to transmit across areas. This stock of knowledge increases in a region as local inventors discover new ideas. It could still diffuse but probably requires much more personal contacts and face-to-face interaction. It can be considered as ‘a local public good’ as it benefits scientists in the region or close to it, but it is sensitive to distance because of reduced necessary contacts and interactions (Baptista, 1999, 2000; Bottazzi and Peri, 2002).

From a more theoretical perspective, some authors have investigated the properties of knowledge that can explain localized nature of knowledge spillovers. Most findings point to the fundamental role of geographical proximity in facilitating the transmission and absorption of knowledge (Baptista, 2003). The more tacit and complex the knowledge is, the more likely geographical proximity plays an important role (Breschi, 1998; Winter, 1987). In this sense, one can also argue that geographic patterns of knowledge spillovers differ across different sectors because their knowledge bases are different in terms of tacitness, codification, complexity and so on. Hence proximity plays either an important or negligible role in mediating flows of knowledge (Breschi and Malerba, 1996).

2.1.4.3 Agglomeration and Knowledge Spillovers

An agglomeration economy exists when a geographic concentration of resources creates spillovers which lower the cost of complementary activities. As a result, agglomeration causes industrial activities to cluster spatially (Baptista, 2003; Evans, 1985). Agglomeration economies may increase information transfers, promote spillovers, and thus lower the costs and risks of innovation. Recent literature has singled out two types of externalities associated with agglomeration: diversification and specialization. There is a belief that a large agglomeration of a specialized industry or diversified industry contributes to speed up the exchange of ideas by promoting higher mobility among inter-firm engineers and skilled workers (Audretsch and Feldman, 1996).

Some authors have investigated the relationship between spillovers and the agglomeration of innovation in the US and EU countries, though the results are mixed. Audrestsch and Feldman (1996) find that there is no evidence of specialization externalities, while diversification externalities are at work in the US metropolitan areas. Peri (2000) finds that no positive externalities exist either in the US or European regions.

Paci and Usai (1999) investigate the relationship between knowledge spillovers, externalities and spatial distributions of innovation across 86 industrial sectors and 784 local labor systems in Italy. They compute a production specialization index based on employment and a diversity index based on the reciprocal of a Gini coefficient. The econometric results indicate that both specialization externalities and diversification externalities positively affect innovative activity in a local industry.

It has also been argued and indeed empirically verified that geographical concentration of rivals enhances competitiveness and stimulates the creation and diffusion of innovation (Audretsch and Feldman, 1996; Bapista 2000;Feldman, 1994). Feldman (1994) models the effect of concentration of knowledge on the location of new product innovation. He identifies four key knowledge inputs at the state level: university research, industrial R&D laboratories, related industry presence, and complementary business services. He finds that product innovation exhibits a pronounced tendency to cluster geographically and product innovation at the state level is related to the level of university R&D and industry R&D in that state. This finding is consistent with other similar works (e.g., Jaffe, 1989). He also finds that the clustering of innovation at the state level is related to other innovative inputs, such as the presence of related industries and specialized business services.

It is well observed that innovation tends to cluster spatially more in some industries than in other industries. For example, the location of production is more concentrated in those R&D-intensive industries where knowledge spillovers are prevalent, though knowledge spillovers are not the only determinant of production concentration. Transportation cost is another important factor (Krugman, 1991). One of the reasons that innovation tends to cluster more in some industries is that the location of production is more geographically concentrated for some industries than in others (Jaffe, Trajtenberg, and Henderson, 1993). This raises the issue of endogeneity. To identify why the propensity for innovative activity to cluster spatially varies across industries, one should first control the geographic concentration of production locations.

Audretsch and Feldman (1996) examine the importance of geographic location of different types of industries. They link geographic concentration in manufacturing industries to industry-specific characteristics, mostly the importance of knowledge spillovers. They find that R&D intensive industries have a higher propensity to cluster together, with or without controlling for the location of production concentration. Therefore they conclude that innovative activity is more likely to occur within close geographical proximity to the source of that knowledge.

In short, studies of innovation and knowledge spillovers have been growing very rapidly in recent years, both in theoretical and empirical aspects. In the next section, I focus on the empirical studies of patents and technological change.

2.2 Patents and Technological Change

2.2.1 Measurement Issues

The major problem facing scholars in technology and innovation study is measurement: absence of satisfactory measures of new knowledge and its contribution to technological progress. The main measures of technological change involve one of the three aspects of the innovation process: (1) inputs, such as R&D expenditures or R&D personnel; (2) intermediate outputs, such as patents; and (3) direct measure of output, such as literature counts and new products (Kleinknecht and Baun, 1993). As a result, any knowledge regarding determinants as well as the impact of technological change is shaped by the empirical data used in the corresponding studies.

The pros and cons of using patent statistics to analyze innovative activity have been widely evaluated in the literature (Griliches, 1990; Pavitt, 1985;). Compared to other indicators, patent data have obvious advantages: (1) patents are an output measurement, compared to R&D measures; and (2) patent data provide rich and useful information on the technological specialties and competences of countries, regions, firms and other institutions.

The limitations of patent data are also obvious. First, the propensity to patent differs across sectors and firms: it depends on the relative costs of innovation and the relative importance of patents in protecting innovation. Scherer (1983) describes the propensity to patent:

> The quantity and quality of industry patenting may depends on chance, how readily a technology leads itself to patent protection, and business decision-makers' varying perception of how much advantage they will derive from patent rights. Not much of a systematic nature is known about these which can be characterized as difference in propensity to patent (1983, p107-8).

Recent studies show that patents are relatively unimportant in automobiles, but very important in pharmaceuticals (Arundel, van de Pall, and Soete, 1995; Bertain and Wytt, 1988; Levin et al, 1987;). In addition, patents are not fully measured in information technology fields, such as software, where copyright laws or trade secrets are the main source of protection. Given these differences, the results of R&D and patent statistics are more reliable when they are normalized by sectoral totals (Scherer, 1982).

Second, what the firms do with patents is different, that is, the share of patents to be commercialized is different, depending on the size of the firm and the branch of industry (Griliches, 1990). Further, there are major differences between countries in patent law: both procedures and criteria for granting patents are different. For this reason cross-country comparisons are more reliable when using international patenting or patenting in one country, such as in the US.

There are further criticisms of patents as an indicator of technology, which draw some controversies. Some scholars think that it is a main drawback that patents differ greatly in their economic values (Schankerman and Pakes, 1986). Mansfield (1984) finds that the value of individual patents varies enormously within and across industries, and thus it will influence within and between-industry comparisons. However, the same is true for R&D projects and for the same reason: technological activity involves cumulative learning under uncertainty, therefore there are bound to be failures, major successes, and follow-up improvements (Freeman, 1982). We should expect similar and large variations in the distributions of economic values of both R&D and patents across firms and industries.

2.2.2 Patent Indicators

Different methodologies have been developed to explore patent statistics at the macro, intermediate, and micro levels. A number of different indicators, such as patent shares, growth rates of patents, and patent intensity, have been used to analyze technological patterns at different levels. It is usually assumed that a fast patenting growth rate in a technological field represents an area of strong technological opportunities in the period in question. However, these indicators do not take into account the differing propensities to patent across regions, industries and technological fields (Nesta and Patel, 2004).

An indicator which corrects for this bias is the Revealed Technology Advantage (RTA). This index is similar, in spirit, to the 'Revealed Comparative Advantage' that trade economists are familiar with. It is defined as:

$$RTA_{it}=\left(\frac{p_{it}}{\sum_{t} p_{it}}\right) / \left(\frac{\sum_{i} p_{it}}{\sum_{it} p_{it}}\right), \tag{2.9}$$

where P_{it} is the number of patents held by firm *i* in technological class *t*. This can be interpreted as an index of comparative advantage: with a value above unit indicating an area of relative strength and a value below unit an area of relative weakness. The definition implies that its value is not bound by an upper limit, but could be null or positive, i.e.,

$$RTA \in [0; +\propto]. \tag{2.10}$$

For this reason, some studies prefer to use standardized RTA measure by taking the logarithm of the index. In this case, its threshold value becomes zero, i.e.,

$$\log (RTA) \in [-\propto; +\propto]. \tag{2.11}$$

Positive values indicate areas of technological advantage and negative values indicate areas of technological disadvantage.

The RTA index can be further used to calculate indices that characterize patterns of specialization within or across countries, regions and industries. For example, to determine if a country has established niches of technological excellence or has broaden its technological competence, one can calculate the coefficient of variation (CV) of RTA index:

$$CV=\sigma_{RTA} / \mu_{RTA}, \tag{2.12}$$

where σ_{RTA} and μ_{RTA} are the standard deviations and mean of RTA indexes of all technological fields. A large coefficient of variation means that the country is concentrating its areas of excellence within a few technological areas. Conversely, a small coefficient of variation means that the country is developing its competence more uniformly across the technology fields (Nesta and Patel, 2004).

2.2.3 General Findings

Economists have made serious efforts to assemble and analyze patent data since Schmookler's pioneering study in the1960s (Schmookler, 1966). Much has been learned through those studies and patents have become a well-established proxy variable for measuring technological competence, albeit an imperfect one. In general, we can say that patents appear to be a good indicator for studying the rate and direction of innovative activity (Pavitt, 1985) and they can be used to trace the interaction and technological flows across different sectors of economy (Griliches, 1990). Some significant findings from this body of research are listed in the followings:

1. There is a strong positive correlation between R&D expenditures (or employments) and patents (Griliches, Pakes, and Hall, 1986; Pakes and Griliches, 1980; Scherer, 1965, 1983).

2. There is a positive correlation between patents and market values (the stock market rate of return or Tobin's Q) (Austin, 1993; Griliches, 1981; Pakes, 1985).

3. Values of patents are highly skewed where values are determined by citations or renewal rates (Henderson Jaffe, and Trajtenberg, 1993, 1998; Pakes and Schankerman, 1984; Schankerman, 1998; Trajtenberg, 2002).

4. The weighted patent index based on renewal rates or citations is a better measurement than simple patent counts (Hall, Jaffe, and Trajternberg, 2001; Lanjouw, Pakes and Putnam, 1998; Lanjouw and Schankerman, 2004)

In particular, patent data have been used to address the following important issues: (1) firm size, market power and R&D productivity; (2) inter- and intra-industry differences in the R&D activities; (3) inter- and intra-national differences in the R&D activities; (4) regional development and knowledge spillovers; and (5) long term growth and the return to R&D.

2.2.3.1 International Comparisons

Patent data are used to make international comparisons of strengths and weaknesses in different technological fields among advanced industrial countries. Two common determinants of innovation activity are identified for a country: the relative level of technological endowment, such as research intensity,[4] and the size of a country (Guellec and van Pottelsberghe, 2004).

A pioneering study for analyzing the nature and determinants of technological accumulation among countries was done by Pavitt (1988). Since then, a

[4] Research intensity refers to the ratio of R&D spending to GDP.

number of other scholars have used similar data and methodologies to examine issues related to national technological accumulation. One of the most comprehensive studies on this subject was done by Archibugi and Pianta (1992). They compare technological specializations among the US, Japan, and the EU countries using both the US patent data and the data from the European Patent Office (EPO). Their results show that there are great differences across countries in the technological specialization patterns: larger countries are involved in a broad range of technological fields while smaller countries in a more narrow range.

Nesta and Patel (2004) use the US patent data to describe national patterns of technological activities in Japan and the EU countries for the period of 1971-1980 and 1991-2000. Two properties of countries' technological profiles are confirmed: stability over time and differentiation across countries. The results show that path dependency is a key feature of technological accumulation. They find that in many areas the EU countries have an overall relative advantage, while their performance in the sub-fields of highest technological opportunities, such as the electronics, is weak. Japan seems to have a consistently high performance both in the aggregate and in the fast growing areas.

Some authors use patent statistics to explain the different growth rates across countries, though the results are mixed. The underlying assumption is that innovation plays an important role in economic growth. However, it should be noted that the propensity to patent is different for different countries and thus patent variables tend to overestimate the difference of technological level between countries.

Pavitt and Soete (1982) use two variables, patents per capita and patent growth rate, along with other conventional variables to analyze the relationship between innovation and economic growth in fourteen OECD countries from 1890 to 1977. Their results fail to support the assumption at all: they do not find any stable relationship between GDP growth rate and patent variables. Fagerberg (1987) uses a modified model with growth rate of patent applications as an explanatory variable along with two other control variables, country's investment level and imitation potential. He finds that there is a close relationship between the level of economic development and patent statistics for twenty-five industrialized countries for the period of 1960-1983.

2.2.3.2 Inter- and Intra-industry Comparisons

Industrial sectors differ greatly in technological opportunities, market demands and appropriability conditions. Patents have rarely been analyzed at the industry level because of the difficulty in assigning patents to the specific industry.

In general, studies find that sectors which tend to generate substantial innovation also tend to engage in high patenting and R&D activity. In most industrialized countries, more than 75% of the production of new technologies is concentrated in the core sectors, such as machinery and instruments, and the main focus in these sectors is on the product innovation. In contrast, the main user sectors in manufacture are textiles, food, paper and printing which have relatively few patenting activities (Patel and Pavitt, 1995).

Scherer (1965) estimates the rates of innovation (patent rates) across firms and industries. He finds that 42.5% of total variance is due to the inter-industry components. He suggests that difference in technological opportunities is a major factor for inter-industry difference in inventive outputs. Other analyses tend to confirm such a view (e.g., Pakes and Schankerman, 1984).

Mansfield (1986) evaluates the effects of patent protection on the development and commercialization of inventions. His findings shed some light on inter-firm and inter-industry differences in terms of propensity to patent. Based on a random sample of 100 US manufacturing firms, he finds that patent protection is judged to be essential for the development of 30% or more of new inventions in only two industries, pharmaceuticals and chemicals. In office equipments, automobiles, rubbers, and textiles, patent protection is not important at all. Within each industry, there are also considerable variations among firms. The R&D-intensive firms regard patents much more important than less R&D-intensive firms. He also finds that in most industries there is a positive correlation between a firm's size and patenting activity.

Many researchers have pointed out that there are large differences among industries in patents per R&D dollar. Scherer (1982) suggests that these differences might be due in part to inter-industry difference in the propensity to patent. Mansfield (1986) tests this hypothesis and finds some supporting evidence: the number of patentable inventions per R&D dollar varies less among industries than the number of patents per R&D dollar. However, his results also indicate that much of inter-industry variation is the variation in the yield of patentable inventions per R&D dollar among industries.

2.2.3.3 Inter-temporal Comparisons

With a long period of data, patent statistics can reveal technological opportunities and technological change historically. Anderson (2004) examines the evolution of technology historically using the US patent data from 1890 to 1990. His analysis indicates that the evolution of technological opportunities can be characterized as creative, incremental, and accumulative: new technology is built upon the old one, rather than substitutes it. In addition, technological opportunities become increasingly interrelated, wider ranging, and complex.

Volga (1999) presents a detailed analysis of innovation activity in high technology industries in the US. Based on a large patent data set from 1970 to 1992, he finds that the West and the South have increased their shares of patenting in high technology fields, while the Northeast and the Midwest have decreased their contributions to innovation in the same fields. Although major metropolitan regions in the Northeast and Midwest are losing their competitiveness in the most dynamic high technology industries, both regions seem to have increased their innovation specialization and competitiveness in drugs, medicine, and chemicals.

2.2.3.4 Patents and Firm Characteristics

In recent years, more studies have been conducted at the firm level due to the improvement of data. These studies shed some light on the nature and determinants of patenting and consequently technological activity at the firm level. A firm's patenting and R&D activity vary according to its size and corresponding industrial sector. Further, the size distribution of innovation firms depends on technological characteristics of each sector. Thus studies of patenting activity at the firm level are more challenging: (1) patents may not capture all the aspects of technological change, such as informal innovative activity; (2) some of the inter-firm variations must be attributed to differences in the actual technological opportunities and appropriabilities; and (3) some firms may not patent or innovate but still do R&D for keeping up and adapting what their competitors are doing (Dosi, 1988). Accordingly, conflicting findings are not uncommon.

Scherer (1965) was the first to analyze the relationship between firm size, market structure and patents. His main sample consists of 448 biggest US firms in 1955. He uses a simple patent equation to link innovation with firm size:

$$I = \beta_0 + \beta_1 S + \beta_2 S^2 + \beta_3 S^3, \tag{2.13}$$

where I represents innovation activity (patent counts) and S is a proxy for firm size, such as sales or employment. A positive and significant sign of β_3 is an indication of increasing returns of scale in R&D. However, if this coefficient turns to be insignificant and can be dropped from the equation, then a negative sign of β_2 is an indication of decreasing returns of scale. He finds that patent output generally increases with sales but at less proportional rate and the result is quite consistent across different sectors. However, he points out that this observed relationship might be questionable because the equation does not take into account the propensity to patent of different firms. Scherer also analyzes the relationship between diversification, monopoly power and patenting activity among these largest firms. He finds that patents have a stronger relationship with diversification than with sales, but patents do not seem to be systematically related to the market power.

Soete (1979) analyzes the relationship between firm size and innovative activity in the US in the late 1970s. He also estimates a cubic regression model, similar to equation 2.13, with both patents and R&D personnel as dependent variables and sales (or employments) as a proxy for firm size. He finds that innovation efforts, either measured as R&D personnel or patents, increase proportionally with firm size, though the picture is less clear at the industry level.

Baldwin, Hanel, and Sabourin (2000) examine the determinants of innovative activity in Canadian manufacturing firms. They include a wide range of explanatory variables which can be grouped into three categories: firm characteristics, firm activity, and industry characteristics. They find that firms which innovate take out patents, but firms and industries that make intensive use of patents do not tend to produce more innovations. While R&D is important, developing other capabilities such as marketing and technological competency is also important. Firm size is an important determinant and the largest firms tend to be more innovative. With respect to market structure, they find that an intermediate level of competition is the most conducive one to innovation.

2.2.4 The Patent Product Equation

In general, empirical studies show a very strong relationship between patent counts and R&D activity. Patents are considered as an accurate indicator of R&D activity and a good proxy for knowledge output.

Assuming that new knowledge produced by a firm in a given period is related to its R&D, Griliches and Pakes (1980) articulate a simple patent equation, in which patent is a function of current and past R&D expenditures, a set of firm specific dummy variables and a set of time dummy variables. The appropriate form of dependent variable (patents), P_{it}, can be either in logarithms or in levels. In log-log form, the reduced patent equation can be expressed as:

$$\log P_{it} = \alpha_i + \beta_1 t + \beta_2 \log K_{it} + \mu_{it}, \qquad (2.14)$$

where α_i is firm i's specific fixed effect; t is the time trend; K_{it} is the knowledge capital for firm i at time t, which is a weighted sum of its current and past R&D expenditures; and μ_{it} is all unmeasured variances in patents, which could be decomposed into a firm-specific variance and an independent and identically distributed disturbance. Thus β_2 measures the elasticity of patents to R&D expenditures.

Based on the estimation of this patent production equation, Griliches and Pakes (1980) find a statistically significant relationship between R&D expenditures and patent applications at the firm level. The relationship is much stronger in cross-sectional dimension than in time series dimension. The median R-square of estimated patent equations is about 0.9, which indicates that patents may be a good indicator of unobserved inventive outputs. In addition, they find that the relationship between patents and R&D is close to contemporaneous. This finding is consistent with the fact that patents tend to be taken out relatively early in the stage of innovation activity.

Patents can be used as a proxy for knowledge capital K in the standard knowledge production function like equation 2.1. Patent stocks can be computed in the same way as R&D stocks. Lach (1995) estimates a knowledge production equation with patent stocks as knowledge capital at the industry level for the period of 1959-1983. His results show that the estimated elasticity of TFP growth to the growth rate of patent counts is around 0.3.

There are specific econometric problems in estimating such a patent equation. As mentioned earlier, simple patent counts generate a highly skewed distribution both in economic values and in innovators. Many firms simply do not perform either patenting or R&D activities, so there is a strong selection bias. Hausman, Hall, and Griliches (1984) were the first to develop a Poisson-based econometric model for the patents-R&D relationship. Since then, a number of researchers have followed their method to estimate the patent production equation (Griliches, Pake, and Hall, 1986; Jefferson et al.; 2003).

2.2.5 Patents and Knowledge Spillovers

In general, empirical studies of knowledge spillovers show that productivity of a firm or industry is not only related to its own R&D spending but also to the R&D spending of other firms or other industries. Due to firm size and technological closeness between firms, spillover effects also tend to be different across firms and industries.

2.2.5.1 Technological Flows and Technological Distance

Early studies of knowledge spillovers often use an input-output table to measure the closeness of industries, which is proportional to their purchases from each other (Brown and Conrad, 1967; Terlecki, 1974). However, this is not a true knowledge spillover. According to Griliches (1998), it is just a consequence of conventional measurement.

Based on patent data, different methodologies have been developed to measure technological distance and /or technological flows. Scherer (1982, 1984) was the first to use patent classification codes to assign industry of production and industry of use. Based on a large patent data set, he classifies patents both by the industry where the invention has occurred and by the industry or industries where it is expected to have major impacts. Thus he constructs a technological flow matrix to identify the direction of spillovers. However, the US patent data are classified based on product codes, so assigning patents to corresponding industrial sectors is not only very challenging but also time consuming. Understandably, it is followed by very few researchers.

The Yale Technology Concordance (YTC) is developed by using patent data collected by the Canadian Patent Offices, which is one of the few patent offices assigning each granted patent to the sectors which are considered as potential producers (industry of manufacture or IOM) and also to potential user sectors (sector of user or SOU) declared by patenting firms (Evanson and Johnson, 1997). The concordance links patent classification codes directly to the Standard Industrial Classification (SIC) codes. Based on a probability distribution of patent classification codes of IOM (or SOU), the concordance assigns each patent proportionally to the sectors where the innovation may have originated or be used.

The YTC has been tested on several subsets of the Canadian patents by comparing out-of-sample prediction with industrial assignments made by the Canadian Patent Offices (Kortum and Putnam, 1997). In general, predictions from the YTC seem to give a reasonably accurate picture of patenting patterns by industries (Lach, 1995; Moreno, Paci, and Usai, 2003; Paci and Pigliaru 2001).

More recently, the OECD Technology Concordance (OTC) has been developed (Johnson, 2002). The process of translating IPC to the International Standard Industrial Classification (ISIC) is completely borrowed from the YTC. Currently, the OTC is still at an early experimental stage and the stability of probability distribution of IPC to ISIC is yet to be tested.

In practice, one should be cautious using such patent flow matrices. These matrices should be country-specific, as the propensity to patent is presumably different for different countries. Hence using same probability distribution of patents for different countries might be inappropriate. Scherer (2002) compares the patent flow matrix based on the YTC with his own input-output flow matrix built in the late 1970s. He finds that the two flow matrices measure somewhat different phenomena and suggests that further research is required to investigate the discrepancies between the two technological flow matrices.

2.2.5.2 Spillovers in Technological Space

Jaffe (1986) was the first to estimate R&D spillovers in technological space. He bypasses the difference of SIC codes and patent classification code. His distance measure is based on the proximity in a technological space which does not imply flows in a particular direction. The underlying assumption is that two firms are more likely to benefit from each other if they are active in the same technological areas. Using firm-level patent data, he constructs a distribution vector to characterize each firm's technological position. He uses the angular separation or uncentered correlation of distribution vector F_i and F_j to measure the technological proximity between firm i and j:

$$P_{ij} = F_i F_j^{'} / [(F_i F_j)(F_{ji})]^{1/2}, \tag{2.15}$$

where P_{ij} is the measure of technological distance between two firms. It is unity for firms whose position vectors are identical and it is zero for firms whose vectors are orthogonal.

He uses a modified Cobb-Douglas knowledge production function to estimate the R&D spillovers on the intensity of patenting activity of firms. The estimated patent equation in the logarithms (small letters denote the logarithm form) is:

$$k_i = \beta_1 r_i + \beta_2 r_i s_i + \gamma_1 s_i + \sum_{c=1}^{21} \delta_{1c} D_{ic} + \varepsilon_{1i}, \tag{2.16}$$

where k_i is the new knowledge generated by firm i; r_i is its R&D spending; and s_i is the potential spillover pool. The potential pool, S_i, is simply:

$$Si = \sum_{j \neq i} P_{ij} R_j, \quad (2.17)$$

where P_{ij} is the technological distance between firm i and j and R_j is the summation of all other firms' R&D spending. D_{ic}s' are a set of dummy variables for technological clusters. These technological clusters are identified by each firm's technological position vector. The term ε_{1i} is a random disturbance which includes unobserved firm-specific attributes. Equation 2.16 implies that knowledge output of each firm is not only determined by its own R&D spending, but also is linked to other firms' R&D spending both directly and through its influence on firm's own R&D spending. Thus each firm's elasticity of knowledge output to its own R&D spending is $\beta_1 + \beta_2 s_i$.

Assuming only a fraction of new inventions is patented, patents, I_i, are linked to knowledge output, K_i, by the following equation:

$$I_i = \exp\left[\sum_{c=1}^{21} \alpha_a D_{ic}\right][\exp(\eta_i)]K_i. \quad (2.18)$$

Here, patents are a function of technological cluster dummies (D_i), the firm's knowledge stock (K_i) and a firm-specific component (η_i). The ratio of patents (I_i) to knowledge output (K_i) is a measure of propensity to patent.

In addition to equation 2.16, Jaffe also estimates a profit equation and a market value equation with the similar form. Based on the results from those three equations, the evidence of R&D spillovers is compelling: firm's elasticity of patents to others' R&D is, on average, about 1.1. The effect of spillover is quite substantial: if every firm increased their R&D by 10%, then total patents would increase by 20%.

2.2.5.3 Geographic Spillovers

A growing literature on knowledge spillovers and regional innovative activity has appeared in recent years (Anselin, Varga, and Acs, 1997; Keller, 2002;

Moreno et al, 2003; Paci and Batteta, 2003; Paci and Pigliaru, 2001; Peri, 2002). Most of those studies provide strong evidence of localized knowledge spillovers on innovation activity. If technology flows are bounded by spatial dimensions, then some regions or countries, given an initial technological endowment, will deepen their patterns of specialization through the cumulative process. Therefore geographical concentration of knowledge spillovers may play a key role in shaping national and regional patterns of specialization and comparative advantage (Grossman and Helpman, 1991).

Spillovers from University. Jaffe (1989) also provides the first examination of R&D spillovers from universities to local firms at the state level. He uses a modified patent production equation:

$$\log P_{is} = \beta_1 \log I_{.s} + \beta_2 \log UNIV_{is} + \beta_3 \log POP_{.s} + \beta_4 (\log UNIV_{is} * \log C_{.s}) + \varepsilon_{is}, \quad (2.19)$$

where P_{is} is the number of corporate patents in technological area i at the state s; $I_{.s}$ is the total corporate R&D expenditures at state s; $UNIV_{is}$ is the university research expenditures in technological area i at the state s. State population, $POP_{.s}$, is included to control for the size difference. In addition, Jaffe constructs an index of geographic coincidence of universities and industrial research labs, $C_{.s}$, to measure the geographical spillovers. His hypothesis is that research will yield more innovative activity if universities and industrial R&D labs are geographically concentrated. He finds that there is a positive spillover from university research to corporation's patenting activities. The effect is statistically strongest in the drug industry, slightly smaller and less significant in chemicals. In addition, he finds that university research appear to have an indirect effect on local innovation by inducing more industrial R&D

spending. However, he finds that spillover is not facilitated by the geographic coincidence of universities and research labs within the state.

Acs, Audretsch, and Feldman (1994) replicate Jaffe's study but using a more direct innovative output, the counts of significant innovations. They find similar results as Jaffe's, but the impact is stronger than that of patents. In contrast, they also find the substantial evidence that spillover is facilitated by the geographical coincidence of universities and research laboratories within the state.

Localization of Knowledge Spillovers. Moreno et al. (2003) investigate the effects of knowledge spillovers on innovative activity in 138 regions of 17 European countries. They use a modified patent production function, similar to Jaffe's spillover model of equation 2.19, by adding a number of factors related to the economic and institutional environments within a region as well as some external factors that may capture knowledge spillovers from other regions. Those external factors could be patents or R&D efforts in the neighboring regions. The estimated equation is:

$$I_i = RD_i^{\partial_1} Z_{1i}^{\partial_2} Z_{2i}^{\partial_3} e_i , \tag{2.20}$$

where I_i is patent counts in region i; RD_i is R&D expenditures in region i; Z_{1i} is a vector of internal factors in region i; Z_{2i} is a vector of external factors reflecting knowledge spillovers from other regions; and e_i represents a stochastic error term. Their results confirm the importance of internal R&D efforts within a region. They find that knowledge spillovers from other regions are positive and significant, but knowledge diffusion among European regions is localized, with 250 kilometers as first order impact and 500 kilometers as second order impact.

Bottazzi and Peri (2002) conduct a similar study on knowledge spillovers among European regions and confirm that knowledge spillovers are localized. In contrast, they find that the size of spillovers is small: doubling R&D spending in a region would increase the output of new ideas in other regions within 300 kilometers only by 2-3%.

Robbins (2003) investigates the localization of knowledge spillovers in 2-digit US manufacturing industry at the state level. Compared to the previous studies of knowledge spillovers (e.g., Feldman, 1994; Jaffe et al., 1993), she directly estimates the impacts of inter-state, intra-industry and inter-industry spillovers on the relative TFP. She uses both a Gravity model and a non-linear model to estimate the elasticity of relative TFP with respect to patent stocks and the distance at which innovative knowledge loses half of its power to effect the relative TFP. The estimated gravity model is:

$$\log F_{sit} = \alpha_s + \alpha_i + \alpha_t + \beta_1 \log P_{sit} + \beta_2 \log \sum_{k \neq s} P_{kit} / D_{ks}^2 + \varepsilon_{sit}, \qquad (2.21)$$

where F_{sit} is the relative TFP of technological class t in industry i at the state s; α_s, α_i, α_t are a set of dummy variables for the state, industry and technology-specific fixed effects, respectively; P_{sit} is the patent stock of technological class t in industry i at the state s; D_{ks} is the distance between two states; and ε_{sit} is the random disturbance. She finds that the elasticity of TFP to patent stocks of in-state and same-industry is 0.038 and the elasticity of TFP to patent stocks of out-of-state and same-industry is 0.166. In addition, she finds that IT-based industries receive greater benefits from innovative knowledge and spillovers than less IT-intensive industries. Her findings also confirm that the effects of knowledge spillover effect are localized: the spillover half-distance is about 447 miles.

International Spillovers. There is an increasing trend towards the internationalization of knowledge generation. Consequently, R&D spillovers have been investigated at the international level (Coe and Helpman, 1995; Coe, Helpman, and Hoffmaister, 1997; Keller 2002). Coe et al. (1997) examine spillovers between developed countries and developing countries, based on the data for twenty-two industrialized countries and seventy-seven developing countries. Their results suggest that R&D spillovers from developed countries to developing countries are substantial.

Based on the US patent data, Guellec and von Pottelsberghe (2004) find that the degree of technological internationalization is higher for small countries and for countries with low R&D intensity. They identify three main factors which facilitate international knowledge spillovers: geographical proximity, technological proximity, and sharing a common language.

2.2.5.4 Patent Citations and Spillovers

Increasingly, recent literature on geographical knowledge spillovers has used patent citations as a paper trial to track the direction and extent of spillovers. This approach was first proposed by Jaffe et al. (1993). One of the advantages of using patent citation link is that we can construct control samples of patents that are not citations but have the same temporal and technological distribution as the citation ones. Thus we can compare the geographical frequencies between citations and originating patents and between the control samples and originating patents. If frequencies of the former are significantly larger than those of the control samples, they provide the evidence of localized spillovers. Based on this approach, Jaffe et al. (1993) find that the localization of spillovers in the US is quite strong but falls over time.

However, this approach cannot measure whether proximity to an innovation unit affects the productivity of innovation activity. Some results suggest that patent citations are a noisy measure of knowledge flows (Hall et al., 2001). Moreover, some argue that the citation approach does not capture either the non-codified knowledge or embodied knowledge which could be the source of important localized spillovers (Audretsch and Feldman, 1996).

The previous review shows that patent data provide rich information on understanding innovation process, technological change and the importance of knowledge spillovers. In recent years, there has been a rapid growth of patenting activity both in the US and worldwide. This growth in patenting has also renewed economists' interest in evaluating patent statistics and patent system as a whole (Hall, 2005).

In the next section, the empirical studies of patenting activity in China are reviewed.

2.3 Empirical Studies of Patenting Activity in China

Studies using Chinese patent data are still at an early stage. Only a few empirical studies have directly related Chinese patent data to its domestic technological capabilities. From these studies, some empirical evidence on patenting activity in China has emerged in terms of innovative capabilities of domestic firms and universities as well as geographic locations of patenting activity.

2.3.1 Geographic Patterns of Patenting Activity

Disparities in economic development between the eastern region, central region and the western region have been a chronic problem in China and have become increasingly severe in the recent years. Some studies have addressed the regional development problems in China (Demurger et al, 2002; Phillips and Chen, 2004; Wang and Tong, 2005). In contrast, regional patenting activity in China has received little attention. Sun (2000) investigates the spatial patterns of patenting activity in China from 1985 to 1995. He computes two indexes to measure the distribution of patenting in China: the coefficient of variation (CV) and the ratio between observed entropy and maximized entropy. He finds that spatial dispersion of patenting activity occurred across China from the mid 1980s to the early 1990s, while in the mid and late 1990s there was a pattern of increased concentration. In his study, Sun also confirms the central role of R&D in creating domestic innovation. Surprisingly, agglomeration, which has been commonly cited as one important force for innovation in industrialized countries (Feldman and Florida, 1994; Harrison, Kelley, and Gant 1996), shows a negative effect on invention patents and utility model patents. He argues that there are two major factors responsible for this conflicting result. One is that agents in rural areas are more likely to register patents. Secondly, the advantages for facilitating innovation provided by urban environments in China have not been efficiently adopted. His argument is probably valid, considering the time period selected for his study. China's economic reform first took place in rural areas in 1978, while widespread reform in state-owned enterprises only took place in the mid and later 1990s. Thus rural agents had a much stronger sense of technology protection and the market economy than their urban counterparts in the1980s and early1990s.

Sun (2000) also shows that the location of patenting activity in China correlates with the location of more general economic activities, with the eastern coastal regions having the best performance on both measures through the 1980s and 1990s. Other studies also support his findings (Cheung and Lin, 2003; Fai, 2005). In addition, it is found that there is a considerable stability of those regions making patent applications for the period of 1985-1996 and in 2002 (Fai, 2005).

