INNOVATION IN CHINA:

ITS GLOBAL ROLE, FIRMS' BEHAVIOUR AND GOVERNMENT POLICY

BY

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ABSTRACT

This dissertation provides new insights into the innovative behaviour of Chinese manufacturing firms during China's transition from a resource-driven to an innovation-driven economy. It consists of four core studies about innovation-related topics at the national and the firm level. The first study is an exploration into China's changing approach to innovation and the responses of individual economic sectors. It takes into account product-embodied R&D through international trade flow. The results show that China is transforming from a technology absorber to a neutral player who is also a significant knowledge producer. The domestic innovation system is much better interconnected and has become more polycentric. This structure is beneficial to technology diffusion. The second core chapter is a comprehensive analysis of both the internal and external determinants of firms' innovative behaviour. It is found that China's innovative firms are generally bounded by their internal resources in terms of their participation in innovation activities. In addition, the characteristics of local innovation systems are also significant in determining firms' innovative behaviour. The functional mechanisms of these factors are discussed through the adoption of three measures of innovation activities. The third study is an analysis of whether university-industry collaboration promotes firms' innovation efficiency. In this chapter, the innovation process is divided into two linear stages, namely, R&D stage and commercialisation stage. It is shown that university-industry collaboration tends to affect innovation efficiency negatively, while the intensity of university-industry collaboration is found to have a U-shaped relationship with the firm's innovation efficiency. The results also indicate that the regional moderators indirectly affect the efficiency performance differently at the two stages. The fourth study focuses on the assessment of the impact of government intervention on firms' innovation performance, particularly the additionality of national science and technology (S&T) programme to Chinese innovative firms. The results suggest that the effectiveness of national S&T programme in promoting firms' innovation capability might be overestimated. Potential crowding-out effects and problems in terms of resource misallocation are also evident. Within a certain period, positive and significant additionality in terms of R&D investment, especially external R&D investment, is identified after the removal of the common trend. Overall, the findings from this dissertation enhance our understanding of the innovative behaviour of Chinese manufacturing firms and their interactions with other entities in the innovation system. These findings thus provide constructive policy implications for both the business community and policy makers.

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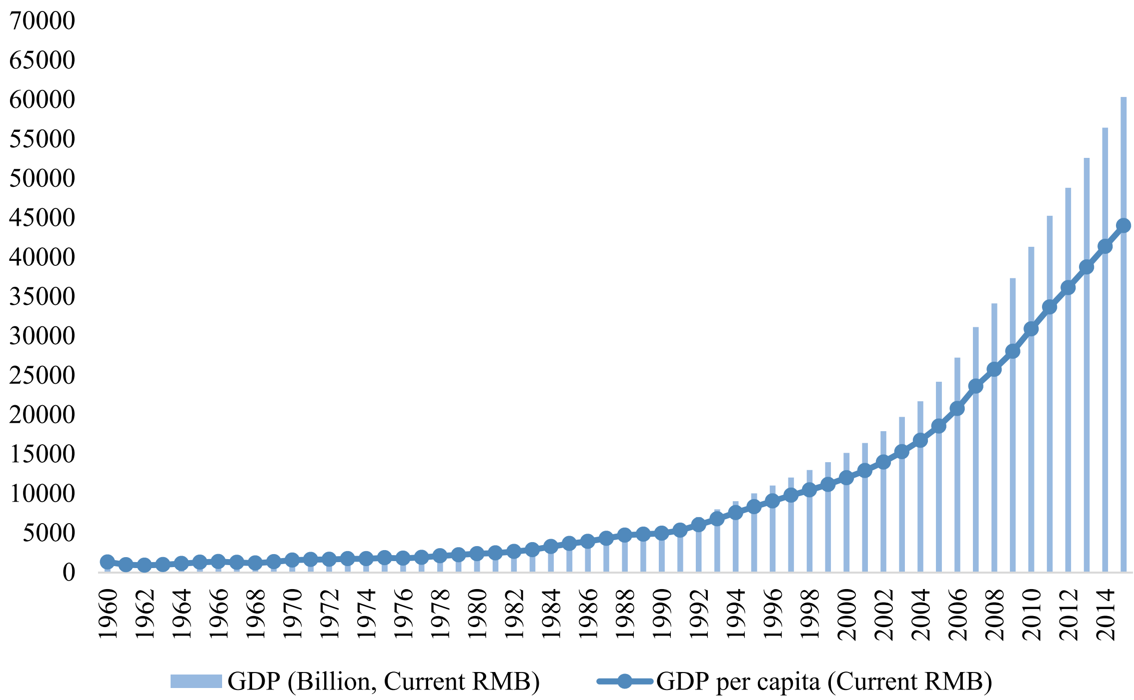
LIST OF ABBREVIATIONS

ANBERD	Analytical Business Enterprises Research and Development
ATET	Average Treatment Effect on the Treated
BRIC	Brazil, Russia, India and China
CIA	Conditional Independence Assumption
CIS	Community Innovation Surveys
CPPCC	Chinese People's Political Consultative Conference
DEA	Data Envelopment Analysis
DID	Difference in Difference
FDI	Foreign Direct Investment
FTE	Full-time Equivalent
HMT	Hong Kong, Macau and Taiwan
IO	Input-output
IOFD	Innovation-oriented Firms Database
IPR	Intellectual Property Rights
IV	Instrumental Variables
KIBS	Knowledge-intensive Business Services
LMEs	Large- and Medium- Sized Enterprises
MBS	Mean Biases
MCR	Marginal Cost of R&D
MIT	Middle-income Trap
MNCs	Multinational Corporations
MOST	Ministry of Science and Technology of China
MSTI	OECD Main Science and Technology Indicators
MRR	Marginal Rate of Return to R&D
NBER	National Bureau for Economic Research
NBSC	National Bureau of Statistics of China
NIS	National Innovation System

NN	Nearest Neighbour
NPC	National People’s Congress
OECD	Organisation for Economic Co-operation and Development
OIM	Observed Information Matrix
PICS	Productivity and Investment Climate Survey
PPP	Purchasing Power Parity
PSM	Propensity Score Matching
RBV	Resource-based View
RIS	Regional Innovation System
RMB	*Ren Min Bi* (Chinese *yuan*)
R&D	Research and Development
SBM	Slacks-based measure
SCI	Science Citation Index
SFA	Stochastic Frontier Analysis
SIPO	State Intellectual Property Office
SMEs	Small- and Medium- Sized Enterprises
SNA	Social Network Analysis
SOEs	State-owned Enterprises
STAN	OECD Structure Analysis Database
S&T	Science and Technology
TFP	Total Factor Productivity
UIR	University, Industry and Research Institutions
VNP	Value of New Product
WIPO	World Intellectual Property Organisation
WTO	World Trade Organisation

CHAPTER 1 - INTRODUCTION

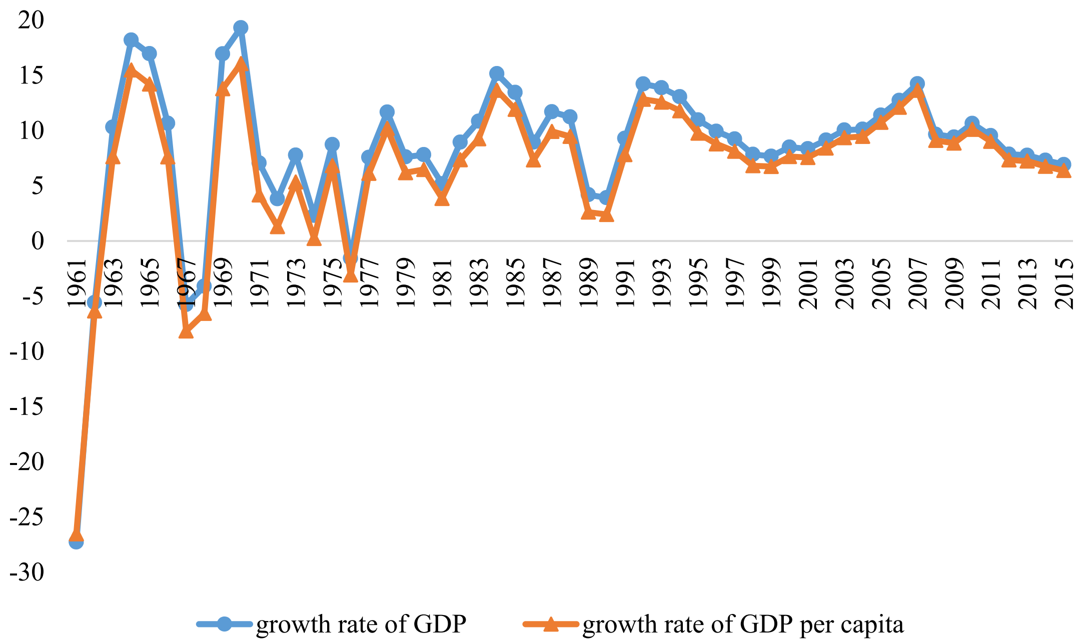
The Chinese economy has experienced extraordinary growth in the past three decades, which is attributed to the stunning transformation from a centrally-planned system to a predominantly market-oriented system, and from an inward-oriented industrial strategy to an opening-up strategy with the aim of integrating into the global economy. The exponential growth (See Figure 1.1) makes China superior to other populous economies (India and Brazil), other transitional economies (Poland and Russia), and other fast-growing economies in Southeast Asia (Malaysia and Thailand). In 2010, China surpassed Japan and emerged as the world's second-largest economy after the United States. According to estimates from the IMF, China already became the largest economy in 2014 based on the purchasing power parity (PPP). However, this does not come without costs.



Source: World Bank 2016.

Figure 1.1 Chinese GDP and GDP per capita, 1960-2015

Along with its remarkable achievements regarding economic growth, China has also accumulated many distortions and structural imbalances. The export-led and investment-driven model implemented in China has performed very well in past decades, but it has progressively reached its limits, particularly after the outbreak of the global financial crisis and the implementation of the 4 trillion RMB stimulus package in 2009. Adverse outcomes include, but are not limited to, widespread pollution, inefficient resource allocation, income inequality, a growing number of non-performing loans and skyrocketing debt, and corruption. China's economic growth has inevitably slowed in the past five years (See Figure 1.2). With the falling proportion of the working age population, and the diminishing returns to investment, it is projected that this slowdown will continue over the medium-term. Therefore, concerns have been voiced that the Chinese economy may not be able to progress as quickly as it has in the past, leaving it lagging behind the leading economies, and that it may get stuck in a so-called "middle-income trap" (MIT) (OECD 2013).



Source: World Bank 2016

Figure 1.2 Growth rates of Chinese GDP and GDP per capita

China is now at crossroads, and further reforms are needed to ensure broad, sustainable and equitable growth in the future. Recent history of economic development provides convincing evidence of the crucial role played by innovation in the "catching up" process of emerging economies and their successful avoidance of the "middle-income trap". When the cost of production factors is still low, it is beneficial to foster industrial upgrading, productivity gains, and competitive advantages via absorbing foreign knowledge and depending on foreign technology. However, it is believed that growth is bound to slow down once a catching-up economy has reaped the lower-hanging fruits of technology imports and urbanisation, and indigenous innovation becomes increasingly important in catching up with global frontiers. Therefore, a wise approach to economic development should focus on building strong local innovation capacity before foreign technology transfers no longer suffice. It is, therefore, both necessary and urgent for us to better understand the development of China's indigenous innovation, the determinants of firms' choices on innovation investment, and the interaction between firms, universities, and governments, especially during the process of transformation from resource-driven growth to more sustainable, innovation-driven growth.

1.1 Innovation and Economic Development

The significance of innovation in economic development has been a topic of ongoing interest both in theoretical and empirical literature. Economic development, rather than economic growth, is discussed since innovation can address environmental challenges and is beneficial for alleviating social problems, in addition to the unanimous consensus on its contribution to economic growth. For example, innovation has become increasingly crucial in dealing with climate change, limiting global greenhouse gas emissions, and maintaining biodiversity. Innovation can also help elderly individuals live healthier and more independently, provide more personal and predictive healthcare products, and most importantly create employment opportunities and address particular challenges faced by lower income groups. Considering the challenges faced by present-day China, there is no wonder that such emphasis is placed on the role of innovation in achieving long and sustainable development, both in economic and social terms.

In macroeconomic theory, one of the most consistent findings is that innovation drives economic growth (Figure 1.3). The notion of endogenous technological progress was present in the world of the classical school, especially in the writings of Adam Smith and Karl Max, and since then has become prominent in work by Schumpeter, the representative of the evolutionary approach (Schumpeter 1934). He contended that evolving institutions, entrepreneurs, and technological change were at the heart of economic growth, and argued that "capitalism can only be understood as an evolutionary process of continuous innovation and 'creative destruction'" (Freeman 2009). At the same time, innovation can cause firm closures and job destruction if products or services become obsolete or are displaced by more competitive offerings (Schumpeter 1942). The evolutionary worldview is one reliant on historical circumstances, complex causal mechanisms that are subject to change over time, and turbulent growth patterns that appear to be far from a steady state, while the neoclassical tradition adheres to a worldview in which cause and effect are clearly separable, and growth is an ordered, steady-state phenomenon. Although debate exists between the two approaches, the basic neoclassical growth models treat knowledge accumulation and technological progress as the ultimate way to achieve long-run and sustainable growth despite diminishing returns to capital (Solow 1956), where the technological change is exogenous to the economic process. Advances in growth theory have recognised the endogeneity of the accumulation of knowledge capital and human capital which derive from investment decisions of individuals and firms in response to economic incentives and therefore to public policies and institutions (Aghion and Howitt 1992, 1998; Romer 1986, 1990; Lucas 1988; Grossman and Helpman 1994)[1].

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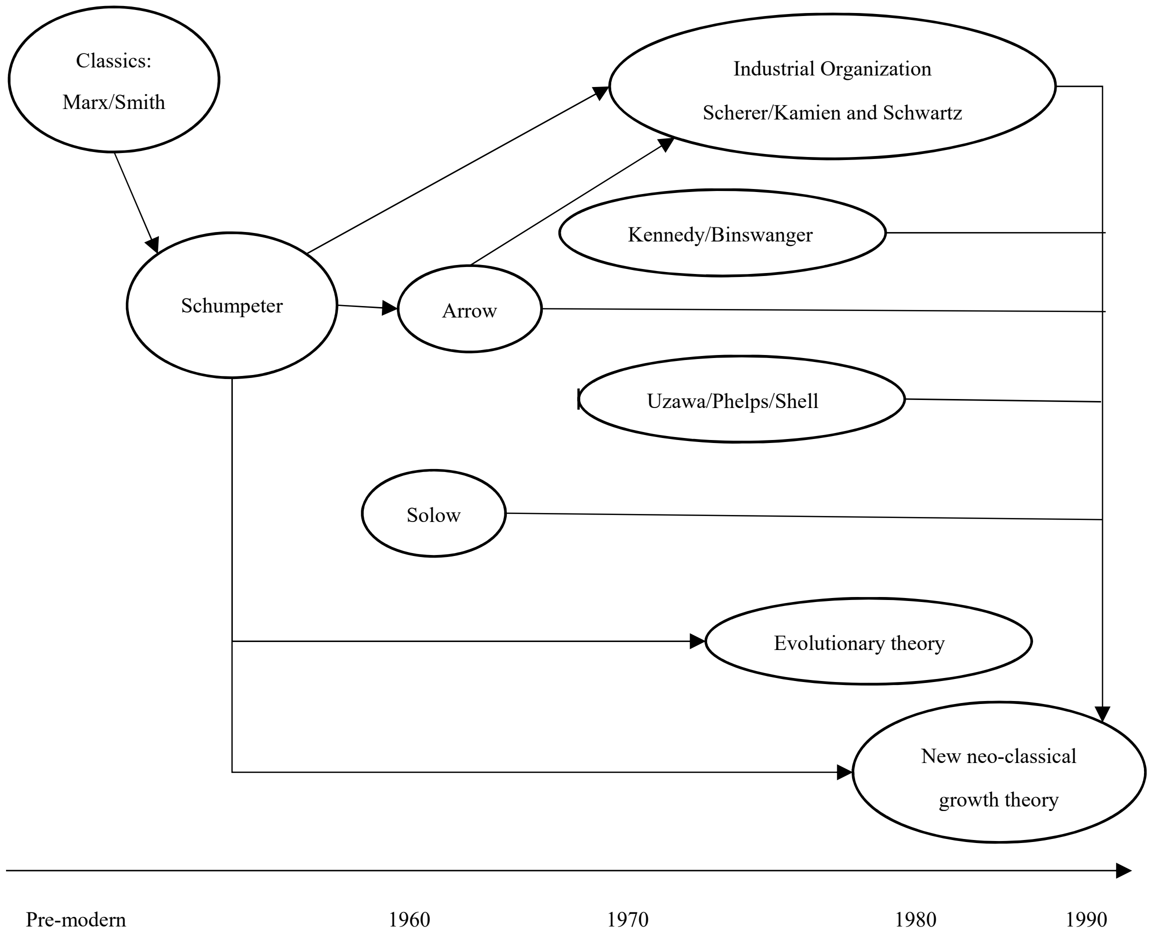
[1] More details are available in Gomulka (1990) and Verspagen (1992).



Source: Verspagen (1992)

Figure 1.3 Technological change and economic growth: the trajectory of ideas

Empirical evidence has supported the aforementioned theoretical arguments widely and consistently. Since at least the 1950s, Abramovitz (1956) measured growth in both inputs (of capital and labour) and the output of the American economy between 1870 and 1950. This study showed that the measured growth of inputs could only account for about 15 per cent of the actual growth in output, which is roughly consistent with findings in Solow (1957). Since then, research on endogenous growth theory has sparked many empirical studies investigating how, and to what extent, innovation might contribute to economic growth (Griliches 1980, 1991; Mansfield 1988; Jorgenson 1990). Empirical evidence, on the whole, suggests that innovation can be expected to make significant contributions to economic growth, and that there are also significant spillover effects of innovative activities (Coe and Helpman 1995; Cameron 1998). As enterprises are the major players in innovative activities, recent studies tend to have a closer look at the micro-level. A strand of literature, following the Schumpeterian tradition, focuses on firms' size and market structure (Baldwin and Scott 1987; Kamien and Schwartz 1982; Scherer 1980; Cohen and Levin 1989; Cohen 1995). Additionally, the role of firm characteristics and industry-level variables (broadly characterised as reflecting demand, technological opportunity, and demand conditions) have also been the topic of extensive discussion (Teece 1986, 1987; Mowery and Rosenberg 1989; Levin et al. 1987; Cohen 2000; Hall and Rosenberg 2010). Meanwhile, a trend since the early 1990s has been to collect more information on innovation activities of firms through surveys based on the so-called Oslo Manual (Smith 2004). Examples include the Community Innovation Surveys (CIS) and Productivity and Investment Climate Survey (PICS). These surveys make the discussion on the relationship between innovation and economic growth more detailed at the micro level (Cre´pon et al. 1989; Jefferson et al. 2006; Almeida and Fernandes 2008).

While firms' innovation in developed economies and other developing countries has already been extensively researched, there has been relatively limited research on Chinese firms, despite the fact that the giant developing economy is undergoing a phenomenal transition in the area of innovation, both in terms of investments and achievements. China, as of 2015, is the second largest R&D investor, only trailing the United States, and has the largest research team. In 2011, China outperformed the United States as the country filing the largest number of patent applications (Hu et al. 2017). Furthermore, conditions in developing countries often turn out to be quite different from those in which the technology was originally developed (Evenson and Westphal 1995). Moreover, Hall and Rosenberg (2010) pointed out that, in comparison to our understanding of the influence of industry-level variables, our knowledge of the role of firm-level variables is more primitive, mainly due to the challenge of collecting suitable data. This thesis aims to systematically investigate the innovative behaviour of Chinese firms, based on emerging firm-level data, and their interactions with other entities in the innovation system during China's transition, thereby contributing to the empirical literature on firms' innovation.

1.2 Innovation in China

China's rapid expansion and development in science and technology (S&T) has attracted growing attention. In 1995, the Chinese People's Political Consultative Conference (CPPCC) issued the "Decision on Accelerating the Progress of Science and Technology" which emphasises the fact that economic development should rely on the advancement of science and technology. Since then, the strategy of "Revitalising the nation through science, technology and education" has been implemented nationwide. Following that, the CPPCC and State Council issued the "Decision on Strengthening the Technological Innovation, Developing High Technology and Realising Industrialisation" which calls for the building of a national innovation system and speeding up the industrialisation process.

In 2006, the announcement of the *National Programme for Medium- and Long-Term Development of Science and Technology* (MLP Plan) further stressed the importance of innovation for China's future development. The ambitious goals of the programme reflect China's commitment to boost investment in science and technology in order to build a sustainable, innovation-oriented country. More recently, as outlined in China's 13th Five-Year plan, innovation is claimed to be the first and foremost force for economic development. Innovation is an important prerequisite of achieving a more sustainable and balanced pattern of growth and, therefore, should be placed at the core of national development. Alongside massive investment in innovation over recent decades, China has achieved impressive results. So far, China has developed faster than most of its peer countries in the developing world towards building the foundations of a world-class innovation system.

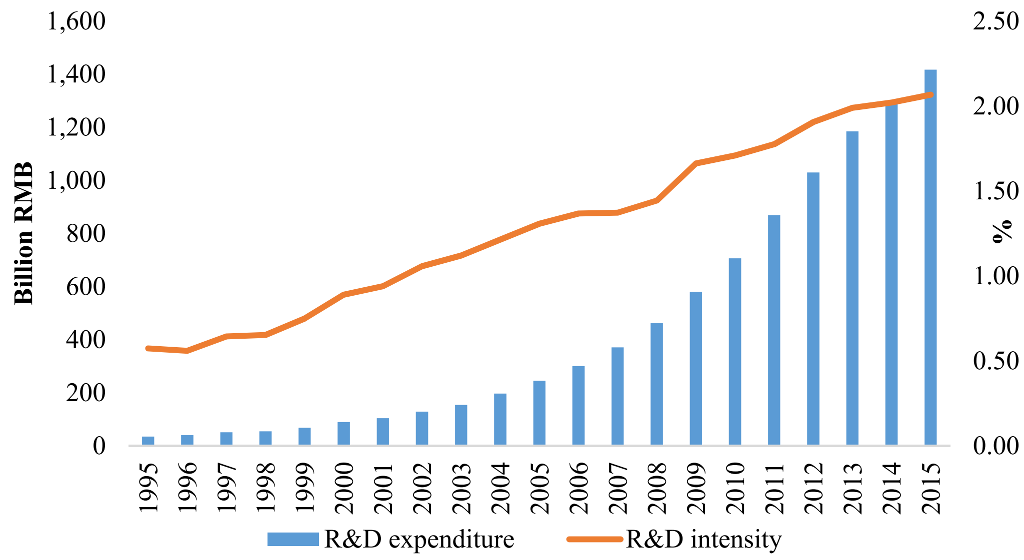
This section presents a detailed description of China's innovation and the ongoing transformation of economic growth into an innovation-driven model. It provides a review of China's progress in building an innovative country based on aggregate and regional statistics of innovation inputs and outputs.

1.2.1 Expansion of Innovation Inputs

The inputs of financial and human resources in the R&D sector directly contribute to the development of science and technology. This section starts by reviewing the expansion of these primary inputs in the R&D sector in aggregate, followed by an international comparison as well as an examination of regional distributions.

❖ ***Aggregate level***

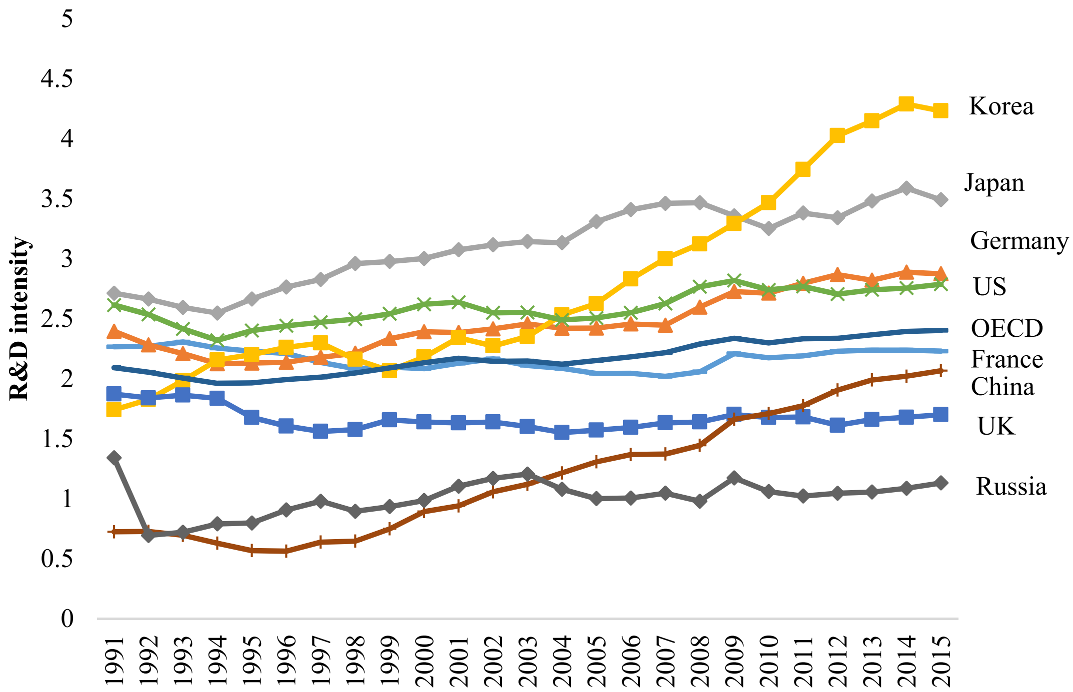
As a critical indicator of innovation efforts, R&D expenditure in China has increased dramatically in recent decades, from 34.87 billion RMB in 1995 to 1416.99 billion RMB, with a growth factor of over 40. Since 2010, China has become the second-largest investor in R&D in the world, and only trails the United States. Figure 1.4 shows the exponential growth in R&D expenditure as well as the steady increase in R&D intensity defined as the ratio of R&D expenditure over GDP. The R&D intensity was 0.57 per cent of GDP in 1995, rising to 2.07 per cent in 2015.



Source: China Statistical Yearbook of Science and Technology (2016)

Figure 1.4 R&D expenditure and R&D intensity in China, 1995-2015

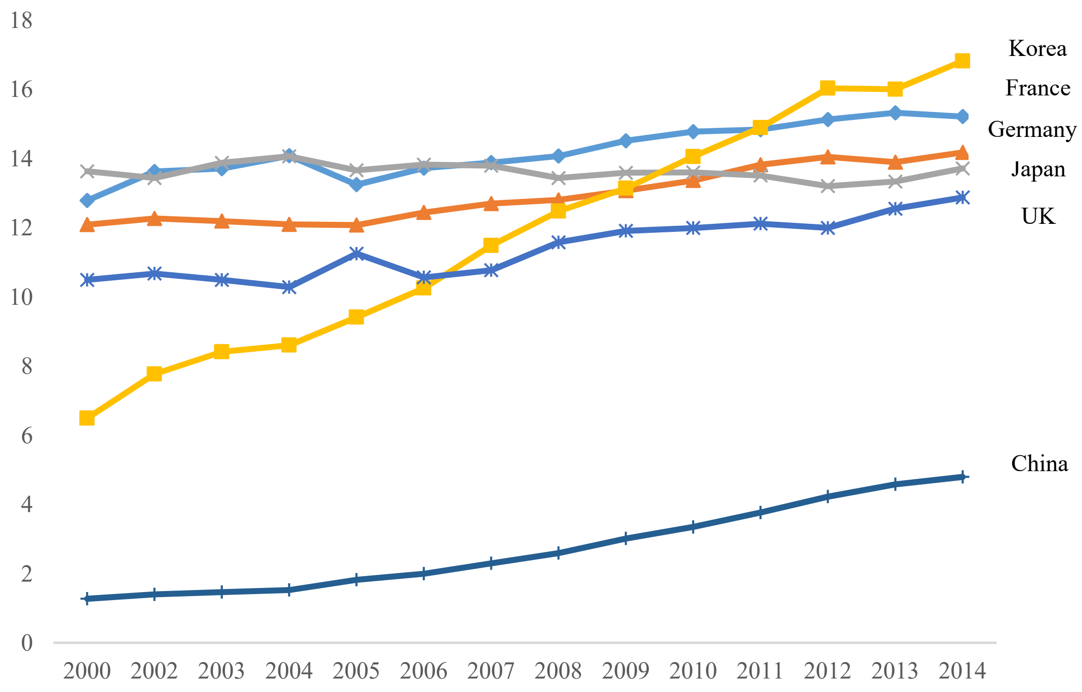
Although China has experienced enormous expansion in the R&D sector, the R&D intensity is still relatively low in comparison with other major OECD economies. The United States, Japan and Germany are the leading R&D performers amongst OECD countries (Figure 1.5). Their R&D intensity ranges from 2.5 to 3.5 per cent of their GDP. Korea has the fastest growth rate of R&D intensity since 2003 and now dedicates 4.2 per cent of its GDP to R&D. In the MLP Plan China sets its goal for R&D spending to be greater than 2.5 per cent of GDP by 2020, which is slightly above the average level for OECD nations, and approaching the level of the United States in 2015.



Source: OECD Main Science and Technology Indicators (MSTI) Database

Figure 1.5 R&D intensity in China and other economies, 1991-2015

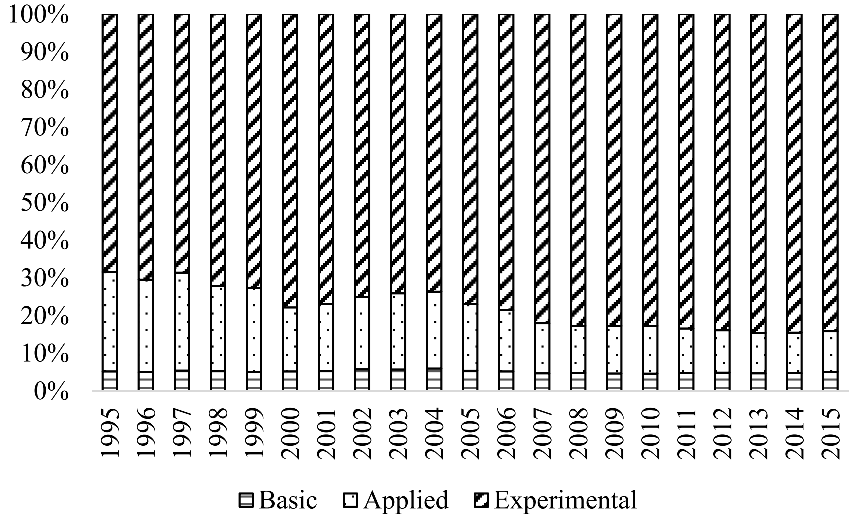
China has the largest research team in the world, along with its vast expansion of R&D expenditure. The number of R&D personnel in China, measured in full-time equivalence (FTE), has increased dramatically from 0.67 million FTE in 1991 to 3.76 million FTE in 2015. However, the ratio of R&D personnel measured per capita is still way behind that of developed economies, and the growth in personnel is relatively modest in comparison with the increase in R&D expenditure (Figure 1.6). This gap could potentially affect the utilisation efficiency of R&D investment and therefore become detrimental to long-term innovation development. Building a qualified and efficient research team proportional to the expansion in financial investment should be made a key priority.



Source: OECD Main Science and Technology Indicators (MSTI) Database

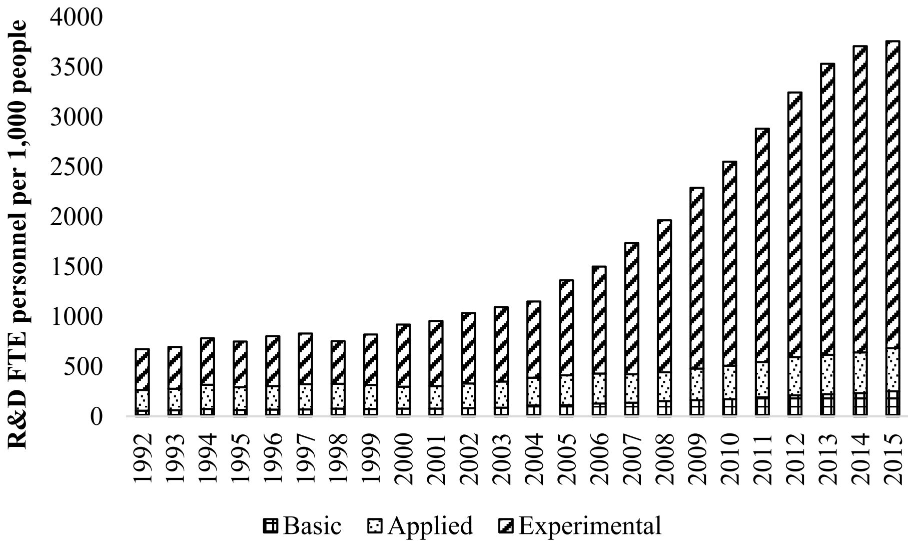
Figure 1.6 Comparison of R&D personnel per thousand people, 2000-2014

R&D activities can generally be broken down into three broad types in accordance with classifications provided by the OECD, namely, basic research, applied research and experimental research. The composition of R&D expenditure by activity type reveals important structural features of China's innovation efforts. Figure 1.7 demonstrates a noteworthy feature: the share of basic research is considerably lower, while spending on experimental research accounts for a much higher share. Thus, the large increase in volume of R&D in past decades is mainly focused on experimental research. The same problem can be observed by examining the breakdown of R&D personnel, displayed in Figure 1.8. While both basic research and applied research are concerned with obtaining new knowledge, experimental research is more focused on using existing knowledge to improve current products, processes or services. Thus, the lack of basic and applied research could hinder China's innovation development in the long run.



Source: China Statistical Yearbook of Science and Technology (2016)

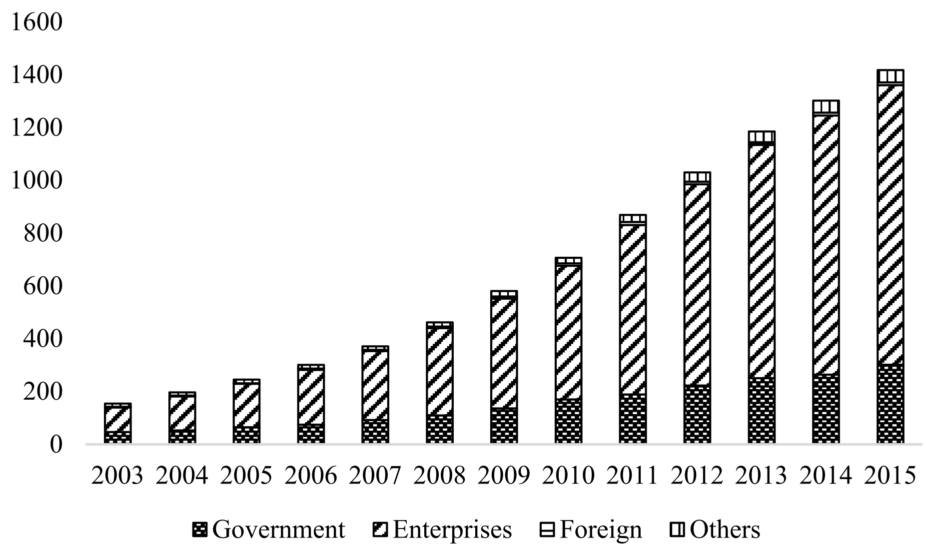
Figure 1.7 Composition of R&D expenditure by types of activities, 1995-2015



Source: China Statistical Yearbook of Science and Technology (2016)

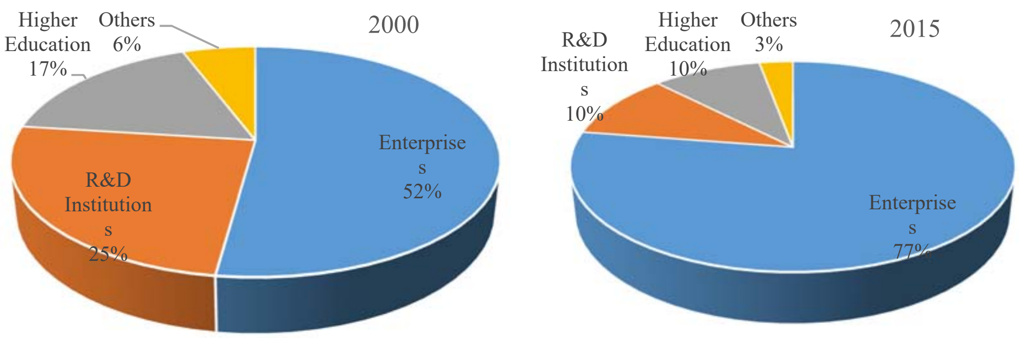
Figure 1.8 Composition of R&D personnel by types of activities, 2003-2015

Furthermore, R&D expenditure can be decomposed according to funding source, namely, funds from government, enterprises, foreign countries, and others. A clear pattern in Figure 1.9 is that enterprises are gradually becoming the primary source of R&D funds, while funding from government also recorded a mild growth. The share of funds from enterprises increased from 60 per cent in 2003 to almost 75 per cent in 2015, alongside a decrease from 30 per cent to 21 per cent in the share of funds from government sources. This trend reflects the structural transition of China's innovation system from a centrally-planned one to an enterprises-dominated one, which is exactly the development goal specified in the MLP plan, that is, to establish the leading role of business enterprises. Accordingly, the share of R&D personnel in enterprises also expanded remarkably, from 52 per cent in 2000 to 77 per cent in 2015, accompanied with a decrease in numbers across the other sectors (Figure 1.10).



Source: China Statistical Yearbook of Science and Technology (2016)

Figure 1.9 Composition of R&D expenditure by funding sources

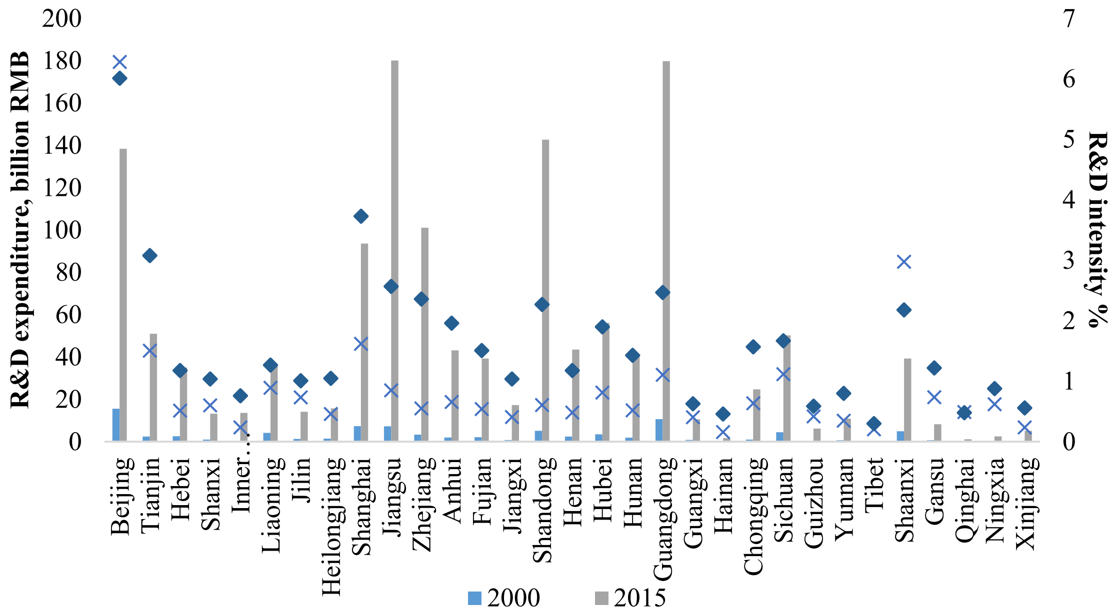


Source: China Statistical Yearbook of Science and Technology (2016)

Figure 1.10 Composition of R&D personnel by executive entities, 2000 and 2015

❖ ***Regional distribution***

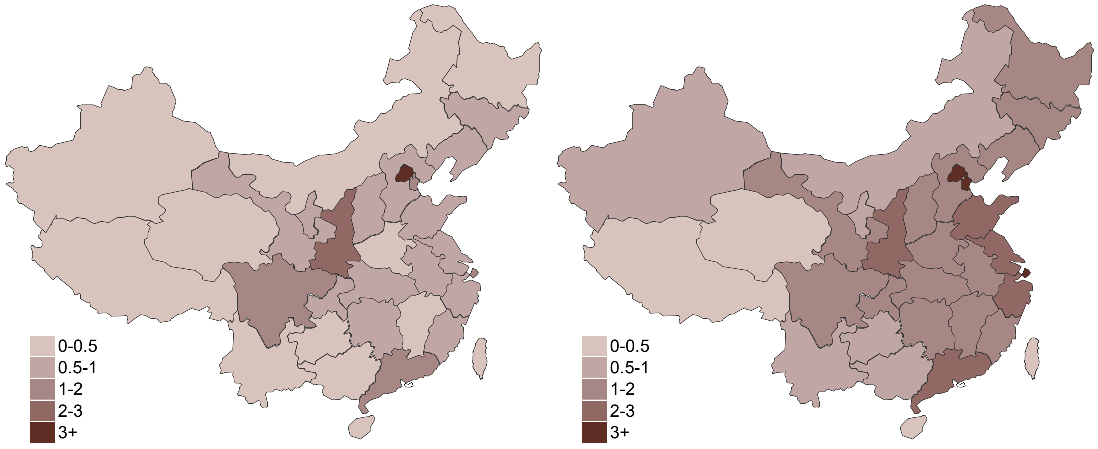
Another notable feature of the Chinese innovation system is the significant regional disparity regarding R&D investment, as illustrated in Figure 1.11. The R&D investment concentrated in a number of key provinces and cities, such as Jiangsu, Guangdong, Beijing, Shandong, Zhejiang and Shanghai, amounted to 59 per cent of total R&D investment, while this figure was 55 per cent in 2000. In 2000, the highest R&D expenditure was found in Beijing, followed by Guangdong, Shanghai, Jiangsu, and Shandong, while in 2015 Jiangsu surpassed other provinces to become the leading hub for R&D expenditure, followed by Guangdong, Shandong, Beijing, and Zhejiang. Additionally, Figure 1.11 demonstrates that almost all provinces experienced a substantial increase in R&D intensity, except Beijing and Shaanxi. Over 19 provinces more than doubled their R&D intensity, while Zhejiang and Shandong increased their intensity to more than four times their previous level.



Source: China Statistical Yearbook on Science and Technology (2016)

Figure 1.11 R&D expenditure and R&D intensity across China, 2000 and 2015

Figure 1.12 further displays the transition in R&D investment and the prevalent regional disparity. Benefiting from reform and the opening up policy, eastern and coastal areas have caught up at a considerable pace over the last fifteen years, against a benchmark of the concentration of investment in Beijing and Shaanxi in 2000. Provinces in the middle area also experienced growth in R&D intensity, but at a modest rate, while western regions remain less innovative. It is worth noting that the large R&D expenditure and R&D intensity in Shaanxi may be explained by the inherited R&D facilities, such as military research bases, government research institutions and universities, which were located there for a strategic reason during the cold war.