2.3.2 Patenting Activity of Chinese Industry

Chinese patent data also can be explored to identify those emerging high-tech enterprises. Fai (2005) finds that the top ten domestic enterprises for patent applications have a considerable fraction of the applications submitted as invention patents. The compositions of the top firms are also relatively stable from 2000 to 2002. Most of the top firms are in the high technology fields, such as electronics, computing and precision instruments.

Recently, Sun (2002) investigates innovative activities of large and medium-sized manufacturing enterprises in China. Three measurements of innovation indicators are used as dependent variables: total numbers of patent applications, total number of patent certifications and new product sales. Two major explanatory variables are in-house R&D expenditures and expenditures on technology imports. The results reveal that in-house R&D efforts are the primary source of innovation in China. However, he finds that domestic technology markets have not been effectively linked to these large and medium-sized enterprises, despite China's continuing efforts in this direction. He concludes that R&D activity within these enterprises is still largely fragmented with only weak linkages between technology importation and assimilation and between R&D activity and business.

2.3.3 Jefferson's Studies

Jefferson and his colleagues (1996, 1997, 2002, 2003) have conducted a series of studies of China's innovation, productivity growth and R&D activity at the firm level. Jefferson et al. (1997) find that ownership of enterprises is an important and significant determinant of innovative output, in addition to other important determinants, such as R&D spending. They find that collectively-owned enterprises demonstrate a higher propensity for innovation, as measured by new product share. However, innovations from those enterprises tend to be "follower" innovations: they are less profitable than the fewer, but more important, new products introduced by state-owned enterprises. In terms of patent applications, Jefferson, Hu, Guan, and Yu. find (2003) that all large and medium-sized enterprises have displayed a distinct trend of rising patenting activity for the period of 1995-1999. They also find that there is an important difference in patent intensity across industries: petroleum and gas lead by a wide margin, while the medical and pharmaceutical industries are at the bottom.

Jefferson, Hu, Guan & Qian (2003) examine the impacts of domestic R&D, technology transfer, and foreign purchasing of technology on productivity and patents of Chinese firms from 1995 to 1999. Following the method of Griliches (1979), they estimate both a conventional production function and a patent production function. A Negative Binomial model (including a fixed effect negative binomial model) is estimated for the patent production function to deal with various econometric issues, such as the skewed distribution of patent counts and firm-specific characteristics. They find that there are strong returns to both R&D and technology transfer in Chinese firms, but technology transfer has no direct impact on either a firm's productivity or its patent applications. More importantly, they find that in-house R&D expenditures are the sole channel for the creation of patentable knowledge.

2.3.4 Other Related Studies

Cheung and Lin (2003) use Chinese patent data to analyze the spillover effects of FDI on the innovation capabilities in China from 1995 to 2000. They include a variety of independent variables in their regression models: the number of personnel for S&T, expenditures on S&T, GDP per capita and FDI values. In both panel data and pooled data analysis, they find that there are significant and positive effects of FDI on domestic innovation, especially on design patents. In contrast, there are only modest effects on invention patents and utility model patents. With respect to other variables, the results show that S&T personnel and expenditures are the most important determinants of innovation output and the impacts are stronger for the major innovations, such as inventions, than for the minor innovations.

Beyond that, Chinese patent data have been used to study foreign firms' patenting activity (Sun, 2003; Liu and Wu, 2004). The statistics show that foreign patents in China are concentrated in a few advanced and newly industrialized economies. The top five foreign countries are Japan, Korea, German, the US and France (SIPO, 2003). Sun (2003) finds that foreign patents in China are largely granted to organizations, while individuals comprise the majority of Chinese domestic patentees. In his study, Sun also investigates the major determinants of foreign patents in China. Patents of different countries from 1985 to 1989 and from 1990 to 1999 are aggregated, respectively. He includes four explanatory variables: (1) innovative capabilities of origin countries, (2) imports from these foreign countries, (3) FDI by the corresponding countries, and (4) the distance between the origin countries and China. His results show that foreign patents in China are primarily driven by market demand such as imports from the origin countries, while technological capabilities and the distance do not play a significant role in explaining foreign patents in China. In addition, foreign firms have become more aggressive in protecting their technologies in recent years.

2.3.5 Concluding Remarks

In this section, I have discussed some of the empirical studies of China's patenting activity and their implications. Although research studies on this topic are relatively few in number, findings are generally consistent with those of industrialized countries, such as the role of R&D activity. Due to the limitations of the data, very few studies are conducted at the industry and firm levels. The review also indicates that particular cautions should be observed in dealing with Chinese patent data. First, there are major differences in terms of technical innovation for the three types of patents: most studies have shown that effects of R&D on the three types of patents are different, ranging from important and significant for invention patents to minor and insignificant for design patents. Second, Chinese patent data have a relatively short longitudinal dimension, and there were major revisions in Chinese patent law in the 1990s. Thus empirical results might be sensitive to the time periods selected.

This review also reveals that studies of Chinese patent data are still mostly limited to descriptive and simple quantitative analysis. Most studies apply a linear regression model to the patent data, ignoring any potential non-linear relationships between patents and their determinants. Given the rapid development of the economics of patents, both in the theoretical and empirical senses, there are huge gaps between Chinese patent studies and those of industrialized countries.

Chapter 3

PATENTING ACTIVITY AND TECHNOLOGICAL DEVELOPMENT IN CHINA: AN INTERPRETATIVE ANALYSIS

3.1 Introduction

This chapter aims to examine innovation activity (patents) by technological fields and by industrial sectors at the national and regional levels. The principle research questions are: (1) what are the strengths and weaknesses of China's technologies and its industries, and (2) whether China's industry has explored new technological opportunities and developed its competitiveness in certain key technological fields. In addition, through the analysis of spatial distributions of innovation activity at the regional level, this study also examines whether and to what extent there are regional variations in terms of technological development.

The rest of chapter is organized as follows. First is a complete explanation of Chinese patent data used for this study, followed by a descriptive analysis of domestic patenting activity. This is followed by a technological analysis of patents at the national level and a spatial analysis of patents at the regional level.

3.2 Chinese Patent Data

3.2.1 Data Collection for the Dissertation

Chinese patent data are available both on-line and on CD-ROMs. There are at least two official databases distributed by the State Intellectual Property Offices

(SIPO): (1)CNPAT ABSDAT, which is in Chinese, and (2) CNPAT ACCESS, which is in English and has been distributed worldwide. However, the covered periods of these two databases are varied: CNPAT ABSDAT is the most comprehensive one which covers the patent applications up to April 1985 when the first Chinese patent was ever filed. In contrast, CNPAT ACCESS began only in November 1985. Thus CNPAT ABSDAT database is more appropriate for this study.

There are two official on-line databases (CNPAT ABSDAT) maintained by the SIPO that have the most complete patent documents up to the present days.[1] I carefully compared the search results retrieved from these two databases to the patent data published by SIPO: the search results from two official on-line databases are identical and comparable to the published patent data. Thus I decide to use one of the official on-line databases (www.sipo.gov.cn) to retrieve the patent data for this study. All the patent data were retrieved between March 10, 2006 and April 30, 2006.

Follow the convention, patent applications are used as a proxy for innovation output in this study. There are mainly two reasons to use patent applications rather than patent grants in this analysis. First, there are potentially long lags between a patent's application and its grant: it might take three to five years for a patent to be examined and granted (and some patents may not be granted at all). Accordingly, if patent grants are used, the most dynamic and interesting period of 2000-04 will be excluded in the analysis.

Second, it is observed that patents are applied relatively earlier in the lifecycle of a research project. Most studies find that there is a very strong relationship between R&D and patent applications at the cross-sectional level: the

[1] The two websites of on-line databases are www.sipo.gov.cn and www.cnipr.com.

median R-square is around 0.9 (Griliches, 1990). This relationship is close to contemporaneous with some small lags which are difficult to be estimated (Hausman, Hall, and Griliches, 1986). Thus most studies use patent applications as an indicator for innovation outputs.

As explained in Chapter 1, there are three types of Chinese patents: invention patents, utility model patents and design patents. An invention patent is comparable to a utility patent in the US; while a utility model patent is a "petty" patent not recognized in the US; and a design patent is for improvement in aesthetic features rather than technical features. For the purpose of analyzing China's true technological capabilities, only invention patents are collected in this study. Hereafter, the term patent refers to an invention patent application.

Because patent documents are not accessible to the public until an application has been filed for eighteen months, the period of patent filings in this study is restricted to the period of April1 1, 1985 to December 31, 2004. To analyze patents by industrial sectors and technological fields, patents were collected by 3-digit and 4-digit International Patent Classification (IPC) codes for both domestic and foreign patents from 1985 to 2004. A sample of these data is listed in Table A.1 (see Appendix tables). To reveal the spatial distributions of patenting activity by technological areas and industrial sectors, patents with detailed IPC codes from each province are collected for the periods 1995-99 and 2000-04. The aggregated five-year period serves to eliminate the cyclical fluctuations of patent filings and to reduce the statistical problems caused by small number of patents at the more detailed level of the IPC codes.

It should be noted that the number of patents from 2004 might be slightly biased downward because some patent filings are not published yet, due to the restriction of eighteen months. In addition, there can be multiple patentees located in different provinces. In this case, both provinces are recorded since the address of first patentees is not separated from those of other patentees in the patent documents. I carefully compared the results of a multiple-provinces search with those of a single-province search and found that the statistical error caused by double counting is very small, on average about 2%.

Certainly, there are other potential biases related to Chinese patent data, First, China's patent law went through a significant change in 1992 and were further revised in 2000. Consequently, we may expect that those changes might have a considerable impact on both domestic and foreign filings; therefore, the subsequent analysis should be considered within this context.

Secondly, Chinese patents include filings from both domestic and foreign patentees, and the majority of invention patents are actually filed by foreigners. I treat domestic patents as those patents with patentees' addresses from the thirty-one provinces and independent municipal cities of China. This may raise the question of patents applied for by the joint ventures with foreign firms. The positive spillovers of foreign firms in these joint ventures are likely more significant, due to their direct exposure to the new technology. Compared to the other domestic firms, firms with foreign partners are more competitive and may have more intensive innovation activities. However, it is impossible to separate patents filed by those joint ventures from other domestic filings, as patentees from joint ventures are classified as having origins in China. But this should not pose a problem for my analysis: I use total patents filed both by foreign patentees and domestic patentees as a base for the comparison of China's relative technological strengths.

With respect to the impact of foreign firms' R&D and patenting activity, the evolution of technological development in China has been greatly influenced and benefited from its increasing exposure to the world-class technology. Increasingly, China's domestic innovation activities are stimulated and pushed forward by their foreign competitors. In the most recent five years, more and more R&D centers of multinational corporations have moved to China. It is not clear how many patents filed by multinational corporations are actually generated in these offshore R&D centers in China. Surely, intensive and high-quality innovative activities in these R&D centers will generate spillover effects on domestic innovation activity. Unfortunately, it is impossible to separate these spillover effects of foreign inventions from domestic firms' own innovations efforts.

3.2.2 Allocation of Patents to Technological Fields

To analyze technological profiles of patents, patent data with detailed IPC codes need to be allocated into technological fields. I adopted a technology-oriented classification system (OST/INIPI/ISI system), which has been developed jointly by the German Fraunhofer Institute of Systems and Innovation Research (ISI), the French Patent Office (INIPI) and the Observatoire des Science and des Techniques (OST).[2] The OST/INPI/ISI classification system links the IPC codes directly to the thirty different technological fields. These thirty technological fields can be further

[2] Detailed discussion of OST/INPI/ISI classification system can be found in Breschi, Lisson, and Malerba (1998)and Hinze, Reiss, and Schmoch (1997).

aggregated into five macro technological areas. Details of the thirty technological fields are listed in Table A.2.

3.2.3 Allocation of Patents to Industrial Sectors

In order to analyze patents at industrial levels, patents need to be allocated into corresponding industrial sectors. Thanks to the OECD Technology Concordance (OTC),[3] patents with detailed IPC codes can readily be allocated to the corresponding industries of manufacture (IOM) and sectors of use (SOU). The industry classification system used by the OTC is the International System of Industry Classification (ISIC). Although Chinese industrial sectors are classified according to a its national standard, they are very similar to the ISIC sectors at the 2-digit level and can easily be converted to the ISIC sectors. Thus the ISIC sectors are used as a proxy for China's industrial sectors.

Since almost all the patents, more than 99% of the total, are from manufacturing sectors, so my analysis focuses on twenty-two 2-digit manufacturing sectors. A summary of results of applying the concordance to Chinese domestic patents from 1985 to 2004 is listed in Table A.3.

There are potential problems using the OTC table, which is based on the Yale Technology Concordance (YTC) table. I found that classifications at less-aggregated industrial levels tend to have more errors, i.e., classifications at three or four-digit levels are less accurate than those at the two-digit level.[4] Some studies point

[3] The OTC table is available on the OECD website (www.oecd.org).

[4] I find that no patents are allocated as originated from chemical fiber industry (a 3-digit chemical sector) for all the years. However, this kind of problems can be mitigated at the 2-digit industrial level, due to the aggregation into broader industrial sectors.

out that the YTC table also tends to undercount the patents from the IT sectors, such as computer and software industries.

3.3 Trends in China's Patenting Activity

3.3.1 Overview

To get some preliminary understanding of Chinese patenting activity at the macro level, a summary of all patents from 1985 to 2004, both domestic and foreign ones, is listed in Table 3.1 and plotted in Figure 3.1. The overall trend is quite clear: both domestic and foreign patent filings have steadily increased over the past twenty years, and the growth rates of patents in recent years are substantially higher than the earlier years.

Comparing domestic patents to foreign ones, we can identify two different features. First, although the average growth rates of patent filings from home and abroad are almost the same for the past twenty years, about 16%, the fluctuations of domestic filing are much larger than the foreign ones: the coefficient of variation (CV) of the growth rate is 118% for domestic ones, compared to 84% for foreign patents. Further, by breaking down twenty years into four five-year periods, we can see that the growth rates of domestic patents are highly variable for different periods: the average annual growth rate was only about 7.54%for the period 1995-99, while it was about 29.79% for the period 2000-04 (see Table 3.1).

Substantial changes in domestic patent filings over the past twenty-years are unlikely due to random fluctuations only. Various reasons can be attributed to these changes, such as a growing propensity to patent by domestic firms, especially after China's WTO accession. However, it is noticeable that the period of low growth,

Table 3.1 Summary of Patent Filings in China from 1985 to 2004

Year	Patent Applications		Growth Rate(%)	
	Domestic	Foreign	Domestic	Foreign
1985	3471	4755		
1986	2924	4429	-15.76	-10.61
1987	3504	4328	19.84	6.51
1988	4060	4987	15.87	15.51
1989	4094	5151	0.84	2.19
1990	5179	4546	26.50	5.19
1991	6308	4249	21.80	8.56
1992	8374	4963	32.75	26.33
1993	10249	8638	22.39	41.61
1994	9274	14176	-9.51	24.16
1995	8446	18564	-8.93	15.18
1996	9436	22907	11.72	19.74
1997	9983	22514	5.80	0.48
1998	11070	28978	10.89	23.24
1999	13089	30231	18.24	8.17
2000	20689	35321	58.06	29.29
2001	23393	43054	13.07	18.63
2002	32920	53234	40.73	29.66
2003	45389	67500	37.88	31.03
2004	45034	70621	-0.78	2.45
Average over periods				
1985-2004	13844	22657	15.86	15.65
1985-1989	3872	4699	5.20	3.40
1990-1994	7877	7314	18.79	21.17
1995-1999	10405	24639	7.54	13.36
2000-2004	33485	53946	29.79	22.21

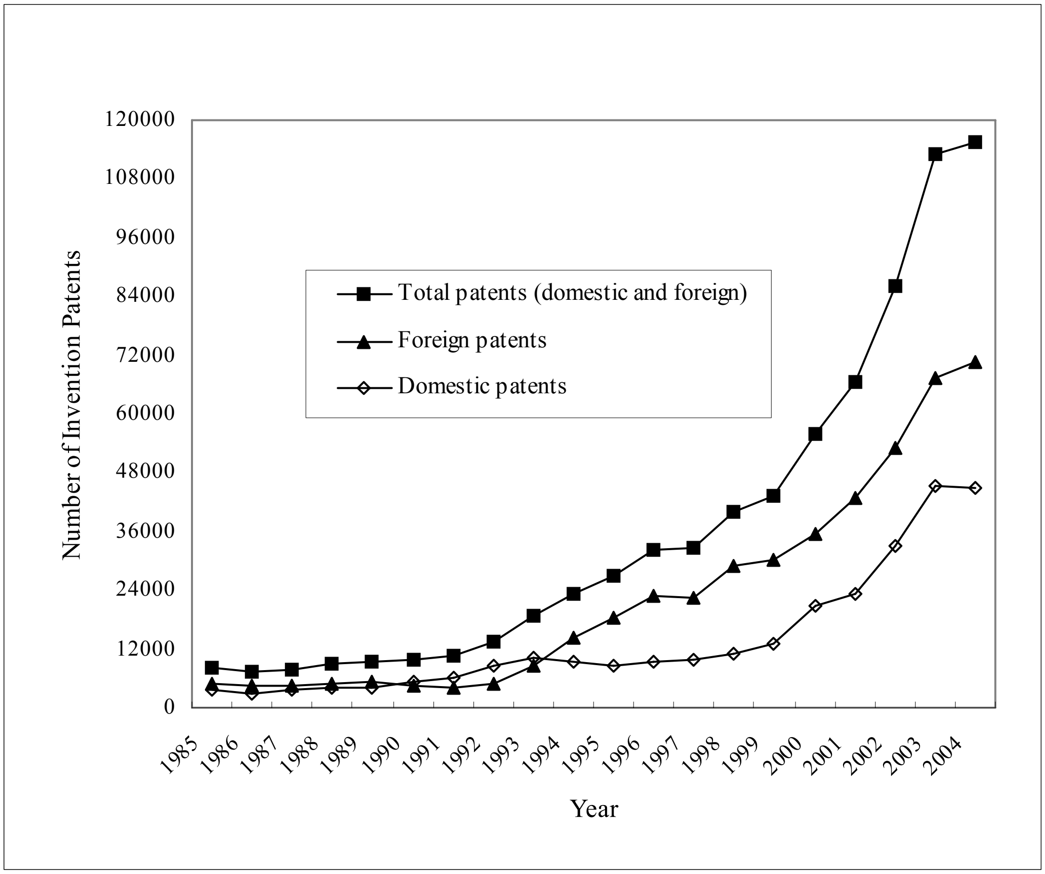

Figure 3.1 Comparisons of Domestic Invention Patents and Foreign Invention Patents from 1985 to 2004

1995-99, is coincidental with economic reform of China's industry, which started nation-wide in 1994 (see discussion in Chapter 1). The impact of China's industrial reforms on its innovation activities will be further analyzed in a later part of this chapter.

The second notable feature of the aggregated data is that the growing paths of domestic patents and foreign patents seem to diverge after 1993 (see Figure 3.1). From 1985 to 1993, patent applications from home and abroad are very close to each other. After 1993, foreign patents started to steadily increase with an annual growth rate about 19%. It seems that foreign firms quickly took advantage of patent protections rendered by the newly revised Chinese patent law (see discussion in Chapter 1). Since then, the majority of invention patents, about 66%, have been filed by foreign firms and the gap between the domestic and foreign filings has been fairly consistent over the years.

Most of the foreign patents are filed by applicants from industrialized countries, such as Japan, the US and Germany. As discussed in Chapter 1, firms in those countries file patents heavily in China and some firms have as many patents filed in China as in the US. Thus I consider that these foreign patents closely reflect the current technological development in the industrialized countries and can be used as a benchmark for comparisons with domestic patents: the gap between foreign and domestic invention patent filings, as displayed in Figure 3.1, simply reflects the distance in technological advancement between China and the more industrialized countries.

3.3.2 Patent Intensity and R&D Spending

Patent intensity, patents per 10,000 persons, describes the total innovation density or the total innovation rate. Patent intensity from 1985 to 2004 is listed in Table 3.2 and plotted in Figure 3.2. The emerging trend is similar to that of Figure 3.1: patent intensity steadily increased from 0.03 in 1985 to 0.09 in 1993, stagnated from 1994 to 1999, and then increased significantly from 0.11 in 1999 to 0.35 in 2004. R&D spending from 1987 to 2004 is also listed in Table 3.2 and plotted in Figure 3.2. The growing trend of R&D spending is almost identical to that of patent intensity (see Figure 3.2). It seems that the overall increase in patent intensity is closely related to the increase in R&D investments. Increases in R&D spending and patent intensity in the last five years are especially impressive: R&D spending grows at 2-digit speed annually and patent intensity has doubled. In particular, R&D spending increased by 22.9% in 2004, compared to the previously year.

However, we should be cautious in interpreting the relationship between R&D spending and patent intensity. It is well known that the propensity to patent tends to increase over the years. As China increasingly merges into the world market, the awareness of the need for patent protection and the availability of it among domestic firms have increased significantly, especially after China's WTO accession in 2001. Facing increasing penetration of foreign firms and their aggressive patenting strategies, domestic firms have responded by increasing R&D investment and innovation activity for their own competitiveness and survival. I will argue that this explosive growth in patenting activity should be interpreted as a result of both growing propensity to patent and increasing R&D spending of domestic firms, though it is difficult to separate one from another.

Table 3.2 Chinese Domestic Patent Intensity and Propensity to Patent from 1985 to 2004

Year	Patent Intensity (Patents / 10,000 persons)	R&D Spending (in 100 million constant 2000 yuans)	Propensity to Patent (Patents / R&D 1 million constant 2000 yuans)
1985	0.03		
1986	0.03		
1987	0.03	74.10	0.47
1988	0.04	89.50	0.45
1989	0.04	112.31	0.36
1990	0.05	121.60	0.43
1991	0.05	149.58	0.42
1992	0.07	174.59	0.48
1993	0.09	190.63	0.54
1994	0.08	189.69	0.49
1995	0.07	184.43	0.46
1996	0.08	197.54	0.48
1997	0.08	241.89	0.41
1998	0.09	263.94	0.42
1999	0.11	329.75	0.40
2000	0.16	433.32	0.48
2001	0.18	500.83	0.47
2002	0.26	623.57	0.53
2003	0.35	736.77	0.62
2004	0.35	905.64	0.50
Average over periods			
1985-2004	0.11	306.65	0.47
1985-1994	0.05	137.74	0.46
1995-2004	0.17	441.77	0.48
1985-1989	0.04	99.37	0.43
1990-1994	0.07	165.23	0.47
1995-1999	0.08	243.51	0.43
2000-2004	0.26	640.02	0.52

Note: R&D spending data are only available from 1987.

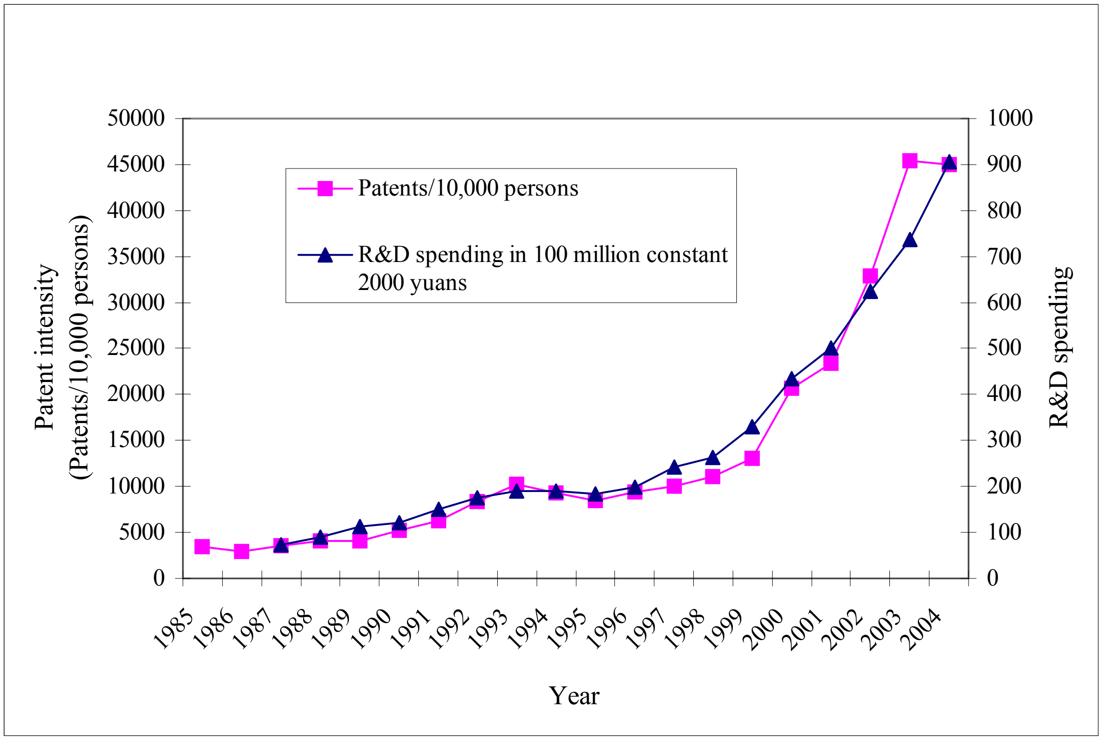

Figure 3.2 Comparisons of Domestic Patent Intensity and R&D Spending from 1985 to 2004.

3.3.3 Propensity to Patent

The propensity to patent is usually measured as the ratio of patents to inventions. However, it is very difficult to measure this property since direct counts of inventions are usually not available. Assuming R&D productivity, the ratio of inventions to R&D spending, has been relatively constant over the past twenty years, the ratio of patents to R&D spending can be used as a proxy for propensity to patent. The computed propensity to patent, as a ratio of patents to R&D spending, from 1987 to 2004 is listed in Table 3.2 and plotted in Figure 3.3. The results show that the propensity to patent increased steadily from 0.36 in 1989 to 0.54 in 1993, but it declined for the next six years: from 0.49 in 1994 to 0.40 in 1999. The years of declining propensity to patent again corresponds to the period of industrial reforms. The same ratio quickly increased from 0.40 in 1999 to 0.62 in 2003. The drop in year 2004 is mainly due to the downward bias in the 2004 patent data, since some of patents have not been published yet. In addition, as discussed earlier, the increase in R&D spending in 2004 was more rapid, thus the ratio of patents to R&D spending is significantly lower, compared to the previous year.

In summary, the descriptive results suggests that the reforms in industrial sectors during the mid to later 1990s might have had a negative impact on patenting activities in terms of corresponding low growth rates, low patent intensities and declining propensities to patent. Both a growing propensity to patent and increasing R&D investments have contributed to the explosive patent growth of 2000-04.

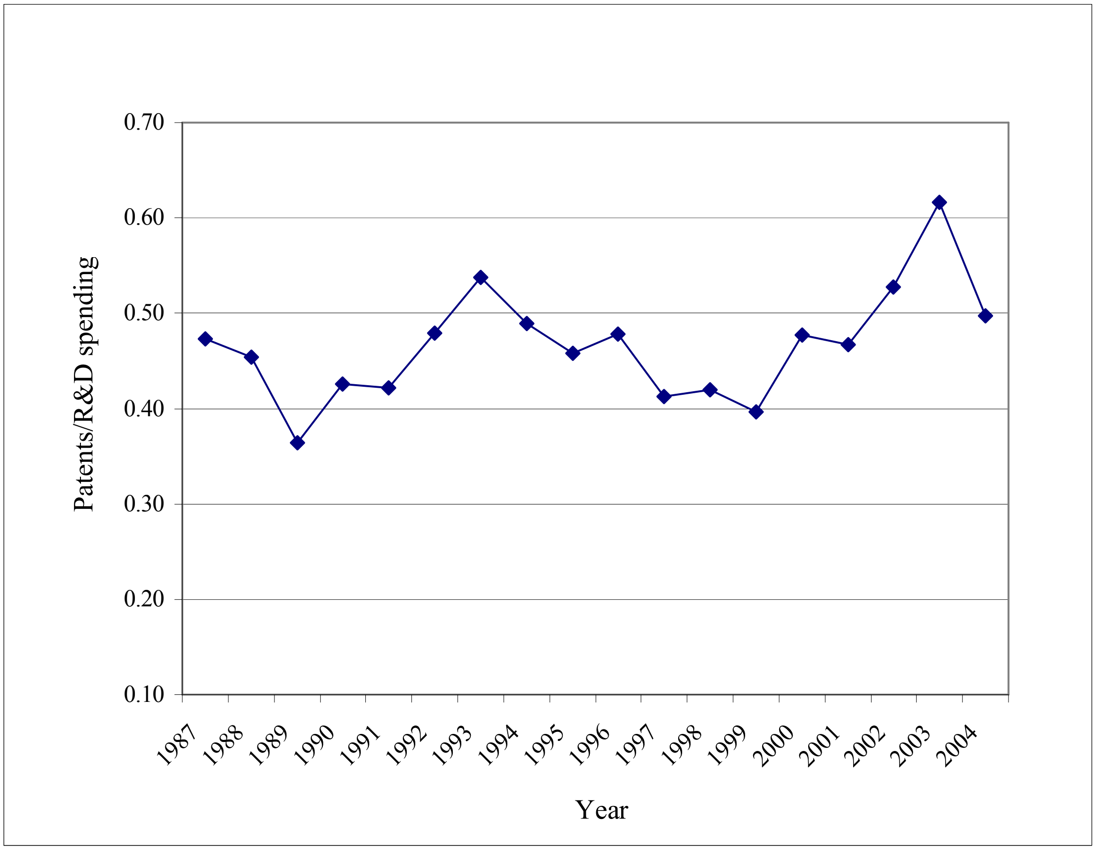

Figure 3.3 Changes in Domestic Propensity to Patent (Measured as Patents/R&D spending) from 1987 to 2004

Note: R&D spending is measured in 1 million constant 2000 yuans.

3.4 The Technological Dimension of Chinese Patenting Activity

3.4.1 Introduction

The analysis of China's technological base has received little attention. This research is the first one to use patent statistics to evaluate China's technological base and its changes over the past twenty years. I have allocated patents with detailed IPC codes to thirty technological fields and twenty-two industrial sectors over the period of 1985-2004, thus a dynamic examination of technologies by industries can be carried out at the national level.

In order to evaluate the changes over different time periods, the twenty years are divided into four five-year periods, which partially reflect different transition periods of social-economic reforms in China. In addition, using five-year average helps to eliminate certain cyclic and short-term fluctuations of patent filings.

3.4.2 Distributions of Domestic Patents by Technological Fields

Patent shares in each technological field with respect to the total patents measure the distributions of patents. Table 3.3 summarizes the distributions of patents in five macro-technological areas and thirty detailed technological fields over the four periods.

3.4.2.1 Distributions of Domestic Patents by Five Macro-technological Areas

Figure 3.4 displays the changes in the distribution of patents among the five macro-technological areas over the past twenty years. First, we can notice that there is an increasing concentration of patenting activities in the Chemistry and Pharmaceuticals during the 1990s: patent shares in the Chemistry and Pharmaceuticals

Table 3.3 Distributions of Domestic Patents by Technological Fields (1985-2004)

	Technological Field	Average Share of Patents (% of total)			
		1985-89	1990-94	1995-99	2000-04
I	**Electrical Engineering**	**11.50%**	**9.30%**	**10.57%**	**19.03%**
1	Electrical machinery and apparatus	6.31%	4.33%	3.62%	4.34%
2	Audio-visual technology	0.49%	0.75%	1.01%	0.93%
3	Telecommunications	1.67%	1.55%	2.29%	8.01%
4	Information technology	2.38%	2.40%	3.39%	4.77%
5	Semiconductors	0.65%	0.27%	0.27%	0.98%
II	**Instruments**	**12.16%**	**11.13%**	**7.95%**	**9.18%**
6	Optics	1.75%	1.11%	0.83%	1.67%
7	Analysis and measurement	7.38%	4.84%	3.87%	5.14%
8	Medical technology	2.84%	5.03%	3.16%	2.27%
9	Nuclear engineering	0.19%	0.15%	0.10%	0.10%
III	**Chemistry and Pharmaceuticals**	**21.03%**	**36.20%**	**42.85%**	**36.09%**
10	Organic chemistry	3.06%	2.53%	3.92%	5.94%
11	Macromolecular chemistry	4.33%	2.43%	4.01%	4.11%
12	Pharmaceuticals	2.64%	11.44%	15.11%	12.05%
13	Biotechnology	1.00%	1.02%	2.02%	3.53%
14	Agriculture and food chemistry	4.36%	9.33%	10.14%	5.38%
15	Chemicals and petrol chemistry	5.64%	9.45%	7.64%	5.09%
IV	**Processing Engineering**	**27.26%**	**21.22%**	**19.83%**	**18.29%**
16	Surface technology and coating	3.05%	2.03%	1.50%	1.49%
17	Materials and metallurgy	10.69%	7.73%	6.49%	5.24%
18	Chemical engineering	4.04%	2.74%	3.07%	2.84%
19	Materials processing	4.19%	3.82%	3.16%	3.24%
20	Handling and printing	1.82%	1.58%	1.55%	1.53%
21	Agriculture and food processing	2.02%	2.10%	2.44%	2.14%
22	Environmental technology	1.45%	1.22%	1.61%	1.81%
V	**Mechanical Engineering**	**28.05%**	**22.15%**	**18.81%**	**17.48%**
23	Machine tools	4.18%	2.71%	1.92%	1.75%
24	Engines, pumps and turbines	3.71%	2.55%	2.02%	1.77%
25	Thermal processes and apparatus	2.38%	2.28%	2.25%	2.93%
26	Mechanical elements	2.95%	1.97%	1.55%	1.44%
27	Transports	3.38%	2.42%	2.33%	2.16%
28	Space technology and weapons	0.90%	0.44%	0.29%	0.22%
29	Consumer goods and equipment	6.51%	5.83%	4.62%	3.72%
30	Civil engineering	4.04%	3.95%	3.82%	3.49%
Coefficient of Variation (%)		68.64	85.87	93.10	74.32

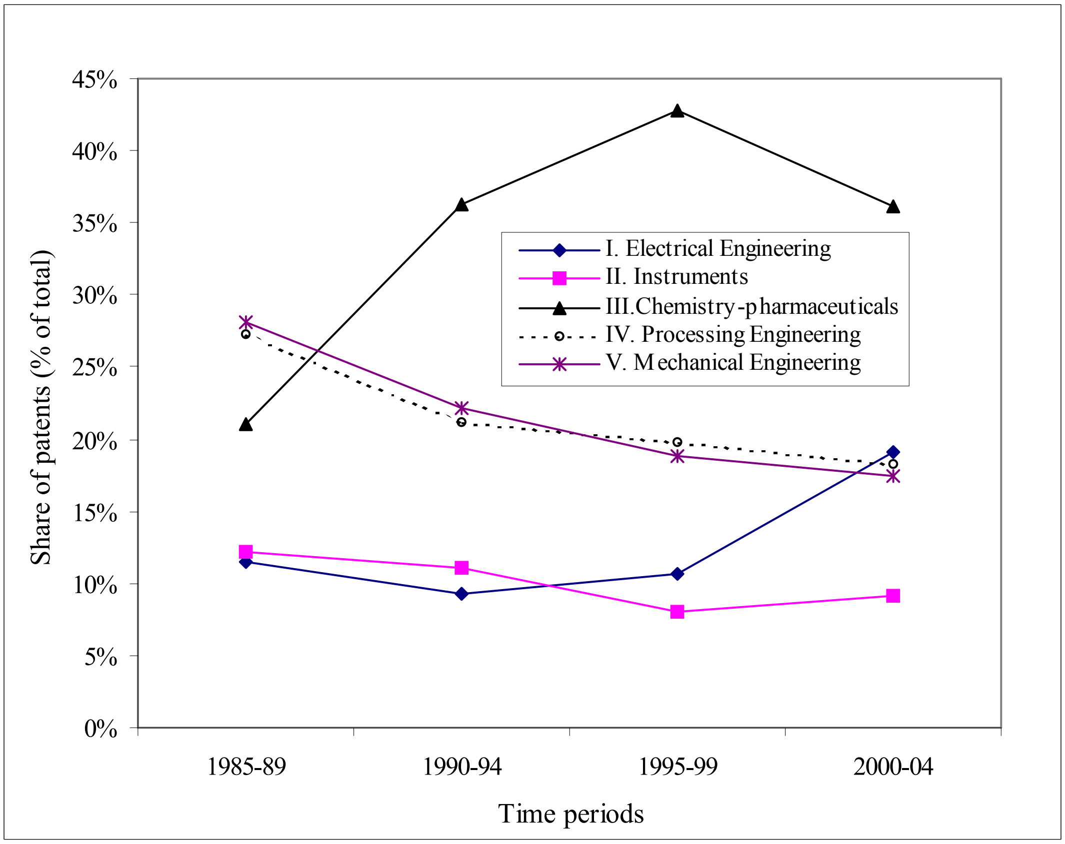

Figure 3.4 Changes in Distributions of Domestic Patents by Five Macro-Technological Areas from 1985 to 2004

increased from 21.04% in 1985-89 to 42.85% in 1995-99 and declined slightly to 36.12% in 2000-04. The coefficients of variation (CV) of patent shares confirm that the heterogeneity of patenting activities across the thirty technological fields increased from 68.64 % in 1985-89 to 93.10% in 1995-99, resulting from an increasing concentration of patent shares in the Chemistry and Pharmaceuticals (see Table 3.3).

Second, we find that the relative importance of patenting activities across technological areas has changed substantially over the past twenty years. The patent shares in the Processing Engineering, Mechanical Engineering and Instruments have steadily declined over the years. During the earlier period of 1985-89, patenting activities were mainly focused on the Processing Engineering (27.29%) and Mechanical Engineering (28.06%). However, total share in these two areas declined sharply to only 36.83% in 2000-04. In contrast, except for the decline during the period 1990-95, the patent share in the Electrical Engineering increased from 11.51 % in 1995-99 to 19.06% in 2000-04.

To examine the reasons behind the increasing concentration of patenting activities in the Chemistry and Pharmaceuticals, it is necessary to take a closer look at the more detailed micro-technological fields.

3.4.2.2 Distributions of Domestic Patents by Thirty Micro-technological Fields

First, I examine to what extent the focus of innovation (patents) has changed over time. During the period of 1985-89, innovations were mainly focused on metallurgy (10.69%), measurement and analysis (7.38%), electrical machinery (6.31%), and consumer goods (6.51%). In contrast, the innovation activities of 2000-04 were reoriented towards pharmaceuticals (12.05%), telecommunications (8.01%), organic chemistry (5.94%), and agriculture and food chemistry (5.38%). Meanwhile, there are consistently fewer patents (less than 1%) in most of the hi-tech fields, such as semiconductors, environmental technology, and nuclear engineering over the years (see Table 3.3).

Next, we find that significant changes in the distributions of patents occurred during the period of 1990-95: patent shares in nineteen technological fields declined sharply (more than 10%), compared to the period of 1985-89, and most of them continually declined in the next five years. Moreover, the shares in almost all the technological fields of Processing Engineering and Mechanical Engineering have declined sharply and consistently from 1990 to 2004. Meanwhile, the shares in pharmaceuticals, agriculture and food chemistry, and petrol chemistry have increased substantially.

Focusing on the most recent five years, it seems that the patenting activities are reoriented again. In the Electrical Engineering and Instrument areas, the patent shares have increased significantly in seven out of nine micro-technological fields. In the Chemistry and Pharmaceuticals areas, the shares in pharmaceuticals, agriculture and food chemistry, and petrol chemistry have all declined, while the shares in organic chemistry and biotechnology have increased more than 50% (see Table 3.3). However, the shares in the Processing Engineering and Mechanical Engineering areas are still declining, though at a smaller rate.

3.4.2.3 Causes of Observed Changes in the Distributions of Domestic Patents: The Role of Industrial Reforms

Although the propensity to patent might vary across the technological fields, patent shares in different technological fields should reflect the corresponding technological opportunities. Thus, the question here is to what extent the distributions of domestic invention patents across the technological fields reflect the corresponding technological opportunities. A survey of European Patent Offices (EPO) patent applications from six EU countries for 1993-1999 reported that the average patent shares in the Chemistry and Pharmaceuticals are about 18%, while the shares in the Processing Engineering and Mechanical Engineering are 25% and 30%, respectively. The shares in the Electrical Engineering and Instrument are 15% and 11%, respectively (PatVal-EU project, 2005). Using these figures as a benchmark, the distributions of Chinese domestic patents in 1985-89 are very similar to those of EU countries, but they are quite different after 1990. In comparisons, the share of Chinese domestic patents in the Chemistry and Pharmaceuticals is exceedingly high, while the share of patents in the Processing Engineering and Mechanical Engineering is too low. This seems to further suggest that significant changes in the distributions of domestic patents during the 1990s are not due to the changes in technological opportunities but may be directly linked to the exogenous changes in China's industry.

Drop in the patent share of a given technological field can be attributed to the declining propensity to patent and/or less innovation activity in that field. Here, I argue that less innovation activity might be the more contributing factor. In general, innovation activity in the Processing and Mechanical Engineering requires more formal R&D activities, which are mainly carried out by the state-owned enterprises (SOE) and their research institutes in China. The significant decline of patent shares in these areas may be linked to the substantial shutdowns in the state-owned research institutes in the heavy industries during the mid and later 1990s, as the state-owned enterprises (SOE) and their research institutes in heavy industries are the main targets of China's industrial reforms (see discussion in Chapter 1). As a result, the research institutes of SOEs were cuts back by more than 30% (Sutherland, 2003), and it is not surprising to find that the patent shares in those fields, such as food chemistry and pharmaceuticals, where research can be carried out at a smaller scale by informal and individual effort, increased significantly.[5]

We can also notice that the patent share in the chemicals and petrol chemistry increased significantly during the same period. The petrol industry is one sector that has been least affected by the industrial reforms: there have been no substantial shutdowns in the state-owned oil companies. Therefore, this further confirms that declining patent shares in the Process and Mechanical Engineering are mainly due to the declining innovation activity caused by the industrial reforms in the heavy industrial sectors.

The evidence here seems to suggest that technological development in China went through a transition period during the mid and later 1990s. Other studies of China's industry seem to support my evidence here. For example, Wu (2004) finds that the contribution of technological progress to total factor productivity (TFP) growth is negative for the 1993-97 periods. In contrast, he finds that the majority of TFP growth from 1998 to 2002 is due to the technological progress.

Although the recent trend suggests that patenting activities are more evenly distributed across the technological fields, it is too soon to conclude that this transition period is over. On the other hand, the reorientation towards the hi-tech

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[5] The exceedingly high level of patenting activity in pharmaceuticals needs a little explanation. The majority of patents in pharmaceuticals are actually filed by individuals for Chinese traditional medicines, which involve mainly informal and individual research efforts and are very active across the country.

fields is more evident in terms of quick and steady increase of patenting activities in most of the hi-tech fields.

3.4.2.4 Fast Growing Technological Fields Identified with Chinese Domestic Patents

The growth rate of patents by technological fields can be used to identify fast growing areas of technologies and are listed in Table 3.4. The average growth rate of patents from 1995-99 to 2000-04 is 286.60 %, while the figure is 36.64% from 1990-941995-99. Again, the extreme low growth rate during the 1990s is another indication of economic shock caused by industrial reforms.

Based on the growth rates of patents from 1995-99 to 2000-04, the fastest growing technological fields are telecommunications and semiconductors with an average growth rate more than 1000%. Other fast growing technological fields are also in hi-tech fields, such as optics, biotechnology and information technology. According to these numbers, China's hi-tech oriented Science and Technology policy seems to have a positive impact to stimulate innovation activities in some hi-tech fields, though not all. Innovation activities in the fields of electrical machinery, audio-visual technology, medical technology and nuclear engineering are much less satisfactory with growth rates all below the average growth rate.

3.4.3 China's Advantages and Disadvantages in Specific Technological Fields

As discussed in Chapter 2, the Revealed Technology Index (see equation 2.9) is frequently used to identify the technological strength and weakness of a firm, a region or a nation. The RTA is the traditional Balassa indicator of revealed comparative advantage applied to the innovation analysis (Balassa, 1965; Patel and Pavitt, 1994; Soete and Wyatt, 1983). It is equivalent to the location quotient when a

Table 3.4 Growth Rates of Domestic Patents by Technological Fields (1985-2004)

	Technological Field	Growth Rate of Patents (% of total)		
		1990-94 vs. 1985-89	1995-99 vs. 1990-94	2000-00 vs. 1995-99
I	**Electrical Engineering**	**99.42**	**61.03**	**579.12**
1	Electrical machinery and apparatus	49.56	10.97	283.14
2	Audio-visual technology	233.71	76.77	196.95
3	Telecommunications	101.66	96.55	1016.21
4	Information technology	120.75	87.22	349.63
5	Semiconductors	-8.55	33.64	1049.65
II	**Instruments**	**110.25**	**-6.07**	**312.81**
6	Optics	38.61	-0.23	537.76
7	Analysis and measurement	42.91	6.09	324.64
8	Medical technology	285.96	-16.57	130.02
9	Nuclear engineering	73.53	-13.56	258.82
III	**Chemistry and Pharmaceuticals**	**284.03**	**85.11**	**235.03**
10	Organic chemistry	81.34	104.00	385.26
11	Macromolecular chemistry	22.89	117.79	228.05
12	Pharmaceuticals	845.70	74.71	155.20
13	Biotechnology	122.78	163.09	458.96
14	Agriculture and food chemistry	366.12	44.00	69.88
15	Chemicals and petrol chemistry	265.36	7.06	112.84
IV	**Processing Engineering**	**78.40**	**32.27**	**208.25**
16	Surface technology and coating	45.19	-2.00	219.01
17	Materials and metallurgy	57.71	11.03	158.79
18	Chemical engineering	48.29	48.20	196.50
19	Materials processing	98.81	9.49	228.79
20	Handling and printing	89.67	29.81	215.31
21	Agriculture and food processing	126.30	54.24	179.67
22	Environmental technology	82.82	75.16	259.71
V	**Mechanical Engineering**	**64.89**	**10.22**	**197.92**
23	Machine tools	41.38	-6.10	192.31
24	Engines, pumps, and turbines	50.07	4.57	180.63
25	Thermal processes and apparatus	109.79	30.33	316.79
26	Mechanical elements	45.22	4.65	198.52
27	Transports	56.07	27.84	196.38
28	Space technology and weapons	8.02	-12.57	149.02
29	Consumer goods and equipment	94.99	5.10	157.26
30	Civil engineering	113.58	27.94	192.42
Average of Growth Rate(%)		123.67	36.64	286.60

region's technological strength is compared to the nation's average. The RTA index is double weighted, so it is not influenced by the propensity to patent in different dimensions. An index larger than one indicates a relative advantage in the specific technological field, compared to the world average, and can be used as a specialization index of technology.

One of the problems with the RTA index is that it is asymmetric: the positive specialization is measured from 1 to infinity, while the measure of negative specialization (or disadvantage) is between 0 and 1. For this reason, some studies prefer to use standardized RTA measure by taking the logarithm of the index or applying the transformation (RTA-1)/(RTA+1) (see discussion in Chapter 2). Since the conclusions are not sensitive to these transformations, no transformations are made in this study.

It should be noticed that the RTA index is a static measurement. This analysis computes the RTA indexes for four consecutive time periods, from 1985 to 2004; therefore the changes in the RTA indexes over the different time periods provide some dynamic information on the evolution of China's technological performance over time.

In order to evaluate China's technological capabilities and to identify the fields in which it has an advantage or disadvantage, the world's average technological level need to be computed and used as a reference. Ideally, patents filed in the international patent offices, such as the European Patent Office (EPO) or the United States Patent and Trademark Office (USPTO), provide a more reliable base for such measurement. However, given the low-tech features of most domestic firms, China's international patent filings are too small to reflect its domestic technological activities in an appropriate way. Considering the high share of foreign patents and the origins of those patent filings, total Chinese patent filings, including both domestic and foreign ones, are used as a proxy to compute the world average in this study.[6]

As a result of using Chinese patent data to assess China's technological abilities, potential biases may arise and should be accounted for. First, there is the home bias problem: Chinese domestic patents have a much larger proportion, compared to any other foreign country. Second, Chinese patent portfolios of foreign firms might be different from their home portfolios, reflecting different local market demands and patenting strategies. To clarify this point, shares of foreign patents in five macro-technological areas are plotted in Figure 3.5. It is noticeable that there is a substantial and consistent increase in the Electrical Engineering over the past twenty years, from about 18% in 1985-89 to about 42% in 2000-04. In contrast, shares in the Chemistry and Pharmaceuticals, Processing and Mechanical Engineering have declined steadily. It seems that foreign firms have increasingly targeted the IT sectors, where China is particularly weak. As a result, computed Revealed Technology Advantage (RTA) indexes for China might be biased downward in IT-related technological fields and upward in the other fields.

On the other hand, the changing focus of foreign patents reflects the relative strengths of domestic technologies: foreign firms are more likely to patent aggressively in the fields where domestic technological levels are low and thus the markets are easy to capture. Therefore, computed RTA indexes should provide a

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[6] The results here should be interpreted within the context of Chinese patent data only. In the future, patent data from the EPO or USPTO should be collected and compared to the results here.

reasonable assessment of China's actual technological capabilities, though the interpretations of the results should be considered with the caveats noted.

3.4.3.1 General Findings

RTA indexes of thirty micro-technological fields are computed based on equation 2.9. A summary of average RTA indexes for the past four periods is listed in Table 3.5 and displayed in Figure 3.6. Through the analysis of these results, the paths of China's technological development over the past twenty years are revealed.

First, the average specialization index of all technological fields increased from 0.99 in 1985-89 to 1.08 in 2000-04. The improvement is modest: there are sixteen technological fields with RTA index above 1 in 1985-89, while the figure is only fifteen in 2000-04. Second, the coefficients of variation (CV) of RTA indexes suggest a similar trend to the one found earlier, that is, the inequality in the levels of innovation activity across technological fields has increased over the years, particularly during the 1990s. The coefficient of variation increased from 36.83% in 1985-89 to 59.43% in 1995-99 and declined to 43.67% in 2000-04. Third, changes in RTA indexes over the past twenty years further indicate that China's industry went through a transition and reorientation period in terms of technological development. RTA indexes in twenty technological fields declined during the period of 1990-95, compared to the pervious period of 1985-89, so the mean RTA index actually declined to 0.95 in 1990-95 and the average growth rate of RTA indexes is negative. In contrast, the growth rate of RTA indexes of 1995-99 to 2000-04 is about 18% (see Table 3.5).

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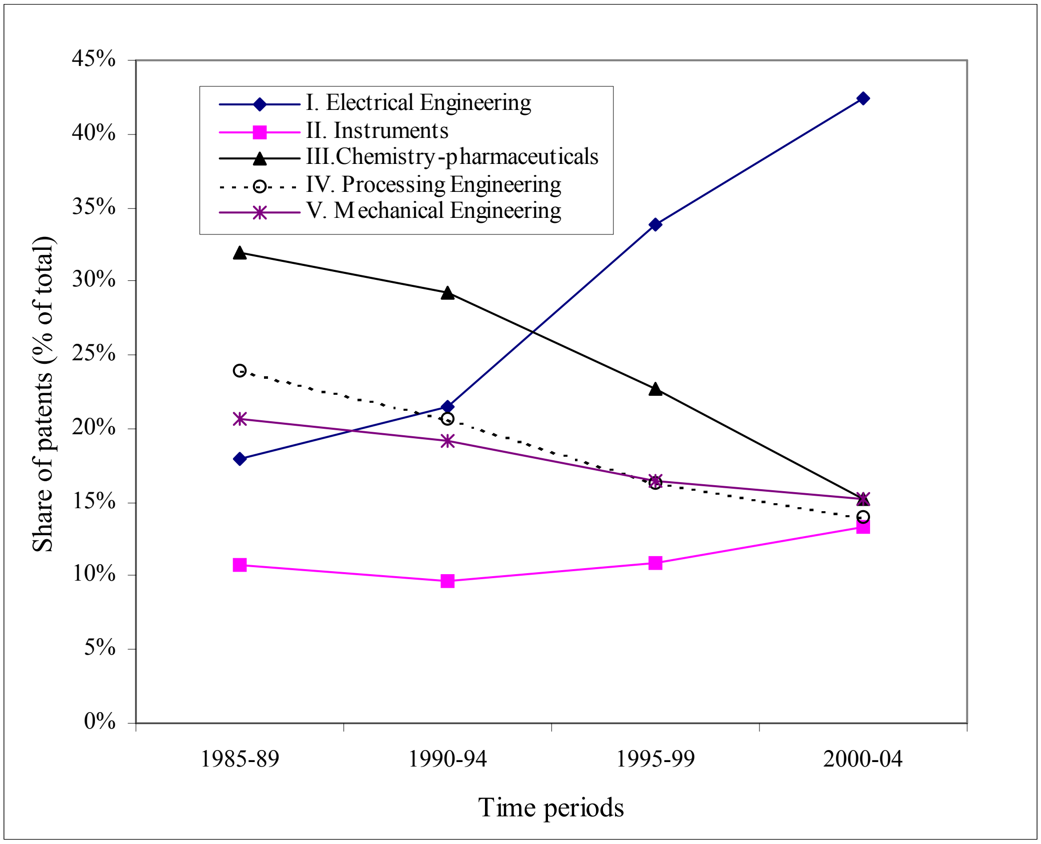

Figure 3.5 Changes in Distributions of Foreign Patents by Five Macro-Technological Areas from 1985 to 2004

Table 3.5 Summary of China's National RTA Indexes by Technological Fields (1985-2004)

	Technological Field	Average RTA index			
		1985-89	1990-94	1995-99	2000-04
I	**Electrical Engineering**	**0.68**	**0.56**	**0.38**	**0.50**
1	Electrical machinery and apparatus	0.90	0.79	0.53	0.60
2	Audio-visual technology	0.28	0.42	0.29	0.27
3	Telecommunications	0.58	0.35	0.23	0.71
4	Information technology	1.00	0.88	0.73	0.66
5	Semiconductors	0.65	0.35	0.13	0.27
II	**Instruments**	**0.87**	**0.89**	**0.69**	**0.77**
6	Optics	0.79	0.53	0.30	0.40
7	Analysis and measurement	1.20	1.14	0.96	1.10
8	Medical technology	1.18	1.32	1.08	0.90
9	Nuclear engineering	0.31	0.55	0.43	0.68
III	**Chemistry and Pharmaceuticals**	**0.94**	**1.05**	**1.52**	**1.53**
10	Organic chemistry	0.38	0.36	0.61	1.19
11	Macromolecular chemistry	0.54	0.48	0.86	1.05
12	Pharmaceuticals	1.18	1.47	2.01	1.73
13	Biotechnology	0.67	0.75	0.99	1.53
14	Agriculture and food chemistry	1.66	1.72	2.89	2.06
15	Chemical and petrol chemistry	1.20	1.55	1.76	1.64
IV	**Processing Engineering**	**1.09**	**1.03**	**1.27**	**1.24**
16	Surface technology and coating	1.22	1.03	0.92	0.95
17	Materials and metallurgy	1.42	1.40	1.76	1.59
18	Chemical engineering	0.88	0.89	1.13	1.22
19	Materials processing	0.87	0.82	0.82	0.97
20	Handling and printing	0.55	0.49	0.47	0.53
21	Agriculture and food processing	1.24	1.41	2.08	1.75
22	Environmental technology	1.44	1.20	1.71	1.67
V	**Mechanical Engineering**	**1.18**	**1.08**	**1.12**	**1.13**
23	Machine tools	1.15	0.99	0.94	0.97
24	Engines, pumps and turbines	1.14	1.04	0.95	0.87
25	Thermal processes and apparatus	1.06	1.05	1.10	1.43
26	Mechanical elements	0.94	0.91	0.85	0.84
27	Transports	1.25	1.04	0.97	0.87
28	Space technology and weapons	1.39	1.27	1.42	1.51
29	Consumer goods and equipment	1.42	1.14	1.14	1.02
30	Civil engineering	1.10	1.16	1.57	1.51
Mean		0.99	0.95	1.05	1.08
Number of fields with RTA index >1		16	15	12	15
Coefficient of Variation (%)		36.83	40.38	59.43	43.67

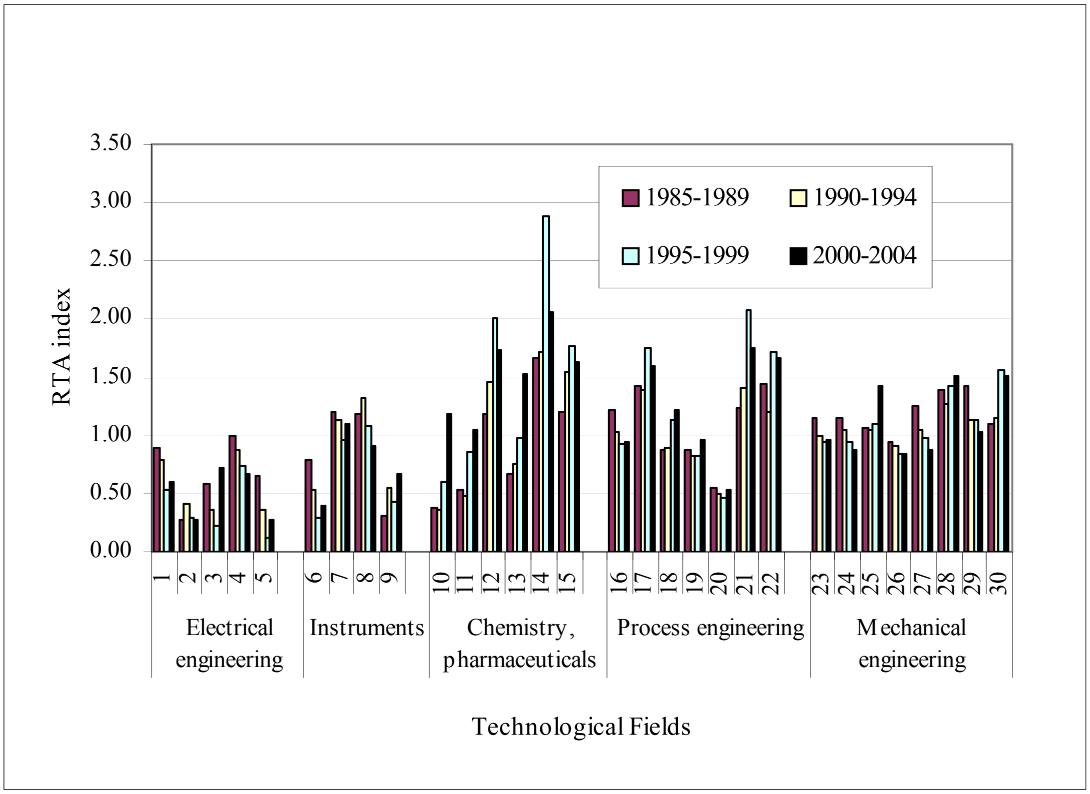

Figure 3.6 Comparisons of China's National RTA Indexes by Technological Fields from 1985 to 2004

Note: Numbers in horizontal axis refer to the thirty micro-technological fields as those listed in Table 3.5.

3.4.3.2 RTA Indexes by Technological Fields

Figure 3.6 indicates clearly that China is particularly weak in the Electrical Engineering and Instruments with almost all the RTA indexes well below 1. Further, it has continually weakened with most of the RTA indexes steadily declining over the years. The only significant improvement in these hi-tech fields is in the telecommunications and semiconductors, however, they still lag far behind the world average and have a long way to catch up.

In contrast, China has built up considerable strength in the Chemistry and Pharmaceuticals over the past twenty years. The average RTA index in this area increased from 0.94 in 1985-89 to 1.53 in 2000-04. The most impressive improvements are in the fields of organic chemistry, macromolecular chemistry and biotechnology.

In the Processing and Mechanical Engineering areas, China already had a certain level of technological strengths in the 1980s. The improvements in these two areas are mixed over the years. In some fields, such as chemical engineering, there are significant progresses in technological advancement. The advantages in the thermal process, civil engineering, and space and weaponry have also improved over the years; however, in other fields, such as surface technology, transports, engines, and machine tools, China has lost its advantages completely over the years.

3.4.3.3 Summary

Combining trends in historical RTA indexes and their relative growth rates, we can identify China's potential growth paths for technologies into the future. Table 3.6 classifies the growth paths of different technological fields into six groups,

Table 3.6 Summary of China's Growth Paths by Technological Fields from 1995 to 2004

RTA index	Increasing	Decreasing	Stable
Technology Advantage	Analysis & measurement Organic chemistry Macromolecular Biotechnology Thermal process	Pharmaceuticals Agriculture Food processing Consumer goods	Petrol Chemistry Metallurgy Environmental Chemical engineering Space & Weaponry Civil engineering
Technology Disadvantage	Electric machinery Telecommunications Semiconductors Optics Nuclear Engineering Material processing Handling and printing	Medical technology Transports	Audio-visual Information technology Surface technology Machine tool Engines Mechanical elements

Note: RTA indexes changed less than 10% from 1995-99 to 2000-04 are classified as stable. RTA indexes changed more than 10% are classified as increasing.

according to the data from 1995 to 2004. It seems that China has strengthened its advantages in such fields as organic chemistry, biotechnology, and thermal process. In addition, it is building up its technology in some hi-tech fields, such as telecommunications, semiconductors, optics, and nuclear engineering. In contrast, medical technology and transports have been continually weakening.

3.4.4 Distributions of Domestic Patents by Industrial Sectors

Although innovation activity of industrial sectors is determined by their underlying technological fields, industrial sectors are not grouped according to their closeness in technological fields. Table 3.7 lists the distributions of domestic patents across twenty-two manufacturing sectors. One distinctive feature is that the distributions of patents are almost same for the four periods. The chemicals and machinery-equipment are the two main sectors that produce patents with each having more than 27% of total patents. In contrast, eleven sectors have less than 1 % share of total patents, and most of these sectors belong to the traditionally low-tech sectors, such as textiles, tobaccos, and wood products. The results here are consistent with other findings in the patent literature, which indicate that patents are concentrated in several science-based sectors only.

We can notice one obvious difference in the distributions of patents between industrial sectors and technological fields: there are no significant changes in the distributions of patents across industrial sectors during the 1990s, though the shares of patterns in the chemical industry are slightly higher during that time. Similarly, the distributions of foreign patents (see Table 3.8) are also relative stable over the years. Two factors may account for the results: the same industrial sectors may have different technological bases and different sectors can have different

Table3.7 Distributions of Domestic Patents by 2-digit Industrial Sectors (1985-2004)

Industry of Manufacturing (ISIC sectors)		Average Share of Patents (% of total)			
.	Industrial Sectors	1985-89	1989-94	1995-99	2000-04
1	Food products and beverages	0.72%	1.36%	1.45%	1.07%
2	Tobacco products	0.16%	0.31%	0.33%	0.24%
3	Textiles	0.72%	0.81%	0.79%	0.73%
4	Wearing apparels	0.10%	0.19%	0.20%	0.15%
5	Leather, luggage, and handbags	0.11%	0.19%	0.20%	0.15%
6	Wood and wood products	0.24%	0.26%	0.26%	0.22%
7	Paper and paper products	0.72%	0.67%	0.63%	0.57%
8	Printing and reproduction of recorded medias	0.23%	0.19%	0.18%	0.20%
9	Coke and refined petroleum products	0.44%	0.38%	0.40%	0.41%
10	Chemicals	28.79%	29.35%	30.63%	28.98%
11	Rubbers and plastics	3.19%	3.09%	2.98%	2.70%
12	Non-metallic mineral products	1.48%	1.30%	1.31%	1.31%
13	Basic metals	0.95%	0.80%	0.79%	0.81%
14	Fabricated metal products	3.58%	3.45%	3.29%	3.07%
15	Machinery and equipment	30.39%	28.62%	27.39%	27.15%
16	Office, accounting and computing machinery	2.81%	2.14%	2.09%	2.80%
17	Electrical machinery	0.32%	0.23%	0.23%	0.39%
18	Radio, television and communication equipments	3.95%	2.90%	2.91%	5.35%
19	Medical, precision and optical instruments	8.41%	10.46%	10.80%	10.18%
20	Motor vehicles	3.39%	2.76%	2.48%	2.48%
21	Other transport equipments	0.91%	0.72%	0.63%	0.61%
22	Furniture; manufacturing n.e.c.	8.41%	9.82%	10.05%	10.43%
	Coefficient of Variation (%)	186.13%	184.69%	185.71%	179.57%

Table 3.8 Distributions of Foreign Patents by 2-digit Industrial Sectors (1985-2004)

Industry of Manufacturing (ISIC sectors)		Average Share of Patents (% of total)			
	Industrial Sectors	1985-89	1989-94	1995-99	2000-04
1	Food products and beverages	0.47%	0.59%	0.55%	0.47%
2	Tobacco products	0.10%	0.13%	0.12%	0.10%
3	Textiles	0.70%	0.73%	0.67%	0.65%
4	Wearing apparels	0.07%	0.09%	0.08%	0.07%
5	Leather, luggage, and handbags	0.08%	0.09%	0.09%	0.07%
6	Wood and wood products	0.20%	0.19%	0.15%	0.13%
7	Paper and paper products	0.72%	0.71%	0.60%	0.55%
8	Printing and reproduction of recorded medias	0.24%	0.23%	0.25%	0.31%
9	Coke and refined petroleum products	0.47%	0.45%	0.34%	0.25%
10	Chemicals	28.81%	28.20%	22.65%	17.40%
11	Rubbers and plastics	3.10%	2.97%	2.58%	2.31%
12	Non-metallic mineral products	1.50%	1.41%	1.15%	0.97%
13	Basic metals	0.96%	0.89%	0.73%	0.60%
14	Fabricated metal products	3.27%	3.03%	2.60%	2.32%
15	Machinery and equipment	30.01%	29.37%	28.71%	28.19%
16	Office, accounting and computing machinery	3.17%	3.10%	4.04%	5.40%
17	Electrical machinery	0.41%	0.44%	0.64%	0.79%
18	Radio, television and communication equipments	5.33%	6.06%	9.32%	11.40%
19	Medical, precision and optical instruments	7.73%	8.16%	9.64%	11.61%
20	Motor vehicles	3.30%	3.03%	2.83%	2.72%
21	Other transport equipments	0.93%	0.85%	0.75%	0.71%
22	Furniture; manufacturing n.e.c.	8.44%	9.29%	11.49%	12.99%
	Coefficient of Variation (%)	184.84%	181.86%	168.81%	161.16%

propensities to patent. In addition, the aggregation level may be too high, so the reorientations of patent shares in detailed technological fields are not revealed at the 2-digit industry-level analysis.

3.4.5 China's Advantages and Disadvantages in Specific Industrial Sectors

Based on the analysis of technological fields, we should expect that China's industries should have an advantage in traditional sectors, such as textiles and the food industry, and lag far behind in IT-sectors, such as radio and communication equipment. The specialization indexes (RTA indexes) of industries sectors are listed in Table 3.9 and plotted in Figure 3.7. Some specific features of China's industrial sectors over the past twenty years can be identified.

First, the mean RTA index of all manufacturing sectors increased from 1.04 in 1985-89 to 1.10 in 2000-04. Again, as expected, the overall improvement in technological advancements is quite modest. At the same time, the inequality of specialization across the sectors has increased substantially, particular during the later 1990s: the coefficients of variation increased from 10.64% in 1985-89 to 34.81% in 1995-99 and dropped to 25.24% in 2000-04.