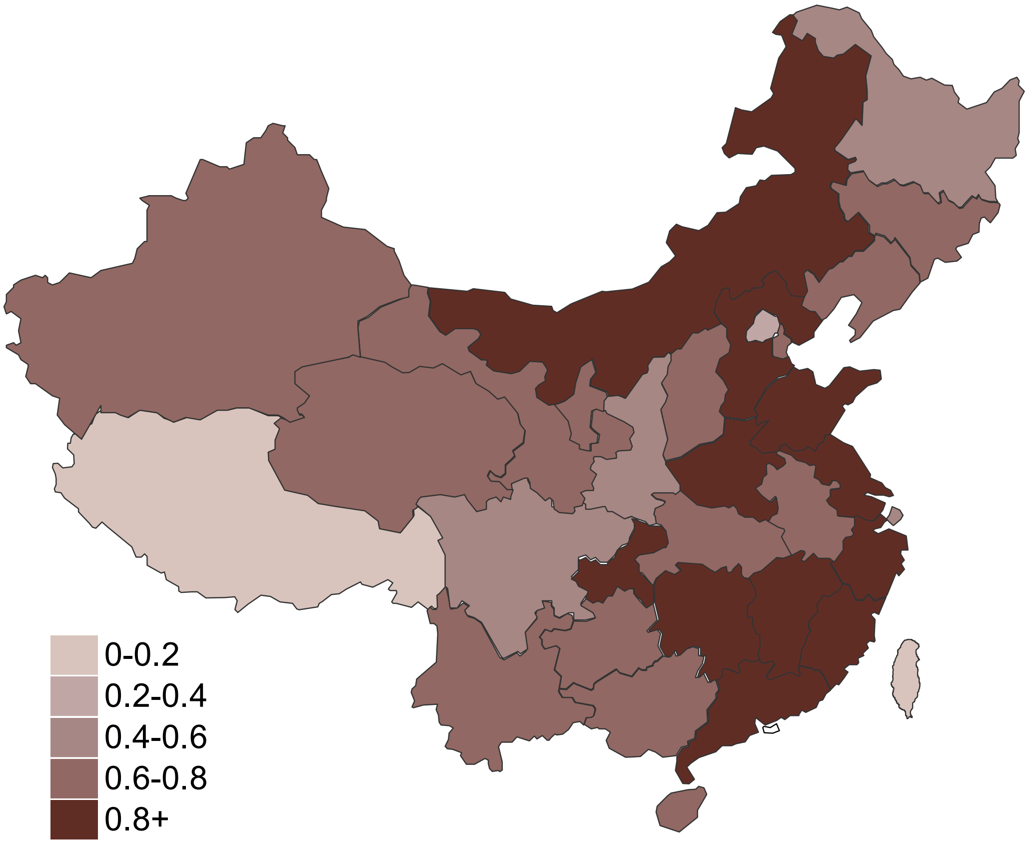


2000 2015

Source: China Statistical Yearbook on Science and Technology (2001, 2016)

Figure 1.12 R&D intensity across China in 2000 and 2015

As mentioned earlier, enterprises are gradually becoming the dominant players in innovation. This trend is primarily manifested in eastern and coastal regions, while the government still plays a major role in accelerating technological advancement in middle and western areas (Figure 1.13). In 2000, the ratios of enterprises-funded R&D of all provinces are below 20 per cent, while in 2015, only that of Tibet is still under 20 per cent. Therefore, the tendency toward enterprise-led innovation is evident, whereas government funding for innovation has become less prevalent across China. Only metropolis locations like Beijing and Shanghai demonstrate strong proportions of funding from foreign and "other" sources.



Source: China Statistical Yearbook on Science and Technology (2016)

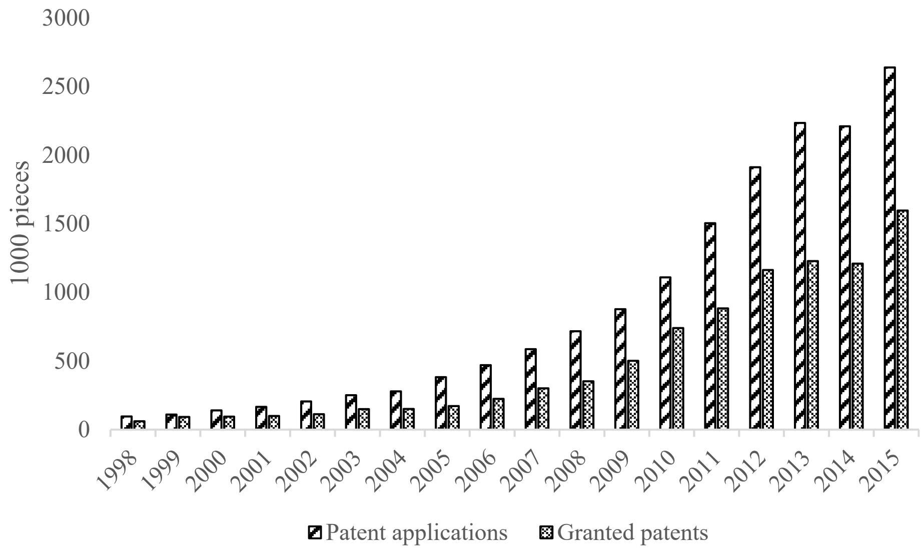
Figure 1.13 Ratios of enterprise-funded R&D over total R&D expenditure in 2015

1.2.2 Achievements of Innovation Development

China's innovation capabilities have been dramatically strengthened by this sizeable investment in the R&D sector. This is evidenced by China's rapid improvement in a number of commonly-used indicators, namely, the number of patents, increases in the number of journal articles and citations, export volume in the high-tech sector, and sales of new products.

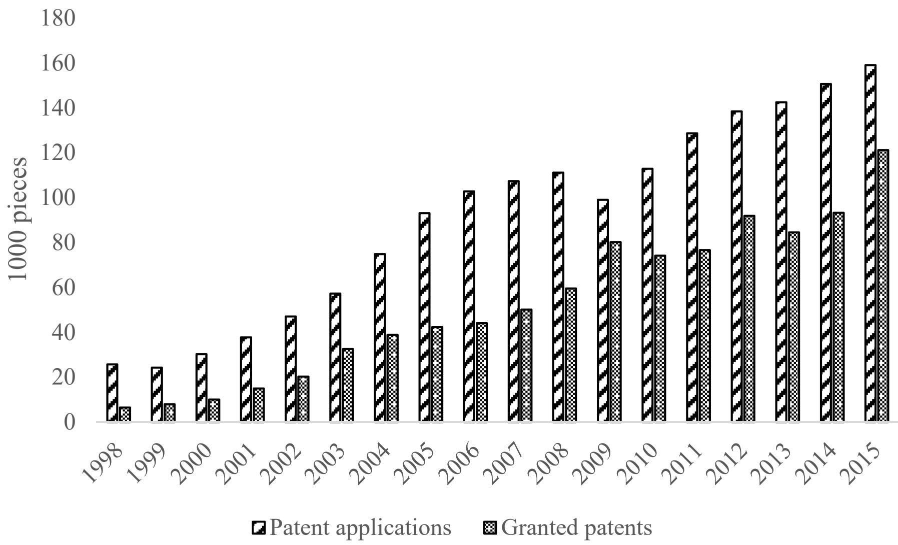
❖ ***Aggregate level***

Domestic patent applications submitted to the Chinese State Intellectual Property Office (SIPO) increased by roughly a factor of four during the period of 1998 to 2005, while the number of granted patents also increased proportionally, about threefold over the same period (Figure 1.14 and Figure 1.15). Concurrently, the number of patent applications submitted and granted in the foreign market increased significantly as well, by factors of nearly four and six, respectively, although these were smaller in absolute terms. This surge in patents can be attributed to the persistent activity in the R&D sector as well as the growing awareness of intellectual property rights (IPR). This upward trend became even steeper after the launch of the MLP plan in 2006. The number of patent applications skyrocketed to 2,639,000 in 2015, from 383,000 in 2005, increasing nearly sevenfold, while the number of granted patents increased by a factor of nine from 172,000 in 2005 to 1,596,000 in 2015. However, the increase in foreign patents is not proportional to that of domestic patents, thus implying a potential bubble in China's patent surge, as the grant of patents also depends on local authorities.



Source: China Statistical Yearbook on Science and Technology (Various years)

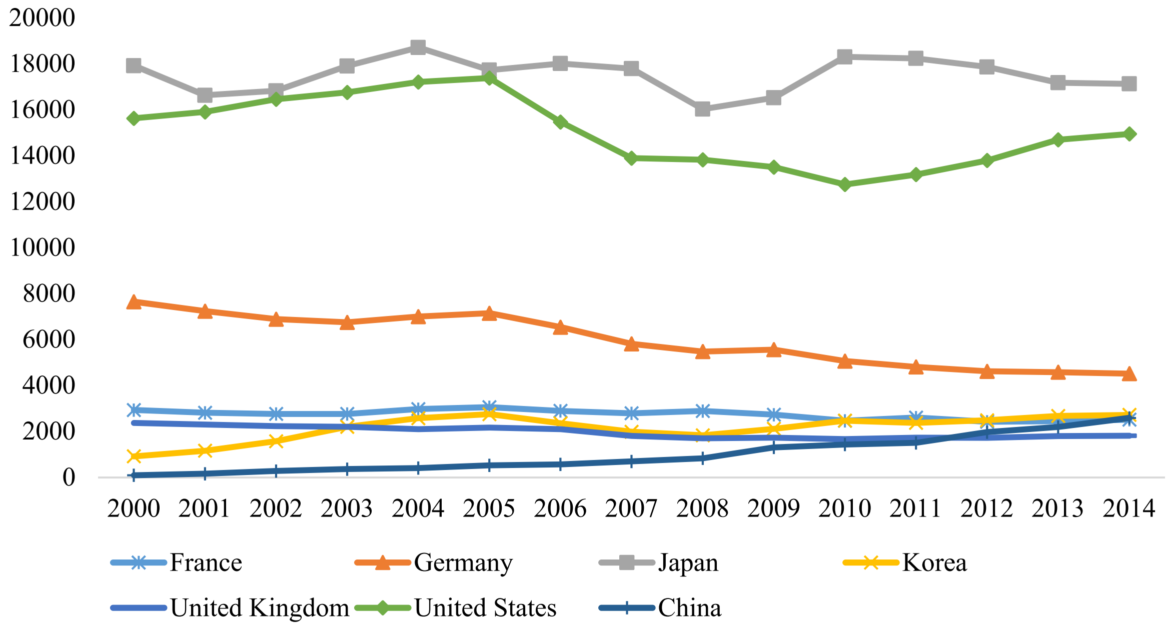
Figure 1.14 Domestic patent applications and granted patents, 1998-2015



Source: China Statistical Yearbook on Science and Technology (Various years)

Figure 1.15 Number of granted patents, 1998-2015

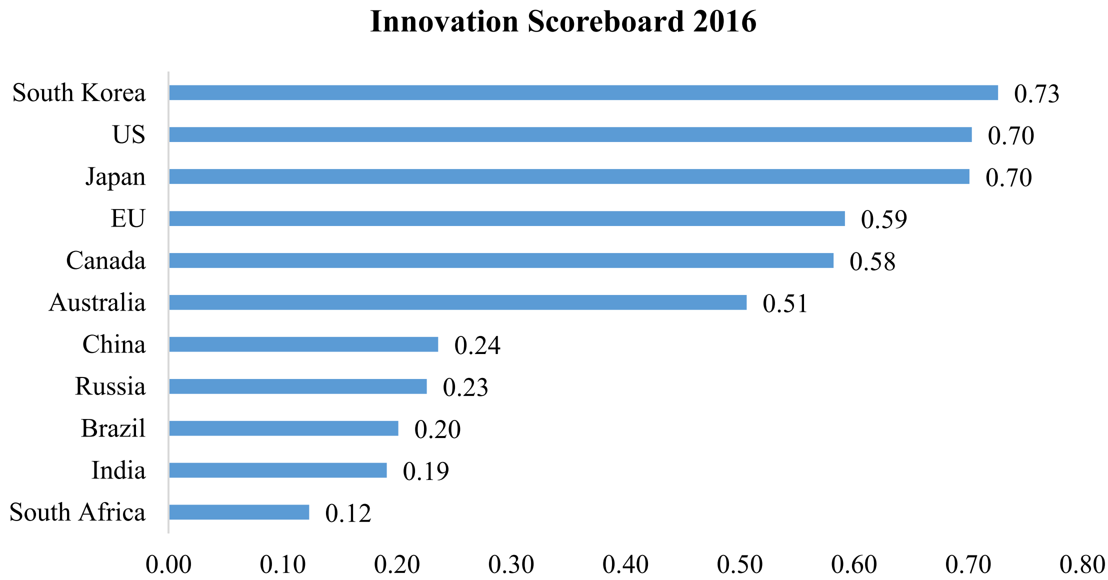
Figure 1.16 presents an international comparison of the number of triadic patent families, which is acknowledged as a better measurement of the value of innovation. As of 2014, China had 2,582 units of triadic patent families, a level much higher than her peers such as the emerging BRIC countries (Brazil, Russia, India and China). In 2000, as demonstrated in Figure 1.16, China had only a two-digit number of triadic patent families, whereas in 2014, China's figure had surpassed that of the United Kingdom and was on par with countries like Korea and France. However, a huge gap remains between China and the leading performers, namely the United States and Japan. China's figure was less than one-fifth of the figure achieved in the United States and Japan.



Source: OECD Main Science and Technology Indicators (MSTI) Database

Figure 1.16 Number of triadic patent families in China and other OECD countries

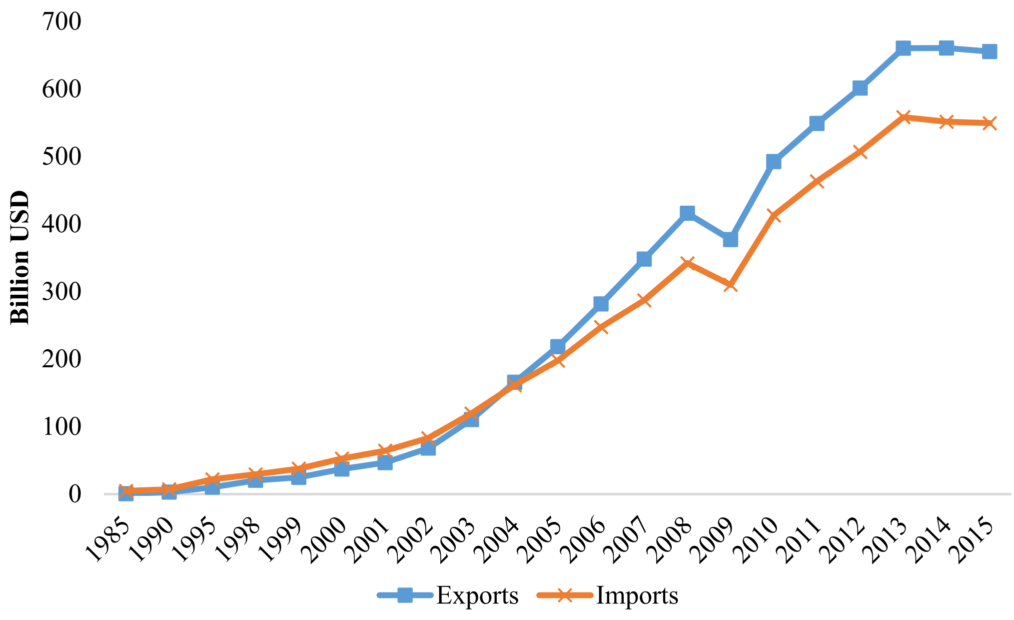
A similar conclusion can be drawn from the innovation scoreboard released by the European Commission in 2016 (Figure 1.17). This scoreboard uses a comprehensive set of indicators to evaluate countries' national innovation capabilities. Although China performed the best of any BRIC country, China's score is only a third of that achieved by the United States, South Korea and Japan. Therefore, strategies to improve the quality of China's innovation and narrow the gap between China and the leading countries should be first on the agenda when planning China's future innovation efforts.



Source: European Commission Innovation Scoreboard (2016)

Figure 1.17 International comparison in overall innovation performance

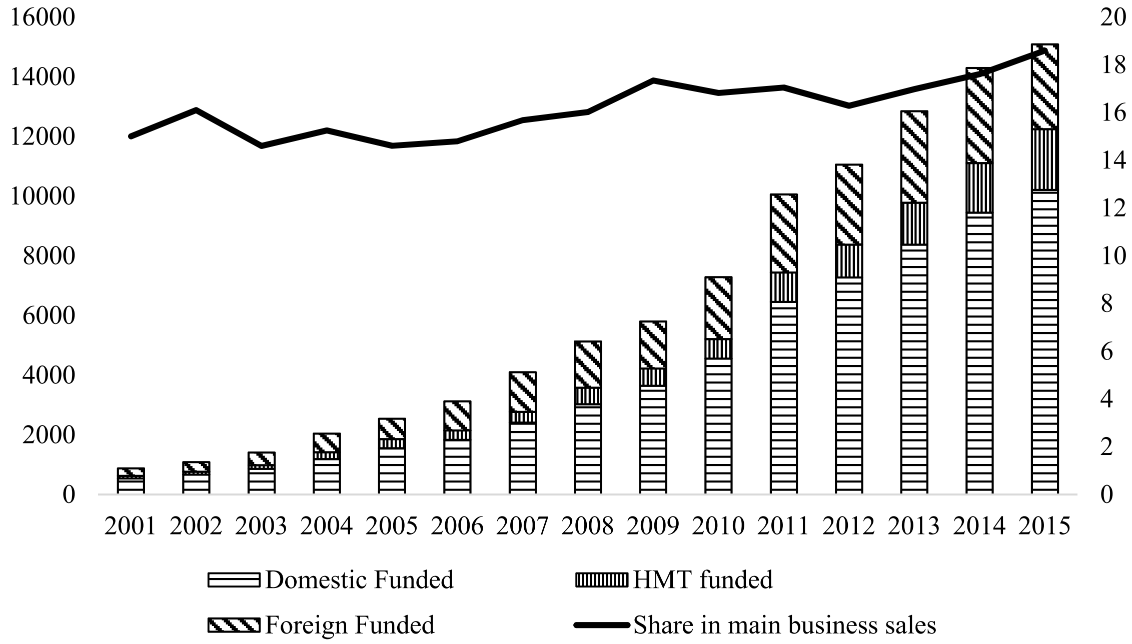
The imports and exports of China's high-tech sector have also expanded drastically over the last two decades (Figure 1.18). From 1985 to 2015, exports of high-tech products from China increased from 0.52 billion USD to 655.3 billion USD, reflecting the growing importance of China's high-tech exports. China has now become a major global exporter of high-tech final products. A noteworthy trend is that the imports of high-tech products have increased at almost the same pace as exports, and only after 2005 did the volume of exports become substantially higher than the imports. This gap proceeded to widen. However, as of 2013, both exports and imports of high-tech products started declining slightly. This reflects the fact that China's export-oriented manufacturing industry is still engaged in processing and assembly operations. As labour and rental costs rose, some manufacturing companies transferred their processing factories overseas in pursuit of lower factor costs, thereby affecting China's high-tech exports.



Source: China Statistical Yearbook on Science and Technology (Various years)

Figure 1.18 Imports and exports of high-tech industry, 1985-2015

The increase in sales of new products, as shown in Figure 1.19, demonstrates the growth in final products of innovation. In 2001, the sales of new products by foreign firms accounted for almost 30 per cent of total sales of new products, while this number decreased to less than 20 per cent in 2015. At the same time, the other two types of firms rapidly increased their sales of new products, especially the domestically funded firms, which occupy the leading role in this metric. However, this increase could be attributed to the expanded market size, rather than the level of innovation within the firms. This is hypothesised because the share of the sales of new products within sales related to the firms' main business did not significantly increase, specifically, from 15 per cent in 2001 to only 18.6 per cent in 2015, including firms funded by Hong Kong, Macau, Taiwan (HMT), and foreign countries. This reflects major challenges faced by China, including the challenge of improving the transfer ratio of science and technology and facilitating the commercialisation of innovation efforts.

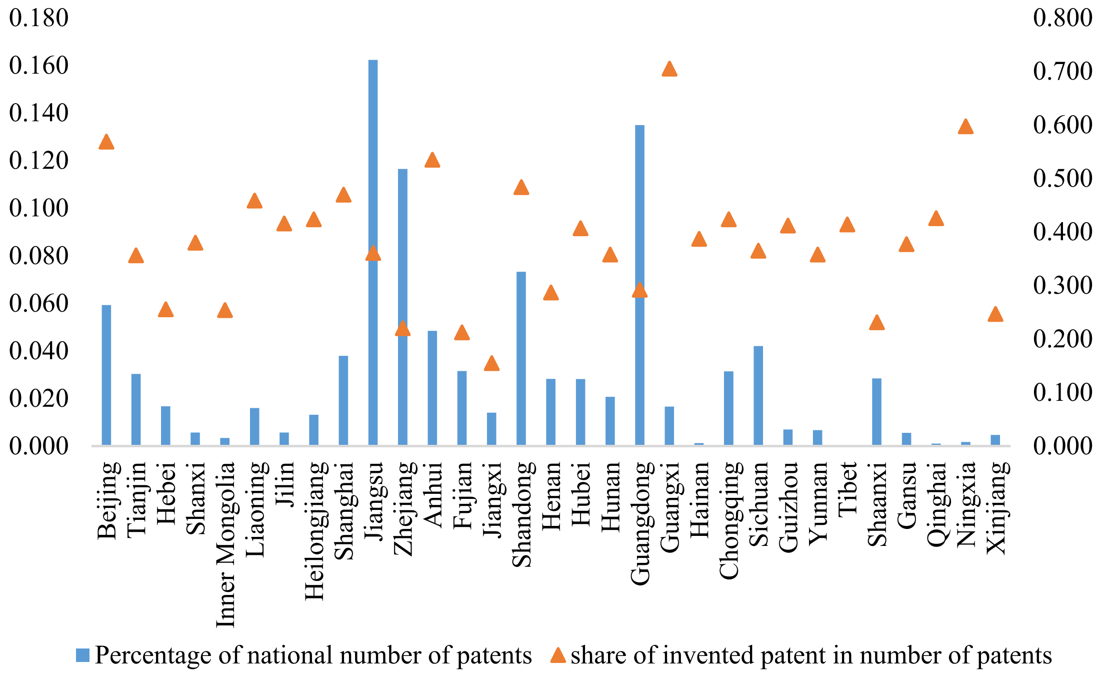


Source: China Statistical Yearbook on Science and Technology (Various years)

Figure 1.19 New product value and its share in main business sales, 1985-2015

❖ ***Regional distribution***

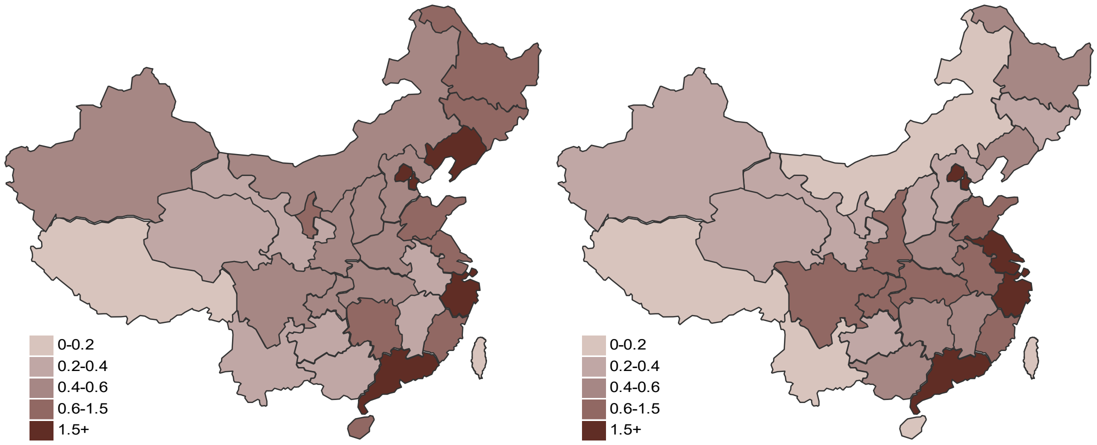
As the output of innovation is a function of innovation inputs, it can be expected that the regional distribution of innovation outputs will resemble the distribution of innovation inputs. In 2015, Jiangsu, Guangdong, and Zhejiang ranked as the top three provinces in terms of number of patent applications, while the share of invention patents in these provinces ranked much lower, which is consistent with the structural features of R&D expenditure by activity types. (Figure 1.20).



Source: China Statistical Yearbook on Science and Technology (2016)

Figure 1.20 Regional distributions of patents

To exclude the potential effect of population size, we use the number of patent applications per capita in order to measure the relative level of each province to the national average level. Figure 1.21 shows that, in 2000, Beijing, Shanghai, Zhejiang, Guangdong, and Liaoning were the five most active locations for innovation in terms of patent applications, while the distribution amongst other provinces is relatively even. However, by 2015, the innovation activities had agglomerated in the coastal area, and activity in the middle area had also increased rapidly, rendering it the second most active region in terms of patent applications, in comparison with the northern and western regions. The regional disparity in terms of innovation is evidently widening, which could further worsen regional inequality.

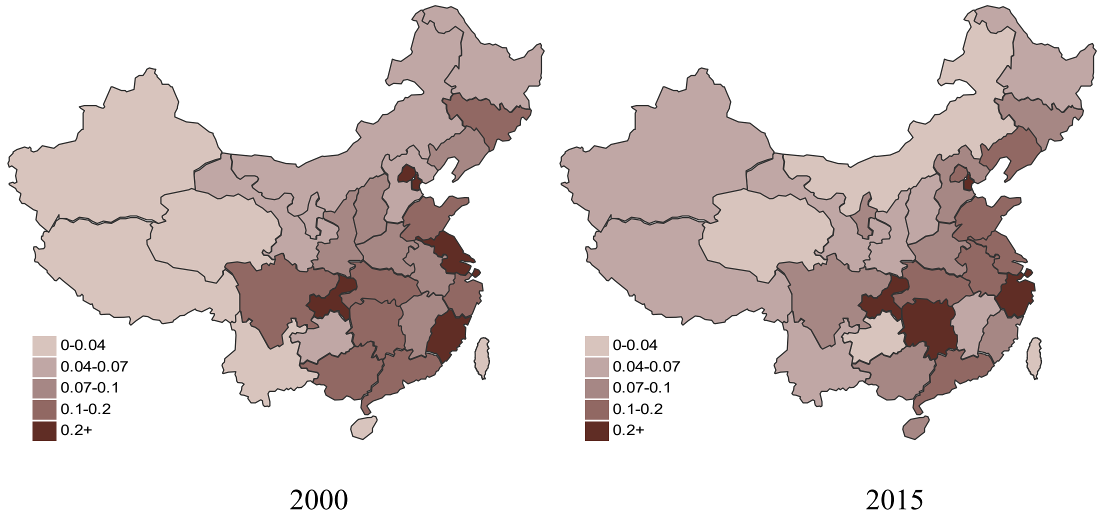


2000 2015

Source: China Statistical Yearbook on Science and Technology (2001, 2016)

Figure 1.21 Regional distributions of patent applications per capita

Figure 1.22 provides information about the distribution of innovativeness in terms of new products. Regional levels are measured relative to the national level in terms of the ratio of new product sales within main business sales. By comparing with the distribution in Figure 1.22, we found that these two distributions are not consistent with each other, implying disorder between regional patenting activities and the commercialisation process. In 2000, Beijing, Shanghai, Jiangsu, Fujian, and Ningxia were the best performers in product-related innovation. By 2015, the Beijing and Fujian provinces had become less competitive in terms of production of new products, while Zhejiang and Hunan had risen to be the advancing provinces regarding the production of new products.



Source: China Statistical Yearbook on Science and Technology (2001, 2016)

Figure 1.22 Regional distributions of innovativeness in terms of new products

1.3 Objective and Contributions

The objective of this thesis is to present a systematic analysis of the innovation behaviour of Chinese firms in the context of a large, open country, which is in the process of transitioning from a growth model that is resource-driven to one that is innovation-driven. It focuses on the transforming role of China in innovation as a whole, as well as the determinants of firms' innovation behaviour and the relationship between firms, universities, and government at the micro level. After its remarkable expansion in the R&D sector and a policy-induced transition to an innovation-oriented economy, has the role of China changed? How did the industrial sector respond to this transition? What are the determinants of firms' choices to invest in innovation activities? Does collaboration with universities contribute to firms' innovation performance? Moreover, is government intervention a valid way to induce firms' innovation investment and promote firms' innovation performance? These research questions frame critical dimensions of China's innovation development and are investigated in this thesis, using a combination of datasets from the national, the provincial, the municipal, and the firm levels.

It is worth noting that constructing the technological flows within a country's economic system is a popular way to identify the primary source of R&D upon which that country depends (Leoncini et al. 1996; Papaconstantinou et al. 1998; Chang and Shih 2005; Hauknes and Knell 2009). However, there is a lack of studies concentrated on emerging countries (Dechezlepretre et al. 2011), especially the underlying changing structure of China's technological system, given the tremendous development in both economic growth and R&D investment. Exceptions like the study by Guan and Chen (2009), and Pan et al. (2012), focused on the domestic system while neglecting the R&D embodiment in international trade flows, which is a major driving force of China's miraculous development.

Moreover, there is limited information about China's innovative activities, particularly at the micro level, despite the increasing significance of the role of business enterprises in building national innovation capability. Although some studies using Chinese firm-level data have emerged recently, they often ignore external factors and therefore fail to give a complete picture of innovative behaviour among China's manufacturing firms (Jefferson et al. 2006; Girma et al. 2009; Dong and Gou 2010; Zhou 2014). Since innovation activities are not isolated activities, but collective endeavours, it is natural to investigate firms' innovative behaviour in the context of their environment.

Another two important players in the innovation system are universities and the government, according to the triple helix model (Etzkowitz and Leydesdorff 2000) and the theory of national innovation systems (Nelson 1993). In contrast to the extensive literature on university-industry collaboration and additionality of public subsidies in developed countries, few studies focus on similar activities in emerging or transitioning economies, let alone activity on the micro level. This is particularly true of China. Exceptions to this rule generally focus on the output additionality, while an efficiency perspective is rarely adopted (Guan et al. 2005; Kafouros et al. 2015; Guo et al. 2016; Liu et al. 2016). Besides, unlike developed countries, China relies heavily on university-industry collaboration to compensate the limited internal R&D capabilities. Furthermore, the assessment of government interventions can provide insights into the effectiveness and functional mechanisms of policy-led programmes, which is an important basis for policy adjustment and implementation in the future. Therefore it is both theoretically and practically important to investigate these questions.

Based on the factors mentioned above, this thesis, therefore, makes several contributions to the existing literature. The findings have implications for entrepreneurs and policymakers, not only in China but also in other transforming countries in the age of the knowledge economy. The specific contributions of this thesis are listed below.

- This thesis, overall, provides a systematic analysis of China's innovation system and its key players during the transition period, particularly at the micro level. Its findings in general have both theoretical and practical significance for emerging countries in terms of what is required to catch up on the technology frontier. It is also, in particular, beneficial for better understanding of China's sustainable development via the innovation-driven model.
- A contribution to the literature is made via incorporation of R&D embodiment into international trade flows in order to construct China's technological system based on the OECD I-O tables. This makes the results more comparable with other studies in developed countries. Given China's great achievements throughout the opening up process, it is necessary and significant to identify China's position in terms of innovation under an open economy framework.
- Additionally, this thesis adds to the literature by combining firm-level data and municipal-level data in order to investigate both the internal and external factors that could affect firms' decisions to innovate, in the context of literature which often ignores the external factors. Unlike papers which use R&D investment only to depict firms' innovative activities and focus mainly on LMEs, this thesis adopts different measurements to capture the potential informal innovative activities and includes all available samples in the analysis, thereby offering a complete picture of China's innovative behaviour at the micro level.

- ❖ This thesis firstly adopts an efficiency view to investigating the contribution of university-industry collaboration to firms' innovation performance, which enriches the existing empirical literature and is beneficial when developing an understanding of the functional impact of collaboration on innovation performance. It also points out that the effect of collaboration on innovation performance might differ throughout the innovation process, which is supported by indirect evidence in this thesis. Moderating effects of heterogeneous regional institutions are considered as well.
- ❖ This study, for the first time, assesses the effectiveness of national S&T programmes in the post-2006 period. Moreover, in addition to the traditional investigation on input and output performance via additionality, this thesis also sheds light on the additionality in terms of efficiency performance, which captures more behavioural additionality as China is characterised by resource-centralisation and policy-promotion. This empirical work, with a unique dataset, also adds new empirical evidence to this area of research.

1.4 Organisation of the Thesis

This thesis falls broadly into the body of literature which discusses firms' innovation in frontier countries and catching-up countries in general, and, in particular, China. Broadly, this thesis deals with several interlinked topics related to firms' innovation activities and how they interact with the environment and other institutions. The four empirical studies start with an examination of innovation in China within an international context, in order to provide an overall impression. Following that, the second chapter investigates the determinants of innovative behaviour of Chinese manufacturing firms. This investigation is based on a combination of a resource-based view and a systematic approach to innovation. Building on this, the third chapter specifically discusses the interaction between firms and universities to see whether collaboration contributes to firms' innovation performance from the perspective of open innovation. Lastly, the fourth chapter focuses on the role of government intervention in firm-level innovation by assessing the effectiveness of government S&T programmes. These four core chapters are supported by a detailed background chapter which provides contextual information regarding the progress of innovation in China.

The thesis is organised as follows. Chapter Two aims to explore to what extent the network of product-embodied R&D in China has changed and how the country's industrial sectors have responded in an open system. Technological flow matrices and social network analysis (SNA) are employed to examine the evolution of product-embodied R&D diffusion at the industrial level in China during 2000-2010. R&D embodied in international trade flow is considered so that the findings in this study can be compared with those from studies of developed countries. Visual representation of industrial linkages in terms of R&D investment helps to depict the underlying changing structure of China's industrial system. The conclusions drawn in this thesis are different to those from previous studies on China, thus providing a different view on the stage of China's advancement in terms of technological innovation.

Micro-level information in China is quite limited, despite the increasing importance of business enterprises, and thus Chapter Three provides a useful addition to the emerging body of literature by merging firm-level data and city-level data in order to investigate both internal and external factors affecting firms' innovation choices. The analysis is based on a theoretical framework which combines resource-based views and the theory of regional innovation system Different measurements of innovation are employed in order to capture the potential informal innovative activities, as R&D is not necessarily the only way to achieve innovation outcomes. It provides interesting insight into firms' innovative behaviours, embedded in different local systems. Policy implications drawn from this study are not only relevant for China but also for the rest of the world, given that Chinese companies are becoming increasingly active globally.

Considering the strong role played by universities in the building of China's national innovation capability, it is both theoretically and practically significant to examine the impact of university-industry linkages on firms' innovation performance in the context of China. Chapter Four contributes to the literature by investigating the impact of university-industry collaboration on innovation efficiency at different stages. This offers a better understanding of the influential mechanism of collaboration under the framework of open innovation. In addition, an efficiency perspective may also eliminate the bias associated with the exclusive use of output indicators, as collaboration might improve or inhibit firms' innovative performance through input reduction or redundancy.

Unlike Japan and Korea, China returned to "techno-industrial policy" which involved direct government intervention in shaping specific industrial sectors, rather than shifting to innovation policies which shed light on knowledge infrastructure, entrepreneurship, and efficient markets, when approaching the technology frontier. Chapter Five, therefore, aims to evaluate whether these government-led programmes induced R&D investment, promoted innovation performance and enhanced firms' productivity. The matching estimator is adopted jointly with a difference-in-difference method to investigate the additionality of undertaking government science and technology (S&T) programmes between the treated group and control group under a diverse matching scheme.

Finally, Chapter Six summarises the main conclusions of the thesis, discusses the implications for entrepreneurs and policy makers in China as well as those for other catching-up economies.

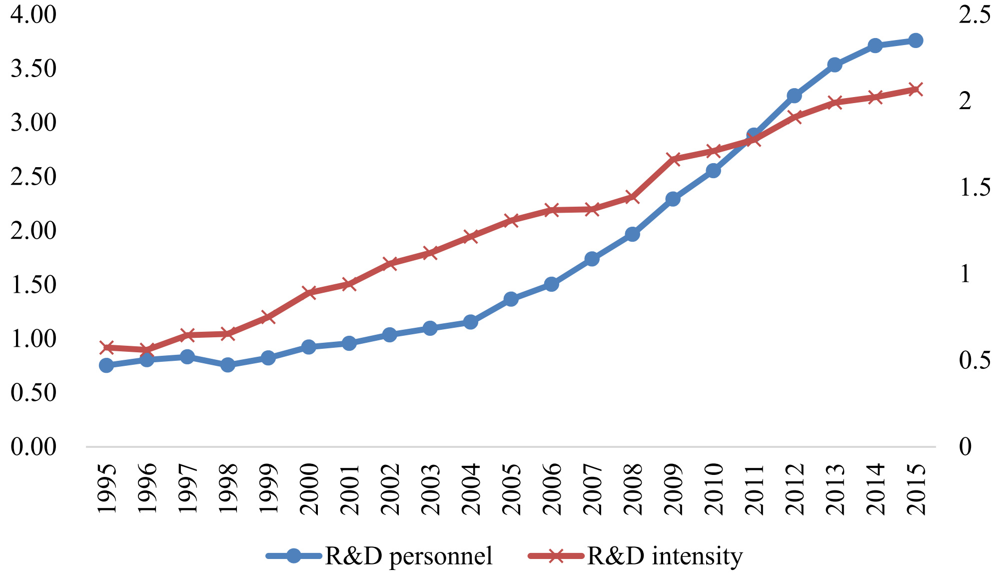
CHAPTER 2 – CHINA'S CHANGING ROLE IN INNOVATION

2.1 Introduction

The contemporary growth theory proposes that technological progress is the major driver of national economic growth, productivity gains and competitive advantage. In the age of accelerating globalisation, the enhancement of national technological innovation capability depends not only on domestic research and development (R&D) investment but also the spillover of international technology. This is especially true for latecomers, as evidenced by the successful experiences of Japan and South Korea (Sun and Liu 2013).

China no longer wants to be a technology follower after benefited from the international technology spillover for years. This makes the discussion of international technology diffusion and indigenous innovation very inspiring within the Chinese context. Supported by a prosperous economy, China has made remarkable progress in science and technology (S&T) in recent decades (Schaaper 2009) and has become a leading R&D investor. If the current growth momentum is maintained, China could transform from being the world's manufacturing powerhouse to a technological superpower (Sigurdson 2004; Wu 2012a). This change would have important implications for the rest of the world, especially China's neighbours (Wang and Zheng 2012).

In reality, China's investment in R&D has grown steadily for decades (see Figure 2.1). During the years of 1998 to 2015, the average growth rate of R&D investment reached 24.7 per cent per annum, which is almost twice the growth rate of China's GDP over the same period. Amongst the world's major investors in R&D activities, China has been ranked number two since 2010, ranking only behind the United States. China also possesses the largest R&D research team, which has experienced exponential growth as shown in Figure 2.1.



Source: NBSC (various years)

Figure 2.1 China's R&D intensity and personnel of full-time equivalent, 1998-2015

R&D intensity (R&D expenditure as a proportion of GDP), as shown in Figure 2.1, has risen from 0.69 per cent in 1998 to 2.07 per cent in 2015, which puts China on par with economies such as Belgium, Canada, the Netherlands and the United Kingdom. Although China's R&D intensity is still behind that of major players, namely, the United States (2.79 per cent), Germany (2.82 per cent) and Japan (3.44 per cent), it is well ahead of other emerging economies such as India (0.80 per cent) and Brazil (1.10 per cent). Associated with the expansion of R&D is the boom of China's innovation capacity. For example, the number of patent applications grew by 21.9 per cent per year on average between 1998 and 2015 (Figure 1.14 and Figure 1.15). In 2011, according to the World Intellectual Property Organisation (WIPO), the number of patent applications in China surpassed the US figure.

With robust economic growth and strong government support, China's investment in R&D, as well as its innovative capacity, is set to expand. Given the volume of the Chinese economy, it can be anticipated that the country will become a global technology leader. It is therefore relevant and also reasonable to pursue in-depth research on the development of China's innovation. While numerous papers have focused on the contributions of various factors to productivity growth, few have examined whether China is a knowledge user or producer in an international context, and how the country's industrial sector has changed in terms of R&D activities, so far, in the context of an open system. The most closely related research on China was done by Guan and Chen (2009). They investigated the technological system of the Chinese manufacturing industry based on China's domestic input-output (IO) tables in 1997 and 2002, which, due to the differences in industrial composition, are not comparable with the IO tables of developed countries. In addition, their analysis is based on a closed system which excludes the R&D embodiment in international trade flows and thus may overestimate China's role in an international context. However, since China entered the World Trade Organisation (WTO) in 2001, China's market has become increasingly open and its economic links with other countries has been extensive (Wang and Zheng 2010). It is important to bring the international dimension into consideration and investigate the evolution of China's technological system using the latest data. Therefore, this study adds to the literature by exploring whether the role of China has changed, and the manner in which it has changed, given the remarkable expansion in the R&D sector and the policy-induced transition to an innovation-driven growth model.

The remaining parts of this chapter are organised as follows. Section 2.2 reviews the literature in the area of international technology diffusion and trade-related R&D spillovers. Section 2.3 defines the method and data involved in this study. Section 2.4 covers the empirical analysis and major results. Finally, conclusions are offered in Section 2.5.

2.2 Literature Review

The core concept of Schumpeterian growth theory is that endogenous R&D and innovation are the determinants of technological progress and economic growth (Romer 1990; Grossman and Helpman 1991b; Aghion and Howitt 1992). Coe and Helpman

(1995) further proposed that productivity in an open economy with international trade and knowledge exchange depends on its own R&D as well as the R&D efforts of its trade partners. This demonstrated that two approaches could be adopted by nations to achieve technological progress, those being endogenous enhancement of their technological innovation capabilities or acquisition of advanced technology through international technology diffusion. Eaton and Kortum (1997) and Keller (2004) even argued that the technological progress which prompted productivity gains in most countries was predominantly sourced from abroad rather than domestically. These studies made international technology diffusion a popular topic in the literature of economics and technology policy (Gong and Keller 2003; Xu and Chiang 2005).

In the literature, technology diffusion normally refers to firms' acquisition of technology from external sources through various mechanisms rather than producing it internally. In general, it consists of two types, namely, disembodied diffusion and product-embodied diffusion (Kim and Lee 2004). In empirical research, however, embodied and disembodied diffusions are not clearly separable. Fortunately, empirical measurements can mainly capture either embodied or disembodied diffusion. Studies on international technological flows through patent data capture disembodied diffusion, while studies using trade data more closely capture embodied diffusion (Papaconstantinou et al. 1998). Based on this classification, the effects of the two types of diffusion on productivity have been widely discussed. Badinger and Breuss (2008), Franco et al. (2011) and Seck (2012) examined the effects of embodied spillovers, while Bernstein and Mohnen (1998), Keller (1998) and López-Pueyo et al. (2008) focused on the effects of disembodied spillovers. These works found that both embodied and disembodied spillovers made positive contributions to total factor productivity (TFP).

Recent research has presented a combined perspective. Ang and Madsen (2013) conducted a study based on six Asian miracle economies and found that the import channel of international knowledge spillovers has probably been the most important for this particular group. Krammer (2014) examined a similar question with a dataset of 47 developed and transition countries and found that trade remains the dominant factor behind productivity growth and technical progress, while the effects of FDI- and patent-related spillovers are significantly smaller. The same conclusion is found in Franco et al. (2011), that is, bilateral trade is still a very significant channel for international R&D spillovers, while the impact of FDI is relatively small (Zhu and Jeon 2007). Hence, trade-related R&D spillovers deserve more thorough investigation (Zhou and Song 2016).

Given the importance of trade-related R&D spillovers, a number of studies have focused on the area of technology flows among industries, with the aim of capturing more detail regarding interactions at the industrial level. Leoncini et al. (1996) employed a systematic view in order to compare the intersectoral innovation flows and national technological systems by using input-output methods and network analysis. By employing this same method, they further compared the technological systems of eight OECD countries (Leoncini and Montresor 2000). Distinctions between different technological systems with different structural characteristics have been clearly identified and an obvious pattern of "convergence" over time has been observed. The pioneering work of Papaconstantinou et al. (1998) employed an input-output method to capture the product-embodied R&D diffusion in 10 OECD countries and investigated which source of R&D each country is most dependent on. Chang and Shih (2005) introduced China and Taiwan, based on the research of Leoncini and Montresor (2000) to make a similar comparison. Shih and Chang (2009) defined the structural configuration of 48 countries and found that the structural configuration exhibits similar patterns in both embodied and disembodied diffusion networks. Hauknes and Knell (2009) proposed an improved method to calculate the embodied knowledge within the interaction of industries with different technology levels in five western countries.

However, these studies mainly concentrated on developed countries, thus neglecting the increasingly important role of emerging economies (Dechezlepretre et al. 2011)[2], especially the evolving, underlying structure of product-embodied R&D in

[2] An exception is Wang and Li-ying (2014) which examined the BRIC's patents granted by the USPTO and delineate the internationalization patterns of the BRIC countries in the global innovation landscape.

China, given the country's tremendous progress, both in terms of economic growth and R&D investment[3]. Scholars in China, like Guan and Chen (2009), analysed the technological system of Chinese manufacturing in 1997 and 2002 by using domestic I-O tables[4]. They found that the provision of technology for diffusion were more concentrated than technology acquisition. Fewer sectors acted as sources of technology diffusion than acquirers of technology. Pan et al. (2012) calculated similarity matrices for 35 industrial sectors over the period of 1997 to 2008 using China's input-output tables for 1997, 2002 and 2007 to measure inter-industry technology spillover. They further investigated the effects of such spillovers on the labour productivity for different industrial sectors.

There is no doubt that these studies have contributed to our understanding of development of innovation in China. However, there is a gap in the literature with respect to the R&D embodiment in international trade, namely, trade-related R&D spillovers. This study therefore attempts to contribute to the literature by comparing static states of China's technological system in terms of product-embodied R&D during the period of 2000-2010. The empirical work combines comparable international I-O tables, information on R&D investment and bilateral data to take international trade-related R&D spillovers into consideration. Additionally, this study also employs network analysis to illustrate the evolution of the whole technological system and the corresponding changing role of each sector.