Second, China has a very strong advantage in traditional sectors with most RTA indexes above 1.5. During the 1990s, traditional sectors seemed to further strengthen their advantages but they started to lose their advantages in the most recent period of 2000-04 with declining RTA indexes. Although those sectors are much less important in terms of technological development, they play a very important role in

Table 3.9 Summary of China's National RTA Indexes by 2-digit Industrial Sectors (1985-2004)

Industry of Manufacturing (ISIC sectors)		Average RTA index			
	Industrial Sectors	1985-89	1989-94	1995-99	2000-04
1	Food products and beverages	1.25	1.39	1.82	1.51
2	Tobacco products	1.27	1.40	1.84	1.52
3	Textiles	1.02	1.06	1.16	1.10
4	Wearing apparels	1.22	1.35	1.74	1.46
5	Leather, luggage, and handbags	1.19	1.33	1.69	1.44
6	Wood and wood products	1.09	1.16	1.46	1.35
7	Paper and paper products	1.01	0.99	1.06	1.04
8	Printing and reproduction of recorded medias	0.97	0.92	0.81	0.78
9	Coke and refined petroleum products	0.97	0.94	1.15	1.33
10	Chemicals	1.01	1.03	1.27	1.33
11	Rubbers and plastics	1.02	1.03	1.14	1.12
12	Non-metallic mineral products	1.00	0.97	1.13	1.21
13	Basic metals	1.00	0.96	1.09	1.21
14	Fabricated metal products	1.06	1.07	1.22	1.19
15	Machinery and equipment	1.01	1.00	1.00	1.00
16	Office, accounting and computing machinery	0.94	0.84	0.63	0.67
17	Electrical machinery	0.87	0.71	0.46	0.65
18	Radio, television and communication equipment	0.84	0.67	0.41	0.62
19	Medical, precision and optical instruments	1.05	1.13	1.12	0.95
20	Motor vehicles	1.02	0.97	0.94	0.97
21	Other transport equipments	1.00	0.93	0.92	0.94
22	Furniture; manufacturing n.e.c.	1.00	1.04	0.94	0.90
Mean		1.04	1.04	1.14	1.10
Number of sectors with RTA index >1		13	11	14	13
Coefficient of Variation (%)		10.64	18.83	34.81	25.24

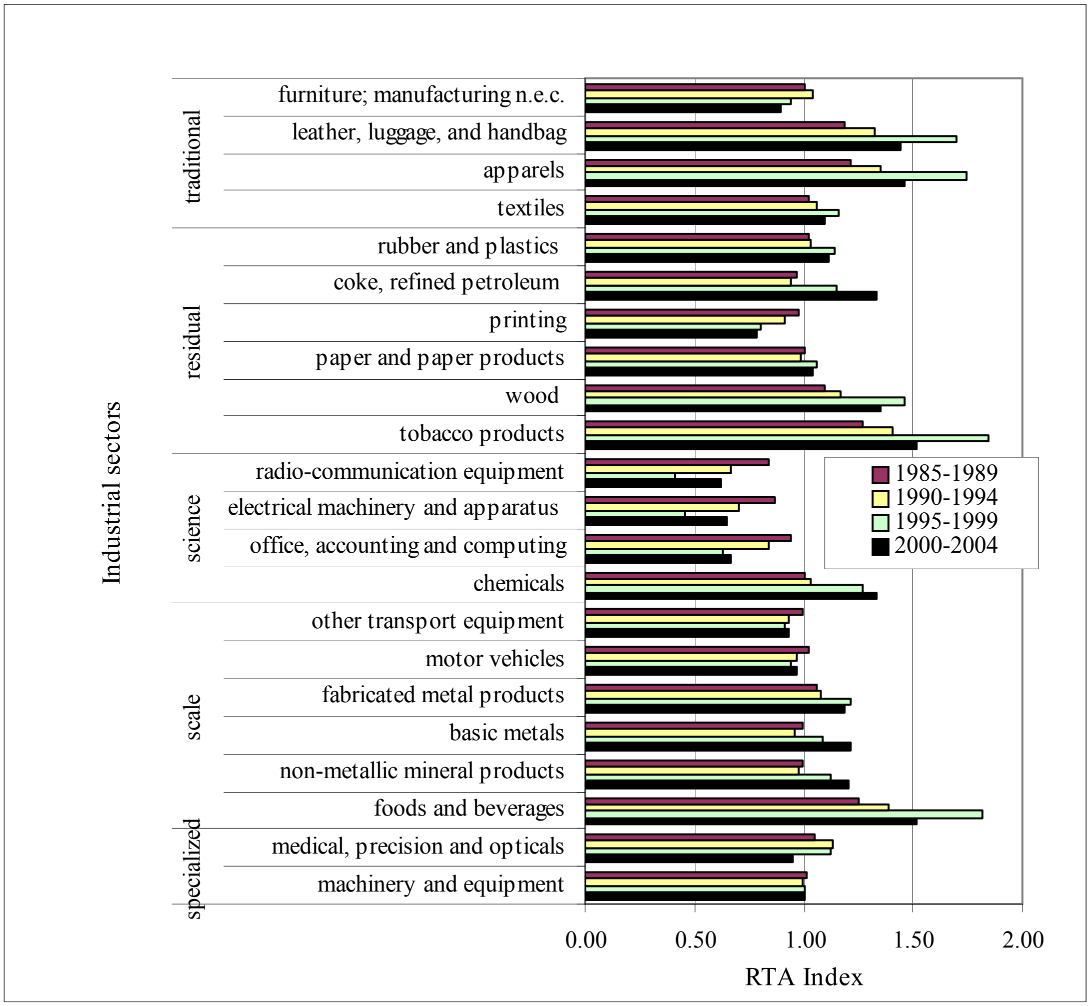

Figure 3.7 Comparisons of China's National RTA Indexes by 2-digit Industrial Sectors from 1985 to 2004

Note: Labels (i.e., "traditional", "residual", "science", "scale"; and "specialized") in vertical axis refer to Pavitt sectors.

China's economy: the share of value added output of these sectors was about 30% of total manufacturing sectors in the 1990s and 26% in 2003, respectively.[7]

Third, consistent with the findings discussed earlier, we find that the chemical industry has built up and strengthened its specialization level with a steadily increasing RTA index in the past twenty years. It should be noted that the chemical industry has the highest share of patents (more than 27%) for the past twenty years. In terms of its contribution to China's economy, the average share of value added output of chemical industry for the past twenty years is 18%. Thus, the chemical industry can be considered as the leading industrial sector in both technological development and economic performance.

Finally, it is not surprised to find that the weakest industrial sectors are all concentrated in the IT sectors, specifically, computer, electrical machinery, and communications. Further, the RTA indexes of these sectors seem to improve very little in the latest years. The findings here are consistent with the facts that most of enterprises in the IT sectors have very low innovation capabilities and are mainly engaged in the processing production (Chen and Shih, 2005). Although Chinese IT sectors have very low innovation abilities, their roles in China's economy have become increasingly important: the share of value added output of these sectors increased from 11% in 1995 to 17% in 2003.

It is worth pointing out that the most disappointing industrial sector is the auto industry with a declining RTA index for the past twenty years. The finding here is consistent with other studies of China's auto industry and further confirms the

[7] The figures are computed based on the data collected from various issues of *China Statistical Yearbook.*

importance of in-house innovation activity for competitiveness and survival. Some studies point out that the failure of China's auto industry can be attributed to a combination of poor implementation of policy, next to nothing in-house technological development and deep fragmentation within the industry (Sutherland, 2003).

We can notice two different trends for the periods 1990-95 and 2000-04 (see Figure 3.7). During the period of 1990-95, RTA indexes of most traditional sectors increased substantially, while other sectors' RTA indexes either dropped or unchanged. In contrast, during the period of 2000-04, the trend is reversed: declining RTA indexes in traditional sectors and increasing RTA indexes in more R&D-intensive sectors. These results seem to further indicate that China's industry went through a transition and reorientation period in terms of technological development during the 1990s, due to the changes in both industrial structures and industrial policies.

3.4.6 Concluding Remarks

Through the analysis of Chinese domestic patent at the national level, some regularity with respect to China's innovation activity in the past twenty years can be summarized. First, overall patenting activity seems to have a S-shape over the past twenty years. Innovation activities are particularly low in terms of growth rates and patent intensities for the years 1993-99, and this may be directly linked to the shock caused by the industrial reforms.

Second, patenting activities seem to be increasingly orientated toward the IT sectors in the most recent years, which may reflect the impacts of corresponding hi-tech oriented Science and Technology (S&T) policy.

Finally, the evidence here suggests that China's overall improvement in the technological strength over the past twenty years is modest, however, growths in domestic patents and RTA indexes in the most recent five years are very remarkable and promising. The recent trend seems to suggest that innovation activities in China have become increasingly active and focused on the areas with high technological opportunities.

3.5 Spatial Analysis of Chinese Domestic Patents

3.5.1 Introduction

In this part, spatial distributions of innovation activity among Chinese provinces are further examined. The main interest is to identify to what extent innovation activities are concentrated or diffused over the time and to determine whether the spatial patterns of innovation vary across the technological fields and industrial sectors. This spatial analysis focuses on the most recent 10 years, i.e., from 1995 to 2004.

Geographically, China can be divided into three macro regions: the eastern region, the central region and the western region. Each macro region includes similar number of provinces, but the differences among three macro regions are very large, both economically and geographically. Provinces in the eastern region are mainly along the eastern coasts with relatively smaller geographic areas but higher populations and higher incomes. In contrast, provinces in the western region are large in geographic size but low in populations and incomes. Provinces in the central region are in the middle both geographically and economically. Naturally, regional variations in patenting activities among three macro-regions are also the interest of this analysis.

There are now a total of thirty-one provinces and independent municipal cities in China. However, Chongqing only becomes an independent municipal city in 1997, so it is included in Sichuan province in the analysis. It also should be noted that Tibet (Xizhang) has very little manufacturing and it is excluded from the analysis (except in the maps).

3.5.2 Spatial Distributions of Domestic Patent Intensity

A summary of regional patents from 1995 to 2004 is displayed in Table 3.10. The spatial distributions of average patent intensity among thirty provinces for the periods 1995-99 and 2000-04 are displayed in Figure 3.8 and 3.9, respectively.

Comparing the two periods, several trends can be identified. First, as expected, the patent intensity has increased for all the provinces over the two periods, though the growth rates of patent intensity are highly uneven across the different macro-regions. The eastern region has substantially much higher patent intensity than the rest of the country.

Second, inequality of innovation activities among three macro-regions has increased significantly over the past ten years, according to the coefficients of variation of patent intensities and patent shares. The growth rate of patent intensity in the eastern region is about 319.69% from 1995-99 to 2000-04, which is almost three times of that of the central and western regions. Therefore innovation activities are increasingly concentrated in the eastern region with a 72.76% share of total patents in 2000-04 (see Table 3.10).

Assuming that R&D productivities are similar across the regions, the average propensity to patent (measured as the ratio of patens to R&D spending) is actually lower in the eastern regions in 2000-04, compared to the other macro regions

Table 3.10 Summary of China's Provincial Patents from 1995 to 2004

Provinces	Share of Patents (% of total)		Patent Intensity (patents/10,000 persons)		Propensity to Patent (patents/R&D spending)	Growth Rates (%)
	1995-99	2000-04	1995-99	2000-04	2000-04	
Eastern region	**59.58**	**72.76**	**0.26**	**1.03**	**26.53**	**319.69**
Beijing	15.21	16.29	1.25	3.84	24.47	251.84
Fujian	1.75	1.48	0.06	0.14	16.09	158.64
Guangdong	7.42	12.85	0.09	0.49	25.33	529.96
Hebei	4.06	2.16	0.07	0.12	23.35	63.93
Jiangsu	5.97	6.10	0.08	0.27	15.38	247.17
Liaoning	6.97	4.74	0.19	0.38	22.60	106.92
Shanghai	5.58	12.89	0.41	2.66	38.94	660.17
Shandong	6.21	4.66	0.08	0.19	19.05	141.21
Tianjin	2.29	5.99	0.24	1.8	51.85	699.91
Zhejiang	4.12	5.61	0.09	0.39	28.27	337.17
Central region	**25.88**	**17.79**	**0.07**	**0.15**	**32.29**	**114.76**
Anhui	1.75	1.09	0.03	0.06	13.43	98.71
Hainan	0.39	0.25	0.06	0.12	77.78	102.55
Henan	3.92	2.08	0.05	0.08	23.76	72.62
Heilongjiang	3.69	2.16	0.11	0.21	31.80	89.48
Hubei	3.78	3.33	0.07	0.18	24.00	184.30
Hunan	3.98	2.96	0.07	0.15	37.37	120.01
Inner Mongolia	1.14	0.54	0.06	0.08	37.45	34.34
Jiangxi	1.65	1.18	0.05	0.11	35.18	148.14
Jilin	2.58	2.11	0.11	0.28	31.20	167.91
Shaanxi	2.99	2.09	0.08	0.19	10.97	129.51
Western regios	**14.50**	**9.42**	**0.05**	**0.1**	**33.65**	**102.17**
Gansu	1.00	0.61	0.05	0.09	20.53	92.51
Guangxi	1.50	0.83	0.03	0.06	30.89	85.87
Guizhou	1.16	0.66	0.04	0.07	43.75	107.99
Ningxia	0.34	0.24	0.07	0.17	46.85	153.09
Qinghai	0.22	0.11	0.06	0.08	21.83	55.32
Shanxi	2.06	1.28	0.07	0.14	30.75	102.57
Sichuan	5.80	4.11	0.06	0.12	17.75	122.10
Tibet	0.04	0.03	0.02	0.05	39.10	125.93
Xinjiang	0.94	0.47	0.06	0.09	43.84	60.78
Yunnan	1.49	1.11	0.05	0.1	46.64	139.27
mean	3.45	3.45	0.13	0.44	30.73	181.52
CV(%)	89.30	118.81	176.73	196.22	46.06	93.27

Notes: R&D spending is measured in 100 million constant 2000 yuans. Growth rate is the average growth of patent intensity from 1995-99 to 2000-04. CV refers to coefficient of variation.

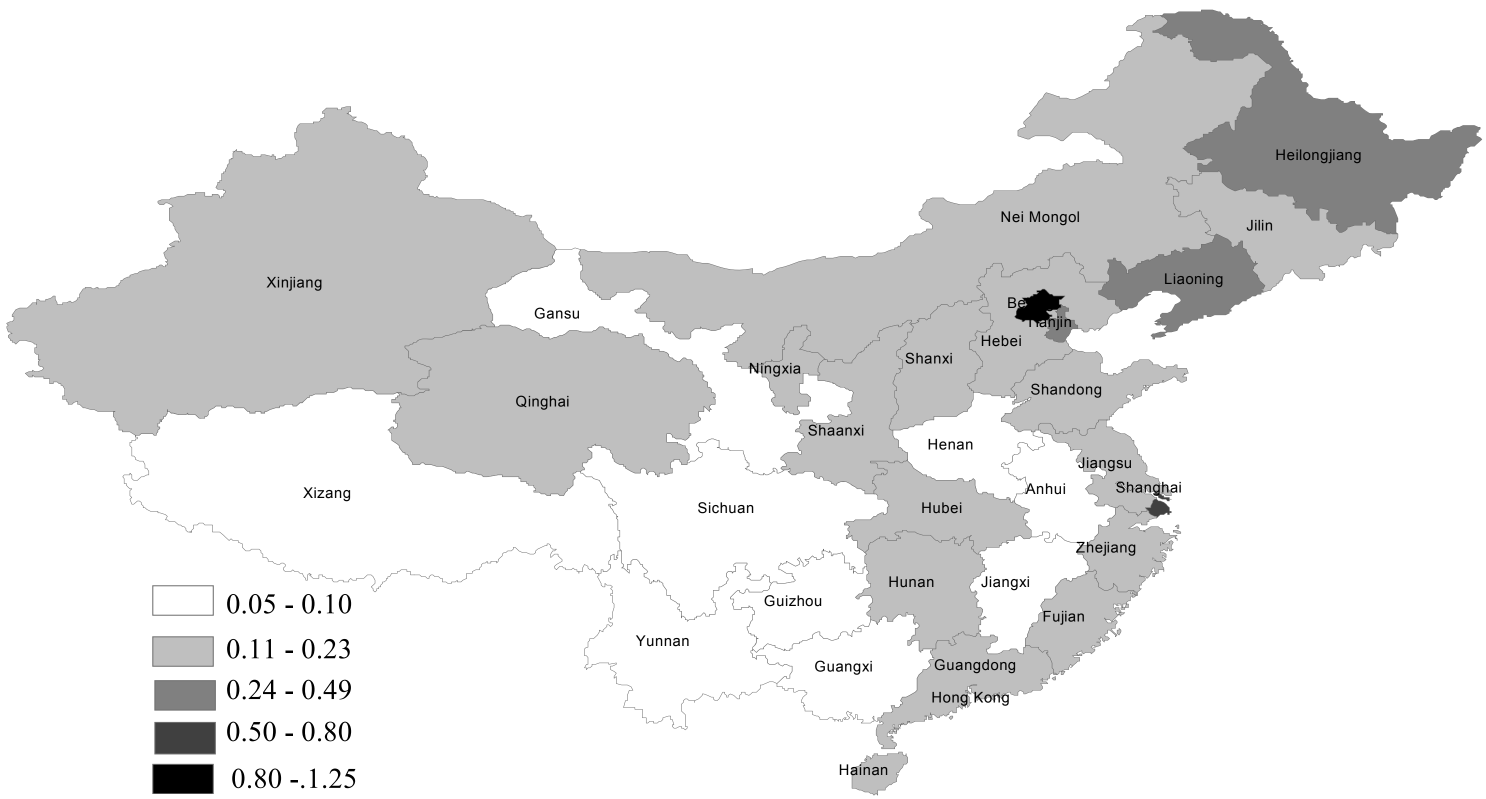

Figure 3.8 Spatial Distributions of Domestic Patent Intensity in 1995-99
Note: Patent intensity is computed as patent applications per 10,000 persons.

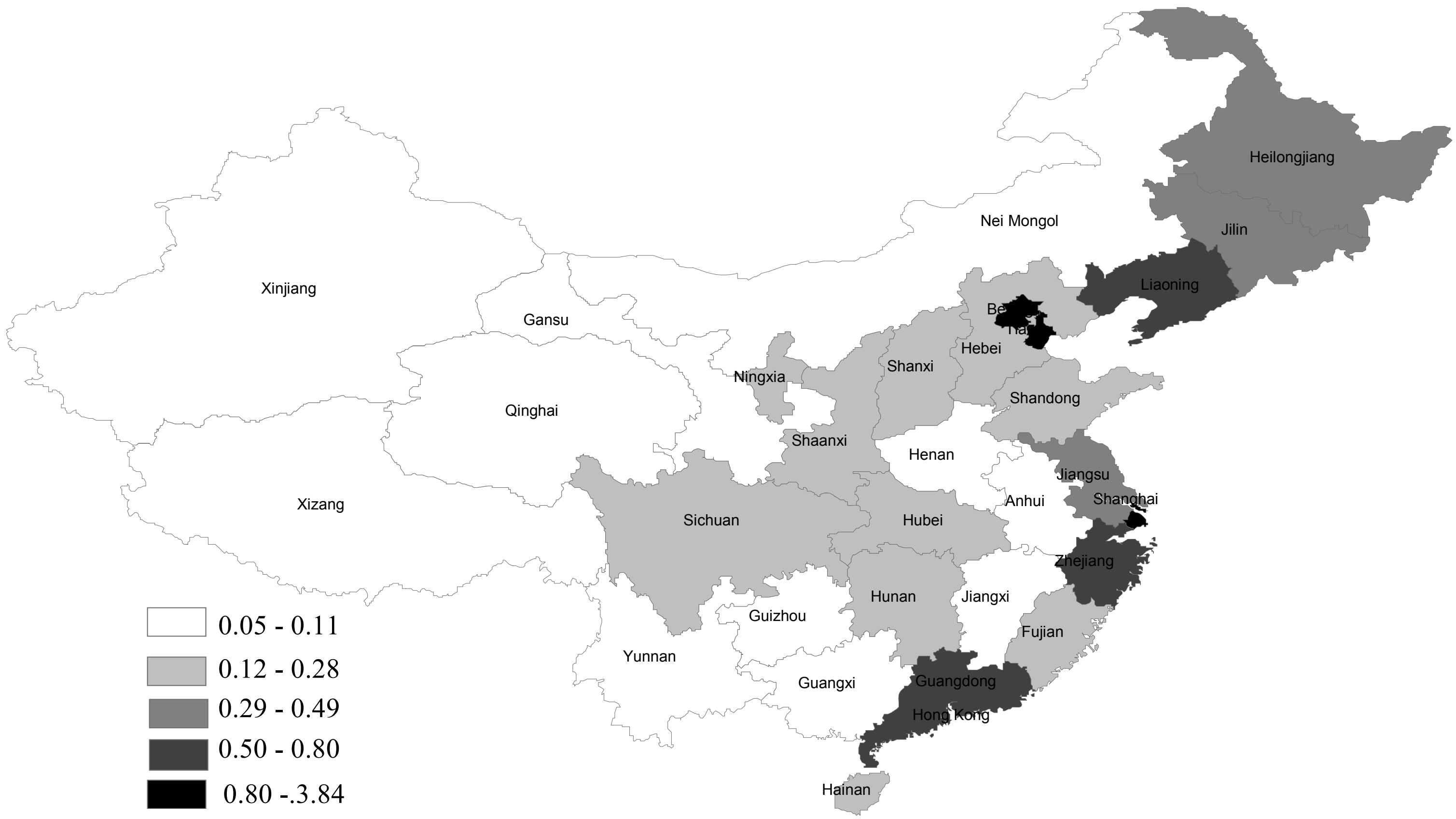

Figure 3.9 Spatial Distributions of Domestic Patent Intensity in 2000-04
Note: Patent Intensity is computed as patent applications per 10,000 persons.

(see Table 3.10). Thus the increasing disparity in patenting activities between the eastern region and the rest of country are mainly attributed to the growing innovation activities in the eastern region, as a result of significant increase in R&D investment and the compelling pressure from the foreign competitors.

Third, during the period of 1995-99, Beijing appeared to be the only innovation center in China in terms of patent intensity and patent share. In contrast, we can identify at least two other important innovation centers for the period 2000-04, Shanghai and Guangdong. The results here are not surprising since these three regions account for about 48% of China's R&D expenditures and 30% of nation's GDP in 2000 (Chen and Shih, 2005). Comparing the spatial distribution of patent intensities in 1995-99 to that of 2000-04 (see Figure 3.8 and Figure 3.9), it seems that patenting activities are spreading out more quickly in the eastern region, while the other regions remain to have fewer patenting activities.

The finding here, i.e., increasing concentration of patenting activities in the eastern region, seems to support the claim that innovations tend to cluster within the specific locations which emphasize the importance of localized knowledge (Feldman, 1999). However, the degrees of concentration and spatial patterns of innovation activities may differ across different technological fields and industrial sectors, and they are further analyzed in the next two sections.

3.5.3 Spatial Distributions of Domestic Patents by Technological Fields

In this section, the diversifications of technological fields among the provinces and within the provinces are examined. For this purpose, the average specialization indexes (RTA index) of five macro-technological areas and thirty micro-technological fields in 1995-99 and 2000-04 are computed for each province.

An index larger than 1 indicates that this region has an advantage in a given technological field, compared to the other regions. The coefficients of variation (CV) of regional RTA indexes are a measure of diversifications of that technology across the regions: a higher CV indicates that patenting activity in that technological field is more spatially concentrated.

3.5.3.1 Diversifications of Technological Fields among the Regions

In this sub-section, the spatial concentration of technological fields among the regions is examined. The average regional RTA indexes of technological fields and their corresponding coefficients of variations are plotted in Figure 3.10 and Figure 3.11. First, it is noticeable that the coefficients of variations in the fields of Electrical Engineering and Instruments are in general higher than those of other technological fields (see Figure 3.11). Over the years, the spatial concentration in telecommunications and in the fields of Mechanical Engineering has increased substantially. In contrast, biotechnology has increased its diversification across the regions significantly over the years.

Second, we can find two distinctive spatial patterns between the Electrical Engineering and Instruments and other technological areas. In the fields of Electrical Engineering and Instruments, the regional RTA indexes are not only well below 1 but also have declined over the years. In contrast, the average regional RTA indexes in the Chemistry and Pharmaceuticals, Processing Engineering, and Mechanical Engineering are not only higher but also have increased over the years.

Different spatial patterns across technological fields are more clearly revealed in Figure 3.12 and Figure 3.13, which are mapped based on each region's highest RTA index among five-macro technological areas. We notice immediately

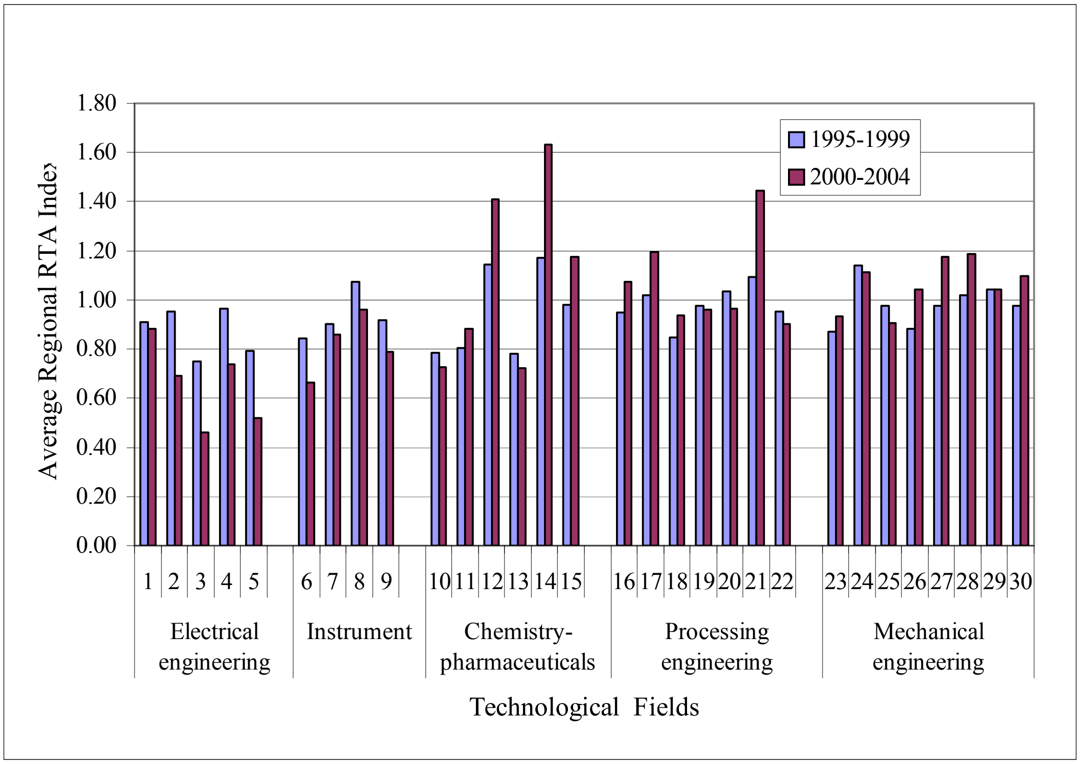

Figure 3.10 Comparisons of China's Regional RTA Indexes by Technological Fields for the Periods 1995-99 and 2000-04

Note: Numbers in horizontal axis refer to the thirty micro-technological fields as those listed in Table 3.5.

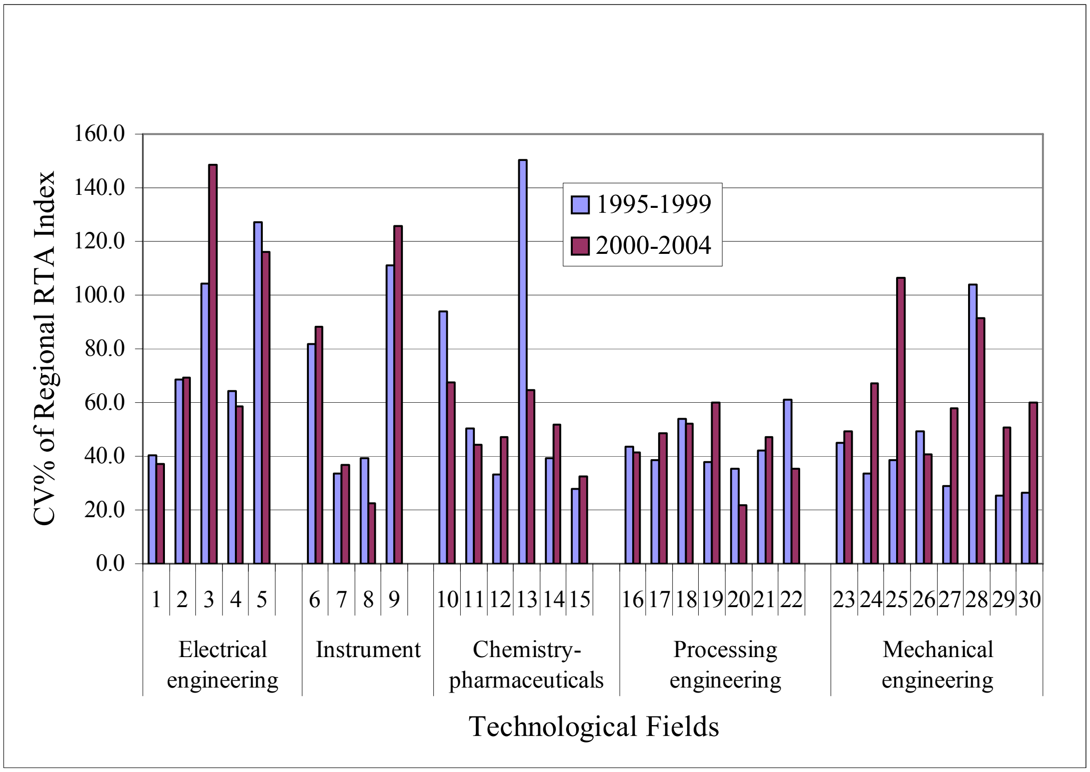

Figure 3.11 Comparisons of Coefficients of Variation (CV) of China's Regional RTA indexes by Technological Fields for the Periods 1995-99 and 2000-04.

Note: Numbers in horizontal axis are thirty micro-technological fields as those listed in Table 3.5.

Figure 3.12 Spatial Distributions of Specialization by Five Macro-technological Areas in 1995-99
Notes The specialization of a region refers to its highest RTA index among five macro-technological areas, i.e., Electrical Engineering (I), Instruments(II), Chemistry and Pharmaceuticals (III), Processing Engineering (IV), and Mechanical Engineering (V).

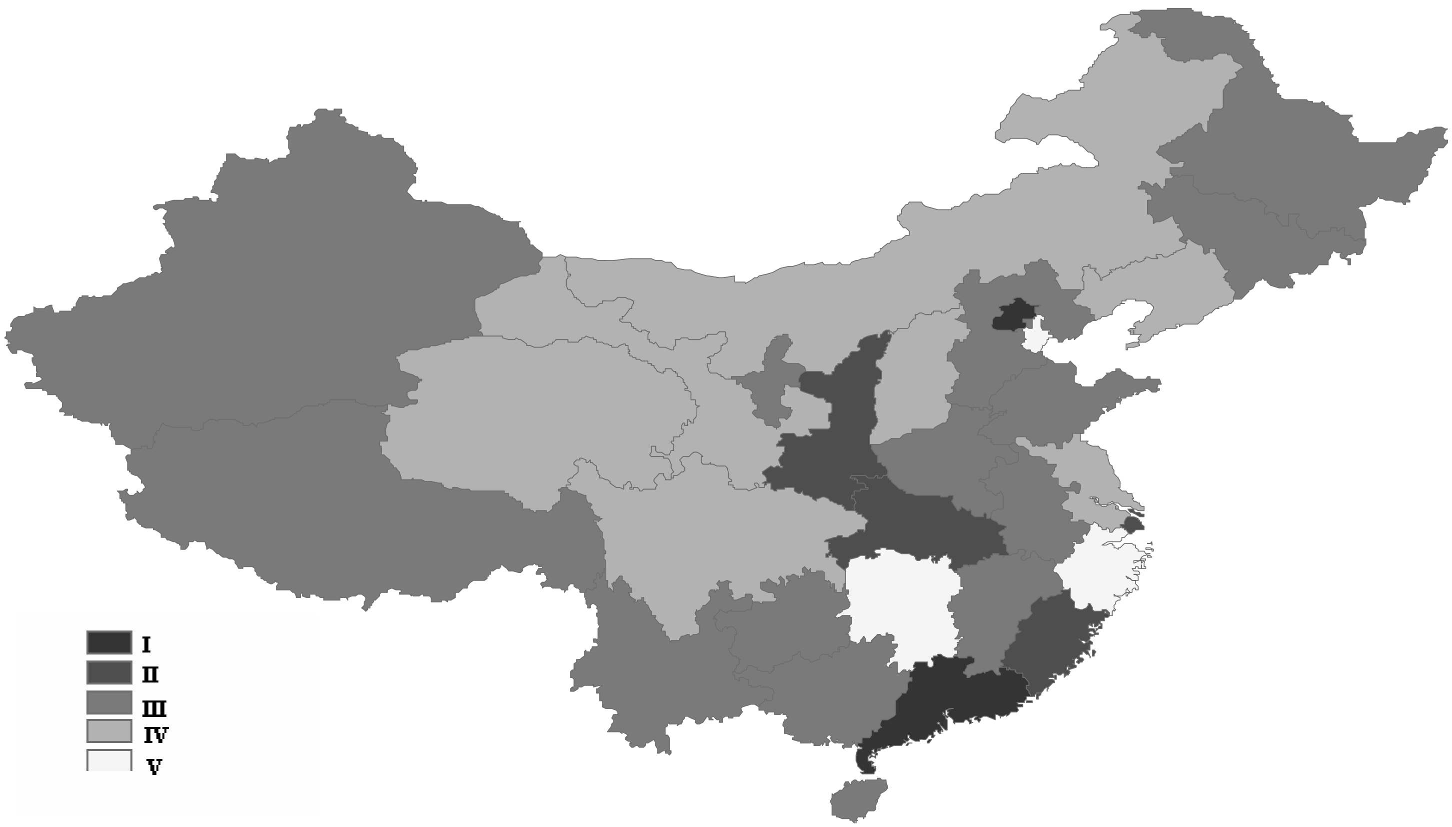

Figure 3.13 Spatial Distributions of Specialization by Five Macro-technological Areas in 2000-04
Notes The specialization of a region refers to its highest RTA index among five macro-technological areas, i.e., Electrical Engineering (I), Instruments(II), Chemistry and Pharmaceuticals (III), Processing Engineering (IV), and Mechanical Engineering(V).

that innovation activities in the Chemistry and Pharmaceuticals are very diffused with many regions highly specialized in that area. A further explore of micro-technological fields in the Chemistry and Pharmaceuticals (see Figure 3.14) reveals that most regions (eleven regions) are actually specialized in the agriculture and food chemistry.

In contrast, spatial concentrations of innovation activities in the Electrical Engineering and Instruments are not only much higher but also have increased over the years. Very few regions are specialized in these two hi-tech areas, while many regions' weakest technological areas are in the Electrical Engineering. Thus we can conclude that hi-tech developments are concentrated in very few regions only, while most regions are highly specialized in low-tech areas. The low-tech specialization levels of most regions explain why China has strong advantages in the fields of food chemistry and food processing and why it is particularly weak in the Electrical Engineering and Instruments.

The evidence here also seems to support the view that technologies with high level opportunities and more tacit knowledge-bases, as those in the hi-tech areas, tend to more spatially concentrated, while the codified and low level technologies are more easily spread out (Breschi, 2000).

3.5.3.2 Diversifications of Regions among the Technological Fields

In this sub-section, regions' technological diversifications are examined. First, the attention is turned to the variations among the three macro-regions. The comparisons of technological levels of 3-macro regions reveal that the disparities between the eastern region and the rest of country are large (see Table 3.11): the eastern region has relatively higher RTA index and more even development with

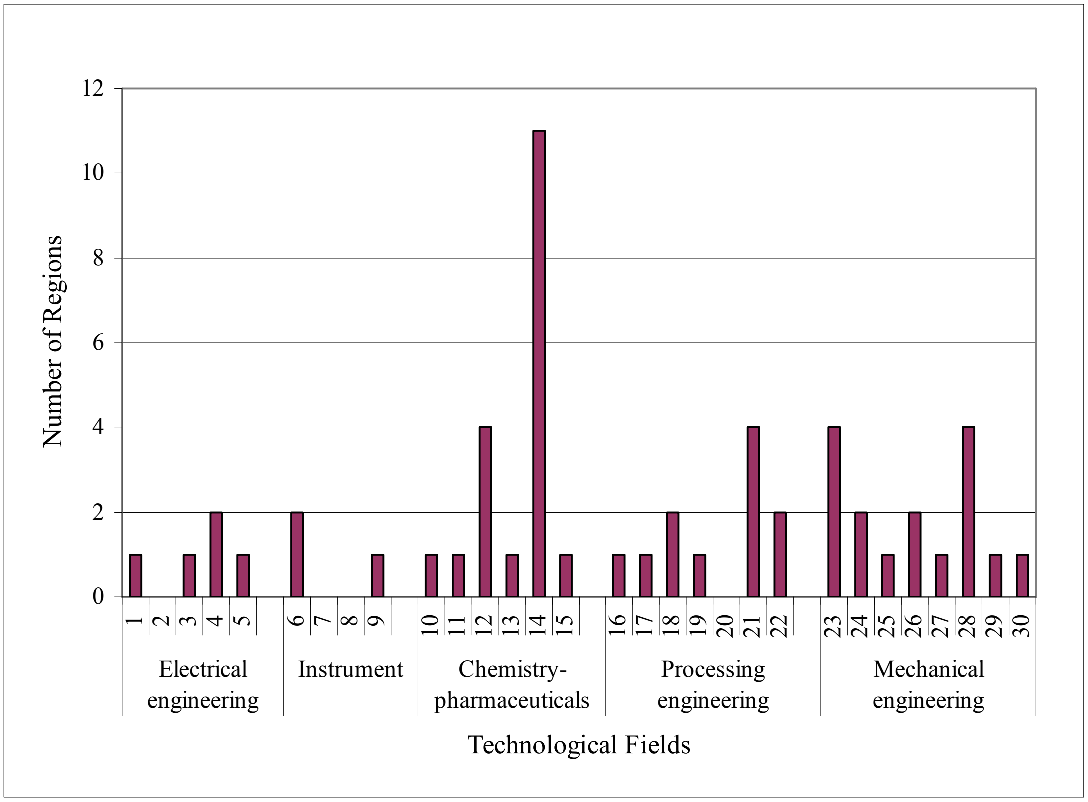

Figure 3.14 China's Regional Specialization by Technological Fields for the Period 2000-04

Note: Regional specialization is based on each region's highest and second highest RTA indexes among the thirty technological fields. Numbers in horizontal axis refer to the thirty technological fields as those listed in Table 3.5.

Table 3.11 Summary of China's Regional RTA Indexes by Technological Fields for the Periods 1995-99 and 2000-04

Provinces	Average RTA index		CV(%) of RTA index	
	1995-99	2000-04	1995-99	2000-04
Eastern region	**1.04**	**1.01**	**48.18**	**54.82**
Beijing	1.14	1.01	41.00	48.38
Fujian	1.05	1.04	50.17	40.42
Guangdong	1.21	0.88	63.52	73.72
Hebei	0.82	0.96	39.98	45.32
Jiangsu	1.11	1.04	32.08	24.60
Liaoning	0.90	1.01	38.45	38.46
Shanghai	1.21	1.06	101.91	66.93
Shandong	0.92	0.94	34.97	47.98
Tianjin	0.99	1.05	37.82	121.42
Zhejiang	1.08	1.08	41.93	40.93
Central region	**0.94**	**0.97**	**56.84**	**62.88**
Anhui	1.08	1.08	48.04	59.68
Hainan	1.17	0.92	98.90	89.35
Henan	0.88	0.90	46.59	52.12
Heilongjiang	0.85	0.92	46.62	58.10
Hubei	1.00	1.02	27.42	32.11
Hunan	0.91	1.11	60.41	99.17
Inner Mongolia	0.70	0.93	71.94	78.79
Jiangxi	0.79	0.76	50.17	74.34
Jilin	1.07	0.98	70.21	44.25
Shaanxi	0.95	1.04	48.08	40.91
Western region	**0.86**	**0.93**	**63.72**	**73.00**
Gansu	1.02	1.03	61.71	58.09
Guangxi	0.88	1.02	59.65	47.44
Guizhou	0.90	0.78	68.53	89.44
Ningxia	0.71	0.84	90.86	92.70
Qinghai	0.67	0.82	94.28	108.35
Shanxi	0.96	0.98	37.03	59.18
Sichuan	0.96	1.05	37.03	37.45
Xinjiang	0.88	0.95	64.22	80.63
Yunnan	0.78	0.92	60.16	83.75

Note: CV refers to coefficient of variation.

lower coefficients of variation across the technological fields, compared to the other macro-regions. Further, all the regions specialized in the hi-tech fields are located in the eastern region, while innovation activities in the central and western regions are mainly focused on the low-tech areas, such as the food chemistry and food processing.

Here, it is worthwhile to make a few remarks to the hi-tech orientated national policy. Since 1995, twenty-eight provinces have established the hi-tech development zones, regardless their local technological infrastructures and industrial strengths. The evidence here suggests that only hi-tech development zones located in Beijing, Shanghai, and Guangdong have become the hi-tech innovation centers, where the local technological infrastructures are in place to support such development. This finding is consistent with other studies of regional innovation activity of China (Turpin et al, 2002), which indicate that most companies in the central and western region have very little innovation capabilities.

3.5.4 Spatial Distributions of Domestic Patents by Industrial Sectors

In this part, I further analyze whether spatial patterns of innovation activities vary across the industrial sectors and to what degree they are related to the regional technological levels. It should be noted that the locations of most industries in China are mainly a result of long-term government interventions, from the 1950s to the 1970s, which aim to move the industrial centers from the coastal regions to in-lands. As a result, redundant presences of industries across and within the regions are a norm.

3.5.4.1 Spatial Distributions of Domestic Patents by Five Macro-industrial Sectors

First, twenty-two manufacturing sectors are further aggregated into five Pavitt macro-sectors: (1) science-based sectors, (2) scale-intensive sectors, (3) specialized sectors, (4) traditional sectors, and (5) residual sectors (Pavitt, 1984). The regional RTA indexes of five macro-industrial sectors from 1995 to 2004 are listed in Table A.5.

Different spatial patterns of innovation activities between the science-based sectors and the traditional sectors are revealed in Figure 3.15, which is mapped based on the region's highest RTA index among five macro-industry sectors in 2000-04.[8] There are only five regions, which include three municipal cities, Beijing, Shanghai and Tianjing, specialized in the science-based sectors. In contrast, there are about eighteen provinces specialized in the traditionally low-tech sectors, such as textiles, tobaccos, and the food industries.

The scale-intensive sectors are a large and very heterogeneous macro-sector. There are only five regions highly specialized in this macro-sector. We noticed that some of in-land provinces, such as Henan, Hunan and Inner Mongoli, are highly specialized in the scale-intensive sectors, reflecting the efforts by the government to move heavy industries to in-land regions in the 1960s and 1970s.

The patterns revealed from the macro-level analysis point out that patenting activities in the traditional sectors are spatially diffused among the regions, while innovation activities in the science-based sectors are more spatially concentrated

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[8] The spatial pattern of patenting activities in the five macro-industrial sectors in 1995-99 is very similar to that of 2000-04, so it is not displayed here.

(see Figure 3.15). On the other hand, the macro-level analysis of industrial sectors could be misleading, in contrast to the macro-level analysis of technological areas that are grouped according to their closeness in the technological distances. The macro-industrial sectors are usually very heterogeneous and some of the results could be puzzling. For example, the map shows that Guandong is specialized in the traditional sectors, while our analysis point out that its technological strengths are clearly in the hi-tech areas.

3.5.4.2 Spatial Distributions of Domestic Patents by Twenty-two 2-Digit Manufacturing Sectors

Figure 3.16 and Figure 3.17 display the mean and coefficients of variation (CV) of regional RTA indexes across twenty-two 2-digit industrial sectors for the periods of 1995-99 and 2000-04. According to the CVs of regional RTA indexes, spatial concentrations of innovation activities have increased for most of the sectors over the past ten years, especially in the sectors of communication equipment and electrical machinery.

Next, it is noticed that innovation activities in the three IT sectors, communications, electrical machinery and computers, are the most spatially concentrated with the highest CVs in both periods. In addition, the regional RTA indexes in these IT sectors are not only the lowest but also have declined over the years. In contrast, innovation activities in other sectors are more spatially diffused, especially in the sectors of chemicals, non-metal products, and basic metals, in which China in general has advantages.

Figure 3.18 are plotted based on each region's highest and second highest RTA indexes among twenty-two manufacturing sectors over the past ten years. The

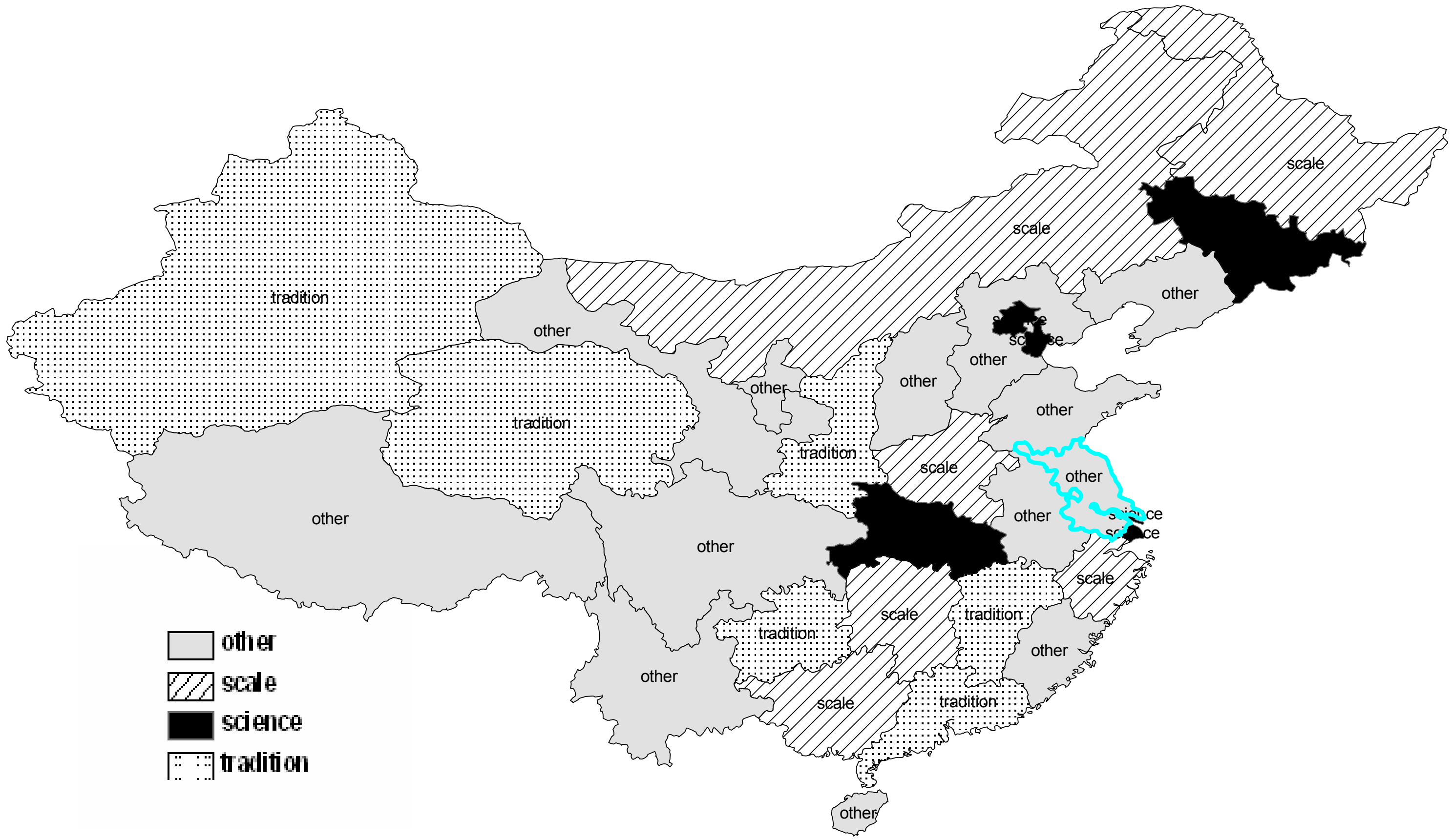

Figure 3.15 Spatial Distribution of Specialization by Five Macro-industrial Sectors in 2000-04
Notes: The specialization of a region refers to its highest RTA index among the five macro-industrial sectors. The sectors are Pavitt sectors ("Other" refers to residual sectors).

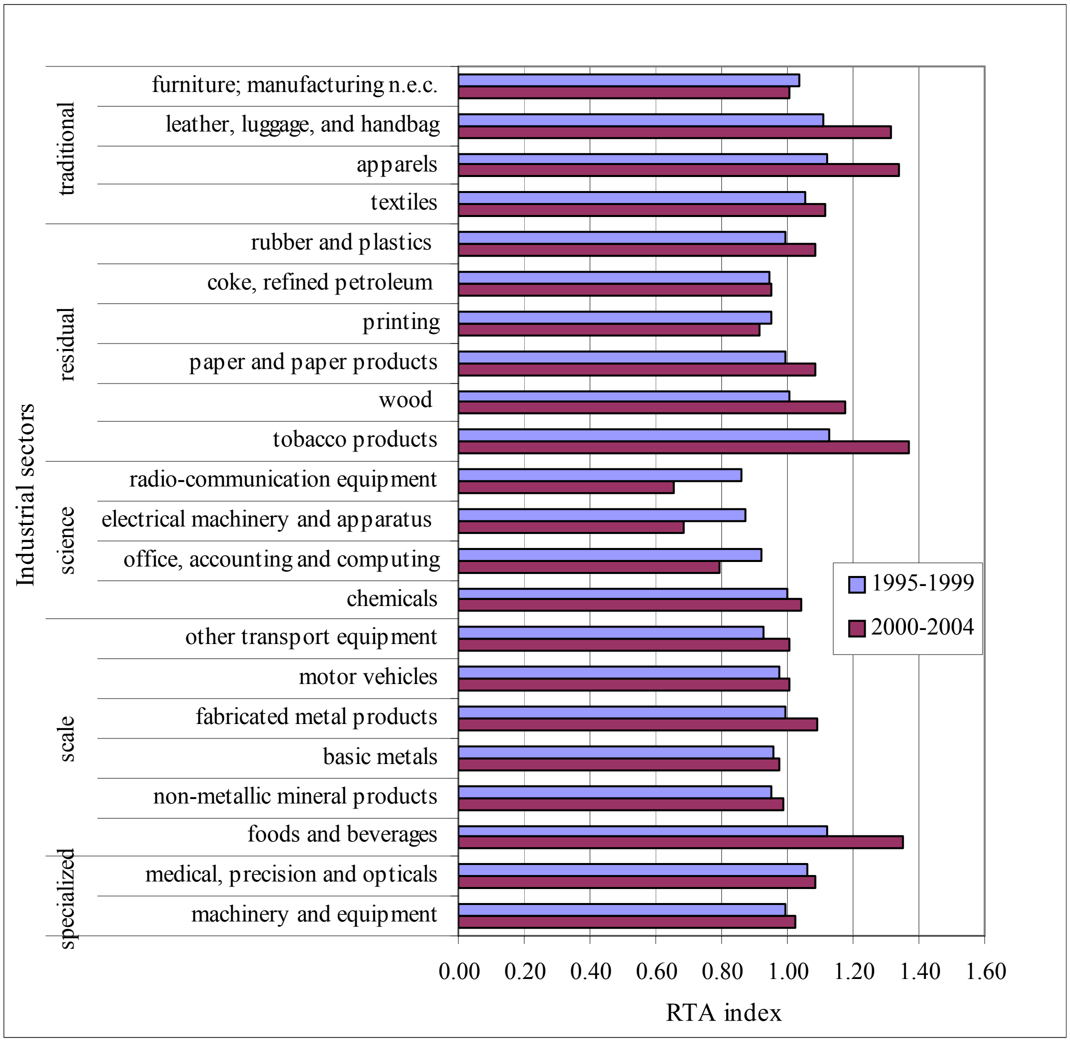

Figure 3.16 Comparisons of China's Regional RTA Indexes by 2-digit Industrial Sectors for the Periods 1995-99 and 2000-04

Note: Labels (i.e., "traditional", "residual", "science", "scale"; and "specialized") in vertical axis refer to Pavitt sectors.

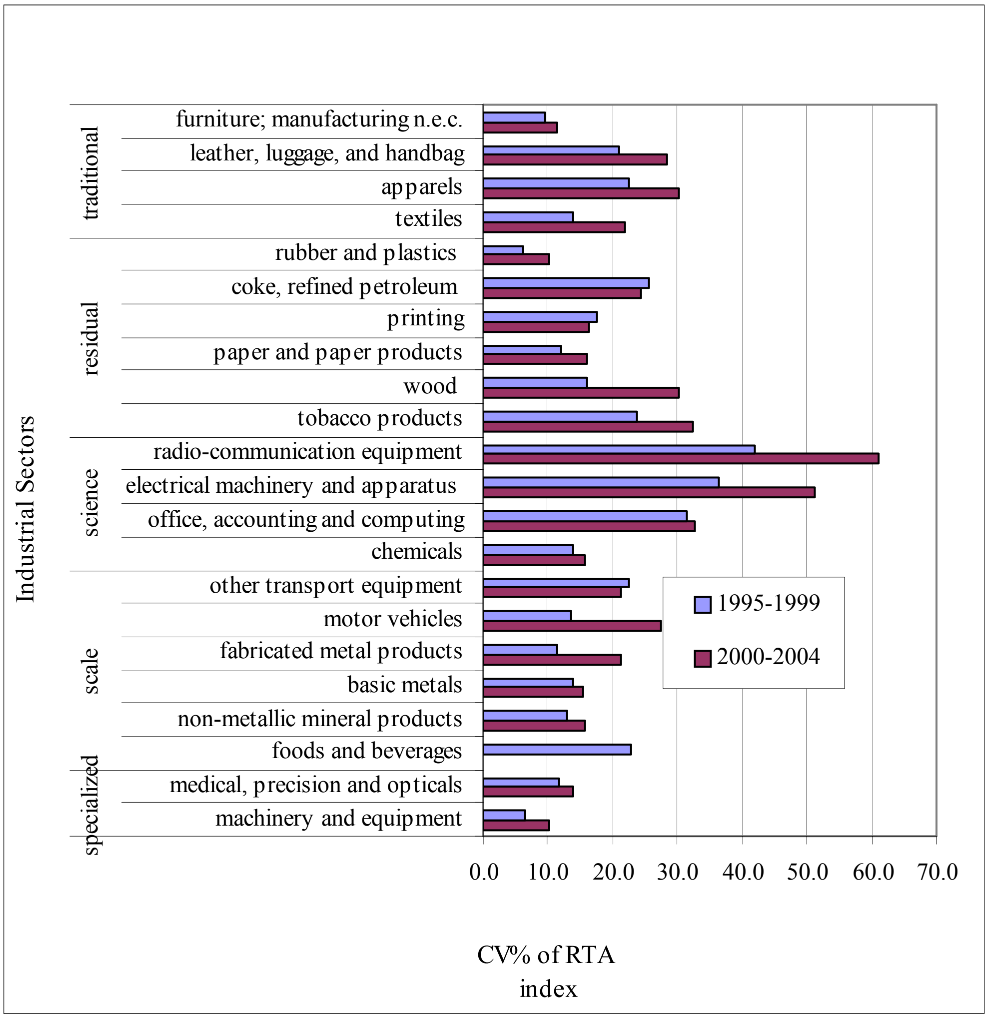

Figure 3.17 Comparison of Coefficients of Variation of China's Regional RTA indexes by 2-digit Industrial Sectors for the Periods 1995-99 and 2000-04

Note: Labels (i.e.,"traditional", "residual", "science", "scale"; and "specialized") in vertical axis refer to Pavitt sectors.

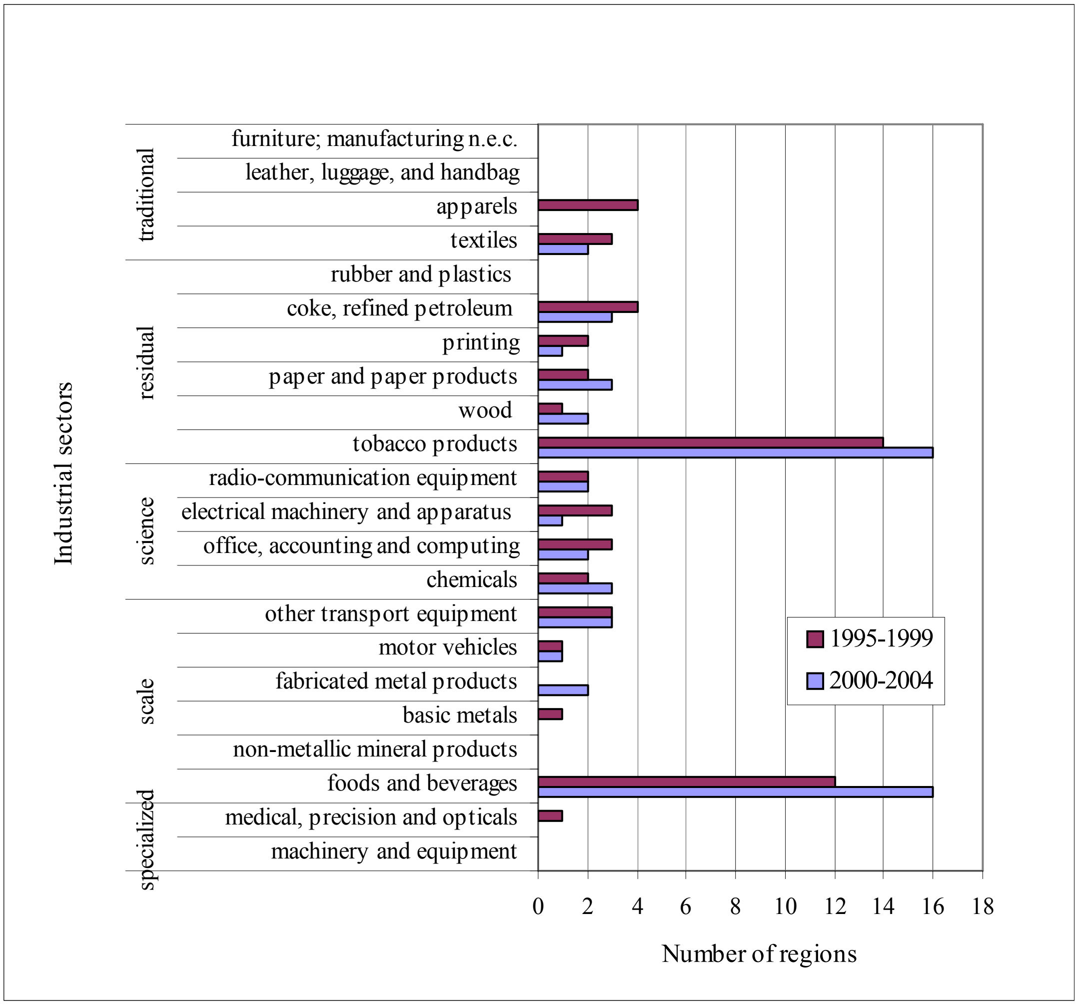

Figure 3.18 China's Regional Specialization by 2-digit Industrial Sectors for the Periods 1995-99 and 2000-04

Note: Regional specialization is based on each region's highest and second highest RTA indexes across twenty-two industrial sectors.

low-tech industrial development in most of the regions is clearly revealed: more than half of the regions are highly specialized in the food and tobacco industries. Correspondingly, most regions are weakest in the IT sectors. In contrast, only five regions are specialized in the three IT sectors in 2000-04 and they are all located in the eastern region.

3.5.5 Concluding Remarks

In summary, we can conclude that spatial concentrations of patenting activities in China have increased over the past ten years: the innovation activities are increasingly concentrated in the eastern region, particularly in the hi-tech areas. In the most recent years, it appears to emerge three major innovation centers, Beijing, Shanghai and Guangdong, corresponding to three pivotal economic centers in China. Meanwhile, the western region lags far behind in terms of innovative activity. It seems that regional variations in the technological development are closely related to the variations in regional economic development, though we are not clear whether the technology gap among the macro-regions is larger than that of economic gap.

Through the spatial analysis of patenting activities by technological fields and by industrial sectors, we find that spatial distributions of innovation activities of industrial sectors reflect the relative technological strengths of the regions. Since most provinces are strong in food chemistry and food process technologies, correspondingly, they have strong presences of food and tobacco industries. In contrast, Guanddong is highly oriented toward telecommunication technology; consequently, it has a very strong radio and communication industrial sector.[9]

[9] Detailed regional RTA indexes by technological fields and by industrial sectors in 2000-04 are listed in Table A.4 and Table A.5.

3.6 Summary of Findings

In general, my analysis points out that innovation activities by industrial sector at both regional and national levels reveal their corresponding technological strengths. The key findings of this chapter can be summarized in the followings.

Innovation activities in China have become more concentrated in the last ten years. In particular, innovation activities in the hi-tech areas are increasingly concentrated in the eastern region, while low level innovation activities are more diffused across the regions.

Regional variations in patenting activities have increased in the past ten years. In specific, the eastern region is increasingly active in the high-level technological development and has a more even development across the technological fields. In contrast, the central and western regions have fewer and low-level innovation activities.

The technology gap between China and the rest of world is mainly in the hi-tech areas. Meanwhile, China is increasingly focusing its innovation activities in those areas, particularly in the IT sectors. The evidence here suggests that the IT sectors are the weakest industrial sectors in China and some of the sectors have continually weakened over the years; thus the task to build up its own technology in these IT sectors is particularly challenging, since foreign companies are increasingly targeting and patenting in the same areas. On the other hand, China has built up significant strengths in some hi-tech areas over the years, such as biotechnology, chemical engineering, and environmental technology.

The evidence here indicates that nation-wide hi-tech oriented S&T policy is not effective in most of the regions. To the contrary, there might result in some undesirable consequences in terms of ignoring the development in other technological fields, where most of the regions already have relative strengths.

The success of chemical industry in the technological development should provide an example for other science-based sectors. The analysis suggests that the technological strength of chemical industry is a result of consistent and active innovative efforts over the long period of time.

In the next chapter, the main determinants of patenting activity at the provincial level are analyzed. I find the econometric evidence of regional variations in patenting activity, the effect of industrial policy and the impact of China's WTO accession on patenting activity.

Table A.1 Chinese Domestic Patents by IPC Codes from 1995 to 2004

IPC class	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
A	3216	3515	3675	3833	3989	5034	6660	7900	11102	10624
A01	294	375	435	515	626	714	760	1135	1422	1338
A21	29	32	45	31	28	38	38	71	82	76
A22	4	4	4	1	1	4	3	1	12	14
A23	907	949	849	911	849	1115	1313	1562	2030	1698
A24	29	45	40	52	45	61	75	77	120	104
A41	18	18	42	35	30	34	65	71	81	78
A42	2	4	6	1	2	4	5	16	7	5
A43	26	18	19	27	29	54	30	34	43	48
A44	2	5	9	7	8	15	11	18	11	11
A45	18	16	17	7	13	15	17	33	37	42
A46	5	7	3	14	6	8	8	13	20	21
A47	105	104	137	149	170	171	227	301	521	451
A61	1714	1872	1992	1987	1968	2681	3998	4365	6444	6424
A62	17	25	29	24	29	28	55	66	120	83
A63	46	41	48	72	63	92	55	136	153	156
B	1012	1144	1254	1330	1563	2316	2638	3688	4882	4756
B01	141	212	212	320	372	493	527	777	963	980
B02	20	21	14	21	18	26	39	44	56	64
B03	19	19	13	22	29	20	43	36	61	54
B04	5	6	4	3	5	5	8	17	15	18
B05	16	13	15	17	21	36	45	56	77	94
B06	0	1	0	0	3	4	0	2	9	7
B07	4	9	7	9	6	13	13	22	25	34
B08	2	3	3	6	9	8	17	28	35	38
B09	9	3	4	9	24	40	43	67	81	59
B21	71	60	69	54	48	88	126	192	197	178
B22	68	53	84	54	70	95	151	210	266	229
B23	73	65	97	77	88	154	190	249	351	412
B24	13	11	25	13	15	25	16	34	75	71
B25	11	15	8	12	18	33	54	82	121	102
B26	4	9	3	3	6	7	11	25	24	33
B27	38	26	34	37	32	49	62	83	101	116
B28	36	35	26	19	49	47	57	84	103	137
B29	59	62	72	88	74	110	138	155	275	229
B30	2	9	5	7	7	4	5	11	23	14
B31	4	8	8	4	5	7	7	10	5	27
B32	31	21	29	25	39	63	49	63	100	72
B41	28	28	32	28	29	32	60	116	105	117
B42	11	21	29	17	29	32	27	52	40	43
B43	21	19	26	25	22	36	37	55	53	36
B44	67	77	72	65	66	89	121	130	176	183

Table A.1 continued

IPC class	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
B60	79	110	108	138	183	305	267	328	567	468
B61	17	16	18	14	25	37	40	59	98	74
B62	36	58	46	67	71	85	94	161	166	186
B63	24	23	19	24	33	49	40	73	108	114
B64	21	13	27	21	26	50	47	63	76	52
B65	67	99	126	105	142	230	235	310	405	311
B66	13	12	14	21	25	37	50	72	72	97
B67	1	3	4	3	8	3	4	6	14	9
B68	1	4	1	2	1	2	3	2	5	6
B81						1	6	12	16	21
B82							6	3	18	19
C	1989	2264	2450	2822	3666	7724	6480	8236	10527	9842
C01	141	164	178	196	155	280	373	549	623	680
C02	94	112	119	146	190	264	343	454	638	613
C03	31	41	30	46	63	56	66	101	157	238
C04	208	224	225	231	230	314	284	514	595	656
C05	102	134	135	142	172	189	172	246	275	244
C06	9	10	7	9	12	13	12	13	42	31
C07	228	288	315	393	827	2878	1436	1660	2069	1901
C08	134	174	245	273	367	601	753	1035	1228	1121
C09	292	307	306	317	348	511	599	881	1133	941
C10	131	192	217	268	264	468	475	528	623	482
C11	83	85	69	76	85	133	119	128	177	129
C12	231	249	303	402	659	1532	1153	1184	1669	1531
C13	9	5	7	3	2	9	14	11	12	14
C14	4	4	12	8	10	16	15	13	19	29
C21	41	48	49	52	55	78	109	136	168	161
C22	139	131	130	138	160	205	308	391	524	419
C23	62	50	58	70	93	111	124	209	276	304
C25	38	31	29	36	42	46	80	128	183	167
C30	12	15	16	16	25	20	45	55	116	103
D	173	194	201	210	235	338	422	791	1086	1090
D01	35	23	33	23	37	80	101	173	216	198
D02	5	10	3	6	8	15	28	27	53	49
D03	14	13	14	8	15	23	18	45	48	55
D04	16	13	8	15	9	27	33	45	73	59
D05	5	1	5	4	30	8	3	16	23	23
D06	58	80	69	87	55	102	125	363	532	506
D07	1	1	1	3	1	0	1	9	7	5
D21	39	53	68	64	78	83	113	113	134	183
E	321	375	370	443	477	633	741	1186	1681	1597

Table A.1 continued

IPC class	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
E01	16	34	42	54	68	71	90	113	160	174
E02	58	75	75	88	95	105	103	181	245	218
E03	35	38	18	30	40	88	83	124	126	134
E04	125	120	112	140	153	196	282	366	695	617
E05	21	28	36	43	50	61	43	104	115	115
E06	17	19	21	27	27	26	40	102	114	92
E21	49	61	66	61	50	86	100	196	226	234
F	524	596	658	765	833	1173	1482	2646	3392	3385
F01	18	21	27	20	36	68	51	78	108	88
F02	61	77	81	90	83	108	87	192	187	243
F03	39	69	74	68	65	75	84	119	134	191
F04	41	41	60	55	63	91	160	280	441	305
F15	5	4	6	8	11	15	14	25	49	54
F16	122	119	139	158	190	204	269	449	571	635
F17	4	5	20	10	8	16	25	15	37	34
F21	12	23	14	20	24	33	28	63	69	79
F22	12	6	14	5	19	10	14	17	15	16
F23	35	36	36	46	113	102	108	143	139	160
F24	87	101	105	172	138	258	406	752	990	868
F25	42	26	36	36	48	73	105	303	379	322
F26	7	9	5	7	5	13	11	33	40	26
F27	13	22	15	12	20	34	40	51	41	36
F28	13	19	13	31	24	46	44	84	130	87
F41	6	9	5	13	14	15	16	17	28	28
F42	7	8	8	14	10	12	20	25	34	30
G	770	832	847	933	1246	1862	2478	4123	5938	6227
G01	225	252	259	317	420	602	809	1271	2007	2214
G02	27	39	38	55	52	91	192	378	572	589
G03	35	23	24	27	29	46	66	107	175	171
G04	11	14	14	9	8	8	22	37	34	32
G05	25	24	24	23	33	23	49	72	135	204
G06	290	322	310	320	515	791	1008	1705	2233	1974
G07	15	8	15	16	21	20	21	42	59	94
G08	18	32	23	39	43	45	47	91	111	171
G09	93	86	99	96	106	132	170	154	229	220
G10	16	16	12	6	12	43	36	74	85	87
G11	12	9	24	19	34	45	46	153	257	351
G12	1	1	1	1	0	1	0	13	19	24
G21	2	6	4	5	9	15	12	26	22	17
H	441	516	528	734	1080	1609	2492	4350	6781	7522
H01	154	212	188	249	362	477	585	1139	1771	1743