2.3 Method and Data Issues

2.3.1 Product-Embodied R&D Diffusion: An Input-Output Approach

[3] Shih and Chang (2009) further pointed out that few studies have captured the relative changing position from a view of historical dataset, which should be a future direction of researches in this area.

[4] For general reviews of China's R&D policy and development, readers may refer to Fischer and Zedtwitz (2004) and Huang et al. (2004).

This study starts with the open Leontief model, which considers technology and final demand separately, to measure the product-embodied R&D diffusion. *N* industries are represented as a vector of output *x* and a vector of final demands *y* in this model[5]:

$$x = \mathbf{A}x + y \tag{2-1}$$

where $\mathbf{A}$ represents the matrix of domestic intersectoral coefficients. Its multiplication with *x* gives the intermediate inputs necessary for production. On the assumption that the inverse of the matrix $\mathbf{I} - \mathbf{A}$ exists, the general solution will be,

$$x = (\mathbf{I} - \mathbf{A})^{-1} y \equiv \mathbf{B}y \tag{2-2}$$

in which $\mathbf{B}$ is the Leontief inverse matrix of $\mathbf{A}$. Therefore, the elements b_{ij} in matrix $\mathbf{B}$ represent the direct and indirect requirements of increased output in industry i necessary to produce one additional unit of final demand in industry j.

In order to measure the innovation flows based on the input-out approach, two assumptions are made: 1) R&D expenditures are treated as a proxy for the expansion of technical knowledge; and 2) intersectoral transactions are assumed to be the carriers of R&D across industries and countries, i.e. R&D efforts are evenly distributed in the transaction flows or trade flows (Papaconstantinou et al. 1998). Thus, the total R&D content in sector *j* (int_j) should include the direct R&D expenditure of the industry (r_j), R&D incorporated in domestic intermediate inputs (pd_j), domestic investment goods and services (cd_j), imported intermediate inputs (pim_j) and imported investment goods and services (cim_j) purchased by industry *j* (Hauknes and Knell 2009).

$$int_j = r_j + pd_j + cd_j + pim_j + cim_j \tag{2-3}$$

The direct R&D intensity for industry *j* is defined as R&D expenditure per unit of gross output, that is

$$r_j = R_j / X_j \tag{2-4}$$

[5] Standard notation: scalar and vector variables are in italics with lower-case variable names, matrix variables in bold, with capitals. Matrix and vector components are given in lower-case italics with the required number of matrix indices.

The sum of the j^{th} column of the Leontief inverse matrix $\mathbf{B}$ measures both the direct and indirect impact on domestic production when final demand for the j^{th} sector changes by one unit. Therefore, the product of the direct R&D intensity of sector *i* and the elements b_{ij} of the matrix B is the matrix P, in which elements p_{ij} indicate the total domestic R&D embodied per unit of final demand in the sector *j*:

$$P = \hat{r}B \tag{2-5}$$

where $\hat{r}$ is a diagonal matrix whose elements are the direct innovation intensities r_j. However, there exists a double counting problem when measuring the R&D intensity by units of production rather than by units of final demand. This issue is dealt with, according to Papaconstantinou et al (1998) and Hauknes and Knell (2009), by dividing the elements of each column by the relevant element of the main diagonal, thus eliminating the elements of the diagonal and establishing a modified matrix $\mathbf{B}$ which is denoted as $\mathbf{B}^*$.

Based on the adjusted Leontief multiplier $\mathbf{B}^*$, the R&D embodied in domestic intermediate inputs for industry *j* is defined by pre-multiplying the direct R&D intensity:

$$Pd = \hat{r}B^* \tag{2-6}$$

and its elements are calculated as follows:

$$pd_j = \sum_{i \neq 1}^{n-1} r_i b_{ij}^* X_j \tag{2-7}$$

The R&D embodied in purchased domestic capital goods for industry *j* can be defined according to the equation:

$$cd_j = \sum_{i=1}^{n} r_i \Big(\sum_{k=1}^{n} b_{ik} Id_{kj} \Big) \tag{2-8}$$

where Id_{kj} is industry *j*'s investment expenditures for the k^{th} product. Since investment expenditures is one of the components of final demand, the traditional Leontief inverse can be used to define the indirect R&D embodied in current capital formation. Because the traditional Leontief inverse matrix neglects the R&D embodied in the stock of capital operated for production, this process therefore is likely to underestimate the actual R&D contribution.

As for the formulation of imported R&D, it is simpler than the treatment of domestic R&D flows because the intersectoral propagation effects in acquired R&D are not considered. First, the R&D embodied in imported intermediate inputs for industry j is defined as the product of foreign direct R&D intensities with the imported amount of intermediate inputs, therefore:

$$pim_j = \sum_{i=1}^{n}\sum_{k=1}^{l} r_{ik}\alpha_{ik}X_{ij}^{im} \tag{2-9}$$

where X_{ij}^{im} represents the intermediate inputs for product i by industry j from abroad, α_{ik} is the import share of country k.

Similarly, R&D embodied in purchased imported capital goods for industry j is calculated using the following equation:

$$cim_j = \sum_{i=1}^{n}\sum_{k=1}^{l} r_{ik}\alpha_{ik}I_{ij}^{im} \tag{2-10}$$

where I_{ij}^{im} is the investment demand for product i by industry j from abroad, and α_{ik} is the import share of country k[6].

2.3.2 Structural Configuration: Social Network Analysis

As the R&D flows are calculated based on an input-output approach, we are able to obtain a matrix R which contains both economic information via the input transactions among the industries and the innovation information through the technological embodied products (as measured by R&D expenditures). By considering

[6] Both equation (2-9) and (2-10) do not take indirect effects into consideration. It means that the imported R&D is generally underestimated in the model. Taking such indirect effects into account would involve solving the model simultaneously across countries.

the industrial sectors as "nodes" and the R&D flows as "edges", we are able to depict the structure of an innovative system in a directed graph via a binary network after dichotomisation (Soofi and Ghazinoory 2011). The dichotomised matrix R^{dic} comprises elements with values of either one or zero, dependent on whether the elements exceed the threshold value c[7]. Specifically, it can be defined as the following:

$$R_{ij}^{dic} = 1 \text{ if } R_{ij} > c \,; R_{ij}^{dic} = 0 \text{ if } R_{ij} < c \tag{2-11}$$

Based on this dichotomised matrix, this study employs SNA to investigate the changing pattern of intersectoral interaction in terms of innovation diffusion in two scenarios (with and without foreign R&D presence). The network as a whole is considered first. The density D of a network with n nodes and e edges is defined as follows:

$$D = \frac{e}{n(n-1)}, 0 \le D \le 1 \tag{2-12}$$

where the denominator indicates the maximum number of connections. In general, a network with a higher density corresponds to a better connected technological system, and vice versa (Leoncini and Montresor 2000; Shih and Chang 2009).

Secondly, the positional characteristics of each sector in the interaction network are observed by using the indicator of centrality. The inward degree (C_{in}) and outward degree (C_{out}) of Freeman degree centrality (Scott 1991) of a given sector are defined as:

$$C_{in}^{j} = \sum_{i=1}^{n} R_{ij}^{dic} ; C_{out}^{i} = \sum_{j=1}^{n} R_{ij}^{dic} ; \tag{2-13}$$

where R_{ij}^{dic} is an element of dichotomised matrix R^{dic}. The inward degree of industry j (C_{in}^{j}) is the summation of column j in R^{dic}, while the outward degree of industry i (C_{out}^{i}) is the summation of row i in R^{dic}. It is possible to determine whether a certain sector is a source, core or terminal of innovation diffusion via an examination of the two

[7] The major limitation of this method is that the threshold value c is chosen exogenously (Leoncini and Montresor 2000; Chang and Shih 2005). However, this study is to compare the structure of different networks on a relative basis and thus the limitation can be ignored.

measures of inward and outward centralities. Industries with more inward degrees are terminals or absorbers of innovation in the intersectoral system, while industries with more outward degrees are considered as sources of innovation or technology diffusors.

Thirdly, we employ centrality indices of a single sector, thus defining the inward and outward centralisation of the entire network with following formulas:

$$H_{in} = \frac{\sum_i (C_{in}^{i*} - C_{in}^{i})}{(n-1)(n-2)}; H_{out} = \frac{\sum_i (C_{out}^{i*} - C_{out}^{i})}{(n-1)(n-2)} \quad (2\text{-}14)$$

where C_{in}^{i*} and C_{out}^{i*} are the inward degree and outward degree centralities of the most central sector, i^*. A high centralisation index implies a very hierarchical technological system which is less conducive to interactive innovation diffusion, whereas a low centralisation index indicates a system with an evenly distributed structure.

2.3.3 Data Issues

In this study, innovation flows are estimated by combining business enterprise R&D expenditure data with input-output (I-O) tables and bilateral trade data. The R&D data are drawn from the OECD Analytical Business Enterprise Research and Development (ANBERD) database. The I-O data capturing intersectoral transaction flows are drawn from the OECD I-O database, which contains information on domestic intermediate flows, imported flows, domestic investment expenditure, imported investment expenditure, and value added components. The related trade data are drawn from the OECD Bilateral Trade database. Industrial classifications in all these data sources conform to ISIC Rev. 3.0, and thus the components of each industry remain the same across years. In addition, the integrated dataset allows us to observe the development of R&D activities in different industries with consideration of R&D embodiment in international trade and also allows us to make the results comparable to studies on developed countries.

2.4 Empirical Analysis

The business sector plays a critical role in the expansion of China's R&D capacity. As of the mid-1990s, business enterprises have grown to become the dominant players in China's R&D activities (Wu 2012a). In 1997, Chinese enterprises collectively accounted for 42.9 per cent of the country's R&D spending. This figure subsequently rose to 60.3 per cent in 2000, 68.4 per cent in 2005 and 73.4 per cent in 2010, almost three-quarters of total investment. Therefore, this study focuses on R&D investment from the private sector, which is representative of China's R&D activities.

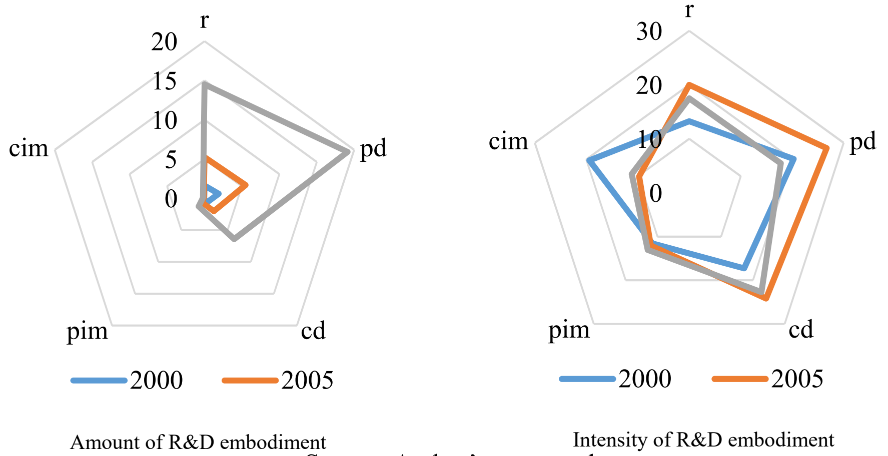
In this section, we first construct the technological matrices for the years of 2000, 2005 and 2010 in order to depict the technology flows among 18 sectors in China and calculate each component of the total R&D embodiment for each industry. Following that, the SNA is introduced, which investigates the changing pattern over time and the industrial responses in detail.

2.4.1 Estimation of Product-Embodied R&D

Based on the aforementioned method, China's performance in the five dimensions of total R&D embodiment, and the intensity of R&D embodiment, are shown in Figure 2.2. The left-hand panel shows the components of the amount of R&D embodiment. It is clear that the three domestic dimensions have experienced exponential growth in the period between 2000 and 2010. Meanwhile, the proportion of imported R&D expenditure has decreased over time. However, the R&D embodied in imported intermediate goods still expanded by more than a factor of seven, and the R&D embodied in imported capital goods by more than a factor of five. Both of these results associated with the gradual opening of the market since China entered the WTO in 2002. This trend confirms that there has been considerate development in indigenous innovation in China, which is consistent with the national strategy highlighted in the *National Programme for Medium and Long Term Development of Science and Technology (2006-2020)* announced in early 2006.

The right-hand panel of Figure 2.2, showing the five components of product-embodied R&D in terms of intensity, is even more significant, and deserves close examination. The pentagon for the year 2000 has a sharp corner pointing to the *cim* which is the intensity of R&D embodiment in imported capital goods. It implies that China's innovation system was highly reliant on the innovation spillover from imported capital goods. This phenomenon, however, disappeared in 2005 and 2010, and the three domestic dimensions took the dominant position. This change implies that China's innovation system became increasingly independent and self-sufficient after a decade of development. Nonetheless, considerable R&D is still embodied in the imported parts. Even though the intensity of R&D embodiment in imported capital goods decreased remarkably over the observed period, it increased slightly for imported intermediate goods over this period.

Following this, it is worth noting that the three domestic dimensions, especially the R&D embodiment in domestic intermediate inputs, have witnessed a decline between the years 2005 and 2010. The underlying reason can be attributed to the four trillion RMB economic stimulus packages which increased the nominal earnings of firms and, therefore, also increased the total output of industries. Since the R&D expenditure in this study is in US dollars and adjusted for purchasing power parity (PPP), this monetary dilution will have a lesser impact on the R&D expenditure figures. Thus, the R&D intensity witnessed a remarkable drop and further affected the other two domestic dimensions. In the original dataset, it can be seen that the R&D expenditure increased considerably during this period, but the output increased even faster, which confirms this theory.



Source: Author's own work

Figure 2.2 Five dimensions of product-embodied R&D

Given the discussion above, we may conclude that China is transitioning from a pure technology absorber to a more neutral role due to its phenomenal growth of R&D investment, despite the contribution from the imported dimensions cannot be ignored. To gain further insight on how each industry responded to this transition process, we conduct further analysis at the industrial level. In accordance with the ISIC Rev. 3.0 industrial classification, there are 34 industries in the international I-O tables from the OECD's Structural Analysis (STAN) Database. This chapter have reduced the number of industries to 18 sectors with the joint aims of, firstly, reducing the number of columns and rows with only zero values, particularly in the service sectors, and, secondly, keeping as many industries as possible in order to preserve a high level of detail (Refer to Table A2.1).

Table 2.1 shows the five dimensions of R&D embodiment for each of the 18 industrial sectors. The far-right column is the technology multiplier, calculated as the total R&D intensity (*int*) divided by the sector's own R&D intensity (*r*). The value of the total technology multiplier declined from 6.18 in 2000 to 4.71 in 2010, which confirms the hypothesis that China is gradually changing from being heavily dependent on foreign technology to being more reliant on indigenous innovation. However, according to Papaconstantinou et al. (1998) and Hauknes and Knell (2009), in selected OECD countries, the share of own R&D is about half of the total R&D content and the technology multiplier is around 2.00. Generally, countries that generate knowledge have lower multipliers, whereas countries that use knowledge from external sources have higher multipliers. For example, the total technology multipliers of Sweden, USA, Germany, France and Norway in 2000 were 1.69, 2.02, 1.74, 1.97 and 2.33, respectively (Papaconstantinou et al. 1998; Hauknes and Knell 2009). Guan and Chen (2009), based on the domestic I-O table, found that China's technology multipliers were 1.83 and 1.65 in 1997 and 2002, respectively, and concluded that there is no obvious difference between China and OECD countries. However, if the dimension of international trade flows was considered, the derived technology multiplier for China up to the year 2010 would still be much higher than that of a developed country. Therefore, although China is now relatively less dependent on foreign technology, there is still a long way to go before it can be considered a true technology provider.

In order to facilitate better understanding of the structure of technological components across industries, the five components of R&D embodiment of each industry are listed in Table 2.1. First, almost all industries' R&D intensity (*r*) has experienced a rapid growth except industry I-6 (C23-Coke, refined petroleum products and nuclear fuel). Specifically, up until 2010, industries I-13 (C30T35E31-Electrical and optical equipment, Transport equipment), I-12 (C29-Machinery and equipment, not elsewhere classified), I-7 (C24- Chemicals and chemical products) were the top three industries for R&D intensity, while industries I-1 (C01T05-Agriculture, hunting, forestry and fishing), I-4 (C17T19-Textiles, textile products, leather and footwear), I-16 (C40T41-Electricity, gas and water supply) were the top three industries for growth rate of R&D intensity. All of the three top R&D players were high-tech industries, which is consistent with our expectations. The top three industries in terms of growth rate of R&D intensity are two traditional industries and one power supply industry. This indicates the fact that progressive technological upgrading is occurring in traditional industries and also that there is ongoing reform in the power supply industry, in the context of serious carbon dioxide emission problems. Secondly, domestic intermediate goods and imported intermediate goods exhibit different trends in terms of the level of

R&D embodied. The R&D embodied in domestic intersectoral transaction flow (*pd*) has declined, with major contributors to this trend being I-11 (C28-Fabricated metal products except machinery and equipment) and I-15 (C36T37-Manufacturing not elsewhere classified; recycling). This implies that these two industries are subject to much less spillover from the domestic system.

The technology multipliers reveal whether an industry is a technology producer or a technology adopter. The multiplier ranges from 1 to infinite, representing from relying only on own R&D activity to relying only on product-embodied R&D. Thus, an industry with a relatively low technology multiplier is typically a technology producer, whereas an industry with a relatively high technology multiplier tends to be a technology user. The changing role of each sector will be viewed more clearly in the following network analysis.

Table 2.1 R&D intensity and product-embodied R&D in China by sector, 2000-2010

	r			*pd*			*cd*			*pim*			*cim*			Technology Multiplier		
	2000	2005	2010	2000	2005	2010	2000	2005	2010	2000	2005	2010	2000	2005	2010	2000	2005	2010
Total	13.25	20	17.49	20.28	26.7	17.78	17.26	24.17	22.7	11.57	12.07	13.06	19.41	9.74	11.18	6.18	4.64	4.71
I-1	0.04	0.08	0.14	0.18	0.31	0.54	0.43	0.59	0.73	0.89	0.89	0.83	1.88	0.7	0.8	91.33	33.45	22.81
I-2	0.84	0.71	1.04	0.92	1.04	0.83	0	0	0	0.77	0.58	0.62	1.05	0.44	0.33	4.26	3.93	2.7
I-3	0.31	0.57	0.56	0.4	0.58	0.51	0	0	0	0.32	0.22	0.19	0.51	0.15	0.15	4.94	2.65	2.51
I-4	0.21	0.4	0.49	0.33	0.52	0.57	0	0	0	0.59	0.65	0.73	1.14	0.44	0.53	10.91	5.1	4.72
I-5	0.31	0.36	0.41	1.28	1.22	0.72	0	0	0	0.58	0.73	0.74	1.07	0.53	0.62	10.58	8	6.05
I-6	0.5	0.38	0.28	1.64	2.12	1.18	0	0	0	0.13	0.21	0.44	0.09	0.04	0.06	4.77	7.32	7.07
I-7	1.17	1.83	1.68	0.38	0.63	0.75	0	0	0	1.13	1.13	1.15	2.64	0.81	0.94	4.54	2.41	2.69
I-8	0.39	0.64	0.56	1.59	2.16	1.2	0	0	0	1.33	1.59	1.56	3.08	1.13	1.36	16.67	8.63	8.38
I-9	0.57	0.63	0.51	1.73	2.2	1.16	1.47	0	0	0.54	0.46	0.56	0.78	0.26	0.23	8.98	5.63	4.86
I-10	0.86	1.63	0.98	0.69	0.69	0.89	0	0	0	0.5	0.6	0.7	0.73	0.47	0.6	3.22	2.08	3.23
I-11	0.54	0.71	0.63	3.37	4.22	1.51	1.67	2.3	2.25	0.39	0.33	0.45	0.47	0.19	0.17	12.04	10.91	8.01
I-12	1.63	2.11	1.93	1.56	1.66	1.4	3.04	4.41	4.28	1.12	1.17	1.32	1.22	1.04	1.22	5.27	4.92	5.26
I-13	4.58	8.05	5.85	1.12	2.38	1.29	6.22	10.46	8.45	1	1.17	1.29	1.37	1.15	1.45	3.12	2.89	3.14
I-14	0.51	0.8	0.82	0.41	0.46	1.07	1.61	2.11	2.52	1.74	1.75	1.85	2.39	1.96	2.2	13.18	8.85	10.38
I-15	0.33	0.44	0.5	2.81	4.37	0.86	0.83	1.42	1.44	0.61	0.67	0.7	1.08	0.49	0.6	17.22	16.88	8.28
I-16	0.34	0.43	0.79	1.18	0.97	1.07	0	0	0	0	0	0	0	0	0	4.47	3.27	2.36
I-17	0.08	0.12	0.15	0.72	1.15	1.77	1.29	1.89	1.93	0	0	0	0	0	0	27.75	27.46	26.78
I-18	0.12	0.19	0.26	0.06	0.09	0.56	0.74	1.03	1.14	0	0	0	0	0	0	8.1	7.14	7.74

Source: Author's own calculation

Industries I-17 (C45-Construction), I-11 (C28-Fabricated metal products except machinery and equipment) and I-12 (C29-Machinery and equipment, not elsewhere classified) are the three industries which have the most intensive embodied technology from the domestic system in 2010, while industries I-18 (C50T95-Total services), I-1 (C01T05-Agriculture, hunting, forestry and fishing) and I-14 (C31-Electrical machinery and apparatus, not elsewhere classified) have the top three growth rates of domestically sourced technology during this period. Therefore, the total service industry, followed by the primary industry, is gradually becoming one of the industries enjoying the most of technological advancement.

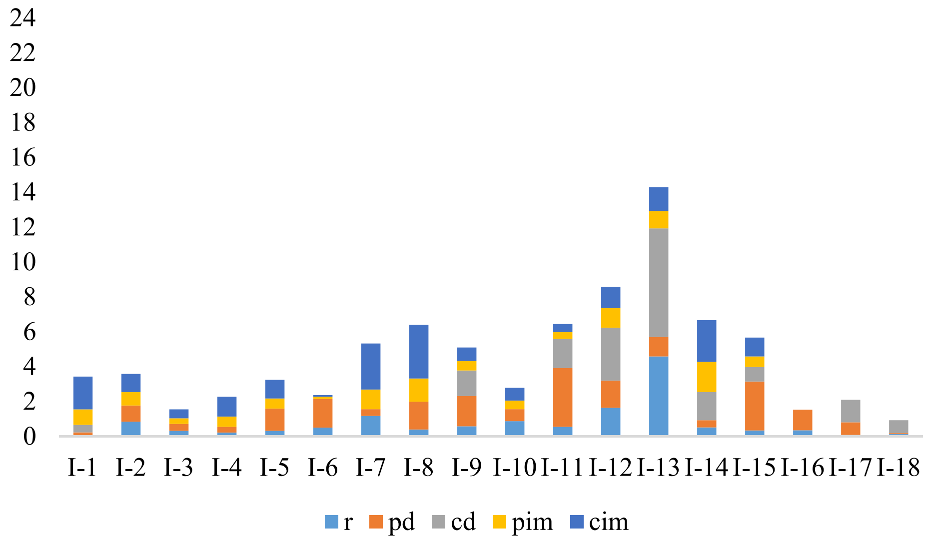


Figure 2.3 R&D intensity profiles in 2000

In contrast, the sum of R&D embodied in intermediate demand from imports (*pim*) has increased slightly. At the industrial level, only three industries' *pim* decreased slightly in this period, namely, industries I-1 (C01T05-Agriculture, hunting, forestry and fishing), I-2 (C10T14-Mining and quarrying) and I-3 (C15T16-Food products, beverages and tobacco). The other industries witnessed a mild upward trend of *pim*, especially the industries I-6 (C23-Coke, refined petroleum products and nuclear fuel), I-10 (C27-Basic metals) and I-13 (C30T35E31-Electrical and optical equipment, Transport equipment). Therefore, knowledge spillover from imports of intermediate goods still plays a critical role in China.

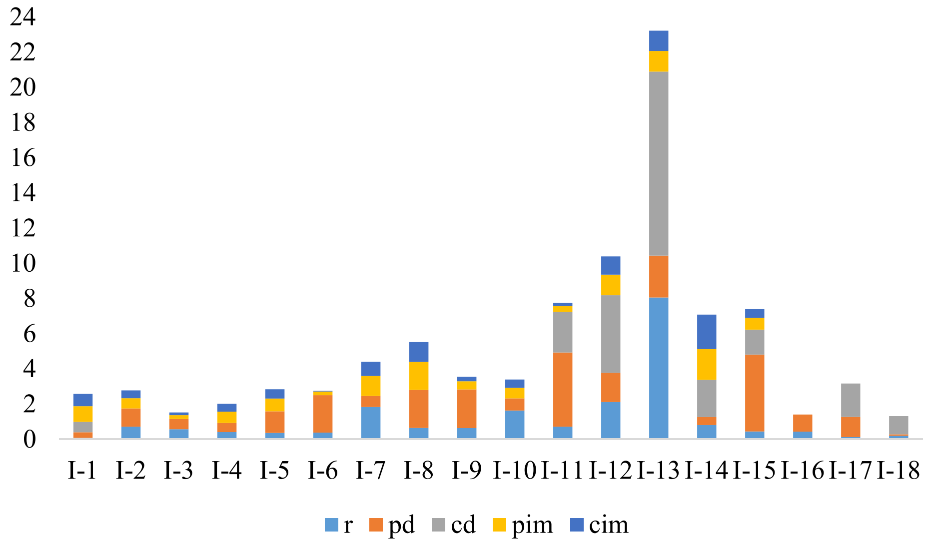


Figure 2.4 R&D intensity profiles in 2005

In spite of this, the trend of China's transition from dependence on foreign innovation towards being a nation with a more self-reliant innovation system is observable across Figure 2.3, Figure 2.4 and Figure 2.5. In addition, the R&D embodied in domestic capital goods increased in a stable manner over the observed period, while the contribution from imported capital goods became much less significant for technology diffusion.

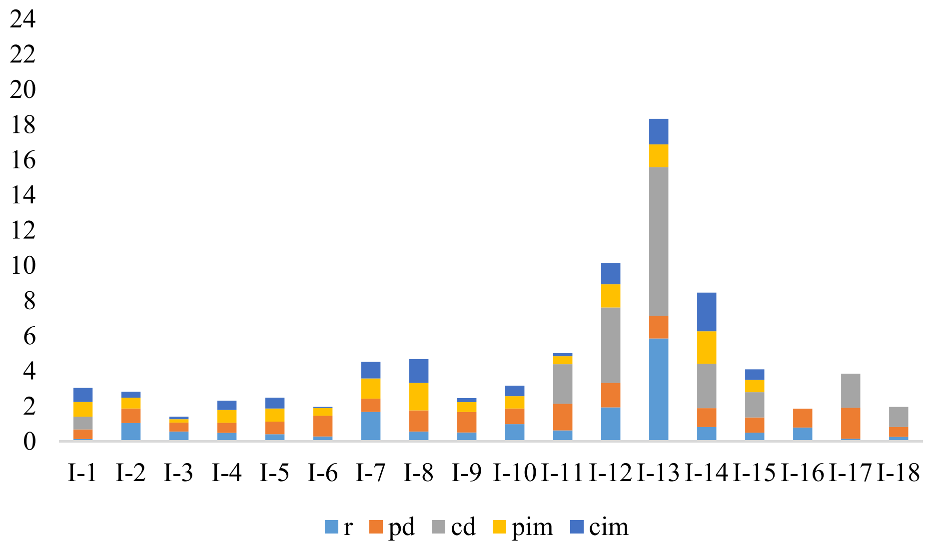
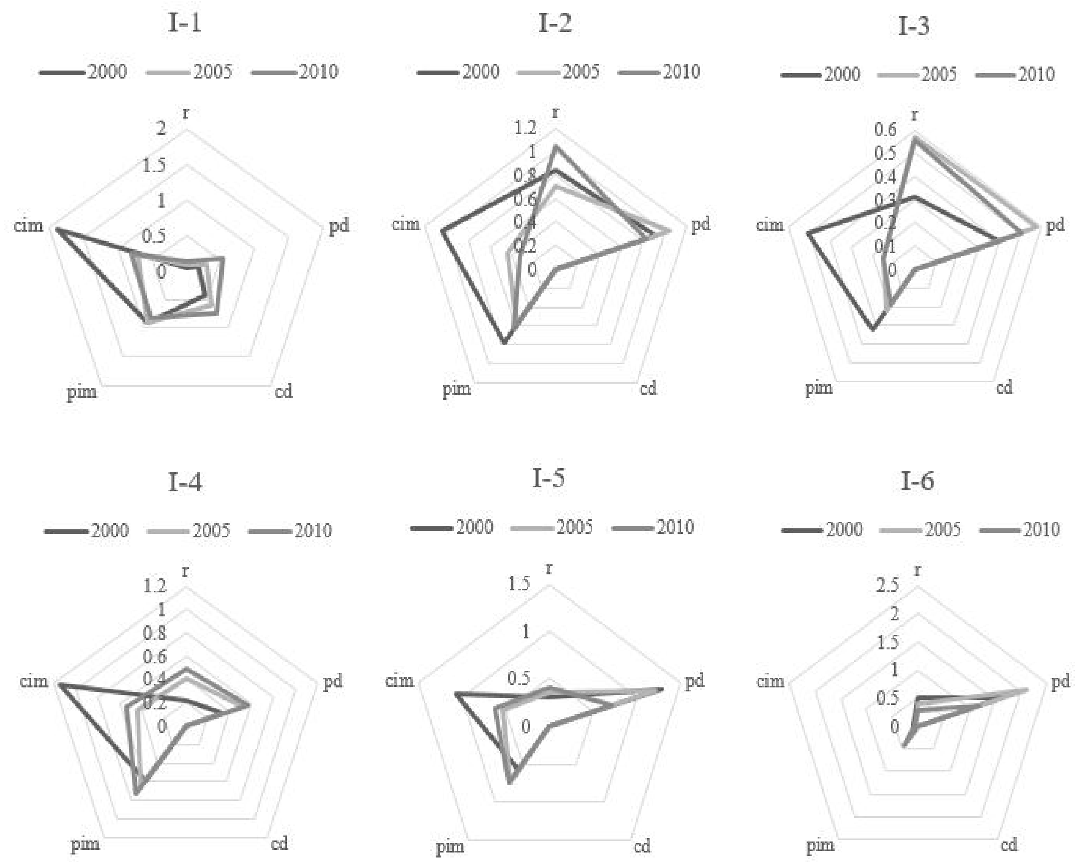


Figure 2.5 R&D intensity profiles in 2010

The evolution process of each industry is summarised as Figure 2.6. It is shown that the industries exhibit different responses to the transformation. One significant feature is that many industries, such as the traditional industries I-1 to I-5 and high-tech industry I-7, remarkably reduced their dependence on the embodied R&D in imported capital goods, while almost all industries developed their indigenous innovation and domestic engagement. Another feature is that the sources of technology grow increasingly diverse during the transformation process. This feature coincides with the increasing complexity of innovation associated with the accelerating globalisation process, which requires the integration of technology across different industries and the infusion of knowledge in various areas. Therefore, the intersectoral interactions become increasingly important in supporting the innovation-driven growth of China.



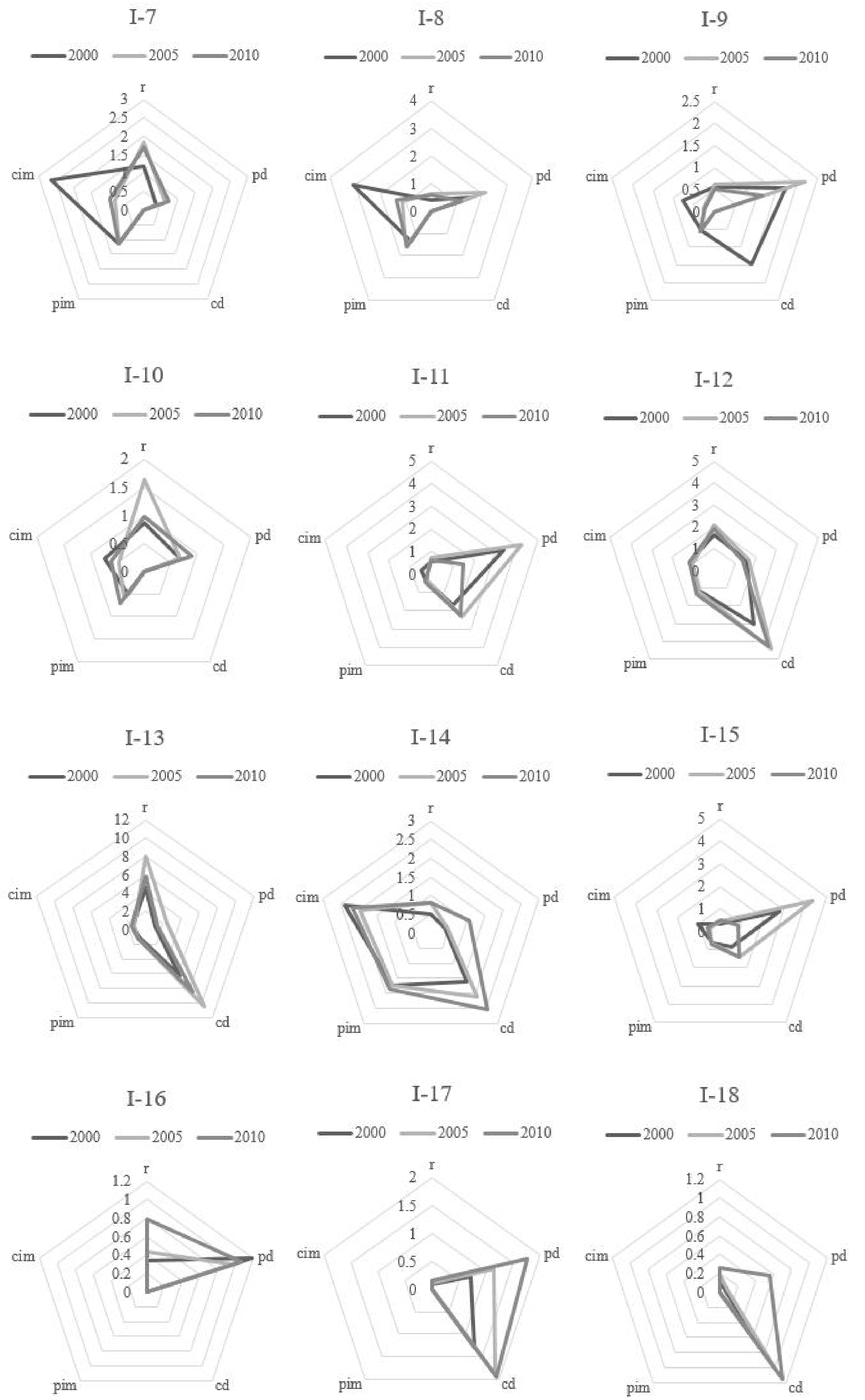


Figure 2.6 Transformation at the industrial level

2.4.2 Network Evolution

This study employs SNA to visualise the structural change across the whole network as well as the characteristics of each node.

To ensure clear patterns of networks, this chapter first dichotomize the previous R&D flow matrices into a network with reasonable density. After several iterations, we choose c equals to 0.0008 as the threshold value. Hence we assume that, when the observed R&D intensity, flowing directly or indirectly, through intersectoral interaction from sector i to sector j was no less than 0.0008, significant technological diffusion between two sectors had occurred.

First, we can demonstrate that the value of c is appropriate, because the density of these networks is around 35 per cent, which ensures a clear picture of critical intersectoral relationships (Table 2.2). This can also be seen from the network graphs (Figure 2.7, Figure 2.8 and Figure 2.9). For the domestic network, the density increased from 0.24 in 2000 to 0.35 in 2010, showing that the domestic innovation system became better connected over time. This can also be observed from the increased mean value of the inward degree and the outward degree. The density of the overall network in each year is higher than the domestic density due to the inclusion of foreign flows.

Table 2.2 Network indicators in 2000, 2005 and 2010

	2000				2005				2010			
	Domestic		Overall		Domestic		Overall		Domestic		Overall	
	In	Out	In	Out	In	Out	In	Out	In	Out	In	Out
I-1	3	1	7	4	4	1	6	4	5	1	8	5
I-2	2	9	7	11	5	11	6	12	6	14	7	16
I-3	2	1	5	2	2	2	5	2	2	2	4	2
I-4	2	1	3	2	2	2	3	2	2	2	5	2
I-5	3	1	6	7	3	2	6	3	3	2	8	3
I-6	3	2	4	5	5	1	6	1	5	1	5	2
I-7	3	15	6	18	3	17	4	17	4	17	5	17
I-8	3	2	4	9	3	5	4	8	4	5	6	8
I-9	7	2	11	2	6	2	6	2	7	2	7	2
I-10	3	8	7	9	4	10	7	11	5	9	7	10
I-11	8	1	9	5	8	4	9	5	8	3	9	5
I-12	6	6	8	14	10	11	10	16	10	11	10	17
I-13	6	16	9	16	10	16	10	16	10	16	10	17
I-14	5	2	6	15	6	4	6	12	9	5	9	13
I-15	4	1	9	1	10	1	12	1	10	1	13	1
I-16	3	3	7	3	3	5	5	5	3	10	6	10
I-17	8	1	12	1	10	1	12	1	11	1	13	1
I-18	3	2	6	2	7	6	7	6	6	8	7	8
Mean	4.1	4.1	7	7	5.6	5.6	6.9	6.9	6.1	6.1	7.7	7.7
SD	1.97	4.68	2.31	5.50	2.83	5.05	2.58	5.51	2.87	5.34	2.51	5.89
Density	0.24		0.41		0.33		0.40		0.35		0.45	
Centralisation	0.26	0.79	0.33	0.73	0.29	0.75	0.34	0.67	0.32	0.72	0.35	0.61

Source: Author's own calculation.

The growth rate of the overall network's density is lower than that of the domestic network. This is explained by the fact that the foreign contribution to the density is almost half in 2000, while this proportion is only about one-fifth in 2010. Thus, it is confirmed that the importance of the domestic system grew over time, although the foreign parts still play a significant role in the system, which is consistent with our earlier discussion.

Secondly, the indicator of centralisation reveals the fact that the sectoral partitions of a diffusion system can be regarded as either a hierarchical network (i.e. high centralisation degree) or an evenly distributed one (i.e. low centralisation degree). In general, China has a more hierarchical structure in outward linkages than it does for in inward linkages in both the domestic network and the overall network. This finding is consistent with Chang and Shih (2005). However, the two aspects of centralisation differ from one another. In both the domestic and overall networks, the centralisation of inward linkages increased mildly and stably across years, while the centralisation of outward linkages continually decreased over this period, especially between 2005 and 2010. This implies that, in terms of inward linkage, China's innovation diffusion networks are growing more evenly distributed over time, while in terms of outward linkage, the networks tend to become more hierarchical over this period. This conclusion is reinforced by the standard deviation field which shows the extent to which the industries are distinguished from each other. This means that more sectors are partaking in the technology diffusion processes as absorbers, while a small group of sectors currently acts as a major innovation source.

Thirdly, and as the second point has illustrated, the outward linkages are becoming more centralised, which suggests that R&D mainly originates in several critical industries that are widely connected with other sectors. Consequently, the role of each sector is becoming clearer than ever before. Therefore, it is worthwhile investigating, at the industrial level, the changing role of each sector and the effect of foreign innovation flow. In 2000, the distribution of inward and outward linkages in the domestic network was relatively even, except in the high-tech industries, due to the low level of technology overall within China. In the upper panel of Figure 2.7, we can clearly see that the network appears relatively sparse, that several sectors are distributed separately and that connectivity occurs mainly via some central sectors (I-7, I-12 and I-13 in this case). In the same year, the network was greatly enriched by the introduction of foreign technology. The lower network is better-connected, and clearly the industries I-7, I-12 and I-13 still holding the dominant position of this network and are the major R&D performers. The top three R&D acquirers are industries I-17, I-11 and I-9.

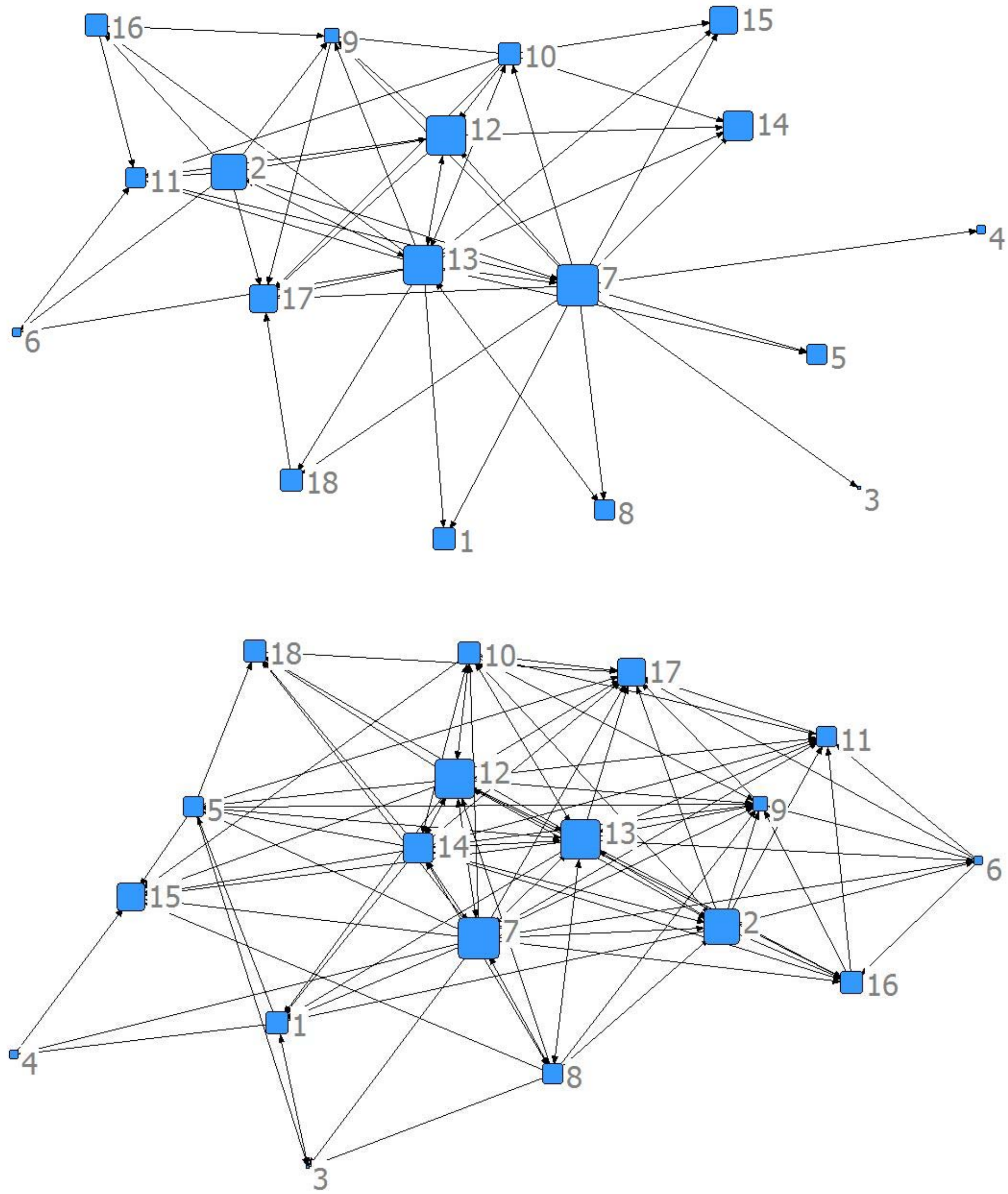


Figure 2.7 Domestic network and overall network in 2000

By 2005, the domestic network had become more complex and the interaction between industries was more extensive than before. In this process, several industries emerged as the system's major R&D performers, even without the participation of foreign players. These are industries I-13, I-12 and I-7, while industries I-1, I-3, I-4, I-5 and I-6 are relatively separated from the network, which can be seen in the upper panel of Figure 2.8. All of these are traditional industries, and this analysis implies that they did not enjoy significant benefits from the domestic network. Industries I-12 (Manufacturing not elsewhere classified; Recycling), I-13, I-15 and I-17 had become the main R&D absorbers in the domestic system. Introducing foreign components into this analysis did not have a dramatic impact, apart from the important fact that industry I-14 emerged as a source of R&D.

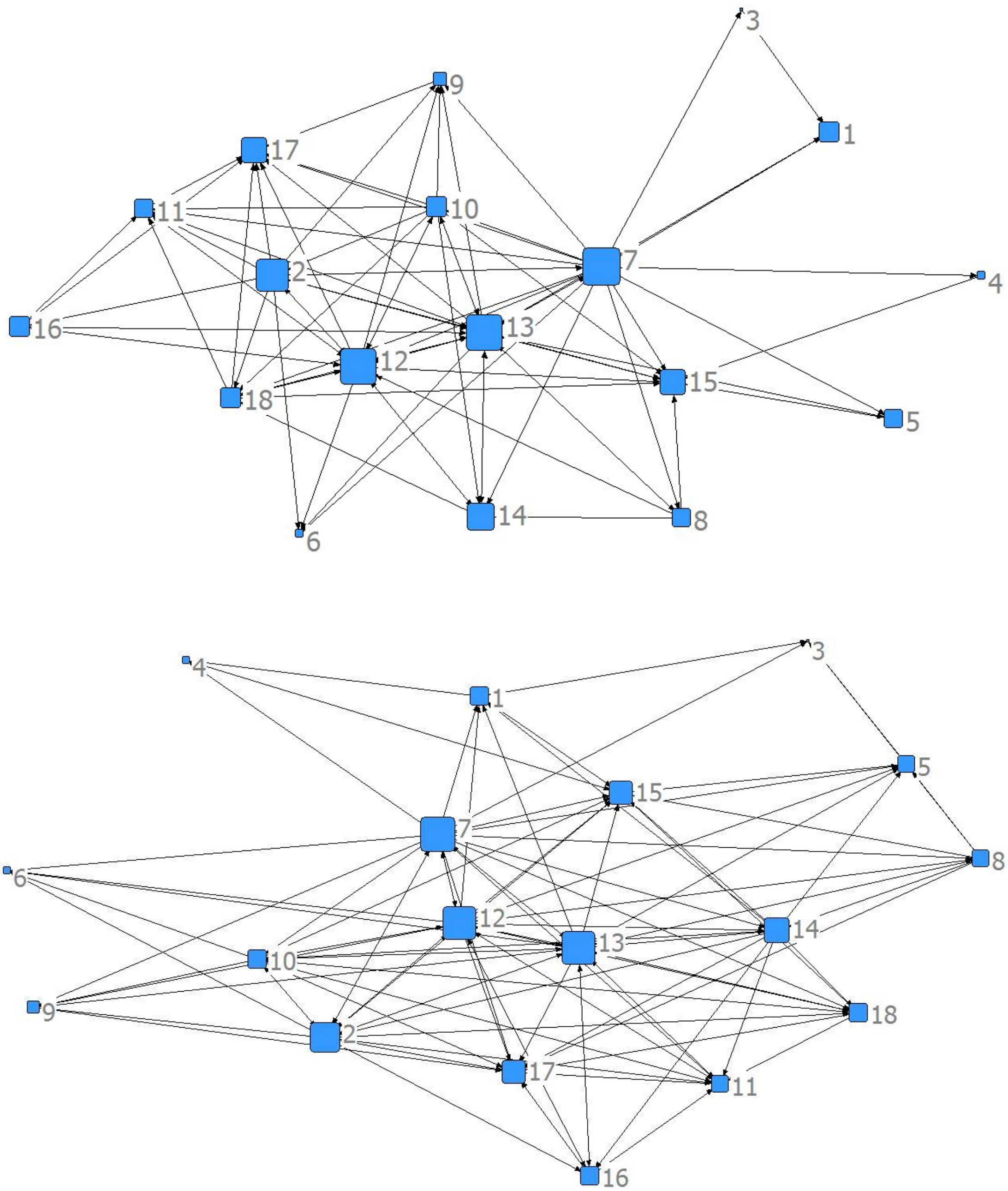


Figure 2.8 Domestic network and overall network in 205

As of 2010, the domestic network was relatively well-connected, and the level of connectedness was even better than that in the overall network in 2005. Although the foreign parts still contributed significantly to the intersectoral interactions, their weight was much lower and the structure of the network was more stable than before. Three industries, I-13, I-12 and I-7 occupied the central positions and acted as the most important R&D sources. In comparison to networks in 2000 and 2005, this kind of polycentric network is much more conducive to technology diffusion.

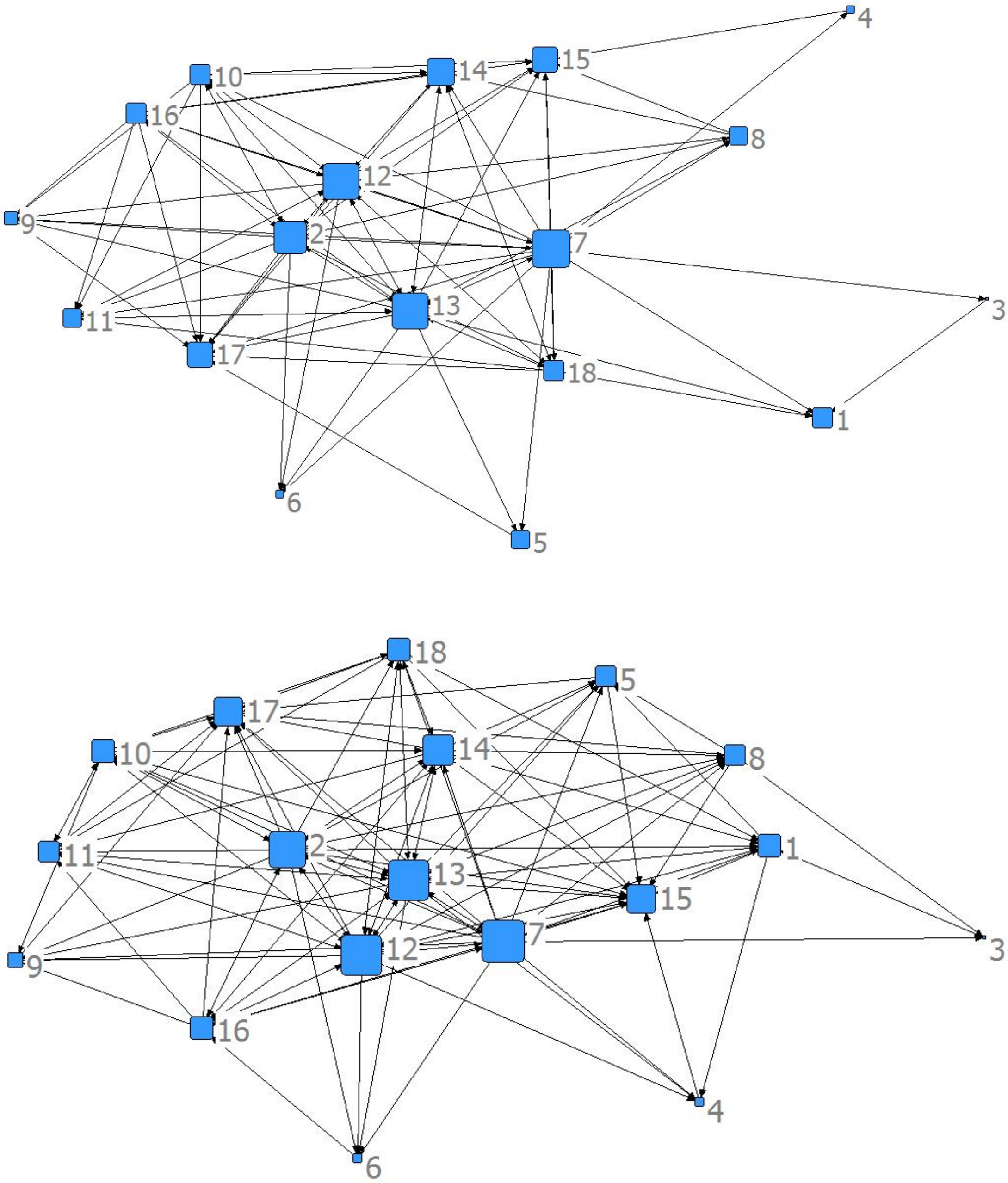


Figure 2.9 Domestic network and overall network in 2010

2.5 Conclusion

This chapter explores to what extent the network of product-embodied R&D associated with intersectoral transactions in China has changed and how the country's industrial sectors have responded in an open system. Technological flow matrices and social network analysis are employed to depict China's evolution in terms of product-embodied R&D diffusion during the period 2000 to 2010. R&D embodiment in international trade flows has been accounted for in order to enable the comparability with studies on developed countries. Our analysis draws different conclusions to those of previous studies on China (Guan and Chen 2009). The results show that China is transforming from being a technology absorber to a neutral player. China is emerging as a source of significant knowledge production. Nonetheless, the technology contribution from imports is far from negligible. Although China's dependence on foreign technology has lessened, there is still a long way for the country go if it is to become a pure technology creator. Additionally, industries with differing technology intensities have exhibited different characteristics throughout this transformation. In terms of network analysis, the density of the domestic network increased from 0.24 in 2000 to 0.45 in 2010, implying that the domestic innovation system grew to become far better connected over time. In general, China has a more hierarchical structure in outward linkages than in inward linkages in both the domestic network and the overall network. China's innovation diffusion networks grew more evenly distributed than they were before in terms of inward linkages, while the networks tended to become increasingly hierarchical with time in terms of outward linkages. Although the foreign parts still contribute significantly to the intersectoral interactions, their weight is much lower and the structure of the network is more stable than before. At the industrial level, three industries occupy the central positions, acting as the most important R&D sources surrounded by other industries, and this kind of polycentric network is much better for technology diffusion.

Appendix A2

Table A2.1 Industry classification

Sector No.	Sector
I-1	C01T05-Agriculture, hunting, forestry and fishing
I-2	C10T14-Mining and quarrying
I-3	C15T16-Food products, beverages and tobacco
I-4	C17T19-Textiles, textile products, leather and footwear
I-5	C20T22-Wood and products of wood and cork; Pulp, paper, paper products, printing and publishing
I-6	C23-Coke, refined petroleum products and nuclear fuel
I-7	C24- Chemicals and chemical products
I-8	C25-Rubber and plastics products
I-9	C26-Other non-metallic mineral products
I-10	C27-Basic metals
I-11	C28-Fabricated metal products except machinery and equipment
I-12	C29-Machinery and equipment, not elsewhere classified
I-13	C30T35E31-Electrical and optical equipment, Transport equipment
I-14	C31-Electrical machinery and apparatus, not elsewhere classified
I-15	C36T37-Manufacturing not elsewhere classified; recycling
I-16	C40T41-Electricity, gas and water supply
I-17	C45-Construction
I-18	C50T95-Total services

Notes: The industrial classification conforms to ISIC Rev. 3.0 and therefore the composition of each industry stays the same across years.

CHAPTER 3 – DETERMINANTS OF FIRMS' INNOVATIVE BEHAVIOUR

3.1 Introduction

China's economic performance over the last few decades has been impressive. However, in order to ensure broad, sustainable and equitable growth in the years to come, further reforms are required. Over the past five years, China's economic growth has slackened. OECD projections suggest that, over the medium-term, this slowdown is set to continue, partly because the working age population will soon start to decrease, and also because returns to investment are diminishing (Song and Zhang 2010). With this in mind, it has been argued that the Chinese economy may fail to sustain economic growth sufficient to catch up to the developed economies, thus getting stuck in a so-called "middle-income trap" (OECD 2013). The trend is unsurprising as growth will usually slow down once a catching-up economy has reaped the lower-hanging fruits of technology imports and urbanisation. At this stage, indigenous innovation becomes an increasingly important source of technological development for China as it attempts to catch up to other more developed economies.

In order to promote indigenous innovation and reduce dependence on foreign technology, in China's current development strategy [8] particularly emphasises the role of business enterprises in driving technological innovation. Despite this importance of business enterprises in building national innovation capacity, information about China's innovative activities, particularly on a micro level, is still very limited. Earlier studies were often based on aggregate statistics (Zhang 2005; Wu 2006). A few recent empirical studies have focused on either one particular region or an industrial sector. For example, Alcorta et al. (2009) conducted a survey of 360 firms in China's Jiangsu province and examined the impact of individual, managerial and cognitive factors on knowledge generation at the firm level. For the sector level studies, Xi et al. (2009) presented a case study of the automobile industry and Li and Xin (2009) investigated the colour TV sector in China.

More recently, studies using Chinese firm-level data have emerged. Jefferson et al. (2006) estimated a knowledge production function and examined the determinants of R&D intensity

[8] In early 2006, after several years of extensive consultation and research, the government announced the *National Programme for Medium and Long Term Development of Science and Technology (2006-2020)* which outlines China's innovation strategy. It consists of four pillars, namely (1) "indigenous innovation" (enhancing domestic innovation capacity), (2) a "leap-forward in key areas" (concentrating resources in priority areas to achieve breakthrough), (3) "sustainable development" (meeting the most urgent demands of economic and social development) and (4) "setting the stage for the future" (preparing for future development with a long-term vision).

and the impact of innovation on performance using firm-level data from 1995-1999. Girma et al. (2009) explored the impact of foreign direct investment (FDI) on innovation in Chinese stated-owned enterprises (SOEs) between 1999 and 2005. Dong and Gou (2010) examined data from listed companies in China and found that the improvement of corporate governance and stock incentive plans might eventually enhance companies' innovation and R&D capabilities. Wu (2012b) focused on R&D behaviour in large- and medium-sized (LMEs) Chinese firms, using a large dataset of 19,880 firms, covering the period between 2005 and 2007. Some authors also focused on the R&D activities in China by multinational corporations (MNCs), like Gassmann and Han (2004), von Zedtwitz (2004) and Schanz et al. (2011). Specific factors have also been discussed separately. For example, Zhou (2014) investigated how variations in institutional quality affect the R&D efforts of firms.

Generally, these papers tend to rely exclusively on R&D investment to depict firms' innovative activities and focus mainly on LMEs. This is partly because R&D data, when used as an innovation indicator, tends to favour large firms over small and medium enterprises (SMEs), due to the fact that SMEs' R&D efforts are often informal (Acs and Audretsch 1990; Kleinknecht et al. 2002) and occasional (Michie 1998). It fails, to some extent, to construct a complete picture of innovative behaviour among China's manufacturing firms. It is argued that the contribution, through R&D and innovation, towards technical progress, from the part of companies that are either young or small-to-medium sized, is also crucial (Acs and Audretsch 1990; Audretsch 2006; Czarnitzki and Hottenrott 2011). In addition, external factors are often ignored. This fails to recognise the systematic nature of innovation. According to the theory of the regional innovation system, innovation activities are collective achievements of numerous entrepreneurs, rather than isolated activity within a firm. Therefore, it is reasonable to investigate firms' innovative behaviour embedded in certain regions.

This study adds to the emerging literature by combining firm-level data and municipal-level data to investigate both internal and external factors that might affect the decisions of firms to innovate. The latter is an under-researched topic in the context of the transitional Chinese economy, though well-documented for firms in many developed economies. The largest dataset available for Chinese manufacturing firms, as opposed to only LMEs, and the detailed information of cities where these firms are located are combined to present a more complete picture of China's innovative behaviour at micro-level. In addition, different measurements of innovation are adopted in order to capture the potential informal innovative activities as R&D is not necessarily the only way to achieve the aim of innovation (Zhou et al. 2012). The findings in this study show that innovative firms in China are generally old, large, engaged in exporting, and state-owned. Firms with better resources, higher efficiency, better technology, more human resources and a better knowledge base are generally more likely to innovate. Financial accessibility is a very important factor for innovation activities, especially for R&D investment. The relationship between the level of competition and the probability of innovation is found to be an inverted U-shaped relationship. Apart from firms' internal resources, region-specific factors such as financial development, FDI and so on also affect the probability of innovation by firms. In particular, environmental regulation, government support and the protection of intellectual property rights (IPRs) are all factors that were found to be positively related to innovative behaviour. These findings have important implications, not only for China but also for the rest of the world as Chinese firms become increasingly active internationally.

The rest of this chapter begins with a theoretical framework related to both internal and external determinants of firms' innovative behaviour in Section 2. This is followed by discussion of data and econometric methods in Section 3. Section 4 is the empirical part including major results and comparison between different models. Robustness tests are provided in Section 5. The final section concludes the paper with some remarks.

3.2 Determinants of Firms' Innovation

There exists a large pool of theoretical and empirical studies of innovation determinants at the firm level (Acs and Isberg 1991; Souitaris 2002; De Jong and Vermeulen 2006). This section reviews relevant works and identifies the potential determinants using Chinese firm level data. The choice of which factors to discuss is determined by the existing theories as well as the availability of information in the sample obtained.

3.2.1 Internal Factors

Studies based on firm-level data generally focus on identifying the internal characteristics of firms that affect their innovative behaviour. Many of studies adopt the resource-based view (RBV), which highlights the heterogeneity of firms and the role of internal attributes in business strategy (Wernerfelt 1984; Vega-Jurado et al. 2008). In this perspective, each firm possesses a unique set of resources and capacities which are acquired and developed over time. Their exclusive resources and capacities play a role in determining the degree of technological efficiency and therefore also determine firms' strategic decisions. As this study discusses the determinants of innovative behaviour at the firm-level, RBV will be fundamental for selecting internal factors.

The age of a firm is a possible measure of its organisational resources (Del Canto and Gonzalez 1999). It represents the experience and knowledge accumulated throughout its history. It is also related to better management of communication channels and creativity resources, which are necessary for innovation and a more effective capacity for absorption. Older firm age may also render some knowledge, abilities and skills obsolete, and therefore induce organisational decay (Loderer and Waelchli 2009).

Firm size is perhaps the most obvious and well-studied factor. Academic inquiries into the relationship between firm size and innovation activities date back to the work by Schumpeter (1942), who argued that the degree of innovation is positively correlated with firm size. Generally, due to capital market imperfections, large companies have more resources with which to innovate and support risky activities than SMEs (Damanpour 1992; Majumdar 1995; Tsai 2001; Becheikh et al. 2006). Large firms can benefit from economies of scale in R&D, production and marketing (Cohen and Klepper 1996; Stock et al. 2002). It is also argued that small firms have greater flexibility, better communication, greater specialisation possibilities, and informal and strategic controls (Klepper and Simons 1997; Galende and de la Fuente 2003; Chang and Robin 2006).

The same argument could be applied to the Chinese state-owned enterprises (SOEs), most of which are large and well connected with government departments. However, on theoretical grounds, the impact of state ownership or control on corporate R&D is ambiguous (Lin et al. 2010). In China, private firms only emerged during the reform period. The SOEs are still in transition and have partially inherited their role from the centrally planned economic system. Therefore, it is anticipated that SOEs may be more likely to invest in innovation.

The impact of exporting on innovation was theorised in Grossman and Helpman (1991a). The underlying points are summarised by Ganotakis and Love (2011). First, competition in foreign markets may force firms to invest in innovation so that they can catch up with, or maintain, global best practices. Secondly, exporting may allow the firms to have access to a larger market and hence the fixed costs of R&D can be more easily recovered, due to larger sale volumes. In addition, Hobday (1995) proposed a technology-gap model and showed that innovation can be driven by foreign demand and, accordingly, firms' exporting activities. Empirical evidence, however, is mixed. Girma et al. (2008) found a positive impact of exporting status on R&D among Irish firms but not among British firms. Criscuolo et al. (2010) found that "locally engaged firms" spend more on innovation. In a transitional economy, Chinese exporting firms are exposed to superior foreign knowledge and technology. The "learning by exporting" effect could boost the firm's productivity and hence provide greater incentives to invest in innovation. Dai and Yu (2013) pointed out that exporting requires prior R&D innovation, which can help a firm maintain a competitive advantage in international markets over potential competitors.

These arguments may not be true for foreign firms that are engaged in exporting to China. These firms may have less incentive to invest in R&D in China due to either the existence of R&D activities at home or their concern about the protection of intellectual property rights (IPRs). In addition, foreign firms producing exclusively for the Chinese market may be less engaged in R&D because of their superior technology or quality relative to the local producers. Love and Roper (1999) made a similar observation using British firm level data. In contrast, Cassiman and Veugelers (2002) suggest that foreign affiliates may perform adaptive R&D to modify technologies that originate in home countries to suit local conditions in host countries.

It is widely accepted that innovations typically result from investment in R&D. As is true for any other investment, R&D activities require financial resources, like debt, equity, retained earnings and so forth. Particularly, however, R&D programmes involve significant sunk costs, and adjusting the level of R&D spending is costly. This is mainly because a major part of R&D spending consists of the wages of R&D employees who are usually high-skilled workers; thus, hiring and training them are very expensive. As such, there is low volatility in R&D spending over time (Hall 2002). Del Canto and Gonzalez (1999) pointed out that, according to the transaction-costs economics and agency literature, availability of internal funds should be more conducive to R&D investment than external funds. Firms may not be able or willing to offer sufficient information about their intended R&D programmes to potential funding providers in order to protect their proprietary information on innovation (Maskus et al. 2012; Zhou 2013).

From the financial perspective, government subsidies may also play a role in promoting firm-level innovation activities when there are market failures, which cause under-investment in R&D activities in private firms. In addition, it is anticipated that more efficient firms may enjoy better financial conditions and hence have greater incentives to invest in innovation. Finally, the existence of firms' long-term investment can imply earnings or cash flows in the near future and hence could convey favourable information about the firms' long-term prospects which possibly increase the likelihood of investment in innovation.

In addition to financial resources, firms' internal knowledge resources matter as well. The most important knowledge resource in a firm is a qualified and motivated workforce, capable of absorbing and creating new technology (Hoffiman et al. 1998; Romjin and Albaladejo 2002;

Simonen and McCann 2008; Batabyal and Nijkamp 2013). Because human resources have the most influence on the knowledge and culture of a firm, it is anticipated that firms with better human resources will be more capable of conducting innovation and have a higher probability of getting involved in innovation activities. As mentioned above, a major part of R&D spending goes to the wages of R&D employees, who are usually high-skilled workers. This demonstrates the importance of highly qualified personnel in innovation and, furthermore, enables us to use firms' average wage to represent the quality of human resources.

Other factors associated with the RBV include the role of intangible assets and level of technology employed in the firms. Firms with intangible assets such as patents and trademarks may be more willing to spend on innovation, potentially because of either their existing commitment to innovation or their desire to maintain their technology lead. Possession of intangible goods also suggests a better knowledge base in that firm, which is beneficial to innovation (Corrado et al. 2012; Fleisher et al. 2013). Similarly, firms with better technology may be keener to invest in innovation.

3.2.2 External Factors

As Fagerberg et al. (2006) pointed out, a central finding in the literature is that, in most cases, firms' innovation heavily depends on external resources. These resources not only include financial or human resources, but also connections with other firms and institutions, public resources and foreign resources. Previous studies generally include region dummies to control for heterogeneity of locations in determining firms' innovative behaviour, which failed to capture the regional differences in detail. As Pavitt (2002) pointed out, in a competitive era, where success depends increasingly upon the ability to invent new or improved products and processes, tacit knowledge constitutes the most important basis for innovation-based value creation. However, as tacit knowledge defies easy articulation or codification (Polanyi 1997), it is difficult to exchange over long distances. Therefore, firms' innovation activities are inevitably embedded in a certain environment, namely, a so-called regional innovation system (RIS) (Asheim and Isaksen 1997; Cooke 1992 2001).

Given the systematic nature of innovation (Nelson 1993; Braczyk et al. 1998; Lundvall 2010), it is obviously suitable to adopt the RIS concept to investigate the external determinants of firms' development strategies. In this perspective, innovation activities are collective achievements that require key contributions from numerous entrepreneurs (Van de Ven et al. 1999), rather than an isolated decision within a single firm. It means that firms' innovative behaviour is not only determined by its internal sources and capabilities, but is also influenced by the local system in which it is embedded. A proxy variable of completeness of the regional network is included to investigate its impact on firms' innovation choices.

Together with private enterprises, universities and public research institutions, local government is one of the key actors in a regional innovation system (Lundvall 2010; Kang and Park 2012). The RIS approach allows for government intervention in the form of industry policies such that resources are effectively allocated to foster innovation. Both R&D tax policy and subsidy for R&D projects have been widely discussed in empirical analyses (Mansfield 1986; González 2008; Carboni 2011; Czarnitzki et al. 2011) which show that the attitude of local government probably played an important role in firms' innovative behaviour, especially in a country like China. The term "policy-induced R&D" also demonstrates the significant role of government in firms' innovation decisions. Therefore, it is anticipated that government support will positively affect firms' innovative behaviour.

As a complement to internal financial resources, external finance availability is determined by regional financial development. Rajan and Zingales (1998) argue that financial development liberates firms from the need to generate funds internally by helping firms raise capital from sources external to the firms at a reasonable cost (Hyytinen and Toivanen 2005). From the perspective of RIS, knowledge intensive business services (KIBS) are the major components of a regional subsystem of knowledge creation and diffusion (Cooke 2002; Diez and Kiese 2009), which plays a significant role in promoting regional innovation development (Shi et al. 2014). Financial services are the most important sector in KIBS. Therefore, regional financial development should have a positive relationship with firms' innovative behaviour.

There is no doubt that IPRs play several important roles in innovation systems. IPRs encourage investment in innovation and dissemination (diffusion) of information regarding the principles and sources of innovation throughout the economy (Fagerberg et al. 2006). Whether the IPR system can correct for over- or under-investment in R&D and innovation, and whether this system distorts, redirects, or blocks technological progress have been extensively debated (Machlup 1958; Mazzoleni and Nelson 1998). More recently, Chen and Puttitanun (2005) pointed out that weak IPRs facilitate the imitation of foreign technologies, but stronger IPRs encourage domestic innovative activities. Given the wide regional disparities in China, the protection of IPRs among regions differs and should be taken into consideration. Another regional policy-related issue is regional environmental protection. Regional disparity in environmental protection is worth investigating since Porter's hypothesis implies that environmental regulation has positive impacts on firms' innovation (Ambec et al. 2013; Jia et al. 2013).

The impact of competition on innovation has previously been debated by economists and practitioners. Schumpeter (1934) argued that competition may reduce the expected payoff from R&D and hence lead to less R&D and a lower rate of innovation. This view has been challenged by other authors such as Porter (1990). Porter claims that competition forces firms to innovate in order to survive, hence boosting R&D activities. More recently, Aghion et al. (2005) postulated an inverted U-shaped relationship between innovation and competition. The prediction of their model is that competition has a positive impact on innovation when the level of competition is low, while at high levels of competition, an increase in competition may reduce investment in innovation. This argument is supported by Poldahl and Tingvall (2006). The inverted U-shaped relationship is tested here by using Chinese firm-level data.

Additionally, FDI has been widely discussed as a factor that may have a positive impact on innovation (Javorick 2004; Fu et al. 2011). This study includes FDI as an external factor in order to examine the foreign knowledge spillover effect, which is quite controversial in the Chinese context (Xu and Sheng 2012). Furthermore, it is argued that incentives to innovate increase with technological opportunities (Manez-Castillejo et al. 2006). "Technological opportunities" refers to the possibility of converting resources into new products or production processes (Cohen and Levinthal 1989). Individual sectors have different R&D intensities. It is possible that high-tech industries are required to spend more, or invest more frequently, in R&D so that they can survive and grow. Thus, there may be cross-sector variations in firms' innovative behaviour. These variations should be taken into consideration in the empirical analysis.

3.3 Research Design

3.3.1 The Database

The sample used in this study comes from a rich, firm-level, panel dataset that covers 177,634 firms in 2002, 294,200 firms in 2006 and 338,040 firms in 2010. The dataset is drawn from an annual survey of manufacturing enterprises, conducted by China's National Bureau of Statistics. It contains relatively complete information from three major accounting records (i.e., balance sheet, profit and loss account, and cash flow statement). There are two major types of manufacturing firms, namely SOEs and non-SOEs whose annual sales are more than five million RMB (or equivalently, \$750 thousand). More than 100 financial variables listed in the main accounting statement of all these firms are included in this dataset. It is reported that the surveyed enterprises accounted for most of China's industrial value added and amounted to 22 per cent of the country's urban employment in 2005 (Cai and Liu 2009). Thus, the surveyed sample should represent China's industrial sector well.

Although this dataset is informative, some samples are noisy and therefore misleading, largely due to reporting errors at the firm level. Following popular practices from the literature (Jefferson et al. 2003; Cai and Liu 2009; Wu 2012b; Dai and Yu 2013), the raw data is "trimmed" by using the following criteria, in order to remove outliers and abnormal observations. First, observations whose key financial variables (such as total assets, net value of fixed assets, sales, and gross value of firm productivity output) are missing or negative were dropped. Secondly, this chapter excluded any firms with less than 10 employees. Levinsohn and Petrin (2003) also covered Chilean plants with at least 10 workers. The final sample has 233,945 observations covering three years. To include the external factors, we also draw data from China City Statistical Yearbook for 286 cities (Lhasa is excluded due to missing data) in which these firms are located.

3.3.2 The Econometric Model

In order to gain insights into the questions raised in the preceding sections, several models are considered. The baseline model can be represented as follows,

$$Y_{it}^{*} = \alpha_0 + \sum \beta_j X_{ijt} + \sum \gamma_j Z_{ijt} + \varepsilon_{it} \quad (3\text{-}1)$$

where Y^{*} is a latent variable which may be interpreted as the expected level of participation in innovation. X and Z are explanatory variables reflecting internal and external factors respectively. In this study, innovative behaviour is defined as a binary variable, indicating whether the firm conducts innovation activities. Therefore, an index function model is needed to transform the baseline model into a probit model which is suitable to deal with this kind of problem. It is defined as

$$Y_{it} = 1 \;\; if \;\; Y_{it}^{*} > 0 \;\; or \;\; 0 \;\; if \;\; Y_{it}^{*} = 0 \quad (3\text{-}2)$$

With the index function model, the corresponding probit model can be specified as

$$Y_{it} = \alpha_0 + \sum \beta_j X_{ij(t-1)} + \sum \gamma_j Z_{ijt} + \varepsilon_{it} \quad (3\text{-}3)$$

where Y_{it} is a binary variable, defined as unity if firm *i* is involved in innovation in year *t*, and zero otherwise. The *X*-variables are lagged by one period to avoid the potential problem of endogeneity caused by simultaneity. *Z*-variables take the current values as they are the municipal-level data which can be treated as their own instrumental variables (Lin et al. 2011, 2012).

Based on the definition of firms' innovative activities provided by National Bureau of Statistics of China (NBSC), Zhou et al. (2012) pointed out that firm innovation consists of R&D activities with the aim of producing new products, providing new technology and improving the quality and the efficiency of current products. However, as argued before, using only R&D investment to depict firms' innovative activities tends to favour large firms. Particularly in China, a country that benefited greatly from catching up with the technology frontier, imitation innovation rather than indigenous innovation dominated the manufacturing sector during the fast development period. Given the critical role of either young businesses or SMEs in technological progress (Acs and Audretsch 1990; Audretsch 2006; Czarnitzki and Hottenrott 2011), some other measurement of innovation activities should be taken into consideration as well. As shown in Table 3.1, firms with R&D investment account for 12.9 per cent, 9.9 per cent and 12.4 per cent in three years, respectively, while firms with new products account for 6.6 per cent, 9.9 per cent and 10.0 per cent in three years, respectively. However, over 50 per cent of firms with new products have no R&D investment, which means if we only use R&D as a measure, tens of thousands firms with successful innovation will be treated as not innovative. Therefore, for the purpose of comparison, this study adopts three alternative measurements of innovation. First, if a firm has R&D investment then it is treated as being innovative, otherwise it is not innovative. This measurement is widely used in previous studies. Secondly, this study employs sales of new product as evidence of innovative activities. It is assumed that sales of new product could result from R&D investment or informal innovative activities. The third measure essentially combines the first and second definition. A firm is innovative as long as it has recorded either R&D investment or sales of new product.

Table 3.1 Distribution of innovative activities

	2002		2006		2010	
Firms	No.	%	No.	%	No.	%
No R&D	146127	80.5%	242115	80.2%	270588	77.6%
With R&D	23481	12.9%	30016	9.9%	43283	12.4%
With New product	11928	6.6%	29830	9.9%	34666	10.0%
With R&D but no new product	17728	9.8%	19661	6.5%	27504	7.9%
With new product but no R&D	6175	3.4%	19469	6.5%	18880	5.4%
With R&D and new product	5733	3.2%	10355	3.4%	15779	4.5%
Total	181536	100%	301961	100%	348537	100%

Sources: Author's own work.

The choice of other variables depends on the objective of the investigation and the availability of information in the database. X and Z in equation (3-1) are observable and explained in the following paragraph (see Table 3.2). Specifically, the internal factors (X) are defined as follows. *Age* is simply the age of the firm (years in existence); *size* reflects the size of the firm, measured by the number of employees; *debt* measures the degree of liability which is defined as the ratio of total liability over the total value of assets; *tech* captures the level of technology in production, measured by the ratio of the value of fixed assets over employment (i.e. the capital-labour ratio); *exp* is a binary variable, with a value of one if a firm is engaged in exporting and zero otherwise; *eff* is an indicator of firm efficiency, measured simply by the firms' labour productivity, which is the ratio of output value over total employment; *hc* indicates the level of human resource in a firm, which is approximated by using firms' average wage; *intang* is a binary variable indicating whether a firm has intangible goods; *invest* is also a binary variable, indicating whether a firm has long term investment; and *subsidy* represents the amount of subsidy a firm received.

Table 3.2 Determinants and their expected relationship with innovative decisions

Notations	Variables	Measurement	Expected Relationship
	Internal Factors		
age	Age	Firm's existing time	Inverted-U
size	Size	Logarithm of number of employees	Undetermined
exp	Export status	Binary – export or not	Positive
debt	Financial constrain	Total liability / total value of assets	Negative
tech	Technology	Capital-labour ratio	Positive
eff	Efficiency	Labour productivity	Positive
hc	Human resource	Average wage	Positive
subsidy	Subsidy	Logarithm of subsidy received	Positive
intang	Intangible goods	Binary – have or not	Positive
invest	Long-term investment	Binary – have or not	Positive
regtype	Ownership dummy	23 registration types	Dummy
	External factors		
hhi	Competition	Herfindahl index four digit classification	Inverted-U
fsint	Regional financial development	Regional density of employees in financial services sector	Positive
fdi	Foreign knowledge spillover	Logarithm of actual use of foreign direct investment	Debatable
recycle	Environment protection	Logarithm of the output of "three wastes" utilisation	Undetermined
govsup	Government support	Regional expenditure on S&T / general budget spending	Positive
ipr	IPRs	Geometric mean of the density of patent applications and the ratio of closing cases over accepted cases of patent infringement	Positive
network	Network	Geometric mean of regional GDP per capita and density of innovation unities like enterprises and universities	Positive
ind	Sector dummy	12 sectors dummies	Dummy
t	Time dummy	3 years	Positive

Source: Author's own work.

The external factors (*Z*) include *hhi* which represents the Herfindahl index to measure the level of competition or concentration of business activities in a sector. The calculation is based on the four-digit classification of Chinese industrial sectors; *fsint* measures regional development of knowledge intensive business services as well as the regional level of financial availability. It is defined as the regional density of employees in the financial services sector; *fdi* measures the foreign knowledge spillover, which is defined as the actual use of foreign direct investment; *govsup* is defined as the ratio of regional expenditure on science and research over the general budget spending of local finance to represent the support degree of local government; *ipr* depicts the degree of IPR protection. It is defined as the geometric mean of the intensity of patent applications and the ratio of closed cases over accepted cases of patent infringement; *network* measures the density and completeness of the local system, defined as the geometric mean of regional GDP per capita and density of innovation entities like enterprises and universities; and *recycle* represents the degree of environmental protection. It is measured by the logarithm of the output of "three wastes" utilisation. Ownership dummies, sectoral dummies and a time dummy are also included to control for potential heterogeneity. (See the appendix for details)

Summary statistics for the sample are presented in Table 3.3. As shown, about 16.38 per cent of the surveyed firms are involved in R&D activities and around 11.37 per cent of the firms sold new products during the period. Around 35.13 per cent of the firms are exporters. The average age of firms is about 14 years old with roughly 175 employees. The mean Herfindahl index (hhi) is 0.038 which is very small. Thus, the firms may be allocated fairly diversely across the four-digit industry sectors.

Table 3.3 Summary statistics

Variable	Mean	Std. Dev.	Min	Max
rdc	0.16	0.37	0.00	1.00
npvc	0.11	0.32	0.00	1.00
inn	0.22	0.41	0.00	1.00
age	13.85	11.96	0	100
size	5.17	1.17	2.30	12.29
debt	0.99	1.93	0	113.26
tech	1.37	14.92	0.00	4379.08
exp	0.35	0.48	0.00	1.00
eff	4.60	15.00	0.00	2005.71
hc	0.10	0.14	0.00	15.80
intang	0.27	0.45	0.00	1.00
invest	0.16	0.37	0.00	1.00
subsidy	0.64	1.92	0.00	13.45
hhi	0.04	0.05	0.00	1.00
fsint	5.32	8.36	0.02	54.52
fdi	10.96	1.96	0.00	13.92
recycle	9.39	20.56	0.00	180.00
govsup	0.01	0.02	0.00	0.08
ipr	0.53	0.14	0.19	0.79
network	1.36	1.24	0.00	6.66

Source: Author's own work. For details of the variables' definition, refer to Table 3.2.

3.4 Empirical Results

Based on above-mentioned research design, the estimation results using the described sample are reported in Table 3.4. Three alternative versions of Model 1 are considered. Model 1A uses R&D investment as evidence of innovation, while Model 1B focuses on firms with new product sales. Model 1C combines the last two by defining innovation as having either R&D investment or new product sales. By doing this, we are able to capture the potential informal R&D or other forms of innovative activities, especially when SMEs are included in our sample. A probit model is adopted here and robust standard errors and covariance are calculated.

Table 3.4 Regression results

Model / Variables	Model 1A Rdc		Model 1B npvc		Model 1C inn	
age	0.00243***	(0.000)	0.00286***	(0.000)	0.00242***	(0.000)
size	0.282***	(0.000)	0.179***	(0.000)	0.260***	(0.000)
debt	-0.219***	(0.000)	-0.119***	(0.000)	-0.162***	(0.000)
tech	0.0546***	(0.000)	0.0375***	(0.000)	0.0533***	(0.000)
exp	0.135***	(0.000)	0.365***	(0.000)	0.229***	(0.000)
eff	0.146***	(0.000)	0.0926***	(0.000)	0.135***	(0.000)
hc	0.580***	(0.000)	0.337***	(0.000)	0.553***	(0.000)
intang	0.206***	(0.000)	0.156***	(0.000)	0.194***	(0.000)
invest	0.221***	(0.000)	0.198***	(0.000)	0.215***	(0.000)
subsidy	0.0325***	(0.000)	0.0247***	(0.000)	0.0295***	(0.000)
hhi	2.355***	(0.000)	1.571***	(0.000)	2.116***	(0.000)
hhi2	-3.282***	(0.000)	-2.804***	(0.000)	-3.073***	(0.000)
fsint	0.501***	(0.000)	-0.417***	(0.000)	0.00265	(0.970)
fdi	-0.000609	(0.858)	-0.0556***	(0.000)	-0.0336***	(0.000)
recycle	0.00499**	(0.043)	0.0510***	(0.000)	0.0268***	(0.000)
govsup	4.359***	(0.000)	10.46***	(0.000)	7.419***	(0.000)
ipr	0.496***	(0.000)	0.784***	(0.000)	0.606***	(0.000)
network	-0.109***	(0.000)	-0.131***	(0.000)	-0.112***	(0.000)
ind2	0.458***	(0.000)	0.689***	(0.000)	0.524***	(0.000)
ind3	0.173***	(0.000)	0.699***	(0.000)	0.360***	(0.000)
ind4	0.217***	(0.000)	0.694***	(0.000)	0.367***	(0.000)
ind5	0.691***	(0.000)	0.808***	(0.000)	0.728***	(0.000)
ind6	1.245***	(0.000)	1.290***	(0.000)	1.317***	(0.000)
ind7	0.384***	(0.000)	0.785***	(0.000)	0.487***	(0.000)
ind8	0.215***	(0.000)	0.707***	(0.000)	0.375***	(0.000)
ind9	0.728***	(0.000)	1.093***	(0.000)	0.839***	(0.000)
ind10	0.880***	(0.000)	1.213***	(0.000)	0.977***	(0.000)
ind11	0.889***	(0.000)	1.207***	(0.000)	1.006***	(0.000)
ind12	-0.479***	(0.000)	-0.430***	(0.000)	-0.490***	(0.000)
regtype120	-0.597***	(0.000)	-0.319***	(0.000)	-0.464***	(0.000)
regtype130	-0.288***	(0.000)	-0.135***	(0.000)	-0.210***	(0.000)
regtype141	0.284***	(0.007)	-0.0424	(0.768)	0.245**	(0.016)
regtype142	-0.509***	(0.001)	-0.416**	(0.014)	-0.461***	(0.000)
regtype143	-0.331***	(0.001)	-0.142	(0.183)	-0.296***	(0.001)
regtype149	-0.362***	(0.007)	-0.227	(0.113)	-0.285**	(0.015)
regtype151	0.371***	(0.000)	0.330***	(0.000)	0.390***	(0.000)

Variables \ Model	Model 1A Rdc		Model 1B npvc		Model 1C inn	
regtype159	0.0113	(0.588)	0.0771***	(0.001)	0.0351*	(0.073)
regtype160	0.114***	(0.000)	0.161***	(0.000)	0.128***	(0.000)
regtype171	-0.384***	(0.000)	-0.266***	(0.000)	-0.337***	(0.000)
regtype172	-0.333***	(0.000)	-0.140***	(0.002)	-0.261***	(0.000)
regtype173	-0.0781***	(0.000)	-0.0909***	(0.000)	-0.0912***	(0.000)
regtype174	-0.0956**	(0.014)	-0.0372	(0.365)	-0.0665*	(0.060)
regtype190	-0.460***	(0.000)	-0.193*	(0.066)	-0.349***	(0.000)
regtype210	-0.150***	(0.000)	-0.177***	(0.000)	-0.161***	(0.000)
regtype220	-0.381***	(0.000)	-0.250***	(0.000)	-0.430***	(0.000)
regtype230	-0.544***	(0.000)	-0.617***	(0.000)	-0.568***	(0.000)
regtype240	-0.100	(0.302)	-0.117	(0.239)	-0.136	(0.137)
regtype310	-0.192***	(0.000)	-0.150***	(0.000)	-0.171***	(0.000)
regtype320	-0.347***	(0.000)	-0.298***	(0.000)	-0.355***	(0.000)
regtype330	-0.453***	(0.000)	-0.537***	(0.000)	-0.452***	(0.000)
regtype340	-0.167**	(0.036)	-0.125	(0.117)	-0.119	(0.113)
t2	0.265***	(0.000)	0.410***	(0.000)	0.358***	(0.000)
_cons	-4.580***	(0.000)	-4.380***	(0.000)	-4.257***	(0.000)
N	156336		156336		156336	
pseudo R^2	0.201		0.162		0.178	

Note: ***, ** and * mean significance at 1%, 5% and 10% level, respectively. Readers may refer to Table 3.2 for details of the variables' definition, and Table A3.1and Table A3.2 for details of the definition of the sector and ownership dummies. One may argue that the production of new product is a function of R&D investment. Therefore R&D investment should be included in the model. This issue is considered and the result doesn't affect the major conclusions here.

According to the regression results, old firms are more willing to invest in innovation. This is different from the observation by Lin et al. (2010) who employed a sample of 2,400 Chinese firms covering the period 2000 to 2002. It is also found that large firms are more likely to invest in innovation. This is consistent with our expectation. A similar finding was also reported by Lin et al. (2010). In our results, it can also be seen from the coefficients that, in terms of firm size, the increased probability of investment in R&D is bigger than the increased probability of producing new products. The debt burden significantly reduced the probability of investment in R&D. This is consistent with our expectation as R&D is costly and uncertain, meaning that it is not affordable for financially constrained firms. This also reflects our prediction that firms generally tend to use internal resources to conduct R&D projects in order to keep them confidential before they are patented. Financial constraints also decrease the probability of producing new products as commercialisation and marketing are also capital-intensive activities, however, the coefficient here is smaller than the one in Model 1A. This is probably because, in this stage, firms can get access to external funds to facilitate their commercialisation processes. Firms with a higher level of technology are more likely to invest in innovation. Exporters are found to have a higher probability of conducting innovative behaviour, especially in producing new products. This is mainly because China's export products are not technology intensive and the higher standard in foreign countries pushes Chinese exporters to improve the quality or design of their products. It also demonstrates that the "learning by exporting" effect is mainly through product-embodied spillover. More efficient firms are proven to have higher probability of innovation. It is not surprising as more efficient firms generally have better performance and therefore sufficient profits to support their innovative behaviour. Efficiency signifies abundant internal resources and strong capability from RBV. Higher level of human resource obviously increases the probability of investing in innovation, as human resource is a critical input of the innovation process and it also represents the absorptive capability of a firm. Firms with intangible goods, long-term investment and subsidies from the government generally are more likely to conduct innovative activities. This is because intangible goods represent the knowledge base of a firm, therefore providing more internal knowledge resources, while long-term investment and subsidies provide extra earnings and cash flow which are beneficial to risky investment like innovation.