Table A.1 continued

IPC class	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
H02	94	110	129	168	196	276	383	538	664	770
H03	31	23	32	47	50	69	83	90	126	161
H04	126	136	153	241	444	715	1338	2438	3986	4447
H05	36	35	26	29	67	72	104	145	228	268

Table A.2 OST/INPI/ISI Technology Classification, Defined by IPC Codes

Macro-technological Areas	Micro-technological Fields
I. Electric Engineering	1. Electrical machinery and apparatus, and electrical energy 2. Audio-visual technology 3. Telecommunication 4. Information technology 5. Semiconductors
II. Instruments	6. Optics 7. Analysis, measurement, and control technology 8. Medical technology 9. Nuclear engineering
III. Chemistry and Pharmaceuticals	10. Organic fine chemistry 11. Macromolecular chemistry, and polymers 12. Pharmaceuticals and cosmetics 13. Biotechnology 14. Agriculture and food chemistry 15. Chemical and petrol industry, and basic material chemistry
IV. Process Engineering	16. Surface technology, coating 17. Materials, metallurgy 18. Chemical engineering 19. Material processing, textiles, and paper 20. Handling and printing 21. Agriculture and food processing, machinery and apparatus 22. Environmental technology
V. Mechanical Engineering	23. Machine tools 24. Engines, pumps and turbines 25. Thermal processes and apparatus 26. Mechanical elements 27. Transport 28. Space technology and weapon 29. Consumer goods and equipment 30. Civil engineering, building and mining

Table A.3 Patents by Industry of Manufactures (IOM) from 1985 to 2004: Results of OTC Runs for Chinese Domestic Patents

Industry of Manufacturing (ISIC sectors)	Total Patents			
	1985-89	1990-94	1995-99	2000-04
Manufacturing sectors	17274	38064	50429	158341
1. Food products and beverages	124	518	730	1690
2. Tobacco products	27	118	166	381
3. Textiles	124	307	397	1160
4. Wearing apparels	18	71	99	232
5. Leather, luggage, handbags,	19	72	100	237
6. Wood and wood products	41	100	131	353
7. Paper and paper products	124	257	316	906
8. Printing and reproduction of recorded medias	39	72	91	317
9. Coke and refined petroleum products	77	146	201	648
10. Chemicals	4973	11171	15447	45879
11. Rubbers and plastics	551	1176	1502	4270
12. Non-metallic mineral products	255	496	658	2082
13. Basic metals	163	305	399	1284
14. Fabricated metal products	619	1312	1661	4857
15. Machinery and equipment	5250	10892	13810	42987
16. Office, accounting and computing machinery	485	816	1052	4439
17. Electrical machinery	55	88	117	617
18. Radio, television and communication equipments	683	1103	1469	8474
19. Medical, precision and optical instruments	1452	3982	5448	16119
20. Motor vehicles	586	1050	1250	3926
21. Other transport equipments	158	272	319	964
22. Furniture; manufacturing n.e.c.	1452	3739	5067	16517
Coefficient of Variations (%)	186.13	184.69	185.71	179.57

Table A. 4 Summary of Average Regional RTA Indexes by Five Macro-Technological Areas from 1995 to 2004

Regions	1995-99 RTA Index					2000-04 RTA Index				
	I	II	III	IV	V	I	II	III	IV	V
AH	0.79	1.16	0.93	1.22	0.98	0.59	1.12	1.17	0.93	1.11
BJ	1.28	1.07	0.97	1.06	0.80	1.37	1.15	0.99	0.92	0.61
FJ	0.94	1.06	1.00	0.98	1.03	0.83	1.20	0.94	1.15	1.06
GD	2.39	1.24	0.65	0.79	1.16	2.44	1.01	0.55	0.63	0.73
GS	0.69	1.16	1.20	0.92	0.74	0.36	0.79	1.19	1.38	1.02
GX	0.93	0.93	1.01	0.74	1.33	0.59	0.79	1.20	0.98	1.19
GZ	0.86	0.60	1.11	0.93	1.07	0.33	0.41	1.69	0.91	0.72
HAN	1.67	0.57	0.91	0.96	1.05	0.59	0.61	1.37	0.79	1.13
HEB	0.68	0.77	1.16	0.87	1.04	0.41	0.80	1.23	1.09	1.20
HEN	0.82	0.91	1.09	0.88	1.06	0.45	0.68	1.22	1.13	1.20
HL	0.64	0.99	1.14	0.78	1.12	0.39	0.80	1.35	0.87	1.20
HUB	0.88	1.24	0.95	0.98	1.11	0.70	1.31	1.00	1.16	0.99
HUN	0.78	0.60	1.09	0.99	1.09	0.51	0.62	0.94	1.12	1.75
IM	0.34	0.68	1.29	0.95	0.88	0.34	0.55	1.26	1.31	1.12
JL	0.70	1.30	1.12	0.92	0.84	0.43	1.32	1.33	0.93	0.84
JS	1.39	1.01	0.78	1.11	1.16	0.97	1.04	0.92	1.13	1.04
JX	1.06	0.77	1.17	0.76	0.93	0.67	0.57	1.51	0.69	0.87
LN	0.62	0.92	1.02	1.16	1.03	0.53	0.92	1.05	1.36	1.09
NX	0.50	1.25	1.14	1.10	0.75	0.29	0.46	1.61	1.16	0.66
QH	0.27	0.63	1.30	0.93	0.95	0.36	0.43	1.33	1.72	0.60
SA	1.20	1.37	1.01	0.78	0.94	1.00	1.40	1.00	0.89	0.90
SC	0.88	0.93	1.03	1.10	0.92	0.68	0.99	1.12	1.16	0.94
SD	0.56	0.92	1.06	1.12	1.00	0.38	0.70	1.26	1.20	1.10
SH	1.10	1.22	1.09	0.89	0.76	1.05	1.18	1.15	0.92	0.64
SX	0.67	0.90	0.96	1.18	1.15	0.33	0.78	1.15	1.49	1.05
TB	0.35	0.00	1.46	1.12	0.60	0.17	0.69	1.69	0.72	0.94
TJ	0.93	1.50	0.92	1.12	0.89	0.52	0.73	0.58	1.14	2.40
XJ	0.76	0.84	1.15	0.99	0.87	0.53	0.71	1.34	0.97	1.00
YN	0.49	0.58	1.22	1.20	0.74	0.24	0.47	1.53	1.20	0.83
ZJ	1.13	0.85	0.75	1.15	1.41	0.78	1.19	0.83	1.11	1.38

Note: Numbers refer to five macro-technological areas as those listed in Table A.2.

Table A.5 Summary of Average Regional RTA Indexes by Five Macro-industrial Sectors from 1995 to 2004

Regions	1999-95 RTA Index					2000-04 RTA Index				
	specialized	scale	science	traditional	residual	specialized	scale	science	traditional	residual
AH	1.06	1.01	0.91	1.08	1.01	1.05	1.04	0.95	1.05	1.06
BJ	0.91	0.93	1.14	0.87	0.96	0.93	0.85	1.09	1.01	0.90
FJ	1.03	0.98	0.94	1.10	0.99	1.04	1.04	0.94	1.02	1.09
GD	1.01	0.96	0.91	1.07	0.92	0.95	0.73	0.92	1.24	0.73
GS	0.92	0.91	1.17	0.91	0.94	0.96	1.15	1.12	0.75	1.16
GX	1.09	1.06	0.86	1.13	0.99	1.05	1.10	0.96	1.02	1.10
GZ	1.05	1.03	0.91	1.13	1.00	1.09	1.03	0.91	1.21	1.10
HAN	1.02	1.02	0.99	0.97	0.97	1.13	1.07	0.87	1.10	1.20
HEB	1.06	1.03	0.90	1.12	1.05	1.10	1.17	0.88	1.04	1.20
HEN	1.07	1.02	0.89	1.12	1.03	1.10	1.15	0.89	1.06	1.13
HL	1.08	1.04	0.87	1.15	1.03	1.07	1.16	0.93	1.02	1.16
HUB	1.01	1.02	0.99	0.98	1.01	0.97	0.99	1.08	0.93	1.04
HUN	1.01	1.06	0.98	1.00	1.01	1.10	1.45	0.85	0.90	1.27
IM	1.08	0.98	0.88	1.24	1.06	1.08	1.11	0.93	1.08	1.11
JL	0.98	0.95	1.03	1.02	0.98	0.99	0.98	1.06	0.99	1.03
JS	1.02	1.03	0.94	0.98	1.00	1.01	1.00	0.98	1.01	1.06
JX	1.03	0.96	0.95	1.12	0.99	1.12	1.01	0.84	1.25	1.08
LN	1.00	1.07	1.01	0.93	1.07	1.02	1.13	1.01	0.89	1.14
NX	0.99	0.94	1.03	1.09	1.01	1.00	0.98	1.06	1.04	1.10
NH	0.98	1.02	1.04	1.05	0.96	0.98	0.96	1.07	1.07	1.06
SA	1.05	0.96	0.93	1.12	0.94	1.03	0.94	0.97	1.07	0.97
SC	0.98	1.00	1.03	0.98	1.00	1.01	1.03	1.01	0.99	1.07
SD	1.03	1.04	0.97	1.02	1.03	1.05	1.13	0.96	0.99	1.14
SH	0.81	0.86	1.33	0.74	0.91	0.83	0.83	1.28	0.81	0.91
SX	1.05	1.11	0.93	0.97	1.09	1.03	1.17	1.01	0.88	1.23
TJ	1.00	0.96	0.99	1.03	1.02	1.25	1.46	0.67	0.96	0.99
XJ	1.04	0.99	0.93	1.14	0.99	1.04	1.08	0.95	1.11	1.09
YN	0.97	0.95	1.08	1.00	0.99	1.03	1.02	1.02	1.04	1.17
ZJ	1.11	1.14	0.81	1.03	1.10	1.09	1.16	0.88	0.98	1.11

Chapter 4

DETERMINANTS OF PATENTING ACTIVITY

4.1 Introduction

This chapter aims to identify the main determinants of patenting activity at the provincial level in China. The patent production equation described in Chapter 2 is estimated with panel data of 30 provinces for the years 1998-2004.[1] In estimating such a patent production function at the provincial level, the main interests are to find: (1) the explanatory power of the patent production function; (2) the elasticity of patents to each region's own R&D investment; and (3) the effects of other local factors, such as market demand, agglomeration economies, and local technological infrastructure.

Based upon the preliminary estimation results, the effects of locations and China's WTO accession on domestic patenting activity are further examined. The separate elasticities of patents to own R&D investment for three macro-regions are estimated. To capture the impact of China's WTO accession, a patent production equation with a set of year dummies is also estimated.

Knowledge spillover effects in China have received little attention in the literature. This analysis is the first to provide econometric evidence of inter-regional knowledge spillovers on patenting activity in China by estimating a patent-spillover production function.

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[1] Tibet is excluded in the analysis.

Section 4.2 describes the regression methods. Section 4.3 describes model specifications. Section 4.4 describes the data sources. Section 4.5 describes the main estimation results. Section 4.6 describes the effects of location and the impact of China's WTO accession. Section 4.7 describes the effects of knowledge spillovers on each region's patenting activity.

4.2 Regression Methods

To identify the main determinants of patent applications by regions, I use a patent production function introduced by Grilirches (1980) and modified by Moreno et al. (2003):

$$P_{it} = RD_{it}^{\alpha} X_{it}^{\beta} e_i . \tag{4.1}$$

Applied at the regional level, this patent production function relates the total number of patent applications made in the region i in a given year t, P_{it}, to its R&D capital, RD_{it}, along with other regional specific characteristics, X_{it}. Taking the logarithm, the equation can be estimated by linear regression.

Since patent applications are integer in nature, the patent production function can also be estimated by a count model. Hausman et al. (1984) have developed a Poisson-based econometric model for the patents-R&D relationships. Following their methods, patent applications, P_{it}, is assumed to be an exponential function of R&D capital and other regional specific characteristics:

$$P_{it} = exp\ (\alpha \log RD_{it} + \beta \log X_{it}) + \varepsilon_{it}. \tag{4.2}$$

The Poisson model is in the linear exponential class, so the estimates are consistent if the mean specification is correct. The robust standard errors are consistent even under the misspecification of the distribution (Wooldridge, 2002). It can be estimated by the quasi-maximum likelihood.

In this chapter, the estimation results of linear regressions along with those of Poisson regressions are reported and compared.

4.3 Model Specifications

In this study, provinces are the unit of observation available. Provinces are a common unit of observation in the regional literature, though they are not considered as an ideal unit of analysis. Ideally, we would like data at a more disaggregated level, such as city or county level; however, most data are collected only at the provincial level. In addition, provinces are an important policy-making unit with respect to stimulating local innovative activities. This analysis attempts to include various control variables to mitigate the aggregation bias caused by using province as the unit of observation. The following important local factors, in addition to each province's own R&D capital, are included in the analysis: (1) agglomeration economies, (2) local market demand, (3) local technological network, and (4) hi-tech policy. These local factors are discussed in the followings.

Agglomeration Economies. As discussed earlier, agglomeration economies may increase information transfers, promote spillovers, and thus lower the costs and risks of innovation. Concentration of local industrial activity reflects the degree of agglomeration economies within a province. The presence of a highly concentrated industrial activity within a region is expected to have a positive impact on that region's patenting activity as it is believed that the higher concentration of industry presence in a region tends to generate more spillovers among the companies and thus leads to more patenting activity (Feldman, 1994). Manufacturing employment is frequently used as a proxy for manufacturing activities. The number of manufacturing employment in the main cities within a province relative to total manufacturing employees in that province can be used as a measure of geographic concentration of manufacturing activity. However, only total manufacturing employment of each province is available, so total manufacturing employment is used as a proxy for the concentration of manufacturing activity within a province in this study.

Local Market Demand. Chinese provinces are less integrated with each other, compared to the states in the US. Due to the local protectionism and high transportation costs, trade across the regions is quite limited. Although economic integration of Chinese provinces has improved in the recent years, factor mobility is still very low and there is a lack of nationwide goods and services markets (Xu, 2002). Compared to the states in the US or the European regions, Chinese provinces are more like a cluster of independent economies and thus each province can be considered having a distinctive local market.

Local population is included as a control for local market size as well as resources for human capital. As mentioned earlier, provinces are a less than satisfactory unit of observation, including local population in the analysis also facilitates the comparisons across the provinces. Regional gross domestic product is included to control for the income level of each region.[2] Together, these two variables are used as proxies for local market demand and are expected to have positive impacts on patenting activity.

[2] GDP per capita is also used as an income variable. The estimation results using GDP per capita (without POP) are very similar to those of GDP and thus are not reported.

Local Technological Network. The presence of more universities should have a positive impact on local patenting activity as R&D activity conducted at the local universities should have spillover effects on local industrial R&D activity. The number of faculty member and/or college students in each province would be a good proxy for the size of the local technological network; however, these data are not available. Thus I use the number of universities as a proxy for the size of local technological network. Due to the economic reforms and increasing demands for higher education, more colleges, mostly private, have been established across the provinces since the 1990s, thus the number of universities is no longer a time-invariant regional-specific variable. However, this proxy is not perfect: the variations across the time dimension are smaller, compared to the other control variables, and thus the estimation results for this variable may be less satisfactory.

Hi-tech Policy. In this Chapter, I further investigate whether nationwide hi-tech oriented Science & Technology (S&T) policy is effective in stimulating regional patenting activity. As discussed in Chapter 3, twenty-eight provinces have established the hi-tech development zones since the 1990s, so gross industrial outputs of hi-tech zones in each region can be used as a proxy for the policy variable. We would expect that higher outputs in the hi-tech zones should have a positive impact on a region's patenting activity, as companies located in those hi-tech zones are considered to be more R&D-intensive and should have more innovations.

Since unobservable region-specific characteristics can also influence either local innovation activity or the propensity to patent, a regional specific variable is included in the specification. Therefore, the estimated patent production equation is specified as:

$$\log(P_{it}) = a(t) + \alpha_i + \beta_1 \log(RD_{it}) + \beta_2 \log(GDP_{it}) + \beta_3 \log(POP_{it}) + \beta_4 \log(EMPLOY_{it}) + \beta_5 og(UNIV_{it}) + \beta_6 \log(HITECH_{it}) + \varepsilon_{it}, \quad (4.3)$$

where P_{it} is the total patent applications made in the region i in a given year t; RD_{it} is the R&D capital in the region i in a given year t; GDP_{it} is the regional gross domestic product in the region i in a given year t; POP_{it} is the population in the region i in a given year t; $EMPLOY_{it}$ is the manufacturing employment in the region i in a given year t; $UNIV_{it}$ is the number of universities in the region i in a given year t; $HITECH_{it}$ is the gross industrial outputs of hi-tech development zones in the region i in a given year t; and α_i is the unobservable regional specific characteristics. A single trend variable, a(t), is included to capture the changing rate of the propensity to patent over time which influences all the regions.

Both the fixed effects estimators and random effects estimators are applied to equation 4.3, though the fixed effects estimators are probably more appropriate since unobservable regional specific effects are more likely correlated with those explanatory variables.

4.4 Description of Data

Data limitation severely constrains the scope of this analysis. First, the data are only available at the provincial level. There are concerns that administrative provinces are not equivalent to the economic regions. With regard to this problem, each province in China can be considered as a more independent economic region, compared to either the states in the US or the European regions: (1) Chinese administrative provinces have been established for centuries with little change in their geographic boundaries, thus regional specific characteristics are very distinctive; (2) local protectionism is very severe across the regions and within the regions; and (3) transportation costs across the regions, especially from the eastern region to the western region, are very high. These impediments have greatly limited trade among the regions and slowed down the integration of different local markets.

Second, R&D data at the provincial level are available only for the years 1998-2004, thus there are only seven years balanced panel data of 30 provinces. This limit the analysis of provincial patent-R&D relationship to the most recent years, and any structural changes which may occur before 1998 are unable to examine. Patent data have been described in Chapter 3. R&D data and other economic data are described in the followings.

4.4.1 R&D Data

The stock of innovation capital is used in the production of new knowledge and R&D spending adds to the stock of innovation capital. The accumulation of R&D spending overtime, i.e., R&D stocks, can be used as a proxy for the stock of innovation capital. For short period data, contemporaneous R&D spending is frequently used as an alternative to R&D stocks. Thus, the stock of innovation capital (R&D capital), RD_{it}, is constructed by both contemporaneous R&D spending and R&D stocks.

R&D stocks are measured as the current and past history of R&D spending. Following the method of Griliches (1980), a perpetual inventory model is used to construct the R&D stocks:

$$RD_{it} = (1-\delta)RD_{i,t-1}+I_{i,t-1}, \tag{4.4}$$

where the R&D stocks, RD_{it}, are the sum of R&D spending in the previous period, $I_{i,t-1}$, plus the depreciated value of the old R&D stocks, $(1-\delta)\ RD_{i,t-1}$. Most studies place the depreciation rate of R&D stocks, δ, in the range of 5% to 25% (Jaffe, 1986; Robbins, 2003). The most popular one is 15% depreciation rate. The higher depreciation rate reflects a more rapid pace of knowledge generation as well as a more rapid rate of destruction of existing knowledge. Since the R&D series used in this study is fairly new, R&D stocks are created with depreciation rates of 5%, 10 % and 15 % depreciation rate.[3]

Since R&D data started in 1998, the initial R&D stock, $RD_{i,98}$, is constructed as:

$$RD_{i,98} = I_{i,98} / (\delta + \gamma_i), \tag{4.5}$$

where $I_{i,98}$ is the gross R&D spending in the region i in the year 1998 and γ_i is the average growth rate of R&D spending for the period 1998-2004 in the region i.[4] R&D data by regions are collected from China Science & Technology Statistics (www.sts.org.cn). R&D spending in each region is reported as total R&D spending from the large and medium enterprises (LME), universities, and research institutes. This accounting ignores the R&D spending in the small and private enterprises, but this is not a problem: most small and private enterprises in China have no R&D investment at all, due to the lack of capital and long-term incentives for innovation.

[3] The estimations of this study confirm that results are not sensitive to the level of the depreciation rates assumed.

[4] The average growth rate of national R&D spending for the period 1991-1997 is much smaller compared to the period 1998-2004, so the average growth rates of regional R&D spending might also be much smaller before the year 1998. However, due to the constraint of data, I have to use the average growth rates of period 1998-2004 by regions.

R&D spending is reported in nominal terms and is deflated to constant 2000 yuan by the ex-factory product price index.[5]

4.4.2 Other Economic Data

Other regional economic data are collected from the various issues of China Statistical Yearbook (NBS, 1999-2005).

Manufacturing employment, $EMPLOY_{it}$, is constructed as the sum of manufacturing staffs and workers from all independent accounting units.[6] This accounting excludes informal employment numbers in the manufacturing sectors. Local population, POP_{it}, is based on the annual sample survey conducted by regions. The presence of local universities, $UNIV_{it}$, is constructed by the total number of all kinds of colleges and universities by regions.

Regional gross domestic product, GDP_{it}, and gross industrial output of hi-tech development zones, $HITECH_{it}$, are reported in nominal terms and are deflated by the ex-factory product price index to 2000 constant yuan. For the regions with no hi-tech development zones, the output values are zero.[7]

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[5] R&D spending is also deflated by the fixed asset price index. The estimation results using the two different price indexes are almost identical to each other, thus only the results with R&D capital deflated by the ex-factory product price index are reported in this study.

[6] The independent accounting units exclude the enterprises below the town level. China's official employment data are more problematic, compared to the other official data. Detailed discussions on employment data are included in the next Chapter.

[7] There is no reporting for the hi-tech output of Xinjiang province in the year 2002, so the missing value of that year is filled by the linear extrapolation

Table 4.1 provides the summary statistics for this panel data set. Table 4.2 reports the correlation matrix of all the variables in the logarithms. The coefficients of correlation between patents and R&D variables are above 0.92, and most of control variables have relatively high correlations with patents. The coefficients of correlation between R&D variables and the other explanatory variables, such as GDP and UNIV, are also high, thus there might be a potential multicollinearity problem. The existence of multicollinearity is not unusual with provincial data as it is more likely that the independent variables may be affected by some common trends or provincial specific characteristics. This may result in inflated estimated variances and lead to less statistically significant coefficients. The estimated coefficients may also have the wrong signs or implausible magnitudes; however, the estimated parameters are still consistent and unbiased (Green, 2000). In general, the use of panel data in the analysis tends to reduce the problem of multicollinearity as more degree of freedom and regional-specific attributes are provided (Hsiao, 2003).

4.5 Main Estimation Results

In this section, the estimation results of linear regressions and the results of diagnostic tests are reported first. The estimation results of Poisson regressions and the results of robustness checks are reported next.

4.5.1 Linear Estimation Results

Table 4.3 presents the results of estimating equation 4.3 by linear regressions. The fixed effects estimators are listed in columns (1) and (2), while the random effects estimators are listed in columns (3) and (4). Results with the contemporaneous R&D spending are compared with those of R&D stocks.

Table 4.1 Summary Statistics of Variables in Levels (1998-2004)

Variables	Mean	Std. Dev.	Min.	Max.
PATENTS (P) (Patent applications)	922.65	1270.02	32	6847
RD (Contemporaneous R&D spending in 100 million constant 2000 yuans)	37.34	49.40	0.70	302.88
RDSTOCK (R&D stock with a 15% depreciation rate in 100 million constant 2000 yuans)	93.20	130.58	1.64	896.81
GDP (Gross domestic products in 100 million constant 2000 yuans)	3773.94	3075.88	220.89	15308.42
EMPLOY (Manufacturing staffs and workers in 10,000 persons)	106.07	72.04	6.48	315.32
POP (Populations in 10,000 persons)	4209.40	2552.82	503.00	9717.00
UNIV (Number of universities)	42.91	22.02	5.00	112.00
HITECH (Gross industrial output of hi-tech products in 100 million constant 2000 yuans)	394.20	540.49	0.00	3266.15

Table 4.2 Correlation Matrix of Variables in the Logarithms

Variables	PATENTS(P)	RD	RDSTOCK	GDP	EMPLOY	POP	UNIV	HITECH
PATENTS(P)	1.000							
RD	0.935	1.000						
RDSTOCK	0.920	0.982	1.000					
GDP	0.826	0.839	0.788	1.000				
EMPLOY	0.724	0.775	0.728	0.885	1.000			
POP	0.470	0.529	0.492	0.800	0.797	1.000		
UNIV	0.841	0.878	0.858	0.906	0.842	0.767	1.000	
HITECH	0.863	0.856	0.832	0.845	0.753	0.590	0.835	1.000

Table 4.3 Linear Estimation Results of the Patent Production Function at the Chinese Provincial Level (1998-2004); Equation 4.3

Dependent Variable: LOG PATENTS				
Independent Variables[a]	Fixed effects		Random effects	
	(1)	(2)	(3)	(4)
LOG RD	0.250**		0.344**	
	(0.001)		(0.000)	
LOG RDSTOCK		0.162**		0.311**
		(0.044)		(0.000)
LOG GDP	0.499	0.507	0.351**	0.474**
	(0.325)	(0.320)	(0.038)	(0.004)
LOG EMPLOY	0.765**	0.734**	0.449**	0.431**
	(0.001)	(0.001)	(0.014)	(0.020)
LOG POP	2.699**	2.693**	-0.479**	-0.499**
	(0.020)	(0.019)	(0.010)	(0.006)
LOG UNIV	-0.147	-0.207	-0.009	-0.059
	(0.358)	(0.178)	(0.941)	(0.647)
LOG HITECH	0.050	0.044	0.094**	0.095**
	(0.355)	(0.423)	(0.028)	(0.022)
TIME TREND	0.113*	0.134**	0.095**	0.086**
	(0.065)	(0.033)	(0.004)	(0.014)
Regional Dummies(omitted)				
Observations	210	210	210	210
R-squared[b]	0.784	0.778	0.901	0.902
Hausman specification test:				
Chi-square statistics[c]	100.110		95.420	
	(0.000)		(0.000)	

Notes: The P-values are reported in parentheses. All estimation results are based on the robust standard errors.* Significant at 0.10 level. ** Significant at 0.05 level.

[a]LOG RD refers to the contemporaneous R&D spending. LOG RDSTOCK is the R&D stock measure with a 15% depreciation rate. The estimation results with depreciation rates 10% and 5% are similar to those with a 15% depreciation rate.

[b]The R-squared is within R-squared for the fixed effects estimators and overall R-squared for the random effects estimators.

[c]The Chi-square statistics are the results of Hausman specification tests of comparing the fixed effects estimators and random effects estimators

First, it is clear that the patent production equations fit well at the Chinese provincial level of China. The fixed effects models have within R-squared around 0.78, while random effects models have overall R-squared around 0.90. The Hausman specification tests for comparing the fixed effects models against random effects models are reported in columns (1) and (2). The Chi-square statistics indicate that the null hypothesis of no systematic differences in the fixed effects estimators and random effects estimators is rejected for both contemporaneous R&D spending and R&D stocks. Therefore, in the subsequent analysis, only the results of fixed effects estimators are analyzed.

The elasticity of patents to R&D capital is 0.250 for the contemporaneous R&D spending and 0.156 for the R&D stocks. The higher elasticity to the contemporaneous R&D spending suggests that patents are more closely related to the contemporaneous R&D spending than to the R&D stocks: one-percent increase in the contemporaneous R&D spending in a region leads to a 0.25% increase in patent applications, controlling for other local factors. The estimated elasticities are in the range of those found in the literature but are much smaller compared to those of developed countries. The estimated elasticity of own R&D capital is around 0.45 to 0.58 for the European regions (Moreno et al., 2003).

The estimated coefficient of the time trend is 0.113 with contemporaneous R&D spending and 0.134 with R&D stock measure. These numbers imply that on average the growth rate of propensity to patent tends to increase by more than 11% each year.

Surprisingly, the coefficients of income (GDP) are not significant. I suspect that there might be certain collinearity between R&D capital and GDP as regions with higher GDP levels also tend to invest more in R&D spending. The manufacturing employment (EMPLOY) and population (POP) are both important and significant: (1) the elasticity to manufacturing employment is 0.765 with the contemporaneous R&D spending and 0.734 with the R&D stocks; (2) the elasticity to population is 2.699 with the contemporaneous R&D spending and 2.693 with the R&D stocks. These results confirm the importance of agglomeration economies and local market size on a region's patenting activity.

The coefficients of the presence of universities (UNIV) are also not significant. The wrong sign of the coefficients indicates a possible multicollinearity problem: the R&D capital includes the R&D investment of local universities, so regions with more universities will also tend to have higher R&D spending.

We expect that higher industrial outputs in the hi-tech development zones will have a positive impact on the patenting activity, as the companies in those hi-tech zones are expected to be more R&D-intensive. However, the coefficients of the policy variable (HIECH) are not only very small but also insignificant. It seems to indicate that hi-tech development zones are not important in stimulating innovation activities at the provincial level.

4.5.2 Diagnostic Test

For the models estimated in Table 4.3, I am mainly concerned with three econometric issues: endogenity problem, heteroscedasticity, and serial correlations.

Endogenity Problem. In general, there are three forms of endogenous problems associated with panel data: omitted important time-varying variables, measurement errors, and simultaneity between the dependent variable and one or more of input variables (Hsiao, 2002). In this analysis, the simultaneity between the dependent variable (PATENTS) and the explanatory variables is the main concern. Patents are an indicator of success in R&D investment, therefore the high number of patent applications might, in turn, feed back to more future R&D spending. To test the possible endogenity problem of R&D capital, an augmented regression test (Durbin-Wu-Hausman test) suggested by Davidson and MacKinnon (1993) is conducted. First, a regression on suspected endogenous variable is estimated as:

$$\begin{aligned}&\log(RD_{it}) = \gamma(t) + \varphi_i + \alpha_1 \log(PERSON_{it}) + \alpha_2 \log(GDP_{it}) + \alpha_3 \log(POP_{it}) + \\ &\alpha_4 \log(EMPLOY_{it}) + \alpha_5 \log(UNIV_{it}) + \alpha_6 \log(HITECH_{it}) + \mu_{it}\end{aligned} \quad (4.6)$$

The additional exogenous variable included is the R&D personnel by regions, $PERSON_{it}$. Next, the augmented regression is estimated as:

$$\begin{aligned}&\log(P_{it}) = a(t) + \alpha_i + \beta_1 \log(RD_{it}) + \beta_2 \log(GDP_{it}) + \beta_3 \log(POP_{it}) + \\ &\beta_4 \log(EMPLOY_{it}) + \beta_5 og(UNIV_{it}) + \beta_6 \log(HITECH_{it}) + \eta RESID_{it} + \varepsilon_{it}\end{aligned} \quad (4.7)$$

where $RESID_{it}$ is the residuals of regression 4.6. The t-statistics of the estimated coefficients of $RESID_{it}$ for both contemporaneous R&D spending and R&D stocks are reported in Table 4.4, which indicate that the coefficients are not significantly different from zero. Thus, we fail to reject the null hypothesis that R&D capital is exogenous and conclude that there is no simultaneity problem between patents and R&D capital.

Heteroscedasticity. The estimated coefficients reported in Table 4.3 are based on the robust standard errors, which are robust to the heteroscedasticity. Thus it is necessary to check whether there is a heteroscedasticity problem with the data, since estimations of coefficients based on the robust standard errors are consistent but are inefficient under the homoscedasticity.

To test for the heteroscedasticity across the panel data, I follow the procedures suggested by the Stata (www.stata.com/support). First, equation 4.3 is

Table 4.4 Results of Diagnostic Tests for the Linear Estimation Results of Equation 4.3

Endogenity test for R&D capital: Ho: R&D capital is exogenous (η=0).		
	t-statistics	P-value
RESID(RD)	0.421	0.674
RESID(RDSTOCK)	1.001	0.319
Heteroscedastic test (Likelihood Ratio test): Ho: There is no heteroscedasticity.		
	Chi-square	P-value
Model with RD	115.31	0.000
Model with RDSTOCK	115.39	0.000
Wooldridge test for autocorrelation in the panel data: Ho: There is no first-order autocorrelation.		
	F-test	P-value
Model with RD	14.678	0.006
Model with RDSTOCK	13.872	0.008

Notes: RESID(RD) refers to $RESID_{it}$ with the contemporaneous R&D spending in equation 4.7. RESID(RDSTOCK) refers to $RESID_{it}$ with R&D stocks of 15% depreciation rate in equation 4.7. Model with RD refers to the results listed in column (1) of Table 4.3. Model with RDSTOCK refers to the results listed in column (2) of Table 4.3.

fitted by the generalized least squares (GLS) with a panel-level heteroscedasticity (treated as the full model), then, the equation is fitted again without the heteroscedasticity (treated as the restricted model). Likelihood ratio tests are conducted for the two models and the test results are reported in Table 4.4. The reported P-values reject the null hypothesis of homoscedasticity and confirm that the robust standard errors should be used for the estimations.

Serial Correlation. Both the fixed effects estimators and random effects estimators assume that error terms are serially uncorrelated conditional on the individual unobservable effects, but the effects of unobserved variables may vary systematically over time. The reported estimators in Table 4.3 are based on the robust standard errors, which are robust to serial correlation but are inefficient under serially uncorrelated error terms. A simple F-test for autocorrelation in a panel-data model is introduced by Wooldridge (2002) and the result of this F-test is reported in Table 4.4. Again, the results of F-test reject the null hypothesis of no first order autocorrelation. Thus, using robust standard errors for the estimation is a suitable choice.