As for the external factors, all dependent variables are shown to have an inverted-U shape relationship with competition, implying that more competition initially increases and then later reduces the probability of innovation participation regardless of its measurement. This is consistent with evidence from other economies (Aghion et al. 2005; Tingvall and Poldahl 2006). Regional financial development, or the development of financial services, is found to be positively associated with the probability of investment in R&D but negatively linked with the probability of producing new products. The reasons underlying this result can be manifold. First, financial services as knowledge-intensive business services generally tend to agglomerate in metropolitan areas which have a more advanced industrial structure and are subject to a higher level of competition. Firms in these areas thus are stimulated to invest in R&D in order to survive but face more difficulties when commercializing them. Secondly, better development of financial services is generally associated with a higher degree of openness. However, the risk of knowledge leakage is generally higher in more open areas, and therefore the probability of successful innovation may be smaller. Thirdly, the finding implies that Chinese firms tend to locate their R&D sector in more developed regions in order to enjoy the knowledge spillover effect, and commercialise their products in less developed regions to avoid competition or seek greater profits. Foreign knowledge spillover doesn't show any significant relationship with R&D choice, however, from the new product perspective it has a negative relationship with innovative behaviour. This result further supports the view that instead of providing positive spillover to local firms, FDI crowds out innovation activities in local firms. To be specific, the effect of FDI on R&D is bidirectional. On the one hand, FDI brings new technology and generates knowledge spillover to local firms and therefore reduce their incentives to conduct internal R&D activities since local firms can have access to technology via imitation. On the other hand, FDI increases the level of competition which stimulates local firms to innovate in order to survive. The two effects might cancel out each other and thus the coefficient of R&D behaviour is not significant. However, in terms of new products, FDI may raise the barrier to commercialisation due to competition in the market. This implies that successful innovation (commercialisation) may be inhibited by FDI. A higher level of environmental protection raises the possibility of conducting innovation which is consistent with Porter's hypothesis. It is undoubtable that government support has a significant effect on both kinds of innovation, especially new product sales. This is probably because parts of R&D projects are launched by government and therefore crowd out firms' R&D investment. IPRs are found to increase the probability of innovation participation. The network variable has a significantly negative impact on innovative activities. This might be because better networks make firms to innovate as an alliance, which probably reduces individual firm's participation in innovation but improves the quality of innovation or increases the probability of successful innovation.

The estimated coefficients of the sectoral dummy variables show that firms engaged in manufacturing activities of fuel and chemicals (ind5), pharmaceuticals (ind6), machinery (ind9), transport equipment (ind10), communication and other electronic equipment (ind11) are more likely to invest in R&D than those in base industries (ind1, mining). These industries are generally considered as high-tech industries. Therefore, those high-tech industries not only invest in innovation more intensively but also more frequently. From the perspective of new products, all industries, except industry 12, are more likely to produce new products. The ownership dummies show that state-owned enterprises are most likely to engage in innovation, while private enterprises, Hong Kong, Macau and Taiwan-owned enterprises and foreign-owned enterprises are less likely to do so. This finding supports the argument made by Bruche (2010) and Zhou (2014). The year dummy variables also show that the probability of innovation has increased over time.

3.5 Robustness and Further Analysis

While important findings are derived from the estimation of Model 1, the results are subject to further investigation. It is argued that firms that innovated in the past are more likely to innovate today (Parisia et al. 2006). This may simply reflect the sunk costs involved in innovation activities or a time-invariant characteristic of the firm such as the quality of the management. The same argument is also made in terms of a firm's exporting decision and hence the intensity of export (Roberts and Tybout 1997). The common practice in the literature is to consider the lagged dependent variable as a regressor in the model. Thus equation (3-3) becomes the following:

$$Y_{it} = \alpha_0 + \beta Y_{i(t-1)} + \sum \beta_j X_{ij(t-1)} + \sum \gamma_j Z_{ijt} + \varepsilon_{it} \tag{3-4}$$

Direct estimation of equation (3-4) using OLS is problematic due to the potential presence of endogeneity. To overcome this problem, various methods such as the dynamic probit models and GMM approach have been proposed. Each has its advantages and shortcomings. In this study, equation (3-4) is estimated by replacing $X_{ij(t-1)}$ by $X_{ij(t-2)}$ and quasi-maximum likelihood (Huber-White) robust standard errors are calculated. The variables have the same definitions as discussed in the previous paragraph. The sample covers one year only. The regression results are presented in Table 3.5.

Table 3.5 Regression results with lagged dependent variables

Model / Variables	Model 2A rdc		Model 2B npvc		Model 2C inn	
rdc	1.943***	(0.000)				
npvc			2.293***	(0.000)		
inn					1.932***	(0.000)
age	0.00124*	(0.059)	-0.00139*	(0.063)	0.000546	(0.380)
size	0.0140***	(0.000)	0.0146***	(0.000)	0.0159***	(0.000)
debt	-0.0945***	(0.000)	-0.0920***	(0.004)	-0.0966***	(0.000)
tech	0.0128*	(0.056)	0.0369***	(0.000)	0.0229***	(0.000)
exp	0.0533**	(0.002)	0.193***	(0.000)	0.128***	(0.000)
eff	0.0875***	(0.000)	0.0121	(0.269)	0.0653***	(0.000)
hc	0.332***	(0.000)	0.200**	(0.002)	0.331***	(0.000)
intang	0.138***	(0.000)	0.115***	(0.000)	0.134***	(0.000)
invest	0.109***	(0.000)	0.109***	(0.000)	0.111***	(0.000)
subsidy	0.00851***	(0.007)	0.00688**	(0.046)	0.00615**	(0.036)
hhi	0.0113	(0.967)	0.646*	(0.063)	0.473*	(0.080)
hhi2	0.316	(0.216)	0.195	(0.511)	0.307	(0.209)
fsint	0.221**	(0.042)	-0.748***	(0.000)	-0.0523	(0.606)
fdi	-0.0186***	(0.001)	-0.0588***	(0.000)	-0.0404***	(0.000)
recycle	-0.0110***	(0.001)	0.0139***	(0.003)	-0.00213	(0.509)
govsup	2.180***	(0.005)	5.912***	(0.000)	2.990***	(0.000)
ipr	0.369***	(0.000)	1.620***	(0.000)	1.056***	(0.000)
network	-0.0341***	(0.000)	-0.0219*	(0.052)	-0.0284***	(0.001)

Variables \ Model	Model 2A rdc		Model 2B npvc		Model 2C inn	
ind2	0.201***	(0.001)	0.840***	(0.000)	0.339***	(0.000)
ind3	0.0256	(0.653)	0.863***	(0.000)	0.251***	(0.000)
ind4	0.0129	(0.828)	0.804***	(0.000)	0.197***	(0.001)
ind5	0.362***	(0.000)	0.909***	(0.000)	0.466***	(0.000)
ind6	0.664***	(0.000)	1.100***	(0.000)	0.775***	(0.000)
ind7	0.205***	(0.000)	0.800***	(0.000)	0.277***	(0.000)
ind8	0.0571	(0.388)	0.845***	(0.000)	0.287***	(0.000)
ind9	0.382***	(0.000)	1.089***	(0.000)	0.544***	(0.000)
ind10	0.480***	(0.000)	1.230***	(0.000)	0.695***	(0.000)
ind11	0.484***	(0.000)	1.153***	(0.000)	0.641***	(0.000)
ind12	-0.230***	(0.001)	-0.325*	(0.052)	-0.229***	(0.001)
regtype120	-0.393***	(0.000)	-0.366***	(0.000)	-0.392***	(0.000)
regtype130	-0.269***	(0.000)	-0.0794	(0.194)	-0.194***	(0.000)
regtype141	0.327*	(0.087)	-0.117	(0.742)	0.238	(0.252)
regtype142	-0.0822	(0.709)	-0.161	(0.655)	-0.0162	(0.938)
regtype143	-0.404**	(0.013)	-0.547***	(0.001)	-0.598***	(0.000)
regtype149	-0.422	(0.104)	-0.0254	(0.917)	-0.146	(0.483)
regtype151	0.210***	(0.002)	0.142**	(0.050)	0.202***	(0.003)
regtype159	-0.0342	(0.321)	0.0696	(0.102)	-0.00366	(0.913)
regtype160	0.117***	(0.007)	0.135***	(0.009)	0.131***	(0.002)
regtype171	-0.287***	(0.000)	-0.241***	(0.000)	-0.289***	(0.000)
regtype172	-0.236***	(0.002)	-0.230**	(0.017)	-0.202***	(0.005)
regtype173	-0.0405	(0.252)	-0.0368	(0.400)	-0.0587*	(0.085)
regtype174	-0.0524	(0.406)	0.0595	(0.442)	-0.0422	(0.491)
regtype190	-0.110	(0.481)	-0.184	(0.381)	-0.290*	(0.075)
regtype210	-0.0659	(0.135)	-0.0427	(0.425)	-0.0526	(0.208)
regtype220	-0.315***	(0.000)	-0.102	(0.221)	-0.355***	(0.000)
regtype230	-0.253***	(0.000)	-0.231***	(0.000)	-0.247***	(0.000)
regtype240	-0.0274	(0.870)	-0.0890	(0.534)	-0.0851	(0.548)
regtype310	-0.112***	(0.010)	-0.000837	(0.987)	-0.0770*	(0.062)
regtype320	-0.132*	(0.097)	0.0194	(0.837)	-0.0744	(0.328)
regtype330	-0.280***	(0.000)	-0.233***	(0.000)	-0.244***	(0.000)
regtype340	-0.0404	(0.766)	-0.282**	(0.040)	-0.125	(0.359)
_cons	-2.609***	(0.000)	-3.987***	(0.000)	-2.911***	(0.000)
N	77987		77987		77987	
pseudo R^2	0.430		0.511		0.441	

Note: ***, ** and * mean significance at 1%, 5% and 10% level, respectively. Readers may refer to Table 3.2 for details of the variables' definition, and Table A3.1 and Table A3.2for details of the definition of the sector and ownership dummy variables.

Obviously, the coefficient of the lagged dependent variable is positive and statistically significant. Thus, firms which invested in innovation in the past are more likely to spend on innovation activities in the future. The coefficients of other variables show some sensitivity in terms of their magnitude, sign and level of significance. The overall findings are consistent with the previous ones. Exceptions include age and competition, which are not significant in model 2 with lagged dependent variables included. This implies that firms might have certain inertness to innovate, and that once past innovation behaviour is controlled for, age and competition are not decisive variables affecting innovation. Protection of the environment reduces the probability of investing in R&D in Model 2A, while it does increase the probability of producing new products.

In addition, to distinguish between firms with R&D only, firms with new products only or firms with both R&D and new products, a multinomial probit model is employed to conduct further analysis, which also makes the results more comparable between different groups (Table 3.6). A firm generally has four choices, namely (1) it has neither R&D nor new products, in which case, it is viewed as a non-innovative firm; (2) it has R&D investment but no new products, whereby it is treated as a serious or major innovator, but thought to be still at the initial stage of innovation; (3) it has new products but no R&D investment, which is treated as a successful innovator through either formal or informal R&D, however, it is treated as a less serious innovator due to its lack of continuous formal R&D; and (4) it has both R&D and new products, which would indicate that it is a relatively successful and mature innovator. Such a firm has commercialised its innovation products and conducted continuous innovative activities.

Table 3.6 Regression results of multinominal probit model

Choice / Variables	Choice (2)		Choice (3)		Choice (4)	
age	0.00191***	(0.002)	0.00226***	(0.001)	0.00555***	(0.000)
size	0.354***	(0.000)	0.207***	(0.000)	0.449***	(0.000)
debt	-0.232***	(0.000)	-0.0637**	(0.013)	-0.405***	(0.000)
tech	0.0736***	(0.000)	0.0516***	(0.000)	0.0804***	(0.000)
exp	0.0507***	(0.001)	0.394***	(0.000)	0.532***	(0.000)
eff	0.184***	(0.000)	0.106***	(0.000)	0.232***	(0.000)
hc	0.687***	(0.000)	0.307***	(0.000)	0.914***	(0.000)
intang	0.250***	(0.000)	0.175***	(0.000)	0.360***	(0.000)
invest	0.238***	(0.000)	0.194***	(0.000)	0.414***	(0.000)
subsidy	0.0337***	(0.000)	0.0198***	(0.000)	0.0592***	(0.000)
hhi	2.865***	(0.000)	1.552***	(0.000)	3.909***	(0.000)
hhi2	-3.807***	(0.000)	-2.641***	(0.000)	-6.221***	(0.000)
fsint	0.506***	(0.000)	-1.02***	(0.000)	0.399***	(0.008)
fdi	-0.00658	(0.192)	-0.0918***	(0.000)	-0.0407***	(0.000)
recycle	0.00501	(0.159)	0.0808***	(0.000)	0.0467***	(0.000)

Variables \ Choice	Choice (2)		Choice (3)		Choice (4)	
govsup	3.908***	(0.000)	12.65***	(0.000)	14.86***	(0.000)
ipr	0.398***	(0.000)	0.811***	(0.000)	1.476***	(0.000)
network	-0.0990***	(0.000)	-0.125***	(0.000)	-0.264***	(0.000)
ind2	0.491***	(0.000)	0.721***	(0.000)	1.578***	(0.000)
ind3	0.0766	(0.107)	0.730***	(0.000)	1.348***	(0.000)
ind4	0.124**	(0.012)	0.698***	(0.000)	1.413***	(0.000)
ind5	0.785***	(0.000)	0.853***	(0.000)	1.934***	(0.000)
ind6	1.468***	(0.000)	1.438***	(0.000)	2.940***	(0.000)
ind7	0.295***	(0.000)	0.757***	(0.000)	1.722***	(0.000)
ind8	0.136**	(0.015)	0.736***	(0.000)	1.387***	(0.000)
ind9	0.724***	(0.000)	1.135***	(0.000)	2.323***	(0.000)
ind10	0.879***	(0.000)	1.223***	(0.000)	2.580***	(0.000)
ind11	0.954***	(0.000)	1.294***	(0.000)	2.561***	(0.000)
ind12	-0.621***	(0.000)	-0.530***	(0.000)	-0.954***	(0.000)
regtype120	-0.687***	(0.000)	-0.280***	(0.000)	-1.071***	(0.000)
regtype130	-0.320***	(0.000)	-0.0693	(0.167)	-0.454***	(0.000)
regtype141	0.434***	(0.004)	0.0375	(0.878)	0.164	(0.484)
regtype142	-0.545***	(0.007)	-0.373	(0.107)	-1.294***	(0.010)
regtype143	-0.464***	(0.002)	-0.187	(0.293)	-0.391**	(0.028)
regtype149	-0.363*	(0.061)	-0.146	(0.482)	-0.758**	(0.015)
regtype151	0.371***	(0.000)	0.277***	(0.001)	0.724***	(0.000)
regtype159	-0.0138	(0.662)	0.0913**	(0.014)	0.0850**	(0.024)
regtype160	0.0630	(0.124)	0.114**	(0.020)	0.259***	(0.000)
regtype171	-0.464***	(0.000)	-0.280***	(0.000)	-0.680***	(0.000)
regtype172	-0.468***	(0.000)	-0.164**	(0.020)	-0.400***	(0.000)
regtype173	-0.0905***	(0.006)	-0.0979***	(0.010)	-0.162***	(0.000)
regtype174	-0.0981*	(0.091)	0.00542	(0.933)	-0.156**	(0.032)
regtype190	-0.568***	(0.001)	-0.157	(0.329)	-0.698***	(0.000)
regtype210	-0.129**	(0.001)	-0.150**	(0.001)	-0.363***	(0.000)
regtype220	-0.684***	(0.000)	-0.480***	(0.000)	-0.388***	(0.000)
regtype230	-0.536***	(0.000)	-0.590***	(0.000)	-1.352***	(0.000)
regtype240	-0.188	(0.210)	-0.241	(0.191)	-0.211	(0.183)
regtype310	-0.186***	(0.000)	-0.109**	(0.016)	-0.389***	(0.000)
regtype320	-0.417***	(0.000)	-0.343***	(0.000)	-0.617***	(0.000)
regtype330	-0.367***	(0.000)	-0.416***	(0.000)	-1.217***	(0.000)
regtype340	-0.143	(0.249)	-0.0577	(0.684)	-0.359***	(0.004)
t2	0.297***	(0.000)	0.510***	(0.000)	0.657***	(0.000)
_cons	-5.690***	(0.000)	-5.369***	(0.000)	-9.303***	(0.000)
N	156336		156336		156336	

Note: ***, **, * mean significant at 1%, 5% and 10% level, respectively. Refer to Table 3.2 for details of variables' definition. Refer to Table A3.1and Table A3.2 for details of sector and ownership dummies.

The estimation results of the multinominal models are presented in Table 3.6 in which choice (1) is chosen to be the reference. In general, apart from some sensitivity in terms of the magnitude of the coefficients, the major findings are highly consistent with those from other models. Hence, the empirical results so far are robust. It is noticed that, in choice (4), the magnitude of the coefficients of major variables is generally larger than that in other models. Therefore, it may be concluded that mature innovators are more likely to possess either of those characteristics, namely, old vintage in terms of commencement date, large scale production, higher level of technology and human resource, more efficient, possession of intangible goods and subsidy, exporters and holding long-term investment. They are also more sensitive to a debt burden and the external environment. In terms of ownership, SOEs are more likely to become mature innovators rather than major innovators, while private enterprises, Hong Kong, Macau and Taiwan-owned enterprises and foreign-owned enterprises are much less likely to be mature innovators. Industries with higher propensity to innovate in the past are much more likely to innovate on an ongoing basis.

3.6 Conclusion

Based on a theoretical framework combining resource-based views and the theory of the regional innovation system, this chapter investigates both the internal and external determinants that affect Chinese manufacturing firms' innovative behaviour by using a rich set of firm-level data and municipal-level data during the period of 2002 to 2010. Panel probit and multinomial probit models are employed to examine the determinants of innovative behaviour under different measurements.

The results show that Chinese innovative firms are generally old, large, exporters, and state-owned. Those firms which are more efficient and have higher levels of technology and human resource are generally more likely to participate in innovation. A better knowledge base, long-term planning and extra subsidies are beneficial to increase the probability of engaging in innovation. A high level of liability or debt burden is detrimental to innovation, especially for R&D investment and mature innovators. This is also observed in other economies such as Canada (Cumming and Macintosh 2000), Japan (Ogawa 2007) and South Korea (Lee 2012). More competition increases initially and then reduces the probability of innovation, regardless of the measurement of innovative behaviour.

Regional financial development increased the probability of investment in R&D but reduced the probability of producing new products. Instead of providing positive spillovers to local firms, FDI crowded out innovative activities in local firms. The regional level of environment protection has a positive effect on firms' innovation choice, which is consistent with Porter's hypothesis. Government support has a significant effect on both kinds of innovation, especially new product sales. IPRs have a positive relationship with R&D investment and new product production. The network variable has a significant negative relationship with innovation participation. Sectoral dummies show that high-tech industries (industries 5, 6, 9, 10 and 11) not only invest in R&D more intensively but also more frequently. From the perspective of new products, all industries, except industry 12, are more likely to produce new products. The ownership dummies show that, unlike SOEs, private enterprises, Hong Kong, Macau and Taiwan-owned enterprises and foreign-owned enterprises are less likely to engage in innovation.

The overall findings are similar, regardless of whether innovation appears in the form of R&D investment or new product sales. Several methods are adopted to ensure the robustness of the results. Although some sensitivity exists in terms of the magnitude of the coefficients, the major conclusions are highly consistent across the different models.

This study also has some limitations. Firstly, due to the limitation of information in the databases, we are not able to include important variables reflecting, for instance, corporate culture or the role of a firm in the regional system. These could be done in the future via field work and interviews with firms' managers. Secondly, the SMEs defined in this study are actually larger than most definitions of SMEs, since the annual sales of firms included in this database are generally more than five million RMB. Thus, many active small- and medium-sized innovators, especially those in emerging industries, are not able to be included, which implies that the results cannot be generalised in those areas. Regardless, as a comprehensive analysis on manufacturing firms' innovative behaviours embedded in regional innovation systems, this study provides a clear and complete picture of the determinants of enterprises' innovation strategy during China's transition to an innovation-oriented economic development path.

Appendix A3

Table A3.1 Definition of sector dummy variables

Dummy No.	Industry Codes	Definition
1	06	Mining & Washing of Coals
	07	Extraction of Petroleum & Natural Gas
	08	Mining & Processing of Ferrous Metal Ores
	09	Mining & Processing of Non-Ferrous Metal Ores
	10	Mining & Processing of Non-metal Ores
2	13	Processing of Food from Agricultural Products
	14	Manufacture of Foods
	15	Manufacture of Beverages
	16	Manufacture of Tobacco
3	17	Manufacture of Textile
	18	Manufacture of Textile Wearing Apparel, Footwear, and Caps
	19	Manufacture of Leather, Fur, Feather and Related Products
4	20	Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products
	21	Manufacture of Furniture
	22	Manufacture of Paper and Paper Products
	23	Printing, Reproduction of Recording Media
	24	Manufacture of Articles for Culture, Education and Sport Activity
5	25	Processing of Petroleum, Coking, Processing of Nuclear Fuel
	26	Manufacture of Raw Chemical Materials and Chemical Products
6	27	Manufacture of Medicines
	28	Manufacture of Chemical Fibres
7	29	Manufacture of Rubber
	30	Manufacture of Plastics
	31	Manufacture of Non-metallic Mineral Products
8	32	Smelting and Pressing of Ferrous Metals
	33	Smelting and Pressing of Non-ferrous Metals
9	34	Manufacture of Metal Products
	35	Manufacture of General Purpose Machinery
	36	Manufacture of Special Purpose Machinery
10	37	Manufacture of Transport Equipment
11	39	Electrical Machinery & Equipment
	40	Manufacture of Communication Equipment, Computers and Other Electronic Equipment
	41	Manufacture of Measuring Instruments and Machinery for Cultural Activity and Office Work
	42	Manufacture of Artwork and Other Manufacturing
12	43	Recycling and Disposal of Waste
	44	Electric Power & Heat Power
	45	Production & Supply of Gas
	46	Production & Supply of Water

Source: Author's own work. Based on National Industries Classification (GB/T 4754-2011)

Table A3.2 Codes of registered types

Code	Registered Types	Code	Registered Types
110	State-owned enterprises	173	Private limited liability company
120	Collective-owned enterprises	174	Private shareholding company
130	Shareholding cooperatives	190	Other domestic-owned enterprises
141	State-owned jointly operated enterprises	210	Hong Kong-Macau-Taiwan joint venture
142	Collective jointly operated enterprises	220	Hong Kong-Macau-Taiwan investors cooperative
143	State- and collective-owned jointly operated enterprises	230	Hong Kong-Macau-Taiwan wholly owned enterprises
149	Other jointly operated enterprises	240	Hong Kong-Macau-Taiwan shareholding limited liability company
151	Wholly state-owned enterprises	310	Foreign joint venture
159	Other limited liability company	320	Foreign cooperative
160	Joint stock limited liability company	330	Foreign wholly owned enterprises
171	Wholly private-owned enterprises	340	Foreign shareholding limited liability company
172	Private-cooperative enterprises		

Source: Annual Survey of Manufacturing Enterprises

CHAPTER 4 – UNIVERSITY-INDUSTRY COLLABORATION AND INNOVATION EFFICIENCY

4.1 Introduction

Tapping into external technology is crucial for innovation since it offers firms with external sources of technology and complements the insufficient technical or commercial competence of firms (Henderson and Clark 1990; Kogut and Zander 1992). Chesbrough (2003, 2006) pointed out that 'even the most capable R&D organisations must identify, connect to, and leverage external knowledge sources as a core process in innovation' since useful knowledge is widely distributed under the framework of open innovation. As a result, industrial firms are increasingly expanding their organisational boundaries to search for external sources of knowledge (Berchicci 2013). A well-established stream of literature has also demonstrated that firms investing in a broader search for external knowledge may have greater ability to innovate (Li-Ying et al. 2014).

In a knowledge-based economy, universities, as producers and transmitters of knowledge, play a critical role in innovative and sustainable economic development, and university-industry collaboration is one of the most widely discussed topics in this area (Etzkowitz and Leydesdorff 2000; Leydesdorff and Meyer 2003). Many scholars have argued that university-industry research collaborations are extremely important mechanisms for generating technological spillovers. This kind of collaboration contributes positively to address market failures related to innovation and help realize the full potential of research and development (R&D) investments (Martin and Scott 2000; Siegel and Zervos 2002; D'Este and Patel 2007). In reality, policy-makers in both developed and developing countries require universities to play a more active role in the national economy and to achieve global competitiveness. R&D thus becomes increasingly organised as a global task that is no longer limited to the leading industrialised nations (Brehm and Lundin 2012).

The university-industry collaboration is even more important to sustainable economic growth in the context of China. Internal R&D is generally considered as one of the most valuable component of firms' innovation strategy in developed countries (Teece 1986; Zhou and Wu 2010), particularly in advanced sectors (Maietta 2015; Maietta et al. 2017). However, a large number of firms in China is lack of, and not able to rapidly build, strong R&D capabilities (Motohashi and Yun 2007; Perks et al. 2009). Thus, in order to complement their limited capabilities of internal R&D, one of the most effective strategies is to rely heavily on university-industry collaboration (Kafouros et al. 2015). Hu and Mathews (2008) empirically demonstrated the strong role played by universities in the building of China's national innovative capacity. Eom and Lee (2010) also pointed out the different motivations and impacts of university-industry collaborations in developing and advanced economies. It is thus both theoretically and practically important to investigate the impact of university-industry linkages on firms' innovation performance in the context of China.

Nevertheless, in contrast with well-documented literature on developed countries, few studies in this field are concerned with the emerging countries which are experiencing phenomenal development in technological progress (Exceptions include Guan et al. 2005; Eun et al. 2006; Wu 2012b; Ang et al. 2014; Kafouros et al. 2015; Chen et al. 2016). China, as the biggest developing country, has attracted significant attention for its impressive economic growth. It is even more impressive to note that China's R&D intensity (R&D expenditure over GDP) soared from 0.6 per cent in 1995 to 2.05 per cent in 2014, which is on a par with the average level of the EU15. China has also had the largest research team in the world since 2012 (OECD 2016). Associated with the expansion in the R&D sector is the increasingly closer relationship between industry and universities. According to the United States Patent and Trademark Office (USPTO), the number of co-patents before 2005 was less than 10, while in 2009 there were 173 co-patents, showing a rapidly increasing trend of collaboration between industry and universities (Lei et al. 2011). In 2006, China announced the *Guideline for the National Medium- and Long-term Science and Technology Development Programmes (2006-2020)*, which aims to transform China's resource-driven growth model to an innovation-driven one. In addition, the market-oriented reforms in higher education also encouraged universities to develop industry linkages, diversify funding sources, and strengthen applied research capacities. Project 211 and Project 985 are two examples among a large number of other initiatives and reforms which intend to push the nation's universities into the global top-league and facilitate economic transition.

This study aims to enrich the discussion on university-industry collaboration in the context of China. Although previous literature made solid contributions to our understanding of the effect of collaboration on regional and firm-level innovation performance through various channels, none of them adopted an efficiency perspective. Such a perspective could be beneficial to the understanding of the role of collaboration in the innovation process. The only exception, as far as we know, is Broekel (2012) who investigated the relationship between collaboration intensity and regional innovation efficiency in Germany through a case study of the Electrics & Electronics industry. Therefore, this study aims to contribute to the literature by investigating the impact of collaboration on innovation efficiency at different stages. It may offer a better understanding of the influential mechanism of collaboration under the framework of open innovation. In addition, an efficiency perspective may eliminate the bias of exclusively relying on output indicators as collaboration might improve or inhibit firms' innovative performance through input reduction or redundancy.

The rest of this Chapter is structured as follows. Section 2 discusses the theoretical framework for empirical analysis and proposes hypotheses to be tested. Section 3 introduces the model and dataset used for efficiency measurement. In addition, trend and distribution of firms' efficiency scores are presented. Sections 4 specifies the regression model and provides empirical results based on the estimation of efficiency in Section 3. Robustness of the results is tested in Section 5. Section 6 presents the conclusions and their implications.

4.2 Theoretical Framework and Hypotheses

Universities are important sources of fundamental knowledge and, occasionally, industrially relevant technology in a modern knowledge-based economy (Mowery and Sampat 2005). Since the 1970s, governments throughout the industrialised economies have launched numerous initiatives to promote close links between universities and industrial innovation, and hence, local economic growth. As a result, the role of universities in applied innovation has expanded (Felsenstein 1994; Anselin et al. 1997; Feller et al. 2002). University-industry collaboration is therefore widely discussed in the literature. The relationship between university-collaboration and innovation is summarised in Figure 4.1. Several points are worthy of note. Firstly, the frequency and intensity of university-industry collaboration are considered separately. Secondly, it is assumed that collaboration affects firms' performance at two sub-processes, namely the R&D stage and commercialisation stage and that these impacts are subjected to the effects of internal and contextual factors. Finally, the potential moderating effects of the contextual factors on collaboration are considered as well. In the following sections, three major hypotheses are proposed.

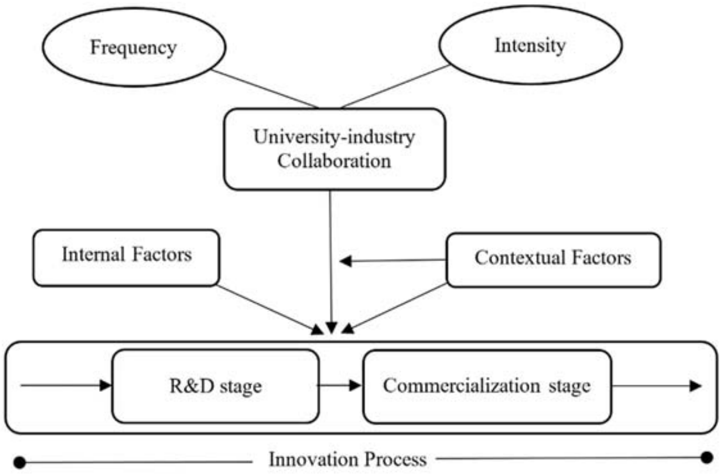


Figure 4.1 University-industry collaboration and innovation

4.2.1 The Two Faces of Collaboration

Universities are widely cited as critical institutional actors which affect the creation, development and diffusion of innovation (Cooke 1992; Nelson 1993; Freeman 1995; Asheim et al. 2011). The literature on national innovation systems sheds light on the significance of strong linkage with these institutions in enhancing national innovative and competitive performance. This applies particularly to universities within the national innovation systems. Gibbons et al. (1994) argue that the increased scale and diversity of knowledge inputs required for scientific research are associated with greater inter-institutional collaboration and more interdisciplinary research. A closely related conceptual framework for analysing the changing position of universities within national innovation systems is the “Triple Helix” model popularised by Etzkowitz (1993) and Etzkowitz and Leydesdorff (1995). This model was proposed as an attempt to understand the shift from an industry-government dyadic system in the industrial society to a growing university-industry-government triadic one in the knowledge society. It is quite clear that, in a knowledge society, potential for innovation and economic development lies in a more prominent role for universities and the hybridisation of elements from university, industry and government to generate new institutional and social formats for the production, transfer and application of knowledge. These works all emphasize the interaction between institutions within a regional system and therefore support the positive role of collaboration.

However, a growing number of scholars considered the potential downside of openness (Ritala 2012; Martinez-Noya et al. 2013). Salge et al. (2013) pointed out that pursuing an open innovation approach can be a double-edged sword since greater openness may enhance not only a firm's accessibility to external knowledge, but also its vulnerability to unexpected knowledge leakage and imitation by others from a resource-based view (RBV). Giarratana and Mariani (2014) argued that the fear of imitation might overshadow the benefits of openness since firms risk spillovers of their own internal knowledge when they tap into external sources. Recent evidence also suggests that increasing the overlap in resources and expertise between firms and universities can lead to knowledge redundancy and coordination expenses, which can reduce the expected returns from university-industry collaborations (Soh and Subramanian 2014). Maietta (2015) and Maietta et al. (2017) also suggest that the expected returns from university-industry collaboration may be reduced because university scholars may actively collaborate with firms only on topics which are relevant for their academic career advancement. Given these competing views, the first hypothesis to be tested in this study is,

H1: The impact of university-industry collaboration on firms' innovation efficiency is expected to be positive, *ceteris paribus*.

The assumption of a positive effect is due to China's heavy reliance upon university-industry collaboration to compensate for the country's lack of internal R&D capabilities. As already mentioned, empirical research has shown the importance of universities in building China's national innovative capacity (Kafouros et al. 2015; Hu and Mathews 2008).

4.2.2 Collaboration in Innovation Process

Since innovation is a series of processes rather than an instantaneous activity, collaborations may manifest distinctive functions at different stages. The nature of early-stage collaboration (e.g. idea generation, research and development) is different from that at later stages (e.g. testing and commercialisation) of the innovation process and thus collaboration may hold different implications for the risk of knowledge leakage (Salge et al. 2013). To be specific, early stages involve a close interaction and intensive exchange of core technological knowledge between collaboration partners (Faems et al. 2010; Li et al. 2012). While this intensive interaction facilitates the transfer of tacit knowledge and fosters creative problem-solving, it also increases the likelihood of unintended knowledge leakage (Roy and Sivakumar 2011). Thus, firms with collaboration must balance between knowledge sharing and knowledge leakages (Grimpe and Kaiser 2010; Laursen and Salter 2014). In contrast, the interaction in late stages is less intense and restricted to solving highly specific problems related to prototyping or commercialisation. Thus, in late stages the focal firm can pursue selective revealing strategies providing partners only with relevant information on a specific problem rather than exchanging core technologies that lie at the heart of a particular innovation (Harhoff et al 2003; Alexy et al. 2013). From this perspective, collaborative firms have less risk of knowledge leakage and benefit more from knowledge exchange in later stages than early stages. Given these arguments, it is hypothesised that,

H2: University-industry collaboration is expected to have different effects on innovation efficiency in the two stages, *ceteris paribus*.

4.2.3 Institutional Heterogeneity across Regions

Apart from firms' characteristics, institutional environment has long been recognised as one of the most important factors affecting regional innovation systems (Roper et al. 2004; Bosker and Garretsen 2008). In developed economies, institutional environments are stable and largely homogeneous within a country. In contrast, emerging countries like China suffer from substantial institutional variations across regions (Chang and Wu 2014). In China, the three phases of administrative decentralisation, unravelled by the open-door policy, further empowered regional governments and led to significant institutional and economic fragmentation within the country (Boisot and Meyer 2008; Kafouros et al. 2015). Regional governments also control and protect their local enterprises and organisations. In addition, the multi-layered institutional system is reinforced by operating market and state-controlled governance mechanisms simultaneously (Peck and Zhang 2013). Since institutions are part of the dynamics of innovation (Crescenzi et al. 2014), they influence the effectiveness of regional university-industry collaboration. Regional governments have distinct motivations, objectives and preferences (Wang et al. 2012) and therefore affect the relationship between universities and industrial firms differently.

Specifically, even though Intellectual Property Rights (IPR) laws are generally universal across regions in China, the enforcement of IPR laws differs remarkably and leads to further variations in the frequency of infringements, the effectiveness of courts, the enforcement of contracts and the rules for innovation subsidies (Li and Qian 2013). Stringent IPR enforcement can better protect the innovation output of firms and therefore increases the pre-innovation rents (Beladi et al. 2016), however, it also raises the barrier to innovate (e.g. greater investment in R&D) and therefore reduces the post-innovation rents (Aghion et al. 2014). Therefore, from an efficiency view, it is expected that stringent IPR enforcement is beneficial for the commercialisation stage, while it might be detrimental for the R&D stage. In addition, institutional variations also determine the attractiveness of regions and the direction of capital flows. Since China's recent growth and transformation has relied on its international openness and ability to attract inward foreign direct investment (FDI), universities in more open regions can benefit from the exposure to foreign knowledge and markets due to both embodied and disembodied knowledge spillovers (Krammer 2014). Furthermore, the university-industry collaboration could be improved when more knowledgeable and globally connected partners are engaged. Finally, uneven institutional environment could lead to variations in university quality across regions. Thus, the third hypothesis is stated as follows

H3: The impact of university-industry collaboration on firms' innovation efficiency is expected to be moderated by regional institutional factors, *ceteris paribus*.

4.3 Innovation Efficiency Measurement

In this section, we first elaborate on the reason for using a non-parametric model and introduce the network DEA employed in this study[9]. After that, the data issues and the selection of indicators are presented and discussed. Following this, the two-stage innovation efficiency of Chinese innovative firms is estimated and analysed. This section also lays the foundation for further investigation on how the university-industry collaboration might affect firms' innovation performance in terms of efficiency.

4.3.1 Network DEA

In evaluating efficiency, two major approaches are widely used in the literature, namely, the parametric approach, called the stochastic frontier analysis (SFA) and the nonparametric approach, called the data envelopment analysis (DEA). SFA uses econometric techniques to estimate the production frontier, while DEA involves the use of linear programming to determine the efficiency frontier. Since there is no clear underlying theoretical model of the innovation process, it is not feasible to define a function connecting inputs and outputs. Therefore, in an uncertain context such as the innovation process, DEA technique is more

[9] The network DEA employed in this study is similar to the model proposed by Tone and Tsutsui (2009). It is also known as relational network DEA (Kao 2009). Therefore, these two terms are used interchangeably in this study.

appropriate than the SFA approach (Hollanders and Celikel-Esser 2007; Chen and Guan 2012). With consideration of the characteristics of innovation process, one of the network DEA models, called the network slacks-based measure (SBM) is employed to estimate the two-stage innovation efficiency. SBM is a non-radial method and is suitable for measuring efficiencies when inputs and outputs may change non-proportionally.

Consider *n DMUs* (*j=1,…,n*) consisting of *K* sub-processes (*k=1,…,K*). m_k and r_k are assumed to be the number of inputs and outputs to sub-process k, respectively. The link leading from sub-process *k* to sub-process *h* is denoted by (*k, h*) and the set of links is denoted by *L*. The observed data are $\{ \mathbf{x}_j^k \in R_+^{m_k} \}(j = 1,...,n; k = 1,...,K)$, which represent inputs to DMU_j at sub-process *k*. $\{ \mathbf{y}_j^k \in R_+^{r_k} \}(j = 1,...,n; k = 1,...,K)$ and $\{ \mathbf{z}_j^{(k,h)} \in R_+^{t_{(k,h)}} \}(j = 1,...,n; (k,h) \in L)$ represent outputs from DMU_j at sub-process *k* and linking intermediates from sub-process *k* to sub-process *h*, respectively. In which $t_{(k,h)}$ is the number of items in link *(k, h)*. Based on these specifications, the production possibility set $\{(\mathbf{x}^k, \mathbf{y}^k, \mathbf{z}^{(k,h)} \}$ can be defined as:

$$\mathbf{x}^k \geq \sum_{j=1}^{n} \mathbf{x}_j^k \lambda_j^k \quad (k = 1,...,K)$$

$$\mathbf{y}^k \leq \sum_{j=1}^{n} \mathbf{y}_j^k \lambda_j^k \quad (k = 1,...,K)$$

$$\mathbf{z}^{(k,h)} = \sum_{j=1}^{n} \mathbf{z}_j^{(k,h)} \lambda_j^k \quad (\forall (k,h)) \text{ (as outputs from } k\text{)} \tag{4-1}$$

$$\mathbf{z}^{(k,h)} = \sum_{j=1}^{n} \mathbf{z}_j^{(k,h)} \lambda_j^h \quad (\forall (k,h)) \text{ (as inputs to } h\text{)}$$

$$\sum_{j=1}^{n} \lambda_j^k = 1 \quad (\forall k), \ \lambda_j^k \geq 0 \ \ (\forall j,k),$$

where $\lambda^k \in R_+^n$ is the intensity vector corresponding to sub-process *k* (*k=1,…,K*). DMU_o (o=1, …, n) therefore can be represented by

$$\mathbf{x}_o^k = \mathbf{X}^k \lambda^k + \mathbf{s}^{k-} \quad (k = 1,...,K)$$

$$\mathbf{y}_o^k = \mathbf{Y}^k \lambda^k - \mathbf{s}^{k+} \quad (k = 1,...,K)$$

$$\mathbf{e}\lambda^k = 1 \quad (k = 1,...,K), \tag{4-2}$$

$$\lambda^k \geq 0, \ s^{k-} \geq 0, \ s^{k+} \geq 0, \ (\forall k),$$

where

$$\mathbf{X}^k = (\mathbf{x}_1^k,...,\mathbf{x}_n^k) \in R^{m_k \times n}$$

$$\mathbf{Y}^k = (\mathbf{y}_1^k,...,\mathbf{y}_n^k) \in R^{r_k \times n} \tag{4-3}$$

and $\mathbf{s}^{k-}$, $\mathbf{s}^{k+}$ are the input, output slack vectors respectively.

In regard to the linking constraints, this study chooses the "free" link value case as the intermediates are not beyond the control of DMUs (Tone and Tsutsui 2009). The linking activities are freely determined while keeping continuity between input and output:

$$\mathbf{Z}^{(k,h)}\lambda^h = \mathbf{Z}^{(k,h)}\lambda^k, (\forall(k,h)), \tag{4-4}$$

where

$$\mathbf{Z}^{(k,h)} = (\mathbf{z}_1^{(k,h)},...,\mathbf{z}_n^{(k,h)}) \in R^{t_{(k,h)} \times n}. \tag{4-5}$$

In regard to the orientation, this study selects input-oriented efficiency, given that, generally, at the firm-level it is more appropriate to choose input-oriented efficiency, as the input end is more controllable especially in an uncertain process like innovation (Tone and Tsutsui 2009). By solving the following linear programme, the input-oriented efficiency of DMUs can be evaluated as follows:

$$\theta_o^* = \min_{\lambda_k, s^{k-}} \sum_{k=1}^{K} w^k [1 - \frac{1}{m_k}(\sum_{i=1}^{m_k} \frac{s_i^{k-}}{x_{io}^k})] \tag{4-6}$$

subject to constraints (4-2) and (4-4). In equation (4-6), $\sum_{k=1}^{K} w^k = 1, w^k \geq 0 \ (\forall k)$ and w^k is the relative weight of sub-process k which is determined corresponding to its importance. Using the optimal input slacks s^{k-*} from (4-6), the input-oriented sub-process efficiency score can be defined as:

$$\theta_k = 1 - \frac{1}{m_k}(\sum_{i=1}^{m_k} \frac{s_i^{k-*}}{x_{io}^k}) \ (k = 1,...,K). \tag{4-7}$$

In the above equation, θ_k is the sub-process efficiency index which optimizes the overall efficiency θ_o^*. If $\theta_k = 1$, then the DMU$_o$ is called input-efficient for the sub-process *k*. In this study, *k* takes the value of 2, thus the innovation production process is divided into a two-stage chain shape model which is shown as Figure 4.2.

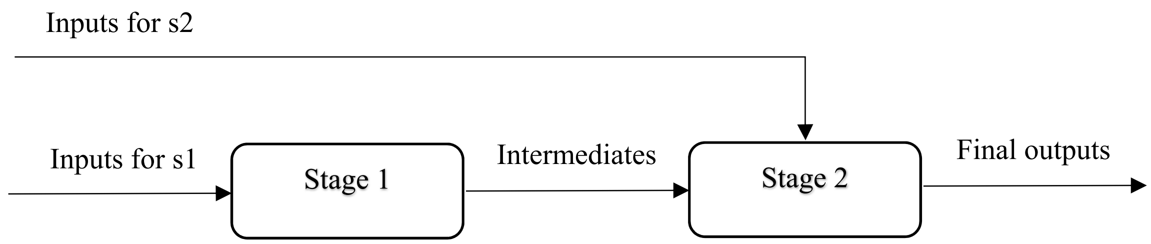


Figure 4.2 Two-stage chain shape model

4.3.2 Data Issues

This study is based on integrated datasets at firm, city and province levels. The firm-level data is drawn from a unique dataset named the "Innovation-Oriented Firms Database" (IOFD). This database is based on an annual survey of 443 most innovative firms across China during the period of 2008 to 2011, which is conducted and complied by the Ministry of Science and Technology of China (MOST). In line with the definition of active and innovative firms in the Oslo Manual (OECD 2005), these firms were screened by the MOST according to their R&D intensity, the number of granted patents weighed by R&D personnel, the share of the sales of new product over total revenue, labour productivity, and organisational and management innovations. Selected firms received a government reward by participating in the survey annually, which guarantees the validity of surveyed data. The survey is the most detailed innovation survey in China and is representative in terms of ownership, industrial and geographic distribution (Kafouros et al. 2015). With regard to contextual variables, data are drawn from China City Statistical Yearbook 2009-2012, China Statistical Yearbook of Science and Technology 2009-2012, and China Statistical Yearbook 2009-2012.