4.5.3 Poisson Estimation Results

In this subsection, the nature of the determinants of the patent production function is further explored by estimating equation 4.3 as Poisson regressions. In Table 4.5, the fixed effects estimators are reported in columns (1) and (2), while the random effects estimators are listed in columns (3) and (4).

Based on the Poisson estimation results, it is further confirmed that the patent production equation is well established at the Chinese provincial level: the McFadden's pseudo R-squared is around 0.82 for the fixed effects estimators and about 0.81 for the random effects estimators.

Table 4.5 Poisson Estimation Results of the Patent Production Function at the Chinese Provincial Level (1998-2004); Equation 4.3

Dependent variable: PATENTS				
Independent Variables[a]	Fixed effects		Random effects	
	(1)	(2)	(3)	(4)
LOG RD	0.398 **		0.396 **	
	(0.000)		(0.000)	
LOG RD15		0.458 **		0.455 **
		(0.000)		(0.000)
LOG GDP	0.949 **	0.952 **	0.901 **	0.906 **
	(0.000)	(0.000)	(0.000)	(0.000)
LOG EMPLOY	0.309 **	0.162 **	0.314 **	0.168 **
	(0.000)	(0.000)	(0.000)	(0.000)
LOG POP	2.082 **	2.481 **	1.989 **	2.389 **
	(0.000)	(0.000)	(0.000)	(0.000)
LOG UNIV	0.071 **	-0.093 **	0.062 **	-0.100 **
	(0.010)	(0.001)	(0.025)	(0.000)
LOG HITECH	0.142 **	0.112 **	0.138 **	0.108 **
	(0.000)	(0.000)	(0.000)	(0.000)
TIME TREND	-0.012	-0.026 **	-0.003	-0.017 *
	(0.220)	(0.008)	(0.778)	(0.083)
R-squared[b]	0.821	0.822	0.809	0.810
Log likelihood	-4858.055	-4841.557	-5186.402	-5170.976
Observations	210	210	210	210
Hausman specification test:				
Chi-square statistics[c]	118.210	38.890		
	(0.000)	(0.000)		

Notes: The P-values are reported in parentheses. All estimation results are based on the robust standard errors. * Significant at 0.10 level. ** Significant at 0.05 level.

[a] LOG RD refers to the contemporaneous R&D spending. LOG RDSTOCK refers to the R&D stocks with a 15% depreciation rate. The estimation results with depreciation rates 10% and 5% are similar to those with a 15% depreciation rate.

[b]The R-squared refers to the McFadden's pseudo R-squared, computed as R^2 = (1-log likelihood of estimated model/log likelihood of restricted model)

[c]The Chi-square statistics are the results of the Hauseman specification test for comparing the fixed effects models and random effects models.

The coefficients of fixed effects estimators and random effects estimators of Poisson regressions are much closer. However, the results of Hausman tests reported in Table 4.5 reject the random effects estimators and I will focus on the results of fixed effects estimators only in the subsequent discussions.

Compared to those of linear regressions, the Poisson estimates of the coefficients of R&D variables are much higher: the elasticity coefficient of R&D capital is 0.396 with the contemporaneous R&D spending and 0.458 with the R&D stock. Turning to the control variables, the effects of agglomeration economies (EMPLOY) and market size (POP) on the local patenting activity are both confirmed. In contrast to those of linear estimations, the income level (GDP) and hi-tech policy (HITECH) are two additional important determinants: the elasticity of patents to GDP is 0.95, while the elasticity of patents to HITECH is 0.142 with the contemporaneous R&D spending and is 0.112 with the R&D stock.

Again the estimated coefficients of local universities (UNIV) indicate the multicollinearity problem: the coefficients of time trend in both models are negative. This is at odds with the general findings in the patent studies that the propensity to patent tends to increase over time. It is suspected that changes in the propensity to patent are probably not linear over the years, so a single time trend might not be a proper choice.[8] It is also likely that the trend is fully accounted for by trends in the other independent variables.

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[8] The over-dispersion tests suggested by Cameron and Trivedi (1990) are performed. It is found that there is an overdispersion problem with the Poisson models. I estimate the count model with Negative Binominal regressions, but in these models no meaningful relationship of the patent-R&D can be established. The results here are not uncommon: most studies found that the estimation results of patent production equations with the Negative Binominal Regressions are much less satisfactory (Jefferson et al., 2003). Therefore, the results from the Poisson models are still reported here.

4.5.4 Robustness Check

I run two alternative models as robustness checks for the estimation results of Tables 4.3 and 4.5: a three-year moving average model and a one-period-lagged R&D spending model. Estimating a three-year moving average model helps to mitigate short-term volatilities of patent applications, while using lagged R&D spending can eliminate possible endogenity problems.

Table 4.6 reports the fixed effects estimation results of a three-year moving average model for both liner regressions and Poisson regressions. The estimated coefficients are in general similar to those reported in Tables 4.3 and 4.5. In comparisons, the overall fit of the moving average model is better with higher R-squared values and increased precision of the estimated coefficients. The coefficients of contemporaneous R&D spending are much closer between the linear regressions and Poisson regressions, but the effect of time trend declines for the linear regressions as short-term volatilities are eliminated.

Table 4.7 reports the fixed effects estimation results of a lagged R&D spending model for both linear regressions and Poisson regressions. Similarly, we find that the results are very close to those with R&D stocks reported in Tables 4.3 and 4.5. Based upon these results, it can be concluded that the estimation results reported here are both consistent and robust.

4.5.5 Summary

The analysis in this section confirms that patent applications are good indicators of innovation output as the patents-R&D relationship is highly significant at the Chinese provincial level. The estimation results of linear regressions and Poisson regressions are similar in general: (1) both the contemporaneous R&D spending and

Table 4.6 Estimation Results of the Patent Production Function at the Chinese Provincial Level with Three-year Moving Average (1998-2004); Equation 4.3

	Robustness Check			
Dependent Variable:	LOG PATENTS		PATENTS	
	Linear Regressions		Poisson regressions	
Independent Variables[a]	Fixed effects		Fixed effects	
	(1)	(2)	(3)	(4)
LOG RD	0.349 **		0.436 **	
	(0.000)		(0.000)	
LOG RD15		0.179 **		0.333 **
		(0.009)		(0.000)
LOG GDP	0.879 *	1.049 **	0.845 **	1.032 **
	(0.054)	(0.018)	(0.000)	(0.000)
LOG EMPLOY	0.856 **	0.805 **	0.532 **	0.356 **
	(0.000)	(0.000)	(0.000)	(0.000)
LOG POP	2.503 **	2.308 *	1.889 **	2.090 **
	(0.039)	(0.069)	(0.000)	(0.000)
LOG UNIV	-0.129	-0.215	0.236 **	0.134 **
	(0.403)	(0.176)	(0.000)	(0.000)
LOG HITECH	0.084	0.063	0.210 **	0.198 **
	(0.185)	(0.328)	(0.000)	(0.000)
TIME TREND	0.050	0.076 *	-0.017 **	-0.020 **
	(0.274)	(0.092)	(0.035)	(0.012)
R-squared[b]	0.847	0.839	0.908	0.906
Observations	210	210	210	210
Hausman specification test:				
Chi-square statistics[c]	184.360	61.600	26.660	27.450
	(0.000)	(0.000)	(0.000)	(0.000)

Notes: The P-values are reported in parentheses. All estimation results are based on the robust standard errors. * Significant at 0.10 level. ** Significant at 0.05 level.

[a]LOG RD refers to the contemporaneous R&D spending. LOG RDSTOCK is the R&D stock measure with a 15% depreciation rate.

[b]The R-squared of Poisson regression refers to the McFadden's pseudo R-squared, computed as $R^2 =$ (1-log likelihood of estimated model/log likelihood of restricted model).

[c]The Chi-square statistics are results of the Hausman specification test for comparing fixed effects models and random effects models.

Table 4.7 **Estimation Results of the Patent Production Function at the Chinese Provincial Level with One-period-lagged R&D Spending (1998-2004); Equation 4.3**

Robustness Check		
Dependent Variables:	LOG PATENTS	PATENTS
	Linear Regressions	Poisson regressions
Independent Variables[a]	Fixed effects	Fixed effects
	(1)	(3)
LOG RD (lagged)	0.149 *	0.369 **
	(0.087)	(0.000)
LOG GDP	0.413	1.146 **
	(0.460)	(0.000)
LOG EMPLOY	0.601 **	0.305 **
	(0.005)	(0.000)
LOG POP	1.617	1.400 **
	(0.150)	(0.000)
LOG UNIV	-0.174	-0.088 **
	(0.334)	(0.005)
LOG HITECH	0.062	0.111 **
	(0.303)	(0.000)
TIME TREND	0.144 **	-0.012
	(0.048)	(0.272)
R-squared[b]	0.751	0.855
Observations	210	210
Hausman specification test:		
Chi-square statisitcs[c]	8.890	19.390
	(0.260)	(0.007)

Notes: The P-values are reported in parentheses. All estimation results are based on the robust standard errors. * Significant at 0.10 level. ** Significant at 0.05 level.

[a]LOG RD (lagged) refers to the one-period lagged R&D spending.

[b]The R-squared of Poisson regression refers to the McFadden's pseudo R-squared, computed as R^2 = (1-log likelihood of estimated model/log likelihood of restricted model).

[c]The Chi-square statistics are the results of the Hausman specification test for comparing fixed effects models and random effects models.

R&D stocks seem to be good measures for R&D capital; (2) agglomeration economies and market size are the two most important internal factors for patent applications; (3) the regional income level is a potentially important control variable; and (4) the role of local universities is unclear due to the multicollinearity problem. The effects of hi-tech policy seem to be positive, based on the Poisson estimation results.[9]

The next step in the investigation is to estimate the effects of locations and the effects of China's WTO accession on the patenting activity.

4.6 Alternative Specifications

The analysis of our main estimation results above shows that equation 4.3 is appropriate for estimating the patents-R&D relationship at the Chinese provincial level. Based upon that, two important issues, specific to China, are further investigated: the regional variations in innovation activity and the effect of China's WTO accession in 2001 on its patenting activity. Alternative specifications are developed and estimated. The estimation results of both linear regressions and Poisson regressions are reported in the followings.

4.6.1 The Effects of Locations

The analysis in Chapter III demonstrates that there are severe regional disparities in the patenting-R&D activities among the three-macro regions. Provinces located in the eastern region tend to invest more in R&D spending and may have higher propensities to patent, due to the existences of more R&D-based domestic

[9] Equation 4.3 is also estimated with patent intensity form, using patents per capita as the dependent variable. The estimation results are similar to those reported in Tables 4.3 and 4.5.

companies, top research institutes and universities, and the competition from foreign firms.

As discussed in Chapter 3, foreign firms have been patenting aggressively since 1993. Furthermore, more foreign firms from industrialized countries have moved their R&D centers to China in the recent past five years. Results in Chapter 3 also point out that there is a substantial increase in both R&D spending and patenting activity of domestic firms since 2000. Naturally, questions are raised as to whether this remarkable surge in domestic innovative activity is somehow related to those foreign firms and their R&D centers. Intensive innovative activities of foreign firms are expected to have spillover effects on domestic firms' R&D and patenting activity. To estimate the explicit spillover effects of foreign firms' innovative activity on domestic patenting activity requires detailed data on foreign firms' R&D spending, patenting activity and/or the number of foreign firms at the provincial level. All these data are difficult to obtain. However, most foreign firms are located in the eastern macro region, in particular, R&D centers of major multinational companies are all located in three main economic centers: Beijing, Shanghai and Guangdong. Therefore the effects of foreign firms on local patenting activity at the provincial level can be partially accounted for by the analysis of the macro-regions, though the specific spillover effects of foreign firms on domestic firms cannot be differentiated from the overall effects of macro-regions.

To estimate the effects of locations, the model specifications of equation 4.3 need to be modified to provide the separate treatment of three macro-regions in estimating the coefficients of R&D capital and the propensity to patent.

4.6.1.1 Elasticity of Patents to R&D Capital

To estimate separate elasticity coefficients of R&D capital, three location dummies, EAST, CENTRAL, and WEST, are created to represent the three macro-regions. Further, these three location dummies are interacted with R&D capital. The modified specification is:

$$\log(P_{it}) = a(t) + \alpha_i + \sum_{j=1}^{3} \beta_j \log(RD_{it}) + \beta_4 \log(GDP_{it}) + \beta_5 \log(POP_{it}) + \beta_6 \log(EMPLOY_{it}) + \beta_7 \log(UNIV_{it}) + \beta_8 \log(HITECH_{it}) + \varepsilon_{it}, \tag{4.8}$$

where β_j is the elasticity of patents to R&D capital in the macro-region j. The estimation results of equation 4.8 are presented in columns (1) and (2) of Table 4.8. To mitigate the multicollinearity problem caused by the variable UNIV, restricted models without UNIV are estimated for the linear regressions.[10] For the linear estimations, the differences in the patent-R&D relationships among the three macro-regions are enormous: the elasticity of patents to the contemporaneous R&D spending in the eastern region is 0.315; the same elasticity in the central region is not only much smaller but insignificant; more puzzling, this elasticity is negative and significant at 0.10 level for the western region. The estimated elasticities of patents to contemporaneous R&D spending in the central and the western region are unexpected: it implies that there is no valid relationship between R&D investment and patent applications in these two macro-regions.

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[10] The F-tests between the restricted models without the variable UNIV and the full models indicate that there is no loss of fit in the restricted models for the linear regressions, but there is significant loss of fit for the Poisson regressions. Therefore, the variable UNIV is excluded only in the linear regressions reported in the following analysis.

For the Poisson estimations, the results are similar but the differences among the three macro-regions are smaller: the elasticity of patents to contemporaneous R&D spending in the eastern region is 0.390, while the same elasticity is 0.218 in the central region and 0.07 in the western region.

Combining the results of the linear regressions and Poisson regressions, we can conclude that estimating separated elasticities of patents to R&D capital is appropriate. The patents-R&D relationship is not established in the western region and is weak in the central region. In contrast, the elasticity of patents to R&D captial in the eastern region is comparable to those of developed countries.

4.6.1.2 Propensity to Patent

To estimate the separate changing rates of propensity to patent in the three macro-regions, the three location dummies are interacted with the time trend. The modified specification is:

$$\begin{aligned}\log(P_{it}) = \sum_{j=1}^{3} a_j(t) + \alpha_i + \beta_1 \log(RD_{it}) + \beta_2 \log(GDP_{it}) + \beta_3 \log(POP_{it}) + \\ \beta_4 \log(EMPLOY_{it}) + \beta_5 \log(UNIV_{it}) + \beta_6 \log(HITECH_{it}) + \varepsilon_{it},\end{aligned} \tag{4.9}$$

where a_j is the changing rate of propensity to patent in the macro-region j. Equation 4.9 is estimated by both linear regressions and Poisson regressions. The results are presented in columns (3) and (4) of Table 4.8.

The estimates of the linear regressions indicate that the changing rate of propensity to patent is different for the three macro-regions for the years 1998-2004: the coefficient of time trend is 0.213 in the eastern region and 0.137 in the central region. In contrast, the coefficient of time tend in the western region is not only smaller (0.091) but also insignificant at the 0.10 level. The differences among the three macro-

Table 4.8 Effects of Locations on Estimations of the Patent Production Function at the Chinese Provincial Level (1998-2004); Equations 4.8 and 4.9

Dependent Variable:	LOG PATENTS	PATENTS	LOG PATENTS	PATENTS
Independent Variables	Linear	Poisson	Linear	Poisson
	(1)	(2)	(3)	(4)
Log RD			0.100	0.336 **
			(0.219)	(0.000)
LOG GDP	0.487	0.721 **	0.244	0.708 **
	(0.312)	(0.000)	(0.607)	(0.000)
LOG EMPLOY	0.347	0.193 **	0.341	0.207 **
	(0.145)	(0.000)	(0.171)	(0.000)
LOG POP	2.140 **	1.786 **	2.110 **	1.810 **
	(0.046)	(0.000)	(0.045)	(0.000)
LOG UNIV		0.098 **		0.112 **
		(0.000)		(0.000)
LOG HITECH	0.017	0.141 **	0.027	0.143 **
	(0.704)	(0.000)	(0.560)	(0.000)
TIME TREND	0.130 **	0.025 **		
	(0.025)	(0.012)		
LOG RD_EAST	0.315 **	0.390 **		
	(0.000)	(0.000)		
LOG RD_CENTRAL	0.076	0.218 **		
	(0.383)	(0.000)		
LOG RD_WEST	-0.197 *	0.070 **		
	(0.107)	(0.043)		
TREND_EAST			0.213 **	0.037 **
			(0.001)	(0.001)
TREND_CENTRAL			0.137 **	0.002
			(0.016)	(0.815)
TREND_WEST			0.093	-0.008
			(0.160)	(0.443)
R-squared	0.810	0.825	0.809	0.823
Observations	210	210	210	210

Notes: The P-values are reported in parentheses. All estimations are based on the robust standard errors. * Significant at 0.10 level. ** Significant at 0.05 level. LOG RD is the contemporaneous R&D spending. The estimations using R&D stocks are similar to those reported here. LOG RD_EAST (CENTRAL and WEST) is the interaction term between LOG RD and the location dummy EAST (CENTRAL and WEST). TREND_EAST (CENTRAL and WEST) is the interaction term between the time trend and the location dummy EAST (CENTRAL and WEST). The R-squared of Poisson regression refers to the McFadden's pseudo R-squared, computed as: R^2 = (1-log likelihood of estimated model/log likelihood of restricted model).

regions are confirmed by the Poisson estimations, though with much smaller coefficients of time trend. Based on these results, we can conclude that the propensity to patent in the eastern region increases more rapidly compared to that of the central region, while there is no change in the propensity to patent in the western region.

4.6.2 The Effects of the Year Dummies

The analysis in Chapter III points out that the average growth rate of domestic patent applications is about 30% for the period 2000-04, which is significantly higher than those in the pervious periods. This rapid growth of patent applications might be related to China's WTO accession in 2001, that is, the propensity to patent might change substantially around and after the year 2001. To test the effects of China's WTO accession, a single time trend is replaced with a set of year dummies in equation 4.3, and the models are re-estimated. The results are presented in Table 4.9. The linear estimation results are listed in column (2) and Poisson estimation results are listed in column (4). For comparisons, the estimation results of equation 4.3 with a single time trend are also listed in columns (1) and (3).

For the linear regression, the coefficients of year dummies after the year 2001 are substantially large: it is 0.384 for the year 2001, 0.614 for the year 2002, and 0.786 for the year 2003. The effect of China's WTO accession is evident: the growth rate of the propensity to patent increases more than 60% in the year 2002, compared to the previous year.

The estimated coefficients of year dummies from the Poisson regression provide the similar evidence: 0.159 for the year 2001 and 0.249 for the year 2002,

Table 4.9 Effects of the Year Dummies on Estimations of the Patent Production Function at the Chinese Provincial Level (1998-2004); Equation 4.3 with the Year Dummies

Dependent Variable:	LOG PATENTS		PATENTS	
	Linear Regressions		Poisson regressions	
Independent Variables	Fixed effects		Fixed effects	
	(1)	(2)	(3)	(4)
LOG RD	0.250 **	0.125 *	0.398 **	0.097 **
	(0.001)	(0.091)	(0.000)	(0.000)
LOG GDP	0.499	0.958 *	0.949 **	1.533 **
	(0.325)	(0.079)	(0.000)	(0.000)
LOG EMPLOY	0.765	1.033 **	0.309 **	0.629 **
	(0.001)	(0.000)	(0.000)	(0.000)
LOG POP	2.699 **	2.162 *	2.082 **	1.359 **
	(0.020)	(0.053)	(0.000)	(0.000)
Log UNIV	-0.147		0.071 **	0.193 **
	(0.358)		(0.010)	(0.000)
LOG HITECH	0.050	0.026	0.142 **	0.108 **
	(0.355)	(0.593)	(0.000)	(0.000)
TIME Trend	0.113 *		-0.012	
	(0.065)		(0.220)	
Year Dummy				
1999		0.089		0.002
		(0.274)		(0.921)
2000		0.308 **		0.245 **
		(0.006)		(0.000)
2001		0.384 **		0.159 **
		(0.023)		(0.000)
2002		0.614 **		0.249 **
		(0.008)		(0.000)
2003		0.786 **		0.318 **
		(0.005)		(0.000)
2004		0.578 *		0.009
		(0.103)		(0.879)
R-squared	0.784	0.822	0.821	0.865
Observations	210	210	210	210

Notes: The P-values are reported in parentheses. All estimations are based on the robust standard errors. * Significant at 0.10 level. ** Significant at 0.05 level. LOG RD refers to the contemporaneous R&D spending. The estimations with the R&D stocks are similar to those reported here. The R-squared of Poisson regressions refers to the McFadden's pseudo R-squared, computed as R^2 = (1-log likelihood of estimated model/log likelihood of restricted model).

which implies a 56% increase in the growth rate of propensity to patent in the year 2002, compared to the previous year.

Compared to the estimation results with a single time trend reported in columns (1) and (3), the overall fits of these models are improved with higher R-squared values. In addition, the estimated coefficients of R&D capital are closer in magnitude between the linear regressions and the Poisson regressions, though the estimated elasticities drop substantially, especially for the Poisson regression. The drop in the estimated coefficients of R&D capital indicates that changes in the propensity to patent are not fully captured by a single time trend, thus some of the effects are picked up by R&D capital. Considering the substantial impact of China's WTO accession on domestic patent applications, the estimations with year dummies are more appropriate.

4.7 The Effects of Knowledge Spillovers

The theoretical and empirical literatures have pointed out that knowledge production in a region not only depends on its own research efforts but also on the knowledge stocks available in the whole economy. Consequently, knowledge generated in one region may spill over and help knowledge generation in the other regions. To estimate such effects, the basic specifications given in equation 4.3 need to be modified to introduce an additional spillover variable:

$$\begin{aligned} &\log(P_{it}) = a(t) + \alpha_i + \beta_1 \log(RD_{it}) + \beta_2 \log(GDP_{it}) + \beta_3 \log(POP_{it}) + \\ &\beta_4 \log(EMPLOY_{it}) + \beta_5 \log(UNIV_{it}) + \beta_6 \log(HITECH_{it}) + \beta_7 W \log(S_{it}) + \varepsilon_{it}, \end{aligned} \quad (4.10)$$

where W is the weight matrix; and S_{it} is the knowledge stock available in the whole economy except regions i at time t. The spillover variable is represent by $W\log(S_{it})$, so the spillover variable is a weighted measure of knowledge available in the other regions.

Two weighted matrixes are constructed: (1) a contiguity-weighted matrix in which its elements are 1 if two regions are bordered and 0 otherwise; and (2) a gravity-weighted one in which its elements are the inverse of the square of bilateral distance between the two regions. The bilateral distance is defined as the distance between the capital cities of two provinces. To remove the scale effect from the unit measure, the distances are normalized by setting the largest bilateral distance to one.

The knowledge stock available in the other regions, S_{it}, is proxied by two measures: (1) R&D capital in the other regions and (2) patent stocks in the other regions. The estimation results of R&D spillovers are presented first, followed by those of patent stock spillovers.

4.7.1 Spillovers of R&D Activity

Equation 4.10 is first estimated using the contemporaneous R&D spending in the other regions as the source knowledge spillovers.[11] Table 4.10 presents the estimation results. The linear estimation results are listed in columns (1) and (2) and the Poisson regression results are listed in columns (3) and (4).

For the linear estimations, there is no evidence of spillovers from R&D activity in the other regions, either with the contiguity weighted or with gravity-weighted spillover variable. In contrast, the Poisson estimation results indicate that there are significant spillover effects from R&D activity in the other regions: the elasticity coefficient of spillover variable is 0.114 with the contiguity-weighted and 0.080 with the gravity-weighted. Compared to the elasticity coefficients of own R&D

[11] R&D stocks in the other regions are also used as the knowledge spillover variable; however, the coefficients of the spillover variables are all insignificant for both linear estimations and Poisson estimations. Thus the results are not reported.

capital, the magnitudes of the spillover effects are smaller, particularly with the gravity-weighted version. We notice that elasticity coefficients of own R&D spending and other control variables are similar to those reported in Tables 4.3 and 4.5. It seems to further indicate that basic results reported in Table 4.3 and 4.5 are consistent and robust.

4.7.2 Spillovers of Patenting Activity

Alternatively, the patent stocks in the other regions can be used as a proxy for innovative knowledge available in the whole economy. Like R&D stocks, the recent patents provide greater spillovers than the patents produced many years earlier, thus a social depreciation rate should be applied to the patent stocks. The patent stocks are constructed by the same perpetual inventory model, as the one described earlier for the R&D stocks:

$$PS_{it} = (1-\delta)PS_{i,t-1}+P_{i,t-1}, \qquad (4.11)$$

where PS_{it} is the patent stocks in the region i at time t; $(1-\delta)PS_{i,t-1}$ is the depreciated value of the old patent stocks, and $P_{i,t-1}$ is the patent applications in the previous period. Three depreciation rates are applied: 0%, 7% and 12%, respectively. The initial patent stock, $PS_{i,98}$, is constructed as:

$$PS_{i,98} = P_{i,98} /(\delta+\gamma_i), \qquad (4.12)$$

where γ_i is the average growth rate of patent applications in the region i for the period 1985-1997.

Equation 4.10 is then estimated using the patent stocks in the other regions as the source of spillovers. The estimation results are presented in Table 4.11. The

Table 4.10 Effects of R&D Spillovers on Estimations of the Patent Production Function at the Chinese Provincial Level (1998-2004); Equation 4.10

Dependent Variable:	LOG PATENTS		PATENTS	
	Linear Regressions		Poisson regressions	
Independent Variables[a]	Fixed effects		Fixed effects	
	(1)	(2)	(3)	(4)
LOG RD	0.236 **	0.231 **	0.353 **	0.379 **
	(0.006)	(0.006)	(0.000)	(0.000)
LOG GDP	0.528	0.565	0.995 **	0.980 **
	(0.293)	(0.252)	(0.000)	(0.000)
LOG EMPLOY	0.777 **	0.781 **	0.314 **	0.310 **
	(0.001)	(0.001)	(0.000)	(0.000)
LOG POP	2.679 **	2.677 **	2.052 **	2.077 **
	(0.021)	(0.023)	(0.000)	(0.000)
LOG UNIV			0.098 **	0.081 **
			(0.032)	(0.004)
LOG HITECH	0.050	0.050	0.143 **	0.139 **
	(0.352)	(0.350)	(0.000)	(0.000)
TIME TREND	0.097	0.079	-0.035 **	-0.029 **
	(0.159)	(0.281)	(0.001)	(0.016)
Spillover Variables				
LOG SPILLOVER (RD)	0.066		0.114 **	
(Contiguity-weighted)	(0.638)		(0.000)	
LOG SPILLOVER (RD)		0.131		0.080 **
(Gravity weighted)		(0.503)		(0.018)
R-Squared[b]	0.784	0.785	0.822	0.821
Observations	210	210	210	210

Notes: The P-values are reported in parentheses. All estimations are based on the robust standard errors. ** Significant at 0.05 level.

[a]LOG RD refers to the contemporaneous R&D spending . The estimations using R&D stocks and one-period-lagged R&D spending are similar to those reported here. LOG SPILLOVER (RD) refers to the knowledge stocks available in the other regions, proxied by the contemporaneous R&D spending in the other regions.

[b]The R-squared of Poisson regression refers to the McFadden's pseudo R-squared, computed as R^2 = (1-log likelihood of estimated model/log likelihood of restricted model).

Table 4.11 Effects of Patent Spillovers on Estimations of the Patent Production Function at the Chinese Provincial Level (1998-2004); Equation 4.10

Dependent Variable:	LOG PATENTS		PATENTS	
	Linear Regressions		Poisson regressions	
Independent Variables[a]	Fixed effects		Fixed effects	
	(1)	(2)	(3)	(4)
LOG RD	0.263 **	0.263 **	0.404 **	0.400 **
	0.000	(0.001)	(0.000)	(0.000)
LOG GDP	0.320	0.235	1.046 **	1.215 **
	(0.511)	(0.635)	(0.000)	(0.000)
LOG EMPLOY	0.687 **	0.679 **	0.326 **	0.355 **
	(0.002)	(0.002)	(0.000)	(0.000)
LOG POP	2.924 **	2.884 **	2.022 **	2.064 **
	(0.016)	(0.020)	(0.000)	(0.000)
LOG UNIV			0.059 **	0.043
			(0.032)	(0.120)
LOG HITECH	0.043	0.048	0.133 **	0.099 **
	(0.416)	(0.350)	(0.000)	(0.000)
TIME TREND	0.067	0.028	-0.003	0.039 **
	(0.264)	(0.689)	(0.756)	(0.000)
Spillover Variables				
LOG SPILLOVER (PATENTS)	0.255 *		-0.097 **	
(Contiguity-weighted)	(0.095)		(0.000)	
LOG SPILLOVER (PATENTS)		0.485 *		-0.339 **
(Gravity weighted)		(0.075)		(0.000)
R-Squared[b]	0.786	0.787	0.821	0.823
Observations	210	210	210	210

Notes: The P-values are reported in parentheses. All estimations are based on the robust standard errors. * Significant at 0.10 level. ** Significant at 0.05 level.

[a] LOG RD refers to the contemporaneous R&D spending . The estimations using R&D stocks and one-period-lagged R&D spending are similar to those reported here. LOG SPILLOVER (PATENTS) refers to the knowledge stocks available in the other regions, proxied by the patent stocks with a 7% depreciation rate in the other regions. The results are similar with patent stocks using a 0% depreciation rate and a 12 % depreciation rate.

[b] The R-squared of Poisson regression refers to the McFadden's pseudo R-squared, computed as R^2 = (1-log likelihood of estimated model/log likelihood of restricted model).

linear estimation results are listed in columns (1) and (2) and the Poisson regression results are listed in columns (3) and (4).

For the linear estimations, the results indicate that there are significantly positive inter-regional spillover effects from patent stocks: the elasticity coefficient of the patent spillover variable is 0.255 with the contiguity-weighted and 0.485 with the gravity-weighted. The magnitude of patent knowledge spillovers is comparable to the own elasticity coefficient of R&D capital in the contiguity-weighted model and is even larger in the gravity-weighted version. The linear estimation results suggest that the inter-regional knowledge spillovers are more powerful when the patent stocks are the sources of knowledge spillovers.

In contrast, for the Poisson regressions the estimated elasticities of the spillover variables are negative and significant. The unexpected negative sign of the spillover variables may be caused by some multicollinearities between the spillover variables and the other control variables and/or caused by the misspecification of the model, such as omitted variables. In the case of possible misspecification, the estimated coefficients are biased. The unexpected estimation results with the Poisson regressions indicate that the results from the Poisson regressions are not as robust as those of the linear regressions. More investigation of this issue is needed in the future.

4.7.3 Summary

In this section, the effects of spillovers on patent applications are estimated by using both R&D activity and patenting activity in the other regions as the sources of knowledge spillovers. The linear estimations point out that there are powerful spillover effects from the patent stocks available in the other regions, while the Poisson estimations suggest that there are positive spillover effects from the contemporaneous

R&D spending in the other regions, though with smaller magnitudes compared to those of patenting activities in the other regions. These two results seem to imply that there is a positive and significant inter-regional innovative knowledge spillover effect on the patenting activities in China.

This analysis finds that the inter-regional spillover effects on patents are more powerful from patenting activities in the other regions than R&D activities performed in the other regions. One reason might be that R&D activities are an input measurement and some of the R&D activities are not directly related to innovations. On the other hand, patents are an output measurement and thus indicate the direct technological change in the near future. Patents also reflect the success of R&D investment; therefore, the spillover effects on outputs (patents) are more evident as firms are more likely to respond to the success of R&D activities.

The estimation results of linear regressions and Poisson regressions on the spillover effects are no longer similar, compared to the other estimation results in this Chapter. This suggests that the estimation results of spillover effects are less robust and the model specifications, the construction of the spillover variables, and the aggregation levels need to be further refined in the future.

4.8 Conclusion

In this chapter, the patent production equations are applied to the Chinese provincial data. The equations are estimated by both linear and Poisson regressions. The estimations results suggest that the patents-R&D relationship holds well for China's provinces. This analysis confirms that agglomeration economies and local market demands are the two important internal factors for patenting activity at the provincial level.

The estimations of separate coefficients of R&D capital and time trend for the three macro-regions provide the solid empirical evidence that the regional disparity is severe in both the patents-R&D relationship and the propensity to patent. The econometric evidence here supports the findings of Chapter III with respect to the regional variations in technological development. The eastern macro region is not only has a much higher elasticity of patents to R&D capital but also has a much higher propensity to patent. On the other hand, the patents-R&D relationship is not yet well established in the western macro region.

This analysis also provides some empirical evidence that China's WTO accession in the 2001 has had significantly effects on domestic patent applications. The results of spillover effects point out that the inter-regional knowledge spillovers are positive and important for regional patenting activity.

Chapter 5

THE RETURN TO R&D

5.1 Introduction

The estimation results in Chapter IV point out the close relationship between the R&D investment and innovation activities at the provincial level of China. However, not all the innovations are utilized and commercialized. In China, the percentage of patents being commercialized is probably even lower, as the linkage between the generation of new technology and its commercialization is still weak. Studies on developed countries has pointed out that the adoption and diffusion of technology are the major factors leading to the possible divergence among advanced countries, given each country's difference in the ability to develop innovations (Archibugi and Pianta, 1994). Thus it is particular valuable to examine the return to R&D investment, that is, the contribution of technology to economic growth.

To estimate the return to R&D investment, a value-added Cobb-Douglas knowledge production function is estimated at the provincial level. The measure used to reflect the effect of technology (patenting activity) is the valued-added industrial output. A balanced panel data of 30 provinces for the period 1991-2004 is collected. The estimation results indicate that technology plays a positive role in China's industry growth, but the contribution from technology is far too small.

Next, the effects of inter-regional innovative-knowledge spillovers on value added industrial output are further examined. Econometric evidence for the inter-regional knowledge spillovers is found, however, the magnitude of spillover effects is smaller than that of the own technology effect.

Section 5.2 describes the basic model specifications. Section 5.3 describes data sources and problems. Section 5.4 presents the preliminary results of estimated regressions. Section 5.5 describes the alternative model specifications and the estimation results. Section 5.6 presents the impact of knowledge spillovers on value-added industrial output.