In terms of indicators adopted to evaluate the overall and sub-divisional efficiency, this study refers to a series of studies conducted by Guan and Chen (2010, 2012) and Chen and Guan (2012). Guan and Chen (2010) modelled a typical innovation production process with consideration of the internal operations associated with a relational network DEA approach and applied this framework to China's regional high-tech industry. Chen and Guan (2012) adopted a relational network DEA model to the systematic evaluation of the efficiency of China's regional innovation systems (RIS) by decomposing the innovation process into two connecting sub-processes, namely, technological development and subsequent technological commercialisation. Guan and Chen (2012) further extended this analytical framework to an international study of 22 OECD countries and evaluated the efficiency of China's national innovation system (NIS). The above-mentioned studies are all related to regional or national-level investigations. This study extends the existing literature to firm level data. The indicators used in this study are listed in Table 4.1.

The inputs for stage 1, the R&D stage of innovative firms, include the internal R&D expenditure, the full-time equivalence of R&D personnel and the total number of patents belonging to the firm[10]. The input of human resources is probably the most important input

[10] The internal R&D expenditure is the total amount which includes the expenditure on R&D personnel.

besides capital input in a production process, and even more so for the innovation process. The total number of existing patents represents the knowledge capital stock of a firm, which follows the basic hypothesis behind the Romer knowledge production function (Romer 1990; Furman et al. 2002; Hu and Mathews 2008). Romer argues that idea generation does not "fall from heaven", but derives from prior knowledge stock available and human capital.

Table 4.1 Indicators used to estimate efficiency

Stage 1 inputs	Stage 2 inputs	Intermediates	Final outputs
Internal R&D expenditure	S&T personnel excluding R&D personnel	Number of patent applications	Value of new product
R&D personnel	S&T expenditure excluding R&D expenditure	Number of patents approved	Value added
Total number of patents		Number of invention patent applications	Profit
Total number of invention patents		Number of invention patent approved	Revenue
			Tax

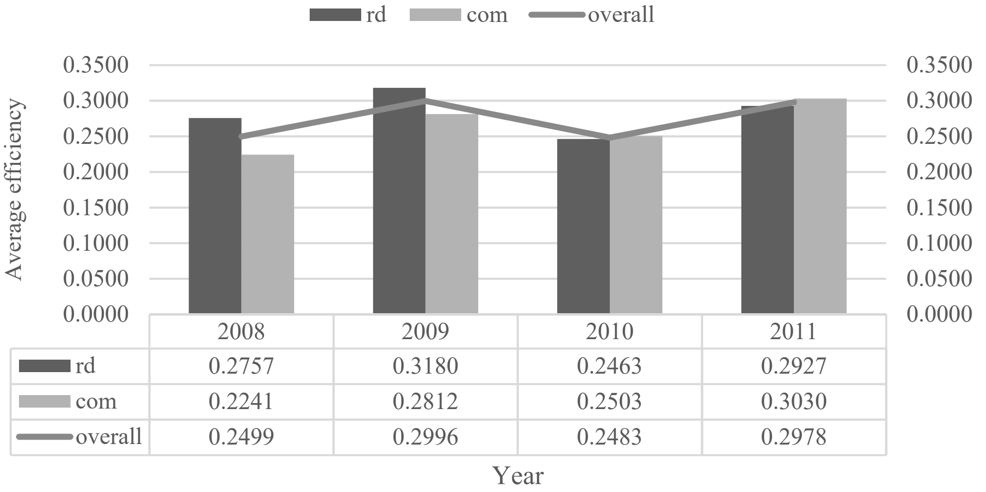
Source: Author's own work.

With respect to the output of stage 1, namely, the intermediate technological products of a simplified innovation process, the number of patents (applied or granted) may be the most appropriate proxy (Fritsch 2002; Broekel and Brenner 2007; Guan and Chen 2010). Although Griliches (1990) pointed out that not all inventions are patentable, not all inventions are patented, and the inventions that are patented differ greatly in quality, the sample used in this study focused on the most innovative firms in China, which have a high propensity to patent and also a high ratio of conversion. Empirical evidence also suggests that patents provide a fairly reliable measure of innovative activity (Acs et al. 2002; Wu 2011; Yu and Wu 2014). This study incorporates four types of data on patents (See Table 4.1) as the intermediates linking two sub-processes. Both the numbers of patent applications and patents approved are included. Using the number of patents approved only may suffer from certain biases caused by uncertainties during the examination process. Although the number of patent applications cannot represent the valid innovation outputs, it can manifest the vitality of firms' innovative activities and therefore compensate for the disadvantages of relying on the number of patents approved as an indicator. Corresponding indicators for invention patents are considered as well since invention patents generally stand for high quality and valuable patents.

In the second sub-process, together with the intermediates, expenditure on science and technology (S&T) activities excluding R&D investment are treated as the capital investment and the S&T personnel excluding R&D full-time equivalent personnel is treated as the human resource input. Freeman and Soete (1997) argued that innovation in the economic sense is accomplished only with the first commercial transaction, namely the final realisation of economic profits by commercialisation stage (second sub-process). The value of new products is used as the final output of innovation, which is widely consistent with the literature. As innovation contributes to firms' productivity and therefore ultimately improves firms' overall performance, four indicators regarding firms' operating performance are included as the final outputs as well (See Table 4.1), where the tax refers to the revenue tax. Furthermore, an important aspect is the existence of time lags during the transformation of innovation inputs into innovation outputs. According to the extant studies, there is no generally accepted length of time lags for R&D to output (Wang and Huang 2007; Guan and Chen 2010). Since Hollanders and Celikel-Esser (2007) empirically showed that the use of time lags has little effect on the innovation efficiency estimation, this study uses current values to evaluate efficiency scores given that only four-year data is available in the dataset.

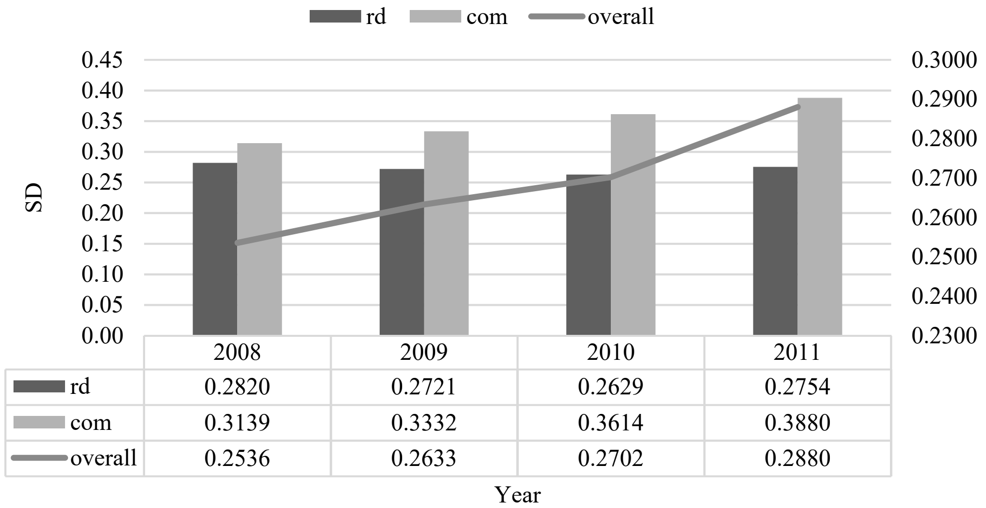
4.3.3 Innovation Efficiency Estimation

Based on the network DEA, the two-stage efficiency and overall efficiency can be estimated. In Figure 4.3 it can be seen that both the average efficiency in R&D stage and commercialisation stage increased remarkably during the 2008 to 2009 period, then experienced a fall during 2009 to 2010, and went up again during 2010 to 2011. This trend is probably because of the downward movement of the production frontier during the Global Financial Crisis (GFC). It is worthy to note that the average R&D efficiency is higher than commercialisation efficiency before the significant fall, while the commercialisation efficiency overtook R&D efficiency after the fall. The underlying reason might be attributed to the four trillion RMB economic stimulus package which pushed up the nominal earnings of firms but can hardly affect the efficiency in R&D stage. Most of these efficiency scores are smaller than 0.30 implying that the innovation efficiency of Chinese high-tech firms is still very low, given the full efficiency value is 1. The standard deviation of the efficiency scores at the R&D stage doesn't vary a lot, while it shows an upward trend at the commercialisation stage (Figure 4.4). This indicates that the gap in commercialisation efficiency among firms are widening.



	2008	2009	2010	2011
rd	0.2757	0.3180	0.2463	0.2927
com	0.2241	0.2812	0.2503	0.3030
overall	0.2499	0.2996	0.2483	0.2978

Figure 4.3 Firms' average efficiency across years



	2008	2009	2010	2011
rd	0.2820	0.2721	0.2629	0.2754
com	0.3139	0.3332	0.3614	0.3880
overall	0.2536	0.2633	0.2702	0.2880

Figure 4.4 Standard deviation of efficiency across years

In Figure 4.5, it is clear that the distribution of all three sets of efficiency scores is skewed to the left, especially the commercialisation efficiency. By comparing the distribution of R&D efficiency and commercialisation efficiency, the lack of coordination between two stages becomes obvious. The overall performance is dominated by the efficiency of the lagging behind stage, thereby leading to waste of resources and disorder in resource allocation.

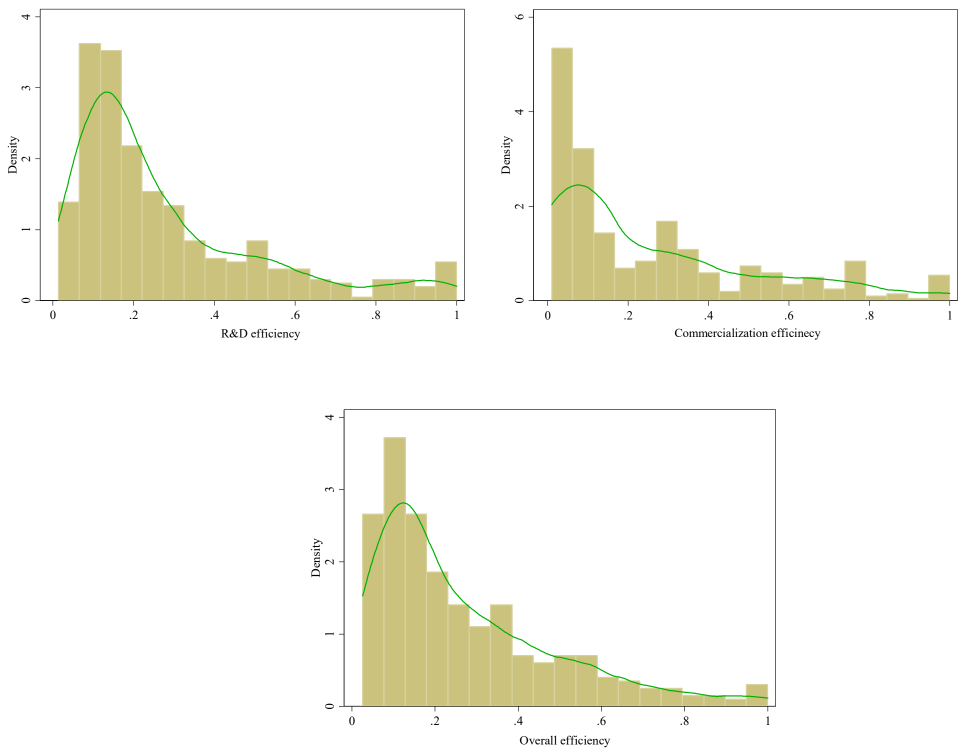


Figure 4.5 Distribution of innovation efficiency

Figure 4.6 illustrates the relationship between R&D efficiency and commercialisation efficiency by using a sunflower plot. For individual firms, the efficiency scores are distributed relatively evenly if the frequency of similar scores is ignored. The incoordination between the two stages at the firm-level is even clearer in this graph. Some firms have high R&D efficiency scores but suffer from low commercialisation efficiency, while other firms have high commercialisation efficiency scores but do not demonstrate good performance in the R&D stage. By dividing the panel into four equal quadrants, it is shown that many firms agglomerate at the dual low efficiency quadrant. Given that our sample is based on the most innovative firms in China, it is important to understand the determinants of inefficiency. Most importantly, according to the theoretical discussion, collaboration might be able to harmonize this incoordination. Therefore it is essential to investigate the mechanism of collaboration in innovation process, which is the purpose of this study.

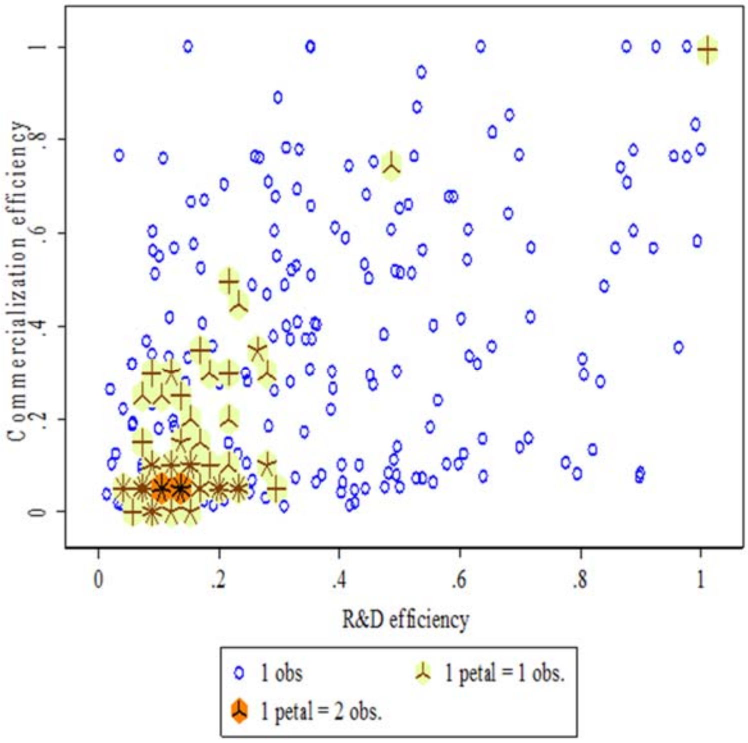


Figure 4.6 Firms' average two-stage efficiency

4.4 Collaboration and Innovation Efficiency

Based on the efficiency scores estimated in the previous section, this section further investigates the impact of collaboration on firms’ innovation efficiency. In this section, the regression models are specified in accordance with the data characteristics and the variables incorporated are also defined.

4.4.1 Model Specification

Since the dependent variables in this study are the efficiency scores which range from 0 to 1, estimation by ordinary least squares (OLS) would provide biased estimates. Therefore, the Tobit maximum likelihood method is employed in estimating the regression coefficients. The standard approach of regressing on DEA scores is to use a two-limit Tobit model, with limits at zero and unity (Simar and Wilson 2007). Ramalho et al. (2010) argued that the Tobit approach to second-stage DEA analysis does not constitute a reasonable data-generating process for DEA score, while they proposed fractional regression models. However, they do not provide a feasible way to deal with the endogeneity problem with fractional regression models. In the baseline regression, this study also adopts the fractional regression model which do not make any big differences.

The baseline model is specified as follows:

$$Eff_{i,j,t} = \alpha + \beta_j \times Col_{i,t} + \boldsymbol{\varphi}_j \times \boldsymbol{\Phi}_{i,t} + \boldsymbol{\gamma}_j \times \boldsymbol{\Psi}_{\mathbf{i,t}} + \varepsilon_{i,j,t} \tag{4-8}$$

with the dependent variable left-censored at 0 and right-censored at 1. In equation (4-8), $Eff_{i,j,t}$ is the j^{th} efficiency score of firm i in year t and $Col_{i,t}$ is the indicator of collaboration conducted by firm i in year t. Here the Eff includes three types of efficiency score, namely, the overall efficiency, the R&D stage efficiency and commercialisation stage efficiency. $\boldsymbol{\Phi}$ and $\boldsymbol{\Psi}$ are a series of control variables. $\boldsymbol{\Phi}$ includes those internal factors that might affect a firm's innovation efficiency based on a resource-based view (Wernerfelt 1984; Vega-Jurado et al. 2008), while $\boldsymbol{\Psi}$ represents a group of contextual factors affecting firms' innovation efficiency externally, both at the city-level and the province-level, from a systematic view (Nelson 1993; Braczyk et al. 1998; Lundvall 2010). Since the idiosyncrasies of institutions exist across China, the effect of collaboration on efficiency might be moderated by some contextual factors such as IPR enforcement, international openness and research quality (Kafouros et al. 2015). This study thus incorporates interaction terms later in the model to capture the potential moderating effect and make comparisons. The interaction terms are all mean-centred in order to alleviate potential multicollinearity problems and to increase the interpretability of the findings (Wooldridge 2015). The model therefore can be further specified as,

$$\begin{aligned} Eff_{i,j,t} &= \alpha + \beta_j \times Col_{i,t} + \boldsymbol{\varphi}_j \times \boldsymbol{\Phi}_{i,t} + \boldsymbol{\gamma}_j \times \boldsymbol{\Psi}_{\mathbf{i,t}} \\ &+ \eta_j \times (Col_{i,t} \times IPR_{k,t}) + \chi_j \times (Col_{i,t} \times OPEN_{k,t}) + \delta_j \times (Col_{i,t} \times UNI_{k,t}) + \varepsilon_{i,j,t} \end{aligned} \tag{4-9}$$

where *IPR*, *OPEN* and *UNI* represent the three moderators to be specified later in Table 4.2. Therefore, interaction terms with three institutional moderators are included and k is the k^{th} region where those firms located.

The selection of variables depends on the objective of the investigation as well as the availability of information in the dataset. The specification of variables and expected sign of the coefficients are listed in Table 4.2. Specifically, three dependent variables are used to estimate separate regressions. These variables are: the overall efficiency denoted by *overall*; and efficiency for the R&D stage and commercialisation stage, denoted by *rd* and *com* respectively. All of them are estimated via the network DEA model. To depict the key variable university-industry collaboration, this study adopted the investment on collaborative projects and the number of collaborative projects to measure the intensity of collaboration and the frequency of collaboration between the firm and local universities and research institutions (URIs), respectively. A dummy variable is also employed to investigate the extensive margin of university-industry collaboration. Given the lack of detailed information, this study is not able to discuss the differences among various types of collaboration even though it would be ideal to do so. According to the theoretical framework, firms would accumulate experiences in collaborating with URIs by having more collaborative projects with URIs, that is, they would collaborate with URIs more frequently, thereby improving the efficiency of their innovation process. However, the intensity of collaboration is expected to witness a U-shape relationship between collaboration and innovation efficiency due to the existence of the dark side of open innovation discussed in theoretical section.

Table 4.2 Specification of variables

Notations	**Variables**	Definition	**Expected Sign**
	Dependent variables		
overall	Overall efficiency	Estimated by network DEA elaborated in section 3.2	
rd	R&D stage efficiency		
com	Commercialisation stage efficiency		
	Independent variables		
col_dum	Collaboration	Whether or not have collaborative projects	+
col_fre	Frequency of university-industry collaboration	Number of collaborative projects	+
col_int	Intensity of university-industry collaboration	Logarithm of total investment on collaboration (TIC)	+
	Control variables		
age	Firm age	Firm's existing years	+/-
size	Firm size	Logarithm of number of employees	+/-
hc	Human capital	Schooling years of firms' employees	+
listed	Listed firms	Dummy variable - listed or not	+/-
guanxi	Guanxi	Dummy variable - has or doesn't have member in NPC or CPPCC	+
frd	Foreign R&D	Dummy variable - has or doesn't have foreign R&D investment	+
hightech	Industry dummy	Whether or not belong to high-tech industry	+
gdppc	Economic status	Regional GDP per capita	+
govsup	Government support	(Expenditure on S&T activities) / (regional budget) at city-level	+
fslq	Financial development	Location quotient of financial sector at city-level	+

Notations	Variables	Definition	Expected Sign
ipr	IPR enforcement	(Closed IPR infringement cases) / (Total number of IPR infringement cases accepted)	+
open	International openness	Actual use of FDI over gross regional product	+
uni	Research quality of University	SCI indexed paper per faculty member	+

Source: Author's own work.

This study controls for a number of firm-specific idiosyncrasies as well as the regional heterogeneity. At the firm level, firm age and firm size are generally controlled in empirical research from a resource-based view (Del Canto and Gonzalez, 1999; Becheikh et al. 2006). In this study, firm age is the number of years since a firm's establishment and firm size is measured by the logarithm of total number of employees. Human capital also plays a significant role in the innovation process, especially from an efficiency perspective (Simonen and McCann 2008; Batabyal and Nijkamp 2013). This study also takes four dummy variables into consideration, namely, 1) whether a firm is listed, 2) whether a firm has membership in the National People's Congress (NPC) or Chinese People's Political Consultative Conference (CPPCC), 3) whether a firm has R&D projects or investment overseas and 4) whether a firm is classified as a high-tech firm. At contextual level, according to the conceptual framework of RIS, the environment in which a firm is embedded exerts a considerable effect on firms' innovation performance. The regional economic status is measured by GDP per capita. The local government's attitude towards science and technology (S&T) is calculated by the share of S&T expenditure over local government expenditures. Regional financial development is also crucial for innovation, especially for commercialisation. This study adopts the location quotient of the financial sector to represent the regional specialisation in financial services. Three institution-related variables are also included, as China presents observable heterogeneity across regions. The enforcement of IPR protection is measured by the ratio of closed IPR infringement cases over the total number of IPR infringement cases accepted. FDI over regional GDP represents the openness of the local economy, while the number of papers per researcher published in science citation index (SCI) journals reflects the quality of local universities.

In Table 4.3, the descriptive statistics show that most of the correlations are fairly low, and the variance inflation factors range from 1.06 to 2.92, with a mean of 1.46. These numbers are all well below the acceptable level of 10, indicating that our models are not suffering from multicollinearity problems.

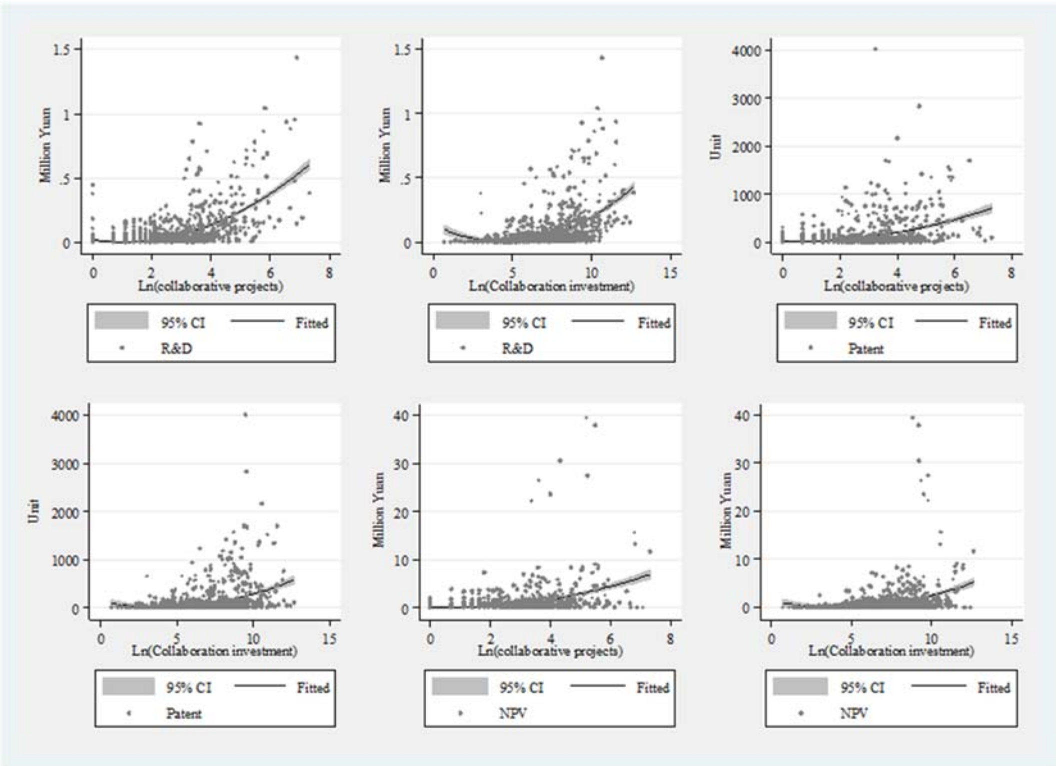
Table 4.3 Descriptive statistics

Variable	Mean	SD	overall	rd	com	col_fre	col_int	age	size	hc	listed	guanxi	frd	hightech	gdppc	govsup	fslq	ipr	open	uni
overall	0.27	0.27	1.00																	
rd	0.28	0.27	0.82	1.00																
com	0.26	0.35	0.90	0.48	1.00															
col_fre	26.05	88.90	0.22	0.17	0.20	1.00														
col_int	8.33	9.72	0.17	0.10	0.17	0.70	1.00													
age	22.76	17.76	-0.14	-0.20	-0.06	0.05	0.00	1.00												
size	8.32	1.82	0.05	-0.16	0.20	0.39	0.35	0.20	1.00											
hc	2.93	2.70	-0.12	-0.06	-0.13	-0.14	-0.12	-0.05	-0.49	1.00										
listed	0.54	0.50	-0.02	-0.15	0.08	0.13	0.10	0.07	0.48	-0.27	1.00									
guanxi	0.36	0.57	0.13	0.03	0.18	0.36	0.31	0.10	0.57	-0.23	0.28	1.00								
frd	0.12	0.33	-0.08	-0.13	-0.02	0.18	0.16	-0.03	0.25	-0.09	0.17	0.16	1.00							
hightech	0.72	0.45	-0.15	-0.05	-0.20	-0.28	-0.22	-0.14	-0.54	0.32	-0.21	-0.35	-0.08	1.00						
gdppc	5.37	2.50	0.07	-0.05	0.14	0.12	0.10	0.04	0.20	0.04	0.10	0.11	0.06	-0.13	1.00					
govsup	0.03	0.02	0.09	-0.02	0.16	0.18	0.11	0.04	0.24	0.08	0.11	0.18	0.09	-0.14	0.66	1.00				
fslq	1.86	2.14	0.06	0.07	0.04	-0.02	0.02	-0.05	-0.09	0.08	-0.03	-0.06	-0.02	0.03	-0.06	-0.13	1.00			
ipr	0.86	0.09	0.13	0.07	0.14	0.09	0.06	-0.03	0.12	0.03	-0.01	0.09	0.02	-0.16	0.22	0.35	0.05	1.00		
open	0.01	0.00	-0.01	0.00	-0.01	-0.03	-0.02	-0.07	-0.11	0.14	-0.10	-0.03	0.07	-0.01	0.32	0.26	-0.02	0.05	1.00	
uni	0.13	0.12	0.14	0.02	0.21	0.24	0.15	0.12	0.33	0.02	0.13	0.27	0.05	-0.21	0.49	0.78	-0.16	0.44	0.09	1.00

Source: Author’s own work. Refer to Table 4.2 for details of variables’ specification.

4.4.2 Empirical Results

As a preliminary analysis, we firstly plot the two measures of collaboration against three major indictors related to innovation performance, namely, the R&D expenditure, the number of granted patents and the value of new product. It can be clearly seen in Figure 4.7 that they are all positively correlated. Thus, generally, firms with more collaborative projects or greater investment in collaboration tend to have more R&D expenditure, as well as more patents and new products. This is consistent with the expected relationship. However, in an efficiency view, the impact of collaboration is likely to be ambiguous, since intuitively, even though the output increases with collaboration the input increases as well.



Notes: "R&D" indicates R&D expenditure, "Patent" is the number of granted patents and "NPV" represents the value of new product.

Figure 4.7 Correlation between collaboration and major indicators

Based on the panel data discussed in section 3, this study adopts a random-effects Tobit model to investigate the hypotheses discussed in section 2. The robust standard errors are estimated by the observed information matrix (OIM). We use three efficiency scores in turn as the dependent variable to run separate regressions, and also compare the models with and without cross-terms. Three measures of collaboration are employed to depict different aspects of collaboration. The collaboration dummy is used to measure the extensive margin of collaboration, while the other two are related to the intensive margin of collaboration. It is assumed a firm with a greater number of collaborative projects has a wider breadth of collaboration, while the amount of investment in collaboration represents the strength or intensity of collaboration. The results are listed in Table 4.4, Table 4.5 and Table 4.6, respectively.

In Model 1, it can be seen that the extensive margin of collaboration is negative and statistically significant at the 1 per cent level (Hypothesis 1). It provides evidence for the dark side of open innovation as the innovation efficiency scores of firms with collaborative projects tends to be lower than firms with no collaborative project. This can also be directly observed upon examination of the data (Left of Figure 4.8). This finding is consistent with Salge et al. (2013), but differs from Kafouros et al. (2015). However, the size and profit of those firms without collaborative projects is much smaller, less than half that of those of firms with collaborative projects (Right of Figure 4.8). Therefore, their relatively high efficiency scores are possibly caused by a smaller magnitude of inputs in innovation activities. It also implies that smaller firms and firms with less profit might lack enough resources to engage in collaborative activities which require corresponding investment in absorptive capability and coordination costs at initial stage.

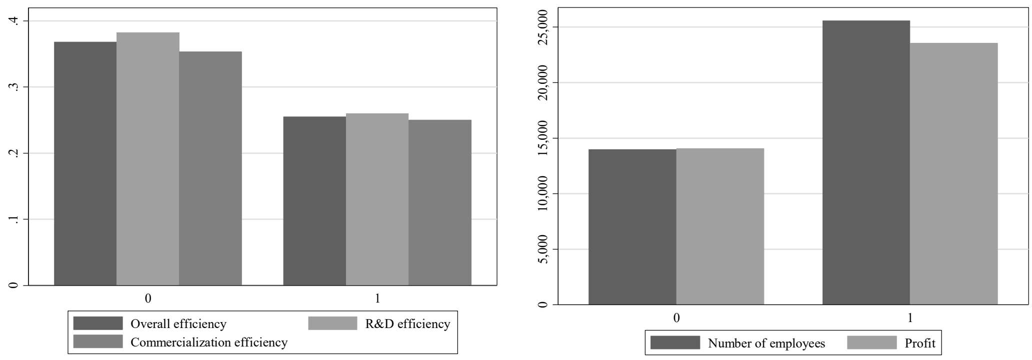


Figure 4.8 Distinction in efficiency and size between two groups of firms

Table 4.4 Results for collaboration dummy

	Overall efficiency		R&D efficiency		Commercialisation efficiency	
	Model 1		Model 1		Model 1	
col_dum	-0.0654***	(0.000)	-0.0547***	(0.001)	-0.0931***	(0.002)
age	-0.00255***	(0.000)	-0.00285***	(0.000)	-0.00252***	(0.002)
size	-0.0236***	(0.006)	-0.0485***	(0.000)	0.00387	(0.753)
hc	-0.0312***	(0.001)	-0.0380***	(0.000)	-0.0258*	(0.076)
hc2	0.00145*	(0.063)	0.00177**	(0.015)	0.00119	(0.312)
listed	-0.0248	(0.236)	-0.0393*	(0.057)	-0.0100	(0.738)
guanxi	0.0560***	(0.003)	0.0489***	(0.007)	0.0618**	(0.023)
frd	-0.0595**	(0.028)	-0.0600**	(0.021)	-0.0682*	(0.085)
hightech	-0.0802***	(0.000)	-0.0561***	(0.003)	-0.103***	(0.001)
gdppc	-0.00128	(0.811)	-0.00585	(0.272)	0.00246	(0.745)
govsup	-0.535	(0.461)	-0.261	(0.694)	-0.488	(0.665)
fslq	0.0120***	(0.001)	0.0117***	(0.000)	0.0154***	(0.005)
ipr	0.182	(0.118)	0.0713	(0.519)	0.336*	(0.051)
open	-0.172	(0.955)	0.484	(0.872)	-0.514	(0.906)
uni	0.404***	(0.002)	0.320**	(0.012)	0.520***	(0.005)
year dummy	Yes		Yes		Yes	
_cons	0.470***	(0.000)	0.824***	(0.000)	0.0764	(0.692)
N	1503		1503		1503	

Notes: *, ** and *** denote significance level at 10%, 5% and 1%, respectively. Refer to Table 4.2 for details of variables' specification.

Table 4.5 Results for collaboration frequency

	Overall efficiency				R&D efficiency				Commercialisation efficiency			
	Model 2		Model 3		Model 2		Model 3		Model 2		Model 3	
col_fre	0.000626***	(0.000)	0.000359**	(0.034)	0.000650***	(0.000)	0.000479***	(0.002)	0.000670***	(0.000)	0.000250	(0.358)
age	-0.00257***	(0.000)	-0.00249***	(0.000)	-0.00285***	(0.000)	-0.00282***	(0.000)	-0.00258***	(0.002)	-0.00242***	(0.004)
size	-0.0339***	(0.000)	-0.0332***	(0.000)	-0.0594***	(0.000)	-0.0592***	(0.000)	-0.00703	(0.572)	-0.00561	(0.654)
hc	-0.0336***	(0.000)	-0.0331***	(0.001)	-0.0409***	(0.000)	-0.0399***	(0.000)	-0.0274*	(0.059)	-0.0275*	(0.058)
hc2	0.00161**	(0.038)	0.00157**	(0.043)	0.00196***	(0.007)	0.00187***	(0.010)	0.00131	(0.267)	0.00133	(0.259)
listed	-0.0192	(0.354)	-0.0184	(0.375)	-0.0345*	(0.088)	-0.0319	(0.116)	-0.00318	(0.915)	-0.00498	(0.868)
guanxi	0.0480***	(0.010)	0.0486***	(0.009)	0.0429**	(0.016)	0.0440**	(0.013)	0.0520*	(0.057)	0.0521*	(0.057)
frd	-0.0753***	(0.005)	-0.0721**	(0.007)	-0.0758***	(0.003)	-0.0745***	(0.004)	-0.0862**	(0.030)	-0.0804**	(0.044)
hightech	-0.0696***	(0.000)	-0.0689***	(0.001)	-0.0467**	(0.011)	-0.0456**	(0.013)	-0.0901***	(0.003)	-0.0893***	(0.004)
gdppc	-0.000233	(0.965)	-0.0000717	(0.989)	-0.00490	(0.346)	-0.00507	(0.329)	0.00377	(0.616)	0.00443	(0.556)
govsup	-0.539	(0.455)	-0.493	(0.495)	-0.270	(0.681)	-0.165	(0.802)	-0.501	(0.656)	-0.526	(0.641)
fslq	0.0120***	(0.001)	0.0118***	(0.001)	0.0118***	(0.000)	0.0117***	(0.000)	0.0151***	(0.006)	0.0148***	(0.007)
ipr	0.192*	(0.096)	0.188	(0.125)	0.0796	(0.466)	0.0103	(0.928)	0.353**	(0.040)	0.444**	(0.017)
open	0.346	(0.908)	-1.491	(0.645)	0.859	(0.770)	0.117	(0.970)	0.239	(0.956)	-3.476	(0.468)
uni	0.348***	(0.006)	0.339***	(0.008)	0.263**	(0.036)	0.270**	(0.032)	0.460**	(0.013)	0.422**	(0.024)
cpipr			-0.000242	(0.933)			-0.00474*	(0.061)			0.00627	(0.194)
cpopen			-0.135	(0.114)			-0.0767	(0.333)			-0.237*	(0.083)
cpuni			0.00128	(0.217)			0.00220**	(0.016)			0.000211	(0.906)
year dummy	Yes		Yes		Yes		Yes		Yes		Yes	
_cons	0.469***	(0.000)	0.475***	(0.001)	0.842***	(0.000)	0. 899***	(0.000)	0.0446	(0.815)	-0.0216	(0.913)
N	1503		1503		1503		1503		1503		1503	

Notes: *, ** and *** denote significance level at 10%, 5% and 1%, respectively. Terms of cpipr, cpopen and cpuni are interaction terms of collaboration frequency with IPR, openness and university quality, respectively. Refer to Table 4.2 for details of variables' specification.

Table 4.6 Results for collaboration intensity

	Overall efficiency				R&D efficiency				Commercialisation efficiency			
	Model 4		Model 5		Model 4		Model 5		Model 4		Model 5	
col_int	-0.00839***	(0.000)	-0.00801***	(0.000)	-0.00645***	(0.000)	-0.00645***	(0.000)	-0.0127***	(0.000)	-0.0119***	(0.000)
col_int sqr	0.00127***	(0.002)	0.00117***	(0.005)	0.000849**	(0.024)	0.000713*	(0.058)	0.00184***	(0.005)	0.00181***	(0.006)
age	-0.00254***	(0.000)	-0.00252***	(0.000)	-0.00285***	(0.000)	-0.00281***	(0.000)	-0.00250***	(0.003)	-0.00248***	(0.003)
size	-0.0273***	(0.002)	-0.0281***	(0.002)	-0.0505***	(0.000)	-0.0511***	(0.000)	-0.00107	(0.934)	-0.00234	(0.856)
hc	-0.0324***	(0.001)	-0.0321***	(0.001)	-0.0385***	(0.000)	-0.0373***	(0.000)	-0.0275*	(0.058)	-0.0282*	(0.053)
hc2	0.00153**	(0.050)	0.00149*	(0.055)	0.00181**	(0.013)	0.00170**	(0.019)	0.00131	(0.266)	0.00132	(0.261)
listed	-0.0228	(0.274)	-0.0224	(0.283)	-0.0379*	(0.066)	-0.0384	(0.061)	-0.00754	(0.800)	-0.00578	(0.847)
guanxi	0.0518***	(0.006)	0.0522***	(0.005)	0.0464**	(0.011)	0.0498***	(0.006)	0.0555**	(0.042)	0.0543**	(0.047)
frd	-0.0658**	(0.015)	-0.0633**	(0.020)	-0.0643**	(0.014)	-0.0608**	(0.019)	-0.0759*	(0.056)	-0.0747*	(0.060)
hightech	-0.0768***	(0.000)	-0.0752***	(0.000)	-0.0534***	(0.004)	-0.0504***	(0.007)	-0.0981***	(0.001)	-0.0984***	(0.001)
gdppc	-0.00130	(0.806)	-0.00108	(0.838)	-0.00584	(0.272)	-0.00605	(0.251)	0.00226	(0.763)	0.00299	(0.691)
govsup	-0.545	(0.452)	-0.538	(0.457)	-0.276	(0.678)	-0.265	(0.689)	-0.481	(0.669)	-0.516	(0.646)
fslq	0.0121***	(0.001)	0.0121***	(0.001)	0.0118***	(0.000)	0.0119***	(0.000)	0.0154***	(0.005)	0.0154***	(0.005)
ipr	0.180	(0.120)	0.184	(0.113)	0.0715	(0.518)	0.0668	(0.544)	0.333*	(0.053)	0.346**	(0.045)
open	-0.147	(0.961)	-0.802	(0.792)	0.495	(0.869)	-0.00835	(0.998)	-0.465	(0.915)	-1.205	(0.783)
uni	0.390***	(0.002)	0.382***	(0.003)	0.312**	(0.015)	0.300**	(0.018)	0.497***	(0.007)	0.501***	(0.007)
ciipr			0.00367	(0.838)			-0.0304*	(0.058)			0.0366	(0.204)
ciopen			-0.601	(0.161)			-0.416	(0.281)			-0.968	(0.159)
ciuni			0.0173	(0.188)			0.0386***	(0.001)			-0.0114	(0.590)
year dummy	Yes		Yes		Yes		Yes		Yes		Yes	
_cons	0.432***	(0.001)	0.437***	(0.001)	0.788***	(0.000)	0.803***	(0.000)	0.0253	(0.894)	0.0208	(0.914)
N	1503		1503		1503		1503		1503		1503	

Notes: *, ** and *** denote significance level at 10%, 5% and 1%, respectively. Terms of ciipr, ciopen and ciuni are interaction terms of collaboration intensity with IPR, openness and university quality, respectively. Refer to Table 4.2 for details of variables' specification.

In Model 2 (Table 4.5), frequency of collaboration manifests a positive effect on innovation efficiency across stages. This is consistent with previous studies and conforms to the spirit of open innovation as it indicates that firms can benefit from the external knowledge gained through frequent collaborations with academic institutions (Hypothesis 1). In contrast, the theoretical discussion also points out that the excessive exposure to the external environment may raise the risk of knowledge leakage. However, there is no empirical evidence of this adverse effect in the context of China's innovative firms. Therefore, once firms want to tap into external knowledge sources, it is beneficial to search widely and extensively. This view is also observed in social network theory. More connections with other networks increase the probability of generating "Schumpeterian novel combination" (Schumpeter 1939).

Unlike the frequency of collaboration, it is worth noticing that there is a U-shaped relationship between collaboration intensity and innovation efficiency, particularly in the commercialisation stage (significant at 1 per cent level) (Model 4, Table 4.6). This result indicates that less intensive collaboration is detrimental to efficiency performance due to associated costs with collaboration investment, frictions in communication and other fixed coordination costs. In contrast, intensive collaboration contributes to the improvement of firms' innovation efficiency, since the frictions in communication will be smoothed, the complementary investment in absorptive capability and the fixed coordination costs can be diluted via in-depth collaboration. Although the U-shaped relationship is found in both stages, the squared term representing collaboration intensity in the R&D stage is less statistically significant in contrast to that in the commercialisation stage. The underlying reason might be coincident with the discussion for Hypothesis 2, namely, intensive collaboration in the early stage not only facilitates the transfer of tacit knowledge and fosters creative problem-solving, but also increases the likelihood of unintended knowledge leakage (Roy and Sivakumar 2011; Salge et al. 2013). In addition, the turning points for these U-shaped relationships are around 3.3 to 4 across regressions, which are roughly 27.2 to 55 in terms of the logarithm of collaboration investment. Through comparing these numbers with the collaboration investment of firms in the original dataset, it is found that three quarters of those firms are beyond this level, which implies that they all start to enjoy the benefit of university-industry collaboration.

After incorporating the interaction-terms in Models 3 and 5, the general conclusion is consistent with that from Model 1. Moderators affect the two stages differently, which provides direct evidence supporting Hypothesis 3 and indirect evidence in favour of Hypothesis 2. To be specific, with R&D efficiency, the interaction term of collaboration and IPR enforcement is negative and statistically significant, while the interaction term of collaboration and university quality is positive and statistically significant. The former means that stronger IPR enforcement in a region reduces the positive effect of academic collaboration on firms' R&D efficiency. The reason might be stronger IPR enforcement reinforces the barrier for imitation and therefore raises the demand for investment in indigenous innovation, which is harmful to efficiency improvement. In the latter case, it is self-evident that the impact of academic collaboration on firms' R&D efficiency will be greater in regions with higher university quality. It also has been observed that policy-makers in both developed and newly industrialised countries have been focussed on designing policies aimed at raising the quality of public research and education organisations, which makes their role more entrepreneurial and of more benefit to national economic growth (Eun et al. 2006; Wong et al. 2007; Freitas et al. 2013). Moderator international openness (*openness*) doesn't exhibit a significant moderating effect through collaboration on R&D efficiency. Conversely, moderator IPR enforcement (*ipr*) and university quality (*uni*) have no significant moderating effects through collaboration on commercialisation efficiency, while the interaction term between collaboration and international openness (*openness*) is negative and statistically significant. This indicates that the more open a region is, the less effective collaboration is on commercialisation efficiency. Nevertheless, this effect becomes insignificant when conducting further investigation.

Regarding control variables, the findings are consistent across models. Firms' *age* and *size* are found to be negatively related to innovation efficiency, especially in the R&D stage. It seems contradictory to earlier studies as, from a resource-based view, older and larger firms should have more resources to conduct innovative activities and therefore manifest better innovation performance. However, since this study adopts an efficiency view, it possibly can be interpreted as they fail to increase their conversion ratio proportionally with their inputs and therefore show poor efficiency performance. Contrary to popular belief, *human capital* is found to have a non-linear U-shaped relationship with innovation efficiency, particularly with R&D efficiency. Listed firms (*listed*) don't show significant difference to unlisted firms at the R&D stage. It is understandable that a listed firm bears more pressure for financial transparency, which might hurt its R&D performance. Good connection with the government sector (*guanxi*) clearly supports firms' innovation performance, especially in the R&D stage. This is probably because the outputs in this stage, patents, are granted by a government authority. Investment in foreign R&D (*frd*) doesn't improve domestic innovation efficiency but adversely affects firms' performance. Firms in high-tech sectors (*hightech*) exhibit worse performance in terms of efficiency. Thus, even though the high-tech sector has greater innovative output, the enormous input hasn't been utilised efficiently. Regional economic status (*gdppc*) and government support (*govsup*) don't have any significant impacts on innovation efficiency. Financial development (*fslq*) significantly improves firms' innovation efficiency at both stages, indicating that the financial availability is still very important in the innovation process and this is consistent with many empirical studies on financial constraint and innovation performance. The financial services sector is also the major sector in knowledge intensive business services (KIBS) which is another very important intermediary organisation in the framework of regional innovation systems (Shi et al. 2014). For the three moderators, intellectual property protection (*ipr*) shows a positive effect on commercialisation efficiency only at the 5 per cent significance level, while regional openness (*openness*) has no significant effect on innovation efficiency. University quality (*uni*) consistently improves the efficiency in both of the two stages.

Additionally, the dependent variables are constructed via the network DEA, which simultaneously estimates the efficiency scores of the two stages. It is therefore suspicious that the results may suffer from the bias caused by correlated errors across equations, namely, $E(u_{ij}u_{ij'} \mid X) = \sigma_{jj'} \neq 0$ where $j \neq j'$, if we run separate regressions using the efficiency scores in each stage. To deal with this problem, this study utilizes a two-equation censored seemingly-unrelated model to make further investigation (Table 4.7 and Table 4.8). By comparing the results across the models, no significant changes are observed, which support the robustness of our analysis.

Table 4.7 Two equation seemingly-unrelated model

	Collaboration frequency					Collaboration intensity			
	Equation 1 (R&D)		Equation 2 (Commercialisation)			Equation 1 (R&D)		Equation 2 (Commercialisation)	
col_fre	0.000722***	(0.000)	0.000372***	(0.000)	col_int	-0.0118***	(0.000)	-0.00461**	(0.007)
					col_int sqr	0.00147***	(0.000)	0.00102**	(0.001)
age	-0.00269***	(0.000)	-0.00118***	(0.000)	Age	-0.00265***	(0.000)	-0.00117***	(0.000)
size	-0.0665***	(0.000)	0.0236***	(0.000)	Size	-0.0592***	(0.000)	0.0235***	(0.000)
hc	-0.0388***	(0.000)	-0.0187**	(0.002)	Hc	-0.0387***	(0.000)	-0.0196**	(0.001)
hc2	0.00154*	(0.014)	0.00117*	(0.018)	hc2	0.00153*	(0.016)	0.00124*	(0.013)
listed	-0.0375**	(0.002)	NA	NA	Listed	-0.0437***	(0.000)	NA	NA
guanxi	0.0608***	(0.000)	0.0452***	(0.000)	guanxi	0.0747***	(0.000)	0.0504***	(0.000)
frd	-0.0897***	(0.000)	-0.0416**	(0.007)	Frd	-0.0698***	(0.000)	-0.0359*	(0.020)
hightech	-0.0779***	(0.000)	-0.0429**	(0.001)	hightech	-0.0905***	(0.000)	-0.0480***	(0.000)
gdppc	-0.00612	(0.090)	0.00170	(0.543)	gdppc	-0.00752*	(0.042)	0.00136	(0.629)
govsup	0.111	(0.861)	0.131	(0.795)	govsup	0.156	(0.809)	0.120	(0.813)
fslq	0.0102***	(0.001)	0.00316	(0.193)	Fslq	0.0109***	(0.000)	0.00334	(0.172)
ipr	0.102	(0.246)	-0.0288	(0.679)	Ipr	0.0718	(0.421)	-0.0415	(0.554)
open	-0.838	(0.687)	-0.122	(0.941)	Open	-1.857	(0.380)	-0.446	(0.788)
uni	0.203*	(0.026)	0.0975	(0.185)	Uni	0.255**	(0.006)	0.116	(0.118)
year dummy	Yes		Yes		year dummy	Yes		Yes	
_cons	0.901***	(0.000)	0.0234	(0.759)	_cons	0.892***	(0.000)	0.0249	(0.748)
N	1503		1503		*N*	1503		1503	

Notes: *, ** and *** denote significance level at 10%, 5% and 1%, respectively. Refer to Table 4.2 for details of variables' specification.

Table 4.8 Two equation seemingly-unrelated model with interaction terms

	Collaboration frequency					Collaboration intensity			
	Equation 1 (R&D)		Equation 2 (Commercial)			Equation 1 (R&D)		Equation 2 (Commercial)	
col_fre	0.000483***	(0.000)	0.000275*	(0.020)	col_int	-0.0114***	(0.000)	-0.00427**	(0.015)
					col_int sqr	0.00118***	(0.003)	0.000907***	(0.004)
age	-0.00266***	(0.000)	-0.00115***	(0.000)	Age	-0.00264***	(0.000)	-0.00116***	(0.000)
size	-0.0653***	(0.000)	0.0235***	(0.000)	Size	-0.0583***	(0.000)	0.0235***	(0.000)
hc	-0.0380***	(0.000)	-0.0184***	(0.003)	Hc	-0.0370***	(0.000)	-0.0191***	(0.002)
hc2	0.00150**	(0.016)	0.00115**	(0.020)	hc2	0.00150**	(0.017)	0.00123**	(0.014)
listed	-0.0390***	(0.002)	NA	NA	listed	-0.0450***	(0.000)	NA	NA
guanxi	0.0609***	(0.000)	0.0461***	(0.000)	guanxi	0.0740***	(0.000)	0.0495***	(0.000)
frd	-0.0874***	(0.000)	-0.0396***	(0.010)	Frd	-0.0633***	(0.001)	-0.0335**	(0.030)
hightech	-0.0762***	(0.000)	-0.0422***	(0.001)	hightech	-0.0864***	(0.000)	-0.0461***	(0.001)
gdppc	-0.00596*	(0.098)	0.00166	(0.553)	gdppc	-0.00803**	(0.028)	0.00138	(0.627)
govsup	0.192	(0.762)	0.174	(0.730)	govsup	0.263	(0.680)	0.129	(0.799)
fslq	0.0106***	(0.000)	0.00337	(0.166)	Fslq	0.0107***	(0.000)	0.00327	(0.181)
ipr	0.0341	(0.727)	-0.0451	(0.564)	Ipr	0.0400	(0.653)	-0.0464	(0.510)
open	-1.519	(0.525)	-0.972	(0.616)	Open	-2.401	(0.257)	-0.677	(0.684)
uni	0.206**	(0.025)	0.102	(0.170)	Uni	0.218**	(0.018)	0.102	(0.172)
cpipr	-0.00500*	(0.095)	-0.00164	(0.501)	Ciipr	-0.0643***	(0.001)	-0.00935	(0.532)
cpopen	-0.0600	(0.430)	-0.0655	(0.328)	ciopen	0.268	(0.536)	-0.0138	(0.969)
cpuni	0.00282***	(0.002)	0.000770	(0.364)	ciuni	0.0803***	(0.000)	0.0285**	(0.011)
year dummy	Yes		Yes		year dummy	Yes		Yes	
_cons	0.948***	(0.000)	0.0396	(0.624)	_cons	0.924***	(0.000)	0.0330	(0.669)
N	1503		1503		*N*	1503		1503	

Notes: *, ** and *** denote significance level at 10%, 5% and 1%, respectively. Terms of cpipr, cpopen and cpuni are interaction terms of collaboration frequency with IPR, openness and university quality, respectively. Terms of ciipr, ciopen and ciuni are interaction terms of collaboration intensity with IPR, openness and university quality, respectively. Refer to Table 4.2 for details of variables' specification.

4.5 Robustness and Further Discussion

To ensure that our findings are robust, this study adopts various methods to further analyse our results. First, as the final sample used in this study has fewer than 400 firms across 4 years, this sample might suffer the problem of small sample size. Therefore, by assuming the sample is randomly taken from the population, we employ bootstrapping estimation to iterate our regression for 200 times with the aim of alleviating the small sample problem. The results are in shown in Table 4.9 and Table 4.10.

Broadly speaking, the conclusions drawn from the bootstrapping estimation are almost the same as those from the baseline regressions apart from some minor changes in standard errors which don't change the statistical significance. The only exception is that the moderating effects of IPR enforcement (*ipr*) and university quality (*uni*) through collaboration on R&D efficiency are not significant this time, even though the signs remain the same. In terms of bootstrapping estimation with collaboration intensity, the findings are exactly the same as those from the previous estimation.

Another issue is the potential endogeneity problem. Due to the availability of variables in the dataset, the use of current term of indicators, and the short time period, the estimations may suffer from the endogeneity problem caused by omitted variables and simultaneity. The innovation performance may also conversely affect firms' collaborative behaviour and therefore cause upward biased estimation since firms with better innovation performance might seek further collaboration to form a positive loop. Therefore, the instrumental variable method is used to alleviate this estimation bias. Two instrumental variables are selected, namely, the 1 period lagged indicator of collaboration and the region-industry average of the collaboration indicator (Lin et al. 2011, 2012). The results are listed in Table 4.11, Table 4.12, Table 4.13 and Table 4.14.

Table 4.9 Results for collaboration frequency - Bootstrap results

	Overall efficiency				R&D efficiency				Commercialisation efficiency			
	Model 6		Model 7		Model 6		Model 7		Model 6		Model 7	
col_fre	0.000626***	(0.000)	0.000359*	(0.100)	0.000650***	(0.000)	0.000479	(0.101)	0.000670***	(0.000)	0.000250	(0.314)
age	-0.00257***	(0.000)	-0.00249***	(0.000)	-0.00285***	(0.000)	-0.00282***	(0.000)	-0.00258***	(0.000)	-0.00242***	(0.000)
size	-0.0339***	(0.000)	-0.0332***	(0.000)	-0.0594***	(0.000)	-0.0592***	(0.000)	-0.00703	(0.558)	-0.00561	(0.625)
hc	-0.0336***	(0.000)	-0.0331***	(0.001)	-0.0409***	(0.000)	-0.0399***	(0.000)	-0.0274*	(0.067)	-0.0275*	(0.059)
hc2	0.00161**	(0.019)	0.00157**	(0.017)	0.00196***	(0.002)	0.00187***	(0.006)	0.00131	(0.256)	0.00133	(0.239)
listed	-0.0192	(0.223)	-0.0184	(0.264)	-0.0345**	(0.045)	-0.0319*	(0.072)	-0.00318	(0.901)	-0.00498	(0.834)
guanxi	0.0480**	(0.019)	0.0486***	(0.008)	0.0429**	(0.023)	0.0440**	(0.024)	0.0520*	(0.063)	0.0521**	(0.031)
frd	-0.0753***	(0.002)	-0.0721***	(0.005)	-0.0758***	(0.003)	-0.0745***	(0.002)	-0.0862**	(0.017)	-0.0804**	(0.016)
hightech	-0.0696***	(0.001)	-0.0689***	(0.001)	-0.0467**	(0.006)	-0.0456**	(0.013)	-0.0901***	(0.001)	-0.0893***	(0.001)
gdppc	-0.000233	(0.949)	-0.0000717	(0.982)	-0.00490	(0.200)	-0.00507	(0.155)	0.00377	(0.511)	0.00443	(0.365)
govsup	-0.539	(0.470)	-0.493	(0.457)	-0.270	(0.672)	-0.165	(0.794)	-0.501	(0.681)	-0.526	(0.621)
fslq	0.0120***	(0.003)	0.0118***	(0.003)	0.0118***	(0.004)	0.0117***	(0.002)	0.0151**	(0.013)	0.0148**	(0.021)
ipr	0.192*	(0.061)	0.188	(0.135)	0.0796	(0.447)	0.0103	(0.933)	0.353**	(0.043)	0.444***	(0.006)
open	0.346	(0.890)	-1.491	(0.624)	0.859	(0.716)	0.117	(0.968)	0.239	(0.952)	-3.476	(0.386)
uni	0.348***	(0.000)	0.339***	(0.001)	0.263***	(0.008)	0.270***	(0.005)	0.460***	(0.006)	0.422***	(0.007)
cpipr			-0.000242	(0.934)			-0.00474	(0.261)			0.00627*	(0.091)
cpopen			-0.135	(0.200)			-0.0767	(0.484)			-0.237*	(0.084)
cpuni			0.00128	(0.325)			0.00220	(0.267)			0.000211	(0.892)
year dummy	Yes		Yes		Yes		Yes		Yes		Yes	
_cons	0.469***	(0.000)	0.475***	(0.000)	0.842***	(0.000)	0.789***	(0.000)	0.0446	(0.815)	-0.0216	(0.905)
N	1503		1503		1503		1503		1503		1503	

Notes: *, ** and *** denote significance level at 10%, 5% and 1%, respectively. Terms of cpipr, cpopen and cpuni are interaction terms of collaboration frequency with IPR, openness and university quality, respectively. Refer to Table 4.2 for details of variables' specification.

Table 4.10 Results for collaboration intensity - Bootstrap results

	Overall efficiency				R&D efficiency				Commercialisation efficiency			
	Model 8		Model 9		Model 8		Model 9		Model 8		Model 9	
col_int	-0.00839***	(0.000)	-0.00801***	(0.001)	-0.00645***	(0.001)	-0.00645**	(0.001)	-0.0127***	(0.001)	-0.0119***	(0.007)
col_int sqr	0.00127***	(0.002)	0.00117***	(0.006)	0.000849*	(0.072)	0.000713	(0.107)	0.00184**	(0.011)	0.00181***	(0.010)
age	-0.00254***	(0.000)	-0.00252***	(0.000)	-0.00285***	(0.000)	-0.00281***	(0.000)	-0.00250***	(0.000)	-0.00248***	(0.000)
size	-0.0273***	(0.002)	-0.0281***	(0.001)	-0.0505***	(0.000)	-0.0511***	(0.000)	-0.00107	(0.933)	-0.00234	(0.849)
hc	-0.0324***	(0.000)	-0.0321***	(0.002)	-0.0385***	(0.000)	-0.0373***	(0.000)	-0.0275**	(0.031)	-0.0282**	(0.047)
hc2	0.00153**	(0.016)	0.00149**	(0.040)	0.00181***	(0.008)	0.00170**	(0.013)	0.00131	(0.201)	0.00132	(0.204)
listed	-0.0228	(0.172)	-0.0224	(0.216)	-0.0379**	(0.023)	-0.0384**	(0.017)	-0.00754	(0.746)	-0.00578	(0.812)
guanxi	0.0518***	(0.005)	0.0522**	(0.011)	0.0464**	(0.022)	0.0498***	(0.009)	0.0555**	(0.039)	0.0543**	(0.035)
frd	-0.0658***	(0.009)	-0.0633**	(0.011)	-0.0643***	(0.010)	-0.0608***	(0.007)	-0.0759**	(0.031)	-0.0747**	(0.025)
hightech	-0.0768***	(0.000)	-0.0752***	(0.000)	-0.0534***	(0.002)	-0.0504***	(0.004)	-0.0981***	(0.001)	-0.0984***	(0.000)
gdppc	-0.00130	(0.685)	-0.00108	(0.741)	-0.00584	(0.141)	-0.00605*	(0.074)	0.00226	(0.631)	0.00299	(0.543)
govsup	-0.545	(0.422)	-0.538	(0.432)	-0.276	(0.683)	-0.265	(0.675)	-0.481	(0.616)	-0.516	(0.632)
fslq	0.0121***	(0.001)	0.0121***	(0.004)	0.0118***	(0.002)	0.0119***	(0.005)	0.0154***	(0.006)	0.0154***	(0.010)
ipr	0.180*	(0.085)	0.184*	(0.085)	0.0715	(0.532)	0.0668	(0.550)	0.333**	(0.037)	0.346**	(0.032)
open	-0.147	(0.952)	-0.802	(0.759)	0.495	(0.854)	-0.00835	(0.997)	-0.465	(0.902)	-1.205	(0.758)
uni	0.390***	(0.000)	0.382***	(0.000)	0.312***	(0.002)	0.300***	(0.002)	0.497***	(0.001)	0.501***	(0.001)
ciipr			0.00367	(0.843)			-0.0304*	(0.072)			0.0366	(0.229)
ciopen			-0.601	(0.151)			-0.416	(0.301)			-0.968	(0.294)
ciuni			0.0173	(0.313)			0.0386**	(0.014)			-0.0114	(0.684)
year dummy	Yes		Yes		Yes		Yes		Yes		Yes	
_cons	0.432***	(0.001)	0.437***	(0.003)	0.788***	(0.000)	0.803***	0.0253	(0.883)	(0.815)	0.0208	(0.912)
N	1503		1503		1503		1503		1503		1503	

Notes: *, ** and *** denote significance level at 10%, 5% and 1%, respectively. Terms of ciipr, ciopen and ciuni are interaction terms of collaboration intensity with IPR, openness and university quality, respectively. Refer to Table 4.2 for details of variables' specification.

Table 4.11 Results for collaboration frequency - use 1 year lag as IV

	Overall efficiency				R&D efficiency				Commercialisation efficiency			
	Model 10		Model 11		Model 10		Model 11		Model 10		Model 11	
col_fre	0.00111***	(0.000)	0.000562	(0.085)	0.00142***	(0.000)	0.000972***	(0.002)	0.000952***	(0.001)	0.000127	(0.796)
age	-0.00267***	(0.000)	-0.00264***	(0.000)	-0.00298***	(0.000)	-0.00298***	(0.000)	-0.00266***	(0.000)	-0.00259***	(0.000)
size	-0.0433***	(0.000)	-0.0385***	(0.000)	-0.0807***	(0.000)	-0.0767***	(0.000)	-0.0102	(0.402)	-0.00329	(0.796)
hc	-0.0310***	(0.002)	-0.0298***	(0.002)	-0.0423***	(0.000)	-0.0412***	(0.000)	-0.0214	(0.154)	-0.0199	(0.188)
hc2	0.00132*	(0.099)	0.00126	(0.111)	0.00176**	(0.021)	0.00172**	(0.021)	0.000926	(0.449)	0.000835	(0.496)
listed	0.000166	(0.993)	-0.00798	(0.667)	-0.0142	(0.416)	-0.0215	(0.217)	0.0153	(0.585)	0.00333	(0.908)
guanxi	0.0579***	(0.001)	0.0645***	(0.000)	0.0679***	(0.000)	0.0730***	(0.000)	0.0526*	(0.053)	0.0629**	(0.024)
frd	-0.101***	(0.000)	-0.0948***	(0.000)	-0.108***	(0.000)	-0.101***	(0.000)	-0.108***	(0.004)	-0.100***	(0.009)
hightech	-0.0935***	(0.000)	-0.0992***	(0.000)	-0.0936***	(0.000)	-0.0985***	(0.000)	-0.103***	(0.003)	-0.111***	(0.001)
gdppc	-0.00252	(0.570)	-0.00182	(0.681)	-0.00716*	(0.090)	-0.00636	(0.126)	0.00201	(0.766)	0.00304	(0.656)
govsup	0.269	(0.721)	0.310	(0.674)	0.0964	(0.893)	0.0934	(0.893)	0.542	(0.637)	0.589	(0.605)
fslq	0.0123***	(0.002)	0.0130***	(0.001)	0.0108***	(0.004)	0.0117***	(0.001)	0.0161***	(0.007)	0.0167***	(0.006)
ipr	0.204*	(0.060)	0.130	(0.321)	0.130	(0.210)	-0.0494	(0.690)	0.340**	(0.040)	0.371*	(0.066)
open	0.945	(0.724)	-0.592	(0.856)	0.613	(0.810)	-0.155	(0.960)	1.571	(0.701)	-1.401	(0.780)
uni	0.205*	(0.068)	0.257**	(0.029)	0.139	(0.195)	0.210*	(0.057)	0.322*	(0.061)	0.369**	(0.044)
cpipr			-0.000532	(0.900)			-0.00523	(0.193)			0.00512	(0.431)
cpopen			-0.125	(0.272)			-0.0980	(0.378)			-0.184	(0.292)
cpuni			0.00243*	(0.054)			0.00389***	(0.001)			0.00169	(0.391)
year dummy	Yes		Yes		Yes		Yes		Yes		Yes	
_cons	0.616***	(0.000)	0.645***	(0.000)	1.059***	(0.000)	1.174***	(0.000)	0.188	(0.289)	0.122	(0.547)
Wald Test	0.010***		0.941		0.000***		0.196		0.431		0.300	
1^{st} F value	82.36		69.99		82.36		69.99		82.36		69.99	
N	1127		1127		1127		1127		1127		1127	

Notes: *, ** and *** denote significance level at 10%, 5% and 1%, respectively. Terms of cpipr, cpopen and cpuni are interaction terms of collaboration frequency with IPR, openness and university quality, respectively. Refer to Table 4.2 for details of variables' specification.

Table 4.12 Results for collaboration frequency - use region-industry average as IV

	Overall efficiency				R&D efficiency				Commercialisation efficiency			
	Model 12		Model 13		Model 12		Model 13		Model 12		Model 13	
col_fre	0.00125***	(0.000)	0.000871***	(0.000)	0.00147***	(0.000)	0.00105***	(0.000)	0.00125***	(0.000)	0.000781***	(0.006)
age	-0.00246***	(0.000)	-0.00229***	(0.000)	-0.00273***	(0.000)	-0.00254***	(0.000)	-0.00247***	(0.000)	-0.00221***	(0.000)
size	-0.0408***	(0.000)	-0.0395***	(0.000)	-0.0763***	(0.000)	-0.0750***	(0.000)	-0.00968	(0.321)	-0.00838	(0.389)
hc	-0.0340***	(0.000)	-0.0325***	(0.000)	-0.0420***	(0.000)	-0.0401***	(0.000)	-0.0294**	(0.018)	-0.0278**	(0.024)
hc2	0.00147**	(0.032)	0.00137**	(0.041)	0.00167**	(0.014)	0.00155**	(0.018)	0.00142	(0.163)	0.00132	(0.190)
listed	-0.0103	(0.507)	-0.0162	(0.292)	-0.0290*	(0.059)	-0.0354**	(0.018)	0.00867	(0.707)	0.00204	(0.929)
guanxi	0.0394***	(0.009)	0.0383***	(0.009)	0.0450***	(0.002)	0.0432***	(0.003)	0.0354	(0.112)	0.0341	(0.124)
frd	-0.106***	(0.000)	-0.0965***	(0.000)	-0.108***	(0.000)	-0.0966***	(0.000)	-0.121***	(0.000)	-0.109***	(0.001)
hightech	-0.0664***	(0.000)	-0.0665***	(0.000)	-0.0672***	(0.000)	-0.0662***	(0.000)	-0.0704***	(0.010)	-0.0716***	(0.008)
gdppc	-0.00258	(0.514)	-0.00160	(0.680)	-0.00673*	(0.084)	-0.00575	(0.127)	0.00120	(0.837)	0.00254	(0.661)
govsup	0.435	(0.532)	0.472	(0.489)	0.176	(0.797)	0.286	(0.665)	0.815	(0.428)	0.759	(0.457)
fslq	0.0121***	(0.000)	0.0124***	(0.000)	0.0109***	(0.001)	0.0115***	(0.000)	0.0158***	(0.001)	0.0158***	(0.001)
ipr	0.200**	(0.037)	0.143	(0.188)	0.121	(0.202)	-0.0193	(0.854)	0.341**	(0.016)	0.386**	(0.018)
open	0.125	(0.956)	0.177	(0.949)	-0.00324	(0.999)	0.829	(0.759)	0.415	(0.902)	-1.295	(0.757)
uni	0.196*	(0.051)	0.165*	(0.097)	0.156	(0.115)	0.131	(0.176)	0.270*	(0.070)	0.218	(0.144)
mcpipr			-0.00373	(0.312)			-0.00951***	(0.008)			0.00325	(0.563)
mcpopen			0.0147	(0.889)			0.0535	(0.602)			-0.0807	(0.616)
mcpuni			0.00443***	(0.000)			0.00696***	(0.000)			0.00308	(0.117)
year dummy	Yes		Yes		Yes		Yes		Yes		Yes	
_cons	0.505***	(0.000)	0.539***	(0.000)	0.958***	(0.000)	1.055***	(0.000)	0.0479	(0.758)	0.00555	(0.973)
Wald Test	0.000***		0.005***		0.000***		0.001***		0.000***		0.080*	
1^{st} F value	120.41		103.45		120.41		103.45		120.41		103.45	
N	1503		1503		1503		1503		1503		1503	

Notes: *, ** and *** denote significance level at 10%, 5% and 1%, respectively. Terms of mcpipr, mcpopen and mcpuni are interaction terms of region-industry averaged collaboration frequency with IPR, openness and university quality, respectively. Refer to Table 4.2 for details of variables' specification.

Table 4.13 Results for collaboration intensity - use 1 year lag as IV

	Overall efficiency				R&D efficiency				Commercialisation efficiency			
	Model 14		Model 15		Model 14		Model 15		Model 14		Model 15	
col_int	-0.0342***	(0.000)	-0.0337***	(0.000)	-0.0347***	(0.000)	-0.0331***	(0.000)	-0.0385***	(0.001)	-0.0396***	(0.003)
col_int sqr	0.00389***	(0.000)	0.00383***	(0.000)	0.00462***	(0.000)	0.00434***	(0.000)	0.00328**	(0.035)	0.00352**	(0.032)
age	-0.00224***	(0.000)	-0.00227***	(0.000)	-0.00260***	(0.000)	-0.00262***	(0.000)	-0.00210***	(0.004)	-0.00215***	(0.003)
size	-0.0284***	(0.005)	-0.0277***	(0.007)	-0.0672***	(0.000)	-0.0660***	(0.000)	0.0113	(0.465)	0.0116	(0.451)
hc	-0.0313***	(0.002)	-0.0310***	(0.002)	-0.0432***	(0.000)	-0.0428***	(0.000)	-0.0203	(0.187)	-0.0204	(0.186)
hc2	0.00119	(0.149)	0.00125	(0.131)	0.00168**	(0.036)	0.00176**	(0.025)	0.000697	(0.575)	0.000707	(0.570)
listed	-0.0144	(0.441)	-0.0158	(0.395)	-0.0320*	(0.077)	-0.0358**	(0.045)	0.000691	(0.980)	0.00223	(0.937)
guanxi	0.0661***	(0.000)	0.0647***	(0.000)	0.0816***	(0.000)	0.0786***	(0.000)	0.0565**	(0.040)	0.0567**	(0.041)
frd	-0.0682***	(0.010)	-0.0669**	(0.011)	-0.0747***	(0.003)	-0.0696***	(0.005)	-0.0675*	(0.087)	-0.0705*	(0.074)
hightech	-0.119***	(0.000)	-0.118***	(0.000)	-0.123***	(0.000)	-0.121***	(0.000)	-0.127***	(0.000)	-0.129***	(0.000)
gdppc	-0.00691	(0.143)	-0.00733	(0.123)	-0.0112**	(0.015)	-0.0118***	(0.009)	-0.00364	(0.606)	-0.00375	(0.599)
govsup	0.521	(0.502)	0.668	(0.383)	0.341	(0.650)	0.505	(0.490)	0.836	(0.471)	0.922	(0.424)
fslq	0.0135***	(0.001)	0.0136***	(0.001)	0.0124***	(0.001)	0.0128***	(0.001)	0.0171***	(0.004)	0.0169***	(0.005)
ipr	0.129	(0.249)	0.0682	(0.572)	0.0425	(0.696)	-0.0599	(0.604)	0.275	(0.102)	0.251	(0.167)
open	-0.823	(0.765)	-0.840	(0.762)	-1.285	(0.631)	-1.447	(0.586)	-0.312	(0.940)	-0.217	(0.959)
uni	0.271**	(0.019)	0.282**	(0.020)	0.215*	(0.053)	0.199*	(0.085)	0.388**	(0.025)	0.456**	(0.013)
ciipr			-0.0601**	(0.024)			-0.0869***	(0.001)			-0.0366	(0.363)
ciopen			0.662	(0.259)			0.916	(0.104)			0.423	(0.634)
ciuni			0.0419**	(0.025)			0.0889***	(0.000)			-0.0146	(0.613)
year dummy	Yes		Yes		Yes		Yes		Yes		Yes	
_cons	0.599***	(0.000)	0.644***	(0.000)	1.045***	(0.000)	1.128***	(0.000)	0.149	(0.417)	0.158	(0.413)
Wald Test	0.022**		0.043**		0.001***		0.004***		0.239		0.275	
Min(1^{st} F)	25.02		21.84		25.02		21.84		25.02		21.84	
N	1127		1127		1127		1127		1127		1127	

Notes: *, ** and *** denote significance level at 10%, 5% and 1%, respectively. Terms of ciipr, ciopen and ciuni are interaction terms of collaboration intensity with IPR, openness and university quality, respectively. Refer to Table 4.2 for details of variables' specification.

Table 4.14 Results for collaboration intensity - use region-industry average as IV

	Overall efficiency				R&D efficiency				Commercialisation efficiency			
	Model 16		Model 17		Model 16		Model 17		Model 16		Model 17	
col_int	-0.0382***	(0.000)	-0.0409***	(0.000)	-0.0379***	(0.000)	-0.0381***	(0.000)	-0.0455***	(0.000)	-0.0512***	(0.000)
col_int sqr	0.00528***	(0.000)	0.00557***	(0.000)	0.00551***	(0.000)	0.00563***	(0.000)	0.00570***	(0.000)	0.00624***	(0.000)
age	-0.00211***	(0.000)	-0.00203***	(0.000)	-0.00244***	(0.000)	-0.00237***	(0.000)	-0.00195***	(0.001)	-0.00185**	(0.003)
size	-0.0345***	(0.000)	-0.0363***	(0.000)	-0.0694***	(0.000)	-0.0731***	(0.000)	-0.00131	(0.908)	-0.00131	(0.909)
hc	-0.0388***	(0.000)	-0.0391***	(0.000)	-0.0467***	(0.000)	-0.0466***	(0.000)	-0.0342***	(0.007)	-0.0352**	(0.007)
hc2	0.00174**	(0.015)	0.00178*	(0.013)	0.00194***	(0.007)	0.00201**	(0.004)	0.00167	(0.105)	0.00170	(0.104)
listed	-0.0200	(0.211)	-0.0198	(0.221)	-0.0413***	(0.010)	-0.0386*	(0.014)	-0.0000411	(0.999)	-0.00183	(0.938)
guanxi	0.0487***	(0.002)	0.0402*	(0.012)	0.0595***	(0.000)	0.0436**	(0.005)	0.0419*	(0.065)	0.0408	(0.082)
frd	-0.0750***	(0.001)	-0.0725**	(0.001)	-0.0735***	(0.001)	-0.0696**	(0.002)	-0.0844***	(0.010)	-0.0829*	(0.012)
hightech	-0.0851***	(0.000)	-0.0871***	(0.000)	-0.0891***	(0.000)	-0.0926***	(0.000)	-0.0897***	(0.001)	-0.0902**	(0.001)
gdppc	-0.00704*	(0.094)	-0.00769	(0.071)	-0.0110***	(0.009)	-0.0132**	(0.001)	-0.00449	(0.459)	-0.00379	(0.541)
govsup	0.608	(0.398)	0.717	(0.322)	0.329	(0.647)	0.682	(0.335)	1.046	(0.315)	0.907	(0.391)
fslq	0.0126***	(0.000)	0.0127***	(0.000)	0.0117***	(0.001)	0.0122***	(0.000)	0.0163***	(0.001)	0.0159**	(0.001)
ipr	0.123	(0.214)	0.108	(0.285)	0.0407	(0.683)	-0.0167	(0.866)	0.262*	(0.068)	0.295*	(0.045)
open	-2.155	(0.363)	-1.864	(0.446)	-2.339	(0.324)	-1.332	(0.577)	-2.149	(0.531)	-2.572	(0.470)
uni	0.261**	(0.012)	0.197	(0.061)	0.238**	(0.022)	0.113	(0.271)	0.331**	(0.027)	0.331*	(0.032)
mciipr			-0.0120	(0.794)			-0.103*	(0.024)			0.0810	(0.230)
mciopen			0.750	(0.403)			1.335	(0.133)			-0.0267	(0.984)
mciuni			0.0846***	(0.001)			0.195***	(0.000)			-0.0305	(0.406)
year dummy	Yes		Yes		Yes		Yes		Yes		Yes	
_cons	0.559***	(0.000)	0.592***	(0.000)	1.003***	(0.000)	1.080***	(0.000)	0.114	(0.477)	0.101	(0.534)
Wald Test	0.000***		0.000***		0.000***		0.000***		0.004***		0.010***	
Min(1st F)	42.76		36.93		42.76		36.93		42.76		36.93	
N	1503		1503		1503		1503		1503		1503	

Notes: *, ** and *** denote significance level at 10%, 5% and 1%, respectively. Terms of mciipr, mciopen and mciuni are interaction terms of regional-industry averaged collaboration intensity with IPR, openness and university quality, respectively. Refer to Table 4.2 for details of variables' specification.

The Wald Test shows that, when using 1 year lag as IV, only model 7, model 11 and model 12 for overall efficiency and R&D efficiency suffered from an endogeneity problem, while all models have endogeneity problems when using region-industry average as the IV. The reported F value of first stage estimation also denies the possibility that the IV is weak. Apart from this, the overall findings are consistent after the endogeneity problem is taken into consideration, although the coefficients of some control variables show some sensitivity in terms of their magnitude, sign and level of significance. The most noteworthy change is that the moderating effects on commercialisation are not significant any more, while they are still significant on R&D efficiency. By comparing the results for R&D efficiency and commercialisation efficiency, it is obvious that commercialisation efficiency is less sensitive to those control variables and the moderating effects mainly occur at the R&D stage. These results provide evidence for the robustness of our analysis.

4.6 Conclusion

This chapter aims to investigate the impact of university-industry collaboration on firms' innovation performance from the perspective of input-oriented efficiency. By employing network DEA, this study firstly estimated the two-stage innovation efficiency of innovative Chinese firms based on a unique dataset with data on 443 firms during the years 2008 to 2011. The evaluation shows that the two-stage efficiency in Chinese innovative firms didn't coordinate with each other very well. This problem definitely affects their ability to improve the overall efficiency. By using efficiency to measure firms' innovation performance, this study opens the "black box" and therefore investigates the influential mechanisms of collaboration on the efficiency of different stages. This contributes to the current literature, which relies on output indicators only and therefore fails to capture the potential effect of collaboration on firms' innovation performance through input reduction. In addition, the efficiency estimation in this study also allows incorporation of many other important inputs like R&D personnel and additional output indicators to provide a more comprehensive evaluation of firms' innovation performance.

By combining the firm-level dataset with a number of sources on city- and provincial-level data, this study employs a random effects Tobit model to investigate the hypothesized effect of collaboration on two-stage innovation efficiency. A series of control variables and contextual moderators are included. Results show that the extensive margin of collaboration is negative, which supports the existence of a dark side of open innovation. To engage in collaborative activities, firms are required to invest more in absorptive capability and bear coordination costs, which is detrimental to innovation efficiency. Frequency of collaboration positively affects firms' innovation efficiency, while there is a U-shaped relationship between collaboration intensity and innovation efficiency, particularly in the commercialisation stage (significant at the 1 per cent level). This implies that firms can benefit from the knowledge gained through frequent collaborations with academic institutions as experience is accumulated. Intensive collaboration contributes to the improvement of firms' innovation efficiency, while less intensive collaboration might hurt efficiency performance due to lack of absorptive capability and related coordination costs.

According to the results for the interaction terms, the moderators have a different effect in the two stages. With R&D efficiency, the interaction term between collaboration and IPR enforcement is negative and statistically significant, while the interaction term between collaboration and university quality is positive and statistically significant. Moderator international openness (*openness*) doesn't show a significant moderating effect through collaboration on R&D efficiency. Conversely, moderators IPR enforcement (*ipr*) and university quality (*uni*) have no significant moderating effects through collaboration on commercialisation efficiency. This distinction further necessitates the division of the innovation process.

Various methods are adopted to ensure the robustness of this analysis. Firstly, the bootstrap estimation is used to alleviate the potential bias of small sample size. Secondly, this study uses instrumental variables (IV) method to deal with the endogeneity problems. Thirdly, a two-equation censored seemingly-unrelated model is considered in order to investigate the underlying relationship between two regressions on R&D efficiency and commercialisation efficiency. All the results consistently reinforce the validity of our analysis, although the coefficients of some control variables show some sensitivity in terms of their magnitude, sign and level of significance.

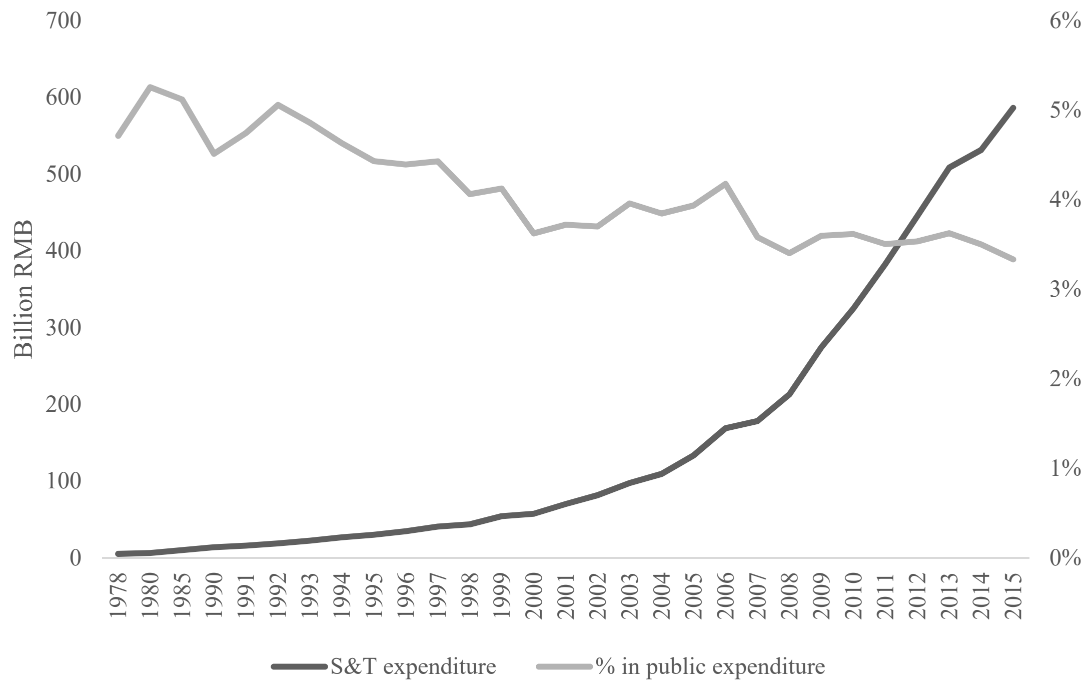
This study also has some limitations. For a start, we are not able to accurately define the characteristics of collaboration due to the lack of availability of data. The frequency and intensity used in this study may overlap with each other to some extent, therefore leading to biased conclusions. In addition, we are lack of information to examine the informal contact between firms and academic institutions, meaning that our analysis may underestimate the contribution of collaboration. Secondly, the indicator used in efficiency estimation, like patent numbers, cannot differentiate the quality of input and output, which might cause biased evaluation and therefore affect our results. Thirdly, since the sample in this study is constrained to the most innovative firms in China, the conclusion may not be able to be generalized to other kind of firms, or to countries with different conditions.

CHAPTER 5 – NATIONAL S&T PROGRAMMES AND THEIR IMPACTS ON FIRMS' INNOVATION

5.1 Introduction

In the Schumpeterian tradition, innovation determines economic growth through "creative destruction" (Schumpeter 1942). Similarly, according to neo-classical growth theory, technological progress is regarded as the only source of sustainable growth (Solow 1956). Influenced by these theories, policy makers in various countries embrace innovation as the means to achieve strong and sustainable economic growth. However, it is shown that profit-maximizing firms generally tend to underinvest in innovation as the positive externalities generated by innovation activities are not fully appropriable (Nelson 1959; Arrow 1962; Usher 1964). This market failure is caused by the non-rival and non-exclusive nature of knowledge and therefore provides economic justification for government intervention, to stimulate the private sector to participate in research and development (R&D) activities with the aim of enhancing innovation capability (Wallsten 2000).

In East Asia, Japan and Korea extensively used targeted industrial policies to accelerate the catch-up process (Johnson 1982; Amsden 1989). As these economies approach the technology frontier, they generally shifted from industrial policies to innovation policies which focus on knowledge infrastructure, entrepreneurship and efficient markets (Frost 1997; Acemoglu et al. 2006). During the twenty-five years from the beginning of economic reform in 1978 to 2003, China seemed to be following a similar trajectory. Market reforms and technological catch-up led to a dramatic reduction in targeted interventions, and the development of an increasingly market-oriented national innovation system (Dahlman and Aubert 2001; Liu and White 2001; OECD 2008). This is demonstrated by Figure 5.1. Although science and technology (S&T) expenditure experienced exponential growth in the past three decades, its share over total public expenditure declined over time.

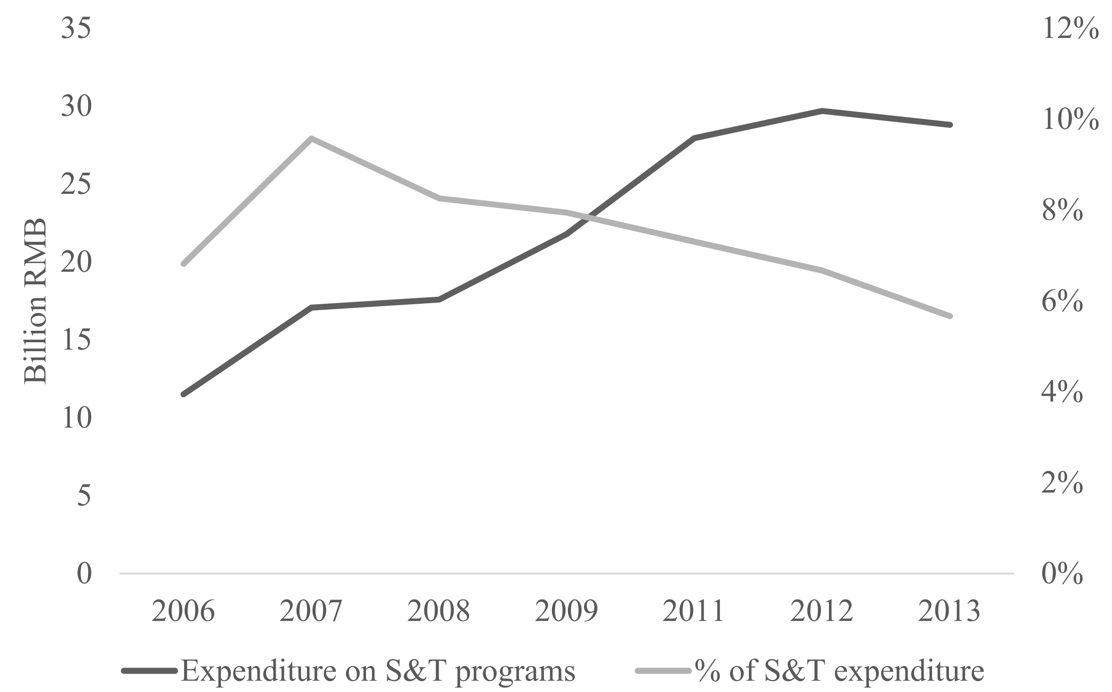


Source: China Statistical Yearbook 2016

Figure 5.1 S&T expenditure and its share in public expenditure

However, after 2003, China broke from this trajectory with a dramatic return to "techno-industrial policy" that involved direct government intervention in developing specific industrial sectors (Chen and Naughton 2016). This change coincided with the implementation of the *National Medium- and Long-term Science and Technology Development Plan* (MLP plan) by the State Steering Committee of S&T and Education, the highest ranked innovation policy body in China. The MLP plan was released in 2006. It emphasizes the importance of increasing the economy's technological sovereignty (Huang 2004). Figure 5.2 shows that, there was a sudden increase of the share of expenditure on national S&T programmes over S&T expenditure since 2006.[11] This share only returns to its original level in 2013. This shift has stimulated a new round of discussions and debates about the role of government in fostering innovation.

[11] Due to data limitation, we are unsure whether this increase happened before 2006. Refer to Heilmann and Shih (2013) for more extensive discussion.



Source: Annual Report of the National Programmes of Science and Technology Development (2006-2013)

Figure 5.2 Expenditure on S&T programmes and its share in total S&T expenditure

Whether the ambitious industrial policy in China has contributed to boosting firms' indigenous innovation capability has attracted the attention of both academia and policy makers. Given this context, this study aims to assess the effect of national S&T programmes on firms' innovation investment, output and efficiency performance. Using a sample of innovative firms in China (screened by Minister of Science and Technology of China - MOST) from 2008-2011, we adopt a matching estimation method jointly with a difference-in-difference (DID) approach to identify the impact of national S&T programmes on Chinese firms' innovation performance. With this research design, we reduce the much-debated selection biases in this type of research and also allow for the selection of programmes to be based on time-invariant unobservable firm characteristics.

Our findings show that the selection of programme recipients is predominantly based on firms' knowledge stock, knowledge infrastructure, and experience in undertaking or joining a programme. State-owned enterprises (SOEs) still have higher probability of undertaking a national S&T programme, while firm size has a U-shaped relationship with the possibility of being selected. These findings are highly consistent with those in recent studies of China (Wu et al. 2012; Hu and Deng 2016; Guan and Yam 2015; Liu et al. 2016; Boeing 2016), and thus indicate that the preference of government has not changed much across programmes and over time. With regard to additionality, the effect of national S&T programmes is overestimated in general. It is found that government grants may crowd out private investment in R&D and lead to potential efficiency deterioration. At the firm level, the treatment effects are heterogeneous in terms of size, ownership, number of programmes undertaken, and amount of government investment received. Particularly, this effect is bigger for large firms and non-SOEs. Deeper engagement with S&T programmes could worsen the crowding out effect and therefore be detrimental to innovation performance. Lastly, after removing time-invariant factors, significantly positive additionality is observed in external R&D investment and patent applications. However, the impact on external R&D investment is not stable over time.

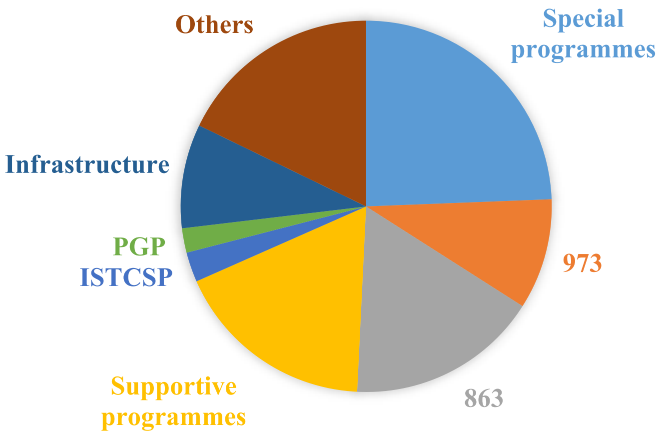
This study contributes to the literature in several ways. Firstly, with a unique dataset, this study is probably one of the first papers on the effects of government S&T programmes in China, especially after China's return to "techno-industrial policy". It complements existing empirical evidence by focusing on the additionality of S&T programmes in the post-2006 period. Secondly, this study also sheds light on the additionality of efficiency performance besides traditional investigation of inputs and outputs additionality. By doing so, it captures more behavioural additionality, given that China is characterized by resource-centralisation and policy-promotion. Thirdly, this study focuses on the effect of indirect support from national S&T programmes rather than the popular assessment of direct subsidies. This is because firms are expected to benefit more from interacting with governments in China as the country is transitioning from a planned economy to a mixed market economy (Lerner 1999; Boeing et al. 2016).

The following section will briefly introduce the institutional background of national S&T programmes in China, and discuss potential channels through which undertaking S&T programmes can affect firms' innovation performance. Section 5.3 presents a theoretical model and reviews empirical literature in this field. In section 5.4, the method and data issues are discussed. Based on the research design, section 5.5 shows the empirical results and discussions. The paper concludes in section 5.6.

5.2 Background and Empirical Studies

5.2.1 Institutional Background of National S&T Programmes

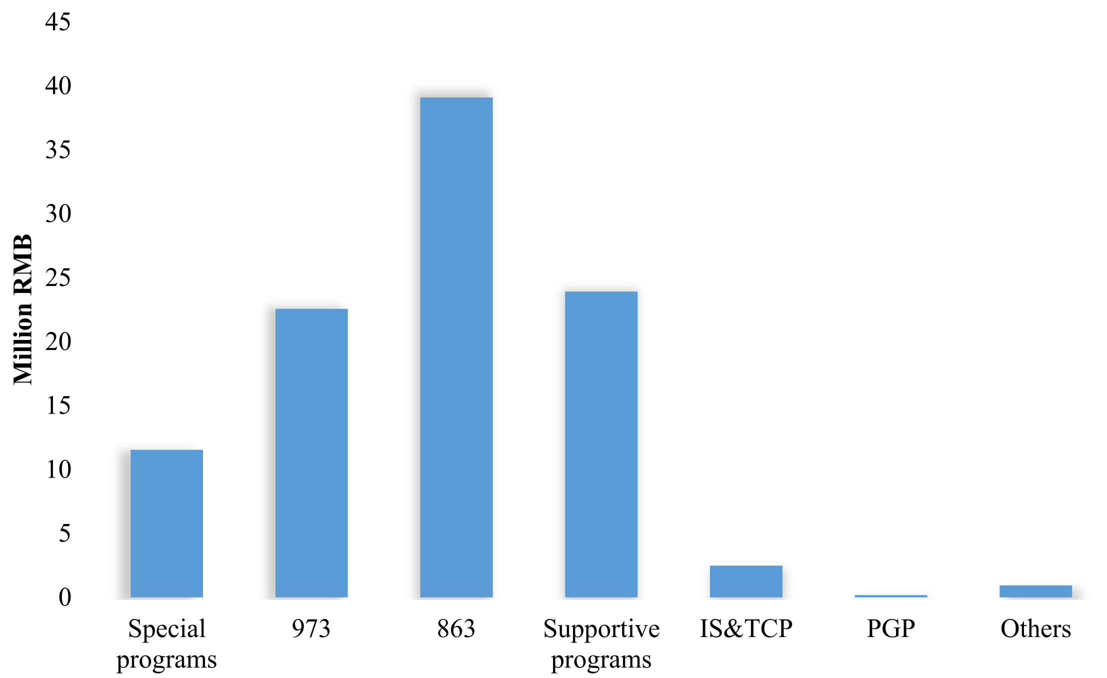
National S&T programmes are managed by the Minister of Science and Technology of China (MOST) and funded by the treasury to support basic, applied, strategic, and demonstrative S&T research-oriented programmes. These programmes are divided into fundamental programmes and special programmes. Special programmes are to develop critical strategical products, key generic technology and major construction projects. They are supported, organised and implemented by the government with a focus on several important areas. The fundamental programmes consist of five major programmes, namely, 973 Programmes, 863 Programmes, Supportive Programmes, Infrastructure Platform, and Policy-guiding Programmes (PGP)[12]. Others, like International Science and Technology Cooperative Special Programmes (ISTCSP), are specially designed for international collaborations. Figure 5.3 shows the funds allocation in the years 2006 to 2013. It is evident that most of the funds went to Special programmes, 973 programmes, 863 programmes and supportive programmes. In addition, within each programme, the number of projects differs. It can be seen from Figure 5.4 that in terms of the funds received per project on average, 973 programmes, 863 programmes and supportive programmes are the best funded.



Source: Annual Report of the State Programmes of Science and Technology Development (2006-2013)

Figure 5.3 Allocation of fund during 2006-2013

[12] The full name of 973 and 863 programmes are national basic research and development programme of China, and national high technology research and development programme of China, respectively. For more contextual information regarding the policy design system, please refer to Huang et al. (2004). Refer to the website of MOST for more details on these programmes: www.most.gov.cn/kjjh.



Source: Annual Report of the State Programmes of Science and Technology Development (2006-2013)

Figure 5.4 Average fund received per project during 2006-2013

Firms need to apply for these programmes and decisions are made by the government based on their intended research areas, current technology competence, foundations and conditions in terms of investment, human resource allocation and infrastructure platform (according to the application forms for these programmes). There are also associated S&T programmes at the provincial level, which are different from S&T programmes at the national level in terms of aims and assessment, even though provincial programmes are supposed to be complementary to national ones. In this study, the differences between national programmes and local programmes are not discussed in detail, however, the participation of provincial level S&T programmes is controlled when the additionality of national S&T programmes is assessed.

5.2.2 Effects of S&T Programmes on the Private Sector

Lee (2011) proposed a formal model to identify potential channels through which public R&D support influences firm R&D based on previous work of Lee (2005) and Dorfman-Steiner (1954). Lee (2011) summarised four channels through which S&T programmes can influence R&D investment in the private sector.

Firstly, and most obviously, financial support from S&T programmes can alleviate firms' financial constraints in uncertain R&D programmes by reducing the unit cost of private R&D

expenditure. Therefore, firms are able to invest in those marginal programmes which they may not consider without public support. However, this effect can be offset by inelastic supply of R&D inputs. It can be expected that extra available funds may push up the prices of R&D inputs. Thus, it is possible that there is additionality on R&D investment but no effect on the output or efficiency. Moreover, S&T programmes may encourage firms to undertake more radical projects, start R&D collaborations and improve R&D management (OECD 2006), and therefore result in higher returns (Bronzini and Piselli 2016). Thus, S&T programmes might affect innovation outputs only, without changing R&D spending or other inputs.

Secondly, involvement in an S&T programme can influence the recipient firm's technological competence due to learning-by-doing effects, technological complementarities through collaboration, and enhanced absorptive capacity for new technological opportunities via joining a new innovation network (Lee 2011). However, given the special characteristics of national S&T programmes, firms also face the difficulty of commercialisation and the sunk cost associated with the diversion of their own R&D resources to national S&T programmes. If firms invest in unfamiliar areas or technology, it may result in the misallocation of R&D sources and therefore hamper efficiency improvement. In addition, Salge et al. (2013) pointed out that in the framework of open innovation, tapping into a wider network can be a double-edged sword as great openness may enhance not only a firm's accessibility to external knowledge, but also its vulnerability to unintended knowledge leakage and imitation by others. Soh and Subramanian (2014) also suggested that increasing overlap in resources and expertise between collaborators can lead to knowledge redundancy and coordination expenses, which can reduce the expected benefit from open innovation.

Thirdly, participating in national S&T programmes may increase demand for the firm's current products, since the technologies or products resulting from national S&T programmes may raise the quality of or demand for the firm's current products. In addition, in general, the government will have various procurement conditions for firms undertaking S&T programmes which may guarantee the demand for the firm's products (Aschhoff and Sofka 2009). Kleer (2010) also argued that government R&D subsidies may serve as a signal for good investments for private investors, which will affect the availability of funds from other sources. In China, this kind of "certification effect" also exists and therefore may push up the demand for firms' products and increase the probability of successful R&D projects (Lerner 1999).

Finally, due to the asymmetric information between firms and governments along with the "picking winners" strategy adopted by the public sector, S&T programmes would possibly fund those programmes which may be funded by private money even without public support.

In this case, a partial or full crowding-out effect will occur and the influence of S&T programmes on private R&D investment will be cancelled out. In fact, unless S&T programmes can also raise their private returns to R&D, it is expected that some crowding-out will take place (Hu and Deng 2016).

5.2.3 Review of Empirical Literature

The effectiveness of public support has been widely discussed and empirically tested. David et al. (2000) surveyed the body of available econometric evidence produced over the 35 years before 2000. García-Quevedo (2004) carried out a meta-regression analysis on studies before 2002. Becker (2015) systematically reviewed the effectiveness of various policy instruments in promoting firms' R&D investment. In a recent study, Dimos and Pugh (2016) conducted a meta-regression analysis of the effectiveness of R&D subsidies, which covered studies since 2000 and extended the review by Zúñiga-Vicente et al. (2014).

The empirical evidence of the effects of public programmes on firms' innovation performance remains mixed and controversial (Czarnitzki and Hottenrott 2011). David et al. (2000) report that over 30 per cent of studies conducted before 2000 fail to reject the crowding out effect. García-Quevedo (2004) found very weak evidence of the crowding-out effect at the firm level. More recently, Zúñiga-Vicente et al. (2014) show that 20 per cent of recent studies using firm-level data fail to reject the crowding-out effect, while 17 per cent report neutrality and the remaining 63 per cent find evidence for additionality. Dimos and Pugh (2016) conclude that their meta-regression analysis rejects the crowding out of private investment by public subsidy and reveals no evidence of substantial additionality.

Czarnitzki and Fier (2001), Almus and Czarnitzki (2003), González et al. (2005), and Bloch and Graversen (2012) all focused on input additionality. The potential endogeneity problem is not properly solved. It tends to increase the size of estimated effects (Dimos and Pugh 2016). In contrast, a few studies found the existence of a substantial crowding-out effect (Hujer and Radić 2005; Hewitt-Dundas and Roper 2010; Czarnitzki et al. 2011; Czarnitzki and Lopes-Bento 2014). In addition, Lach (2002) found additionality in small firms, while large firms aren't affected by R&D subsidies significantly. Goerg and Strobl (2007) demonstrated that small grants significantly stimulate business R&D, while large grants turn out to be substitutes. Boeing (2016) found that there was an instantaneous crowd-out effect, while in the later period the effect of public support is neutral.

Overall, most of the papers are concentrated on developed countries (Zúñiga-Vicente et al. 2014; Dimos and Pugh 2016). The developing countries are, to some extent, neglected (exceptions do exist, such as Almus and Czarnitzki 2003; Özçelik and Taymaz 2008), especially China which experienced a boom in its R&D sector (Wu 2012a). Recently, Guan and Yam (2015) conducted research on the effect of government financial incentives on firms' innovation in Beijing back to the 1990s. The results show that the direct earmarks failed to enhance innovation performance. Boeing (2016) examined the allocation and effect of China's R&D subsidies using listed firms between 2001 and 2006. He concluded that R&D subsidies instantaneously crowd-out business R&D investment but become neutral in later periods. He also provided a brief review of related studies of China either in English or Chinese, which shows that the empirical evidence is quite controversial. Liu et al. (2016) investigated the effect of R&D subsidies on business R&D investment using cross-sectional data on high-tech manufacturing firms in the Jiangsu province of China. They found that public subsidies positively influence business R&D investment. Guo et al. (2016) specifically investigated the effects of the Innovation Fund for Small and Medium Technology-based Firms and found a significantly positive effect on output additionality.

However, these studies are conducted by using either samples before 2006, or cross-sectional data. They also tend to focus on a single dimension of additionality. In contrast, this study aims to investigate the effectiveness of national S&T programmes, which are among the most important S&T policy instruments, particularly in the post-2006 period, by using a balanced panel data of innovative firms in China. It adds new evidence to the existing empirical research and provides multi-dimensional analysis regarding additionality. Panel data also allows us to consider DID estimators after a matching process to reduce potential endogeneity caused by unobservable variables. Lastly, detailed information in the survey data makes it possible to differentiate the additionality in terms of internal R&D, external R&D, patent output, and product output. These may have further policy implications.

5.3 Theoretical Framework and Empirical Model

5.3.1 Theoretical Framework

The theoretical framework in this study combines the structural model developed by David et al. (2000) and David and Hall (2000) with the typical invention production function proposed by Griliches (1979). Howe and McFetridge (1976) reported that firms' R&D

expenditure reaches the equilibrium level when the marginal rate of return to R&D (MRR) equals the marginal cost of R&D (MCR). Both MRR and MCR are functions of R&D and exogenous shifters. The MRR curve is a decreasing function of R&D expenditure, while the MCR curve has an upward slope, as firms have to shift from internal resources to external and more expensive resources. These can be expressed as follows:

$$\begin{aligned} MRR &= f(R, \mathbf{V}) \\ MCR &= g(R, \mathbf{Z}) \end{aligned} \tag{5-1}$$

where R represents the firm's own R&D expenditure. **V** and **Z** are vectors of variables which can shift the curves accordingly. **V** can be proxies of technological opportunities; market demand; and appropriability conditions (e.g. IPR protection), while **Z** includes variables such as innovation policy instruments; macroeconomic conditions; and availability and relative cost of external funds (David et al. 2000).

Where **V** and **Z** are exogenous factors, the optimal level of R&D investment (R^*) at equilibrium condition is the "reduced form" of structural model (5-1),

$$R^* = h(\mathbf{V}, \mathbf{Z}) \tag{5-2}$$

In this theoretical framework, the effect of public subsidy on the equilibrium level of R&D expenditure R^* can be observed by,

$$R = R^* + A \tag{5-3}$$

where A is the incremental R&D expenditure induced by the public support. Therefore, the empirical work required is to test whether A is significantly different from 0.

In addition, it would be natural to investigate the difference in efficiency between government-funded R&D and firm-funded R&D. Departing from a typical invention production function linking innovation output to innovation input (Griliches 1979), we assume that the innovation output of firm $i(O_i)$ is a function of R&D input and a vector of the control variable **C**, which can be expressed as,

$$O_i = f(R_i^*, A_i, \mathbf{C}_i) \tag{5-4}$$

Therefore, the additional output associated with A can be attributed to the additionality of public policy on R&D investment (Czarnitzki and Licht 2006). Apart from that, the third channel discussed in Section 2 implies that public policies can affect firms' output directly through patent approval regulations, various procurement conditions and promotion of the quality and reputation of engaged firms. Therefore, along with the investigation of output additionality, this study also examines efficiency additionality by allowing for public policies to affect firms' output not only directly through R&D investment but also indirectly through the patent activities and final demand (Bronzini and Piselli 2016).

5.3.2 Empirical Approach

It is evident that the selection process of government S&T programmes is far from a randomised process, regardless of the strategy adopted by the government, let alone that firms always weigh the advantages and disadvantages of undertaking a programme. Therefore, a pure comparison of the average impact of public support may lead to biased results. To lessen the bias in the estimation of treatment effects with observational data sets, Rosenbaum and Rubin (1983) proposed the propensity score matching (PSM) approach. The fundamental evaluation question can be illustrated by an equation describing the average treatment effect on the treated firms (ATET):

$$E(ATET) = E(Y^1 \mid T=1) - E(Y^0 \mid T=1) \qquad (5\text{-}5)$$

where Y is the outcome variable. T is a binary variable describing treatment status with $T=1$ for the treatment group, and $T=0$ for the control group. Y^0 is the counterfactual outcome if the treatment group ($T=1$) had not been treated. While $E(Y^1 \mid T=1)$ is directly observable, it is not the case for $E(Y^0 \mid T=1)$. Given the fact that the S&T programmes are not randomly assigned, it would be biased if the counterfactual situation was simply estimated as the average outcome of the non-participants, namely, $E(Y^0 \mid T=1) \neq E(Y^0 \mid T=0)$. Rubin (1977) introduced the conditional independence assumption (CIA) to overcome this selection problem, namely, participation and potential outcome are statistically independent for firms with the same set of exogenous characteristics **X**.

$$(Y^0 \perp T) \mid \mathbf{X} \qquad (5\text{-}6)$$

The basic idea of the matching approach is to imitate a 'natural' experiment where the treatment is randomly distributed between groups of identical twins. Hence, the goal of the matching approach is to find, for each treated firm (which undertakes national programmes), an 'identical' non-treated firm. In this case, 'identical' means that the firms in each pair have sufficiently similar values of all the variables summarised in **X**. Ideally, **X** contains all the factors responsible for engagement in public S&T programmes. Rather than exact matching with all dimensions of **X**, one can match the treated units and control units in terms of their propensity scores, which are the probability of programme engagement conditional on **X** and can be estimated using simple probit or logit models (Rosenbaum and Rubin 1983). A further assumption for the application of PSM is the common support assumption ($p(\mathbf{X})<1$), which requires the existence of some comparable control units for each treated unit (Lin and Ye 2007). If the CIA holds, then it follows that,

$$E(Y^0 \mid T=1, p(\mathbf{X})) = E(Y^0 \mid T=0, p(\mathbf{X})) \tag{5-7}$$

Then the average treatment effect on the treated can be expressed as:

$$E(ATET) = E(Y^1 \mid T=1, p(\mathbf{X})) - E(Y^0 \mid T=0, p(\mathbf{X})) \tag{5-8}$$

In the present analysis, we conduct a variety of commonly used matching schemes. The first one is nearest-neighbour (NN) matching with replacement, which matches each treated unit with the n control units that have the closest propensity scores. The second one is kernel matching, which matches a treated unit with all control units, weighted in proportion to the closeness between the treated unit and the control unit. The third method is local linear regression matching, which is similar to kernel matching but includes a linear term in the weighting function as an additional way to avoid biases.

As the PSM approach is highly dependent on the CIA assumption, we further combine PSM and DID estimators to reduce the potential endogeneity problem caused by unobservable factors which might affect the selection process of government S&T programmes (Blundell and Costa Dias 2000). Thus, the ATET with this integrated specification can be expressed as,

$$E(ATET)^{DID} = E(Y^1_{t1} - Y^1_{t0} \mid T=1, p(\mathbf{X})) - E(Y^0_{t1} - Y^0_{t0} \mid T=0, p(\mathbf{X})) \tag{5-9}$$

where t_0 is the year before treatment and t_1 is the year after treatment.

5.3.3 Data and Operationalisation

The data used in this study is the same as Chapter 4. For more details, please refer to Section 4.3.2.

As discussed in previous sections, the targeted variables in this study are the inputs, outputs and efficiency of innovation activities, as shown in Table 5.1. For the input additionality, we chose R&D expenditure and its detailed composition, namely, internal and external R&D expenditure, as the dependent variables. This helps to provide more insight into potential input additionality in comparison with the popular investigation which uses total R&D expenditure only. Regarding output additionality, this study mainly focuses on two widely used variables in the field of firms' innovation, namely, number of patent applications and value of new products (VNP), which can be viewed as the outputs at different stages in innovation processes (Guan and Chen 2010; Chen and Guan 2012). To represent efficiency additionality, this study uses patent efficiency and efficiency of producing new products, which are measured by number of patent applications over total R&D expenditure and VNP over total S&T expenditure, respectively.

The treatment variable in this study is a binary variable taking the value of 1 if a firm undertakes at least one national programme, or 0 otherwise. As for the covariates, this study considers five aspects associated with the firms to depict the selection process of S&T programmes in line with previous studies, economic theory and institutional background in China (See Table 5.1). These covariates are selected with reference to the application forms for S&T programmes.

Table 5.1 Variable list

Variables	**Definition**	**Details**
Targeted variables (Ys)	Input additionality	R&D expenditure Internal R&D expenditure External R&D expenditure
	Output additionality	Number of patent applications Number of patents granted Value of new product (VNP)
	Efficiency additionality	Patent efficiency Invention efficiency VNP efficiency
Treatment variable (Ds)	Dummy for undertaking programmes	National S&T programmes
Covariates (Xs)	Firms' characteristics	Firm age Firm size Firm Ownership
	Firms' infrastructure	Patent Stock R&D department S&T expenditure S&T personnel Labour productivity
	Firms' network	Guanxi Foreign R&D UIR collaboration
	Firms' experiences	Undertaking programmes Joining programmes
	Fixed effects	Dummies for region Dummies for industry Dummies for time

Source: Author's own work.

Specifically, firms' basic characteristics, namely firms' *age*, *size* and *ownership*, are considered. They are measured by the log of the number of years in existence, log of the number of employees and a binary variable taking the value of 1 if a firm is state-owned and 0 otherwise. Firms' infrastructure or research conditions undoubtedly matter, according to the questions contained in the application form for S&T programmes. For example, the knowledge infrastructure is represented by *patent stock*, namely, the total number of patents held by a firm; the facility condition is represented by whether a firm has an *R&D department*; the research condition can be demonstrated by using the total *S&T expenditure* and the number of *S&T personnel* which show the availability of supporting capital and research teams; *Labour productivity* is measured by the total revenue over the number of employees. In addition, firms belonging to a network of firms may benefit from better communication structures and thus be better informed about possible funding sources including public programmes (Czarnitzki and Lopes-Bento 2013). Firms with good government connections will also be at an advantage in the programme selection process in Chinese institutional context. Therefore, *Guanxi* is included to capture whether a firm has close relationship with government, which taking the value of 1 if a firm has a member in the National People's Congress (NPC) or the Chinese People's Political Consultative Conference (CPPCC) or 0 otherwise. Whether a firm is engaged in foreign R&D activities or collaboration with universities or research institutions (UIR) is included as well to represent the *network* feature. More importantly, firms' *experience* in undertaking S&T programmes has also been listed as a selection criterion in the application form. Therefore, this study includes two binary variables to indicate whether a firm undertook or joined S&T programmes at national or provincial level in the past. Lastly, various fixed effects are controlled for as well.

Table 5.2 presents the descriptive statistics of the main variables. The average age of the firms is about 16 years and the average number of employees is 3,174. 25.3 per cent of the firms are state-owned companies, while 66.1 per cent of them have at least one R&D department such as national enterprise technical centre, national key laboratory, national engineering technology centre and national engineering laboratory. 28.4 per cent of firms have members in NPC or CPPCC, which indicates their closer relationship with governments. 10.6 per cent of them conducted R&D activities overseas, while 85.4 per cent of them have UIR collaboration. 47.3 per cent of them have experience in undertaking at least one programme, while 25 per cent of them have experience in joining at least one programme over the four years.

Table 5.2 Descriptive statistics of main variables

Variables	Sample size: 1772			
	Mean	Std.Dev.	Min	Max
Outcome variables				
R&D expenditure	9.103	1.826	2.890	14.177
Internal R&D	8.962	1.896	0.000	14.177
External R&D	4.487	4.686	0.000	12.841
Applied patents	2.967	2.456	-4.605	8.741
Granted patents	2.323	2.638	-4.605	8.297
VNP	10.731	3.573	0.000	17.490
Patent efficiency	0.007	0.019	0.000	0.405
Invention efficiency	0.004	0.015	0.000	0.389
VNP efficiency	9.101	13.218	0.000	440.300
Covariates				
Age	2.776	0.797	0.000	4.575
Size	8.063	1.859	4.078	14.306
Ownership	0.253	0.435	0.000	1.000
Invented patent stock	2.420	2.250	-4.605	9.019
R&D department	0.661	0.473	0.000	1.000
S&T expenditure	9.479	1.850	2.303	14.755
S&T personnel	6.566	1.530	2.708	11.465
Labour productivity	4.309	0.805	-1.012	7.095
Guanxi	0.284	0.451	0.000	1.000
Foreign R&D	0.106	0.307	0.000	1.000
UIR collaboration	0.854	0.353	0.000	1.000
Undertake programmes	0.473	0.499	0.000	1.000
Join programmes	0.250	0.433	0.000	1.000

Source: Author’s own work.
Note: Apart from binary and efficiency variables, other variables are all in logarithmic form.

5.4 Empirical Results

In order to derive the matching estimators as elaborated upon in section 3, a probit model is estimated to obtain the predicted probability of receiving national S&T programmes. To balance between the plausibility of the unconfoundedness assumption and the variance of the estimates, this study includes as many variables as possible and applies a stepwise process to identify variables which significantly contribute to the prediction probability at least at 10 per cent level. Square terms are incorporated as well to capture the possible nonlinear relationship and to improve the matching. To reduce the potential problem of endogeneity, all covariates are lagged one period, which also conforms to reality since the government generally assesses firms based on their recent performance. The results are shown in Table 5.3.

Table 5.3 Determinants of being selected into national S&T programmes

treat_nation	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Size	-0.414**	0.204	-2.030	0.043	-0.814	-0.014
Size square	0.020*	0.011	1.790	0.074	-0.002	0.042
Ownership	0.300***	0.100	3.010	0.003	0.105	0.496
Stock of invented patents	0.048**	0.022	2.230	0.025	0.006	0.091
Stock of invented patents square	0.013**	0.005	2.490	0.013	0.003	0.022
R&D department	0.305***	0.104	2.920	0.003	0.101	0.510
S&T fund	0.104*	0.056	1.850	0.064	-0.006	0.215
S&T personnel	0.132*	0.073	1.800	0.072	-0.012	0.276
UIR collaboration	0.247*	0.133	1.860	0.064	-0.014	0.509
VNP square	-0.003**	0.001	-2.550	0.011	-0.006	-0.001
Undertake national projects	0.631***	0.085	7.430	0.000	0.465	0.798
Join national projects	0.305***	0.092	3.320	0.001	0.125	0.485
Region dummies	Yes					
Industry dummies	Yes					
Year dummies	Yes					
Intercept	-0.700	0.780	-0.900	0.370	-2.229	0.829
Pseudo R2	0.21					

Source: Author's own work. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Table 5.3 shows that firm size exhibits a U-shaped relationship with the possibility of engaging in national S&T programmes, indicating that smaller and bigger firms are more likely to be selected against medium-sized firms. The underlying reason is not explicit since it is a bidirectional selection process. It might because smaller firms are more actively seeking for supports from the government, while government also prefers larger firms in some big projects. This is slightly different from Hu and Deng (2016) and Liu et al. (2016) who found that public subsidies are more likely to be given to larger firms. State-owned enterprises (SOEs) have a greater possibility of undertaking national S&T programmes, a feature which is prevalent in other studies of China (Hu and Deng 2016; Howell 2016; Liu et al. 2016). It seems that the preference of the Chinese government towards SOEs did not change much in recent decades (Guan and Yam 2015). Firms with better knowledge or technology infrastructure are more likely to be engaged in national S&T programmes, which fits well into China's innovation policy of "picking the winners" (Boeing 2016). Stock of invention patents, rather than all patents contributes to the probability of being selected, which implies that quality rather than quantity of innovation matters in the screening process. This further confirms the result in Boeing (2016) who found that high quality inventions are one of the key determinants of subsidy allocation. UIR collaboration is a significant contributor, which confirms the argument made by Feldman and Kelly (2006) that the government prefers firms with greater potential to disseminate R&D results broadly. Although Feldman and Kelly (2006) don't find significant results for university linkages in the US, our result is reflective of China's reality as the innovation system in China is highly dependent on universities (Hu and Mathews 2008; Kafouros et al. 2015). In line with the existing literature, we confirm prior experience in undertaking or joining at least one programme plays a very important role in the selection process, indicating certain inertia in public support (Boeing 2016). Overall, these results are highly consistent with the information required in application forms for those programmes as well as the findings by some existing studies (Czarnitzki and Licht 2006; Wu et al. 2012).

We further assess the matching quality based on one-to-one NN matching with replacement. It can be intuitively observed in Figure 5.5 that, after matching, the distribution of the two groups is much more similar and the common support area is substantially wider. Details of the matching quality can also be found in Table 5.4. Firms' size, stock of patents, S&T personnel and VNP are significantly different between the treated and control groups before matching, while all differences become insignificant after matching, indicating that the property of balancing is satisfied. In addition, the biases of all variables including those dummy variables are reduced considerably, from an average of 31.5 per cent to 5.20 per cent. The Pseudo R^2 also decreased dramatically from 0.21 to 0.02, implying that the systematic difference between treated and control groups is now removed. To summarize, these results suggest that our matching is successful. It helps us to justify the matching estimators and the reliability of the results in this study.

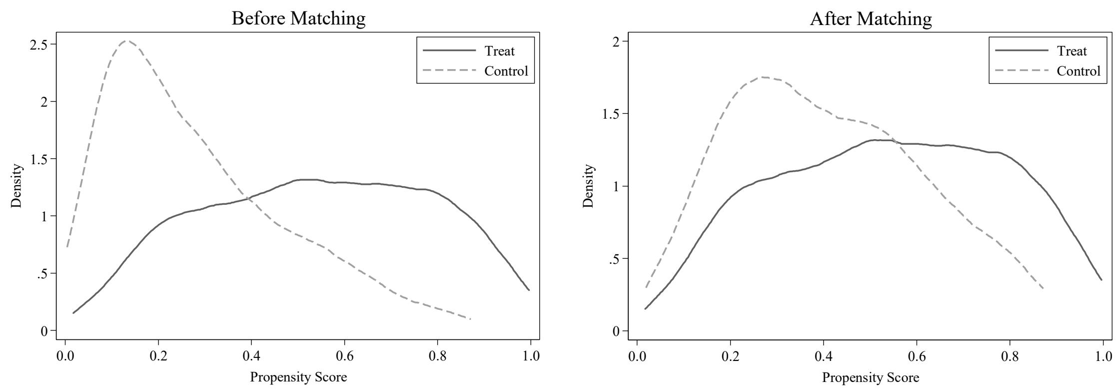


Figure 5.5 Distribution of propensity scores between two groups

Table 5.4 Matching quality

Variables	Unmatched Matched	Mean Treated	Mean Control	%bias	%Reduct |bias|	t-test t	t-test p>|t|	V(T)/V(C)
Size	U	8.66	7.65	55.20		10.04	0.00	1.57*
	M	8.35	8.49	-7.80	85.90	-1.18	0.24	0.94
Size square	U	78.97	61.08	56.30		10.39	0.00	2.01*
	M	72.92	75.49	-8.10	85.60	-1.23	0.22	0.93
Stock of invention patent	U	2.94	1.79	52.80		9.33	0.00	0.97
	M	2.63	2.63	0.30	99.40	0.05	0.96	0.91
Stock of invention patent square	U	13.30	8.03	50.30		9.33	0.00	2.16*
	M	10.93	11.31	-3.70	92.70	-0.63	0.53	0.85
Ownership	U	0.40	0.16	54.00		9.89	0.00	.
	M	0.34	0.34	-1.50	97.20	-0.21	0.84	.
R&D department	U	0.80	0.56	53.50		9.25	0.00	.
	M	0.78	0.78	0.50	99.10	0.08	0.94	.
S&T fund	U	10.05	8.99	60.40		10.78	0.00	1.14
	M	9.79	9.89	-5.70	90.50	-0.89	0.38	0.89
S&T personnel	U	7.09	6.19	60.50		10.87	0.00	1.28*
	M	6.87	7.03	-10.50	82.60	-1.59	0.11	0.94
UIR collaboration	U	0.93	0.84	28.10		4.79	0.00	.
	M	0.92	0.91	2.80	90.10	0.48	0.63	.
VNP square	U	138.05	120.16	34.90		6.30	0.00	1.38*
	M	133.57	136.48	-5.70	83.70	-0.83	0.41	0.91
Undertake national projects	U	0.73	0.37	78.70		13.82	0.00	.
	M	0.70	0.68	3.80	95.20	0.57	0.57	.
Join national projects	U	0.42	0.18	53.20		9.71	0.00	.
	M	0.38	0.35	6.90	87.00	0.96	0.34	.
Sample	Ps R2	LR chi2	p>chi2	Mean Bias	Med Bias	B	R	%Var
Unmatched	0.211	372.71	0.00	31.50	23.40	116.50*	1.43	71.00
Matched	0.021	26.58	0.32	5.20	4.50	34.10*	1.40	0.00

Source: Author's own work. * indicates the two groups are statistically different in terms of this variable.

The main results are shown in Table 5.5. It is clear that, before matching, the contributions from undertaking national S&T programmes to the R&D expenditure, patent activities and final commercialisation were all positive and quite significant. In comparison with firms without S&T programmes, firms undertaking national S&T programmes invest more in both internal R&D and external R&D, possess more patent applications and granted patents, and show better performance in the sales of new products on average before matching. But for efficiency performance, before matching, firms with S&T programmes tend to perform worse especially in terms of patent efficiency and VNP efficiency, which indicates possible problems of misallocation and waste of resources as argued in Section 2.2. The estimated efficiency deterioration suggests that the government should establish an effective mechanism to monitor the utilisation of government funds associated with S&T programmes. However, this significant negative additionality in terms of efficiency becomes insignificant after matching, while the sign remains negative.

Table 5.5 Additionalities

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
R&D expenditure	Unmatched	9.8712	8.7362	1.1349	0.0980	11.58***
	ATET	9.6124	9.6868	-0.0745	0.1591	-0.47
Internal R&D	Unmatched	9.7241	8.6216	1.1025	0.1013	10.88***
	ATET	9.4985	9.5604	-0.0619	0.1611	-0.38
External R&D	Unmatched	5.8294	3.8039	2.0255	0.2537	7.98***
	ATET	5.5792	5.6027	-0.0236	0.3980	-0.06
Patent applications	Unmatched	3.8132	2.5481	1.2652	0.1376	9.19***
	ATET	3.5261	3.2521	0.2740	0.2410	1.14
Patents granted	Unmatched	3.2510	2.0036	1.2474	0.1429	8.73***
	ATET	2.9530	2.7292	0.2238	0.2428	0.92
VNP	Unmatched	11.0289	10.4437	0.5852	0.2135	2.74***
	ATET	10.9720	11.3770	-0.4050	0.3161	-1.28
Patent efficiency	Unmatched	0.0056	0.0072	-0.0016	0.0008	-2.02**
	ATET	0.0058	0.0060	-0.0002	0.0015	-0.16
Invention efficiency	Unmatched	0.0030	0.0032	-0.0003	0.0005	-0.54
	ATET	0.0030	0.0031	-0.0001	0.0010	-0.06
VNP efficiency	Unmatched	7.8385	9.5892	-1.7507	0.8134	-2.15**
	ATET	7.9396	8.0982	-0.1586	0.7763	-0.20

Source: Author’s own work.
Note: 50 out of 508 are off support in treated group. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

The more noteworthy phenomenon is that the input additionality becomes negative after matching, indicating that there is potential evidence of the crowding-out effect of public support, even though the t-test is not significant. The output additionality is positive but becomes insignificant as well. Therefore, we might overestimate the effect of S&T programmes since after matching there is no significant evidence of additionality in all dimensions. Our findings are consistent with Boeing (2016) and also affirm the more general observation by Hu and Jefferson (2008) that the influence of government grants on increases in China’s business R&D is most likely not significant. Liu et al. (2016) found a significant and strong stimulation effect of public support, especially for smaller firms, more financially constrained firms, and privately-owned firms. However, they focused on high-tech manufacturing firms in Jiangsu Province only and hence their conclusions might not be compatible directly with our findings. Hu and Deng (2016) also found a very large stimulating effect, but this stimulating effect largely disappears for firms that report R&D expenditures every year. This is, in fact, consistent with our findings, as the sample in this study includes the most innovative firms across China. Although this study focuses on national S&T programmes which are different from the above-mentioned studies, all findings imply no success of S&T programmes in inducing private investment and promoting private returns. We apply the same exercise to provincial S&T programmes and found similar results[13].

To further investigate whether the ATET effects are stable across years, we divide the panel into different periods and repeat the exercise for each subsample. The matching quality is summarised in Table 5.6 and Figure 5.6. The mean biases (MBS) of all periods are reduced dramatically and the pseudo R^2 becomes insignificant after matching (Table 5.6)[14]. Common support areas after matching are all wide enough to provide qualified partners (Figure 5.6).

Table 5.6 Matching qualities across periods

	2009-2010		2010-2011		2009		2010		2011	
Sample	Ps R^2	MBS	Ps R^2	MBS	Ps R^2	MBS	Ps R^2	MBS	Ps R^2	MBS
Unmatched	0.179^{***}	33	0.247^{***}	31.5	0.152^{***}	37.9	0.211^{***}	36	0.301^{***}	55.9
Matched	0.02	5.5	0.025	5.2	0.005	3.4	0.02	9.5	0.009	5.5

Source: Author's own work.
Note: ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

The additionality results in different periods are summarised in Figure 5.7. Generally, the conclusions drawn are consistent with the full sample estimation results. Therefore, it seems that there is no positive evidence to support the additionality caused by techno-industrial policy schemes. The only exceptions observed are significant additionality in terms of external R&D in 2010, and patent-related activities in the period 2009 to 2010. These results suggest that the S&T programmes might help firms widen their collaboration with other entities and actively appropriate their intellectual property. However, consistent insignificance in terms of VNP and efficiency additionality supports the argument about the difficulty of commercialisation and the misallocation of R&D resources in undertaking national S&T programmes. Clearly, these additionalities are not stable over time.

[13] The results for provincial S&T programmes are omitted due to limited space and are available upon request.
[14] Details of matching quality across periods are omitted due to limited space and are available upon request.

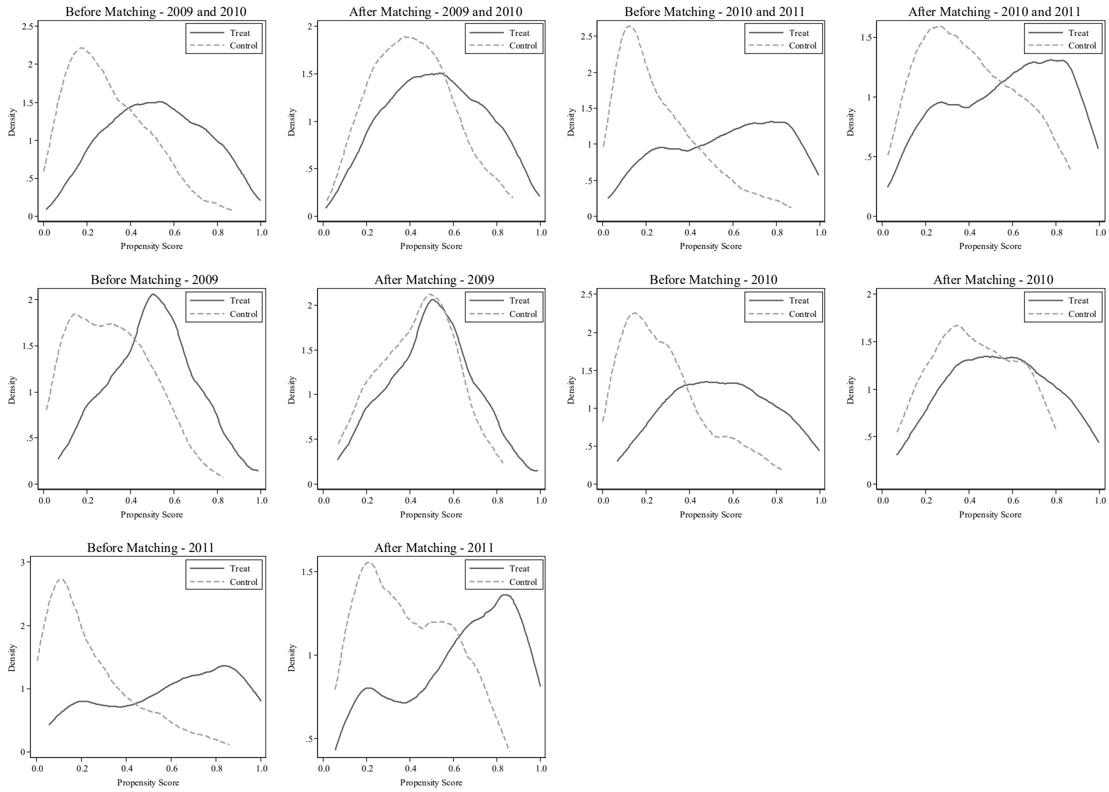


Figure 5.6 Matching qualities of different periods

Table 5.7 Additionality in different periods

		2009-2010		2010-2011		2009		2010		2011	
Variable	Sample	D	t	D	t	D	t	D	t	D	t
R&D expenditure	U	1.0350	8.73***	1.1689	9.61***	1.0698	6.48***	1.0005	5.86***	1.3407	7.75***
	ATET	0.0809	0.39	0.0641	0.32	0.1746	0.68	0.4477	1.68	-0.0666	-0.24
Internal R&D	U	0.9939	7.99***	1.1505	9.43***	1.0113	5.60***	0.9773	5.71***	1.3273	7.66***
	ATET	0.0732	0.35	0.0491	0.24	0.1739	0.66	0.4223	1.58	-0.0828	-0.30
External R&D	U	1.8470	6.27***	2.4363	7.25***	1.1802	3.63***	2.5070	5.28***	2.3638	4.95***
	ATET	0.7102	1.39	0.4192	0.81	0.2581	0.52	1.9396	2.54***	0.5084	0.61
Patent application	U	0.9672	5.76***	1.5468	9.41***	0.7104	2.88***	1.2257	5.39***	1.8719	7.90***
	ATET	0.0285	0.11	0.6876	2.27***	0.1246	0.33	0.6636	1.91	0.4276	1.14
Patent granted	U	1.0084	5.64***	1.4390	8.55***	0.8747	3.34***	1.1443	4.71***	1.7397	7.50***
	ATET	0.1293	0.45	0.8379	2.57***	0.2420	0.60	0.4500	1.16	0.2356	0.65
VNP	U	0.6533	2.50***	0.5598	2.06**	0.6354	1.87	0.6705	1.68	0.4522	1.22
	ATET	0.3043	0.76	0.2108	0.45	0.0625	0.13	0.3375	0.60	-0.3598	-0.68
Patent efficiency	U	-0.0020	-1.88	-0.0009	-0.89	-0.0031	-2.28***	-0.0010	-0.57	-0.0008	-0.75
	ATET	-0.0016	-0.72	0.0014	0.98	-0.0020	-1.35	-0.0018	-0.51	-0.0006	-0.27
Invention efficiency	U	-0.0002	-0.26	0.0000	0.08	-0.0009	-1.17	0.0006	0.51	-0.0005	-0.69
	ATET	-0.0004	-0.28	0.0008	1.13	0.0000	0.01	-0.0001	-0.06	-0.0014	-0.78
VNP efficiency	U	-2.1499	-1.89	-1.7968	-1.57	-1.6756	-2.01	-2.6283	-1.24	-0.9712	-1.10
	ATET	-3.6868	-1.13	-2.0690	-0.59	-0.9942	-0.78	0.1167	0.10	0.7401	0.76

Source: Author's own work.

Note: U for unmatched, D for difference, and t for t-statistics. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

5.5 Further Analysis

5.5.1 Heterogeneity in Treatment Effects

Although the ATET is insignificant, it is questionable whether individual treatment effects vary across certain features. For example, it is widely discussed that the treatment effects vary across firms with different size and ownership (Lee 2011; Liu et al. 2012; Liu et al. 2016). In addition, it is possible for one firm to be affected by more than one programme during the same period, and that the associated government investment varies across projects as well. Previous studies generally apply matching estimators to sub-samples according to certain features to investigate the heterogeneity effects. However, it is inappropriate if the subsamples are not big enough which results in the lack of common support. Therefore, following Czarnitzki and Lopes-Bento (2013), we estimate the individual treatment effects via differencing outcome variables between matched pairs and run a regression against size, ownership, the number of programmes undertaken, and value of these programmes. Square and cubic terms are included in order to capture potential non-linear relationship. However, we stick to linear relationship finally as there is no evidence of the existence of any non-linear relationship. Results are classified