5.2 Model Specifications

The standard knowledge production function introduced by Griliches (1980) is estimated in this Chapter. Assuming a conventional Cobb-Douglas production function, the basic model specification is:

$$\log(Y_{it}) = \alpha_i + a(t) + \beta_1 \log(C_{it}) + \beta_2 \log(L_{it}) + \beta_3 \log(P_{it}) + \varepsilon_{it}, \qquad (5.1)$$

where Y_{it} is the value added industrial output in the region i at time t; a is the rate of exogenous technical progress; C_{it} and L_{it} are capital and labor inputs in the region i at time t; P_{it} is the technology input in the region i at time t and is proxied by the contemporaneous patent applications and patent stocks; and the effects of regional specific characteristics are controlled by α_i.

In this equation the elasticity of valued added output to technology is measured by the coefficient β_3.

5.3 Data Sources and Problems

Fourteen years of industrial data by provinces (1991-2004) are available and are collected directly from the various issues of China Statistical Yearbook (NBS, 1992-2005). Those data are based on the reporting of all the independent accounting units by regions.

Output, $Y_{it,}$ is constructed by value-added industrial output by regions. Capital input, C_{it}, is constructed by regional total assets. Compared to the fixed assets, the total assets are a more proper measurement for capital input as they are the net values of circulated funds plus the fixed assets. Both value-added industrial output and total assets are reported in nominal terms and are deflated to the constant 2000 yuan by the ex-factory product price index.

It is very difficult to find a proper measure of labor input, L_{it}, since no effective working hours are reported in the yearbooks. I have to use the official manufacturing employees (staffs and workers) for labor input, though China's employment data are considered to be deeply flawed (Banister, 2005; Wu, 2001), compared to the other official data.[1] Before the industrial restructuring of 1994-1999, ineffective working hours were common in the state-owned enterprises (SOE), due to the shirking, lack of jobs, shortage of energy and/or political reasons, thus the manufacturing employment figures were highly inflated. Since 1995 there have been massive lay-offs in the SOEs: the total manufacturing employment (staffs and workers) has declined from 66.1 millions in 1995 to 37.5 millions in 2002. Figure 5.1 presents the total manufacturing employment (staffs and workers) along with the value-added industrial output for the years 1991–2004. The structure break in the manufacturing

[1] I have tried to adjust the employment data with human capital. Data on the education levels of employees are only available from 1996 to 2000, so the education levels of employees for the years 1991-1995 and for the years 2001-2004 are extrapolated. The equation are then estimated with labor input adjusted by educational levels, however, the estimation results were barely improved.

employment is very clear: the manufacturing employment has declined continuously since 1995, while the valued added output has a continuous upward trend over the years. Because of the large measurement errors and structure change in labor input, the precision of estimation results may be affected.

Technology input, P_{it}, is constructed by both contemporaneous patent applications and patent stocks. The patent data and the construction of patent stocks have been described in Chapter 3 and Chapter 4, respectively.

Table 5.1 presents the summary statistics for all the variables. The correlation matrix of variables in the logarithms is listed in Table 5.2. As expected, among the three inputs, labor is least correlated with value-added output: the correlation coefficient between the output and labor is only about 0.83. In contrast, the correlation coefficient is 0.98 and 0.92 between the output and capital and between the output and patents, respectively.

5.4 Preliminary Results

As a start, equation 5.1 is first estimated by both a fixed effects estimator and a random effects estimator. Table 5.3 presents the robust estimation results and the Hausman specification tests for comparisons of the fixed effects and random effects estimators. In columns (2) and (5), the contemporaneous patent applications are used as the technology input. In columns (3) and (6), the patent stocks are used as the technology input. The equation without the technology input are estimated and reported in columns (1) and (4).

First, we notice that the estimated coefficients of fixed effects models and random effects models are quite different. Although the random effects estimations seem to be better, with higher R-squared values and better-estimated coefficients, the

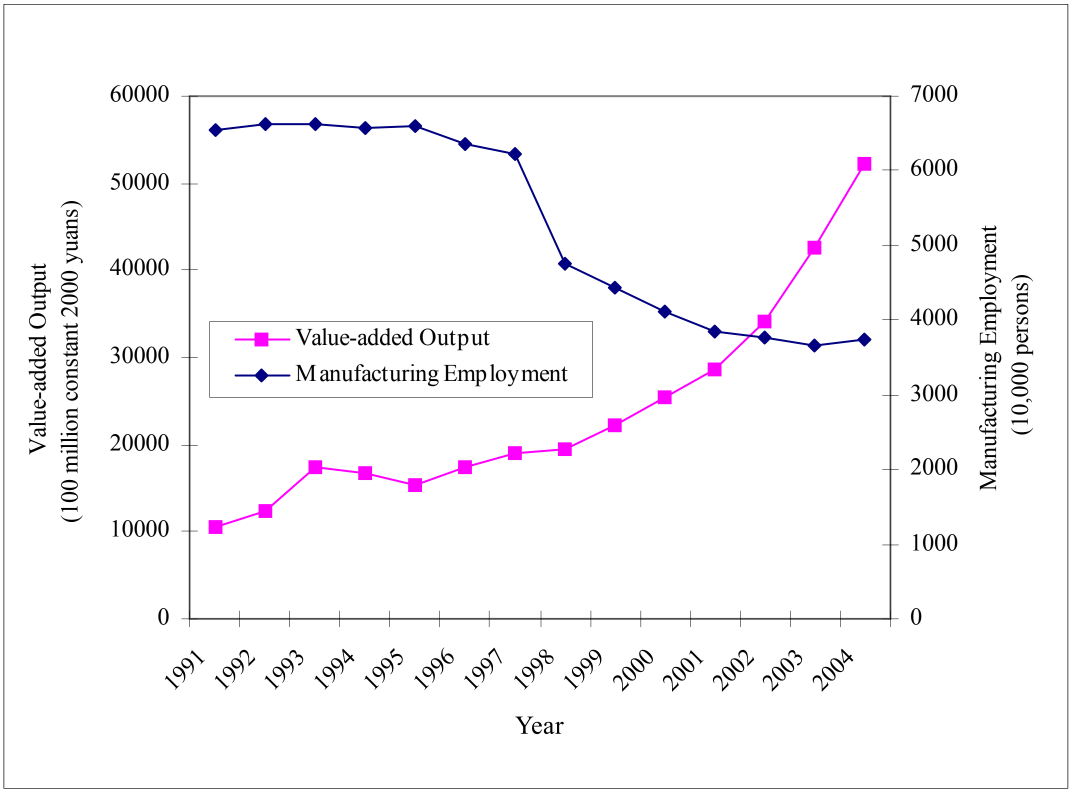

Figure 5.1 Aggregated Value-Added Industrial Output and Manufacturing Employment (Staffs and Workers) in China from 1991 to 2004

Notes: Data are based on the total manufacturing staffs and workers from thirty provinces reported in the various issues of China Statistical Yearbook (Tibet is excluded).

Table 5.1 Summary Statistics of Variables in Levels (1991-2004)

Variables	Observations	Mean	Std. Dev.	Min.	Max.
OUTPUT (Y) (Value-added industrial output in 100 million constant 2000 yuans)	420	793.97	933.63	2.12	6763.23
CAPITAL (C) (Total assets in 100 million constant 2000 yuans)	420	3572.27	3451.51	15.03	20805.20
LABOR (L) (Manufacturing staffs and workers in 10,000 persons)	420	175.87	125.37	1.30	547.60
PATENTS (P) (Patent applications)	420	612.08	973.76	2	6847

Table 5.2 Correlation Matrix of Variables in the Logarithms.

Variables	OUTPUT	CAPITAL	LABOR	PATENTS
OUTPUT	1.000			
CAPITAL	0.980	1.000		
LABOR	0.829	0.812	1.000	
PATENTS	0.916	0.915	0.716	1.000

Table 5.3 Estimation Results of the Knowledge Production Function at the Chinese Provincial Level (1991-2004); Equation 5.1

Dependent Variable: LOG OUTPUT						
Independent Variables[a]	Fixed effects			Random effects		
	(1)	(2)	(3)	(4)	(5)	(6)
LOG CAPITAL	0.194*	0.168*	0.167*	0.629**	0.415**	0.468**
	(0.051)	(0.077)	(0.079)	(0.000)	(0.000)	(0.000)
LOG LABOR	0.305**	0.324**	0.135*	0.420**	0.374**	0.268**
	(0.000)	(0.000)	(0.070)	(0.000)	(0.000)	(0.000)
LOG PATENTS		0.261**			0.274**	
		0.000			0.000	
LOG PATENT STOCKS			0.385**			0.322**
			0.000			0.000
TIME TREND	0.094**	0.066**	0.033**	0.057**	0.042**	0.019*
	(0.000)	(0.000)	(0.027)	(0.000)	(0.000)	(0.071)
R-squared[b]	0.833	0.871	0.850	0.958	0.959	0.953
Observations	420	420	420	420	420	420
Hausman specification test:						
Chi-square Statistics[c]	24.320	17.850	45.490			
	(0.000)	(0.007)	(0.000)			

Notes: The P-values are reported in parentheses. All estimation results are based on the robust standard errors. * Significant at 0.10 level. ** Significant at 0.05 level.

[a]LOG PATENTS refers to the contemporaneous patent applications. LOG PATENT STOCKS is constructed by a 7% depreciation rate.

[b]The R-squared is within R-squared for the fixed effects estimators and overall R-squared for the random effects estimators.

[c]The Chi-square statistics are for the Hausman specification test for comparing the fixed effects models and random effects models (column (1) vs. column (4), column (2) vs. column (5), and column (3) vs. column (6)).

Hausman tests reported in the first three columns reject all the random effects estimators. In the following analysis, only the estimation results of fixed effects estimators are reported. (column (1) to column (3)).

In column (1) without the technology input, the estimated elasticity of value-added output to capital is only 0.194, which is much smaller than the one usually found in the literature. The estimated elasticity to labor is 0.305.

The overall fit of the model is improved when the technology input is included: the R-squared increases from 0.833 in column (1) to 0.871 in column (2) and 0.85 in column (3), respectively. The estimated elasticity of value-added output to technology is 0.26 for the contemporaneous patent applications and is 0.385 for the patent stocks. The higher coefficient for the patent stocks is not surprising, as the magnitude of cumulated patent stocks is much larger than that of contemporaneous patent applications.[2] The elasticity of labor drops significantly to 0.135 when the patent stocks are used. This result is common in the literature: an increase in the elasticity to technology is at the expense of a declining elasticity to labor.

Although the overall fit of models in columns (2) and (3) is good, the large measurement errors in the labor input may have biased the estimates of technology input upward: the elasticities to technology are even larger than those to capital input. The structure break in the manufacturing employment is obviously not captured by the model specifications. Further, it is found that the estimation results are sensitive to the price index used to deflate the capital input.[3] In addition, there might be an omitted

[2] The results are robust to the different depreciation rates of the patent stocks.

[3] The capital input (total assets) is also deflated by the fixed-asset price index and the equation is re-estimated. The precision of estimated coefficients of all variables drops sharply.

variable problem: the R-squared increases significantly when the technology input is included in the estimations. Using a single time trend in the model may be also inappropriate as the exogenous technological change is unlikely to be linear over the years. Because of these problems, the model specification of equation 5.1 is modified to improve the estimation results in the next section.

5.5 Alternative Specifications

As there are large labor shocks during the years 1995-99, I consider using a set of year dummies to capture these changes. The modified equation with year dummies is:

$$\log(Y_{it}) = \alpha_i + \sum_{t=1}^{14} a_t + \beta_1 \log(C_{it}) + \beta_2 \log(L_{it}) + \beta_3 \log(P_{it}) + \varepsilon_{it}, \tag{5.2}$$

where a_t is a set of year dummies from1991 to 2004. The estimation results of fixed effects models are reported in Table 5.4. The estimation results with contemporaneous patent applications are presented in column (2); results with patent stocks are listed in column (3); and results without patent variables are reported in column (1).

5.5.1 Coefficients of Technology

Compared to the models reported in Table 5.3, the overall fit of the regressions has improved with the R-squared around 0.91 for all the three models. The precision of estimated elasticities has also increased: without the technology input the estimated elasticities to capital and labor are 0.449 and 0.326, respectively. Those elasticities are in line with the ones found in the literature (Movshuk, 2004; Wu, 1996). Wu (1996) reports that the elasticities of gross industrial output to capital and labor are 0.54 and 0.23, respectively, at the Chinese provincial level for the years 1985-1990.

Table 5.4 Estimation Results of the Modified Knowledge Production Function at the Chinese Provincial Level (1991-2004); Equation 5.2

Dependent Variable: LOG OUTPUT			
Independent Variables	Fixed effects		
	(1)	(2)	(3)
LOG CAPITAL	0.449**	0.419**	0.424**
	(0.000)	(0.000)	(0.000)
LOG LABOR	0.326**	0.304**	0.237**
	(0.000)	(0.000)	(0.000)
LOG PATENT		0.099**	
		(0.000)	
LOG PATENT STOCKS			0.235**
			(0.000)
YEAR DUMMY	YES	YES	YES
R-squared	0.913	0.911	0.919
Observations	420	420	420

Notes: The P-values are reported in parentheses. All estimation results are based on the robust standard errors. ** Significant at 0.05 level. LOG PATENTS refers to the contemporaneous patent applications. LOG PATENT STOCKS is constructed by a 7% depreciation rate. The R-squared is within R-squared for the fixed effects estimators. The diagnostics tests are performed for the models and both heteroscedasticity and serial correlation are found. Therefore, the estimated results should be reported with the robust standard errors.

Movshuk (2004) estimates a similar Cobb-Douglus production function for Chinese domestic firms for the years 1988-2000 and finds that the elasticities of gross industrial output to capital and labor are 0.14 and 0.63, respectively.

The estimated elasticity of output to technology is 0.099 for the contemporaneous patent applications, which implies that a one percent increase in a region's patent applications results in a 0.099% increase in that region's valued-added industrial output, other things being equal. In comparison, the estimated elasticity to technology is 0.235 for the patent-stocks model. The impact of patent stocks is much larger as expected: a one-percent increase in a region's patent stocks increases the value-added output by 0.235%. However, the magnitude of technology's contribution to the value-added output is small, either with the patent applications or patent stocks. Similar studies conducted at the level of European regions and US states usually find that the elasticity coefficient of technology input is close to that of capital input.

5.5.2 Coefficients of the Year Dummies

Turning next to the effects of the year dummies, the coefficients of the year dummies are plotted in Figure 5.2. The structural break due to the industrial restructuring of 1994-99 is clear: the coefficients of the year dummies started to drop in 1994 and were particularly low in 1995. The effects are most striking when the patent stocks are used in the equation: there was practically no economy-wide exogenous technical progress during the period 1995-99. In contrast, the effects of technical progress increase linearly for the years 2000-04. Those results seem to suggest that using year dummies in the equation is a better choice to capture the effects of structural changes.

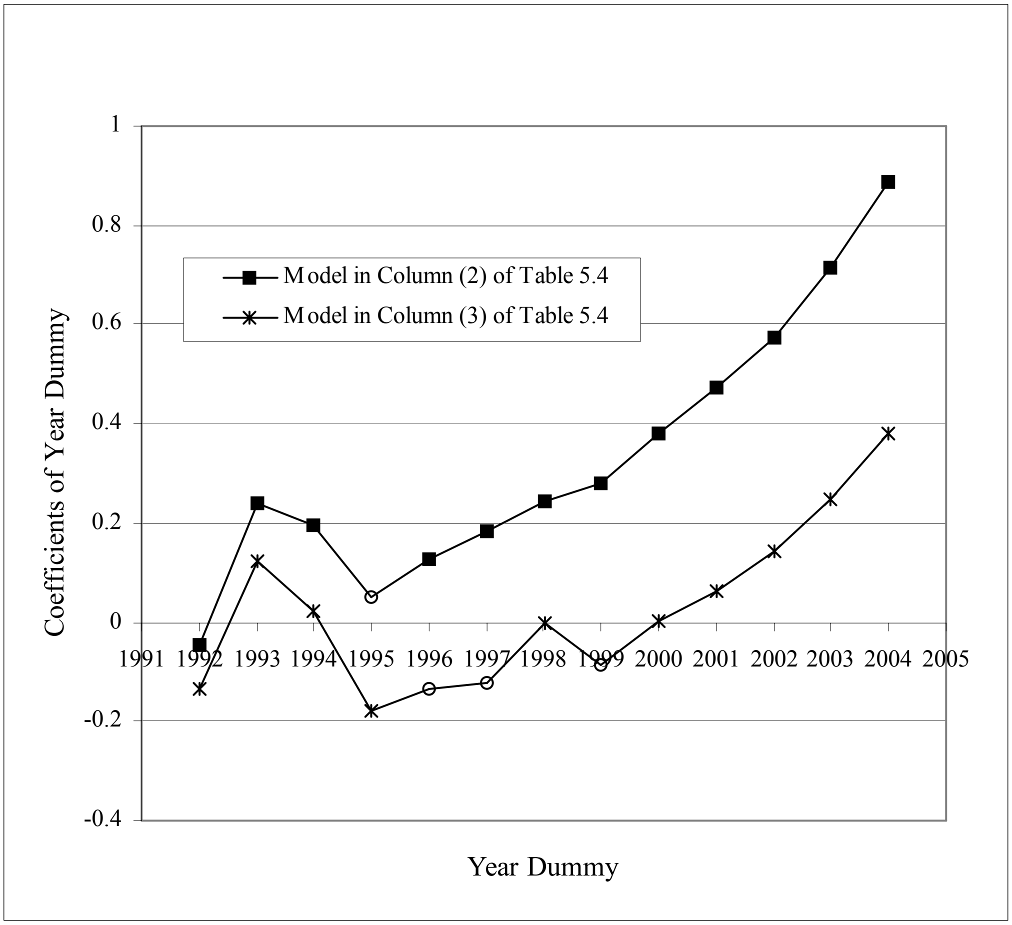

Figure 5.2 Estimated Coefficients of the Year Dummies of Equation 5.2.
Note: The data points marked with "o" mean that the estimated coefficients are not significant at 0.10 significance level.

As a robustness check, capital input (total assets) is further deflated by the fixed asset price index and the equation is re-estimated. The estimation results are similar to those reported in Table 5.4. The results are also robust to the depreciation rates of patent stocks. Thus it can be concluded that the results in Table 5.4 are robust and equation 5.2 is more appropriate for estimating the knowledge production function at the Chinese provincial level. In the following analysis, only the results using patent stocks with a 7% depreciation rate are reported.

5.5.3 The Effects of Locations

The empirical results of Chapter IV point out that there are enormous regional differences in technological development (patenting activity) among the three macro-regions. Here, regional variations in technology's contribution to industrial growth is further explored

Similarly, three location dummies, EAST, CENTRAL, and WEST, are created and are interacted with the technology input (the patent stocks). The estimated equation is:

$$\log(Y_{it}) = \alpha_i + \sum_{t=1}^{14} a_t + \beta_1 \log(C_{it}) + \beta_2 \log(L_{it}) + \sum_{j=1}^{3} \beta_j \log P_{it} + \varepsilon_{it}, \qquad (5.3)$$

where β_j is the elasticity of value-added output to technology input in the macro-region j.

Estimations with separated slopes of patent stocks are reported in column (1) of Table 5.5. The elasticity coefficient of technology in the eastern region is 0.23, compared to 0.21 in the central region and 0.155 in the western region. These estimates suggest that the separate treatment of three macro-regions is appropriate. The evidence points out again that the western region lags behind in terms of technology's

Table 5.5 Effects of Locations and the Year Dummies on the Estimations of the Knowledge Production Function at the Chinese Provincial Level (1991-2004); Equations 5.3 and 5.4

Dependent Variable: LOG OUTPUT		
Independent Variables	Fixed effects	
	(1)	(2)
LOG CAPITAL	0.414**	0.450**
	(0.000)	(0.000)
LOG LABOR	0.263**	0.293**
	(0.000)	(0.000)
LOG PATENTSTOCKS_EAST	0.233**	
	(0.000)	
LOG PATENTSTOCKS_CENTRAL	0.216**	
	(0.001)	
LOG PATENTSTOCKS_WEST	0.155**	
	(0.006)	
LOG PATENTSTOCKS_91_94		0.041**
		(0.038)
LOG PATENTSTOCKS_95_99		0.013
		(0.515)
LOG PATENTSTOCKS_00_04		0.039**
		(0.018)
YEAR DUMMY	YES	YES
R-squared	0.920	0.915
Observations	420	420

Notes: The P-values are reported in parentheses. All estimation results are based on the robust standard errors. **Significant at 0.05 level. LOG PATENTSTOCKS_EAST (CENTRAL and WEST) is the interaction term between LOG PATENT STOCKS and the location dummy, EAST (CENTRAL and WEST). LOG PATENTSTOCKS_91_94 (95_99 and 00_04) is the interaction term between LOG PATENT STOCKS and the time dummy D91_94 (D95_99 and D00_04). LOG PATENT STOCKS is constructed by a 7% depreciation rate. The R-squared is within R-squared for the fixed effects estimators.

contribution to valued-added output. With respect to the role of technology in industrial growth, the differences among the three macro-regions are relatively small, compared to the differences of the patents-R&D relationships found in the previous chapter. It seems to suggest that regional variations in the adoption of new technology are much smaller. Given the small elasticities of output to technology input, the disengagement between innovations and commercialization of new technology seems to be a common problem across the regions.

5.5.4 The Effects of Industrial Reforms

The estimated coefficients of the year dummies only capture certain time-specific effects of industrial reforms on economy-wide rates of technique progress. In this part, the effect of industrial reform on technology's contribution to the value-added output is further examined. Three time dummies are created: (1) D91_94 is 1 if the year is in the pre-reform period of 1991-94; (2) D95_99 is 1 if the year is in the reform period of 1995-99; and (3) D00_04 is 1 if the year is in the post-reform period of 2000-04. The three time dummies are further interacted with the technology input (patent stocks), so the separate slopes of patent stocks of three periods can be estimated. The estimated equation is:

$$\log(Y_{it}) = \alpha_i + \sum_{t=1}^{14} a_t + \beta_1 \log(C_{it}) + \beta_2 \log(L_{it}) + \sum_{T=1}^{3} \beta_T \log(P_{it}) + \varepsilon_{it}, \qquad (5.4)$$

where β_T is the elasticity to patent stocks for the period T. The results are presented in column (2) of Table 5.5.

The elasticity coefficient of patent stocks is 0.041 for the pre-reform period of 1991-1994 and is 0.039 for the post-reform period of 2000-04. In contrast, the coefficient of patent stocks for the period 1995-1999 is not only smaller (0.013) but also insignificant, which implies that there is no technology's contribution to the valued-added output at the provincial level during the industrial reform period. The empirical results here again support the findings in the previous chapter and point out that the effects of industrial reform on China's technological development during the period 1994-99 are very negative: there is no economy-wide technical progress and technology's contribution to industry growth is nonexistent.

We notice that the estimated coefficients of patent stocks for the three separate periods decrease significantly, while the coefficients of capital and labor increase. This is not surprising: the fixed effects estimators only use within variations of the data. The within-variations of the patent stocks decline substantially when fourteen years are divided into three sub-periods. Consequently, the precision of estimated coefficients of patent stocks declines sharply.

5.6 The Effects of Technology Spillovers

In this section, the impact of technology spillovers to value-added industrial output is investigated. Equation 5.2 is extended by including a spillover variable. This spillover variable is proxied by the weighted patent stocks from other regions, which have been described in Chapter 4. The estimated knowledge-spillover production function is:

$$\log(Y_{it}) = \alpha_i + \sum_{t=1}^{14} a_t + \beta_1 \log(C_{it}) + \beta_2 \log(L_{it}) + \beta_3 \log(P_{it}) + \beta_4 W \log(S_{it}) + \varepsilon_{it}, \quad (5.5)$$

where W is the weight matrix and S_{it} is the technology stocks (patent stocks) from other regions. The spillover variable is represent by $W\log S_{it}$. Similarly, two different weighted matrixes are used to construct the spillover variable: the contiguity-weighted and the gravity-weighted.[4]

The robust estimation results of equation 5.5 are presented in Table 5.6.[5] Results with the contiguity-weighted spillover variable are reported in column (1) and results with the gravity-weighted variable are listed in column (2). The coefficient of the contiguity-weighted spillover variable is 0.098, which implies that one percent increase in the patent stocks from the neighboring regions will lead to a 0.098% increase in the region's valued-add output. In comparison, the coefficient of the gravity-weighted spillover variable is 0.134, but it is only significant at 0.16 significance level.

The estimated results seem to suggest that geographical proximity is very important in the inter-regional technology spillovers: solid technology spillovers are only found with the contiguity-weighted spillover variable and the magnitude of technology spillover is much smaller than that of own technology. This implies that the inter-regional technology linkage only exists between the bordering provinces and even that linkage is not strong.

5.7 Conclusion

We find that the knowledge production function is fitted well with Chinese provincial level data. The elasticities of value added industrial output to capital and

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[4] The equation with the unweighted spillover variable is also estimated and no evidence of spillover effects is found at all.

[5] The robustness check for the results reported in Table 5.6 is conducted. The estimation results are insensitive to either the price index used to deflate the capital input or the depreciation rates of patent stocks

Table 5.6 Effects of Technology Spillovers on the Estimation Results of the Knowledge Production Function at the Chinese Provincial Level (1991-2004); Equation 5.5

Dependent Variable: LOG OUTPUT		
Independent Variables	Fixed effects	
	(1)	(2)
LOG CAPITAL	0.425**	0.417**
	(0.000)	(0.000)
LOG LABOR	0.224**	0.232**
	(0.000)	(0.000)
LOG PATENT STOCKS	0.225**	0.227**
	(0.000)	(0.000)
Spillover variable		
LOG SPILLOVER (PATENT STOCKS)	0.098**	
(Contiguity-weighted)	(0.038)	
LOG SPILLOVER (PATENT STOCKS)		0.134
(Gravity-weighted)		(0.164)
YEAR DUMMY	YES	YES
R-squared	0.918	0.917
Observations	420	420

Notes:The P-values are reported in parentheses. All estimation results are based on the robust standard errors. ** Significant at 0.05 level. LOG PATENT STOCKS is constructed by a 7% depreciation rate. LOG SPILLOVER (PATENT STOCKS) refers to the knowledge stocks available in the other regions, proxied by the patent stocks with a 7% depreciation rate in the other regions. The results are similar with patent stocks using a 0% depreciation rate and a 12 % depreciation rate. The R-squared is within R-squared for the fixed effects estimators.

labor are 0.425 and 0.224, respectively. The elasticity of value-added industrial output to the region's own technology is 0.099 for the contemporaneous patent applications and 0.235 for the patent stocks. These estimates indicate that technology plays a positive role in industrial growth at the provincial level; however, the contribution of technology is far too small which indicates that China's economic growth is largely driven by the factor inputs. The results here seem to support the views that the linkages between innovation activity and commercialization of new technology are weak within Chinese domestic firms (Sun, 2002). Domestic firms apparently have difficulties in exploiting and adopting the new technologies. This naturally raises the questions about the current technology policy in China: does current S&T policy emphasize too much on the generation of new technology, compared to the adoption of new technology? For long-term sustainable economic growth, how to facilitate and encourage the adoption of new technology should be the main concerns for China's policymakers.

The results also indicate that the inter-regional technology spillovers are positive but relatively small and weak, compared to the European regions and the states in the US. The evidence here confirms the low developmental stage of China's industry as the ability to adopt and diffuse the new technology is weak across the Chinese provinces.

The estimated results further confirm that the impact of industrial reforms during the period of 1994-99 on China's technological development is negative, as there seems to be neither exogenous technical progress nor technology's contribution to the value-added industrial output at all in those years..

Chapter 6

CONCLUSION AND RECOMMENDATION FOR FUTURE RESEARCH

The study described in this dissertation provides the detailed analysis of patenting activity in China. Patenting activity by technological fields and by industrial sectors is analyzed; spatial distributions of innovative activity are examined; both a patent production function and a knowledge production function are estimated at the provincial level. The effects of inter-regional knowledge spillovers on innovation activity and on the value-added industrial output are estimated.

6.1 Summary of Findings

The key findings of this dissertation can be grouped into four areas: (1) overall technological development in China, (2) regional technological development in China, (3) estimations of the patents-R&D relationships and the return to R&D at the provincial level, and (4) estimations of the inter-regional knowledge spillovers.

6.1.1 Overall Technological Development in China

Through the detailed analysis of patents by technological fields and by industrial sectors, this study points out that the technological strengths of China are mainly in the low and traditional technological fields, however, China has built up its technological strengths in such key areas as biotechnology and organic chemistry. The huge technology gap between China and industrialized countries is mainly in the IT sectors. Consequently, China is increasingly focusing its innovation activities in these areas, though the task to build up its own technology in the IT sectors is particularly challenging.

The growth rates and distributions of patents indicate that technological development in China suffered a setback during the period of industrial reforms in 1995-99. The econometric analysis of this study further confirms that there is neither exogenous technical progress nor technological contribution to industrial output growth during that period.

The substantial growth of domestic patent applications in the most recent years is found to be closely related to China's WTO accession. The econometric analysis of the patent production functions points out that the overall propensity to patent increases greatly after the year 2001.

6.1.2 Regional Technological Development in China

Spatial distributions of patents reveal that there is an increasing inequality of innovation activity among the three-macro regions. Over the past ten years, the innovation activities are increasingly concentrated in the eastern region, particularly in the hi-tech areas.

Estimations of both a patent production function and a knowledge production function at the provincial level further confirm that that there are severe regional disparities in technological development. The eastern region not only has a much higher elasticity of patents to R&D capital but also has a much higher propensity to patent. Further, the elasticity of value-added industrial output to technology is also much higher in the eastern region.

With respect to the technology policy, the evidence here indicates that nationwide hi-tech oriented policy is not effective in stimulating the hi-tech innovations in most of the provinces.

6.1.3 Estimations of Patents-R&D relationship and the Return to R&D

Estimations of the patent production functions indicate that the patents-R&D relationships are well established at the provincial level in China. The estimated elasticities of patents to R&D capital are in the range of those found in the patent literature. This analysis confirms that agglomeration economies and market demandsare two important factors for patent applications at the provincial level. The patent production function seems to work well with both measures of R&D capital, i.e., contemporaneous R&D spending and R&D stocks.

Estimations of the knowledge production functions at the provincial level further confirm that technology contributes positively to industrial output growth, however, the contribution from technology is far too small, compared to that of more industrialized countries.

6.1.4 The Effects of Innovative-Knowledge Spillovers

This analysis provides some econometric evidence of knowledge spillovers at the Chinese provincial level. The spillover effects are analyzed in two ways. First, I estimate the effect of spillovers on patent applications by using both R&D activity and patenting activity performed in the other regions as the sources for knowledge spillovers. Estimations results from the linear regressions point out that there are powerful spillover effects from the patenting activity performed in the other regions, while estimations results from the Poisson regressions suggest that spillover effects from the R&D activity in the other regions are moderate. However, estimation results from the Poisson regressions are less robust compared to those of the linear regressions.

Second, I estimate the effect of technology spillovers (patent activity) on the value-added industrial output directly. The results indicate that there are positive technology spillovers, but the effects from technology spillovers are much smaller compared to its own technology effects. The inter-regional technology spillovers on industrial output growth are not strong and exist only among the bordering provinces

The results of this analysis point out that technological development in China is still at the low level; therefore, the adoption and diffusion of technology across the regions is slow and weak.

6.2 Recommendation of Future Work

The scope of this study is constrained by the limitation of data available and many questions remain unanswered in this dissertation.

First, using Chinese patent data to assess its own technological strength creates a bias on computed RTA indexes. One way to correct this bias is to collect the patent data from the international patent offices, such as the USPTO or EPO, for both China and those developed countries. The computed RTA indexes based on the international patents should be analyzed along with those of Chinese patent data, as using international patent data alone will also cause a severe bias on China's true technological activity.

The second refinement to this analysis is to further separate the patents by patentee's organizations. The search fields of current Chinese patent database cannot separate the patentee's organizations, so this analysis is based upon the patent applications from all organizations, in which a large proportion is from non-industrial identities. Separating industrial innovation activity from other organizations has the obvious advantage over the current study: (1) it will provide a more accurate assessment of industry-based domestic innovation activity; (2) using industrial patents as dependent variables can mitigate the potential multicollinearity problems found in the patent equation estimations; and (3) the spillovers from the patenting activity conducted in the universities to the local industrial patenting activity can be estimated directly at the provincial level.

Some of the estimation results of patent production equations, particularly with the Poisson regressions, point out the potential data problems with the current data set, such as, the time period and the aggregation level. The long-term relationships of patents-R&D in China is still not clear as the estimation period of this analysis is too short to make accurate projections. Extending the estimation periods of patent equations should be very helpful to project a long-term patents-R&D relationships in China.

Another direction for improvement is to use more disaggregated data, such as county-level data and/or firm-level data. Of course, collecting a micro-level economic data is not an easy task, especially with R&D data. This analysis finds that the Poisson regressions of the patent equation have overdispersion problems, but the fitting of Negative Binomial models with the current data set is very poor. With less aggregate data, the fitting of the model, especially with more sophisticated estimation techniques, such as the Negative Binominal models, could be improved.

The major recommendation of this study is on the analysis of knowledge spillovers. This is one of the most neglected research areas in economic studies of

China. This analysis of inter-regional spillover effects in China is basic and preliminary, however, the results are promising and positive. The analysis of spillover effects will be more revealing and solid with less aggregate data. First, from the regional development point, it can be extended to the county-level data to analyze the intra-regional spillover effects, as the diffusion of technology across the regions and within the regions should be one of the key factors to reduce the regional disparity.

Second, from the industrial development point, the analysis of the inter-industry and intra-industry spillover effects are one of the key factors to help understanding the different growing paths of industries. The task is particular challenging, as data at the industry and firm levels are not easily to come by, particularly for China. I have attempted to estimate a knowledge production function at the 2-digit industrial level with much less satisfying results, compared to those at the provincial level. The main reasons are: there are more measurement errors and aggregation errors with industrial level data, compared to the provincial level data. One of the refinements is to obtain 3-digit or 4-digit industry level data, which is very difficult to collect.

The other direction is to obtain firm-level data directly. Even with the firm level data, the actual analysis of spillover effects among the firms is challenging, as spillover effects among the firms are dependent upon firm's closeness in the corresponding technological areas. Thus, it is necessary to either create certain technology distance among the firms and/or group firms to their respective industrial sectors.

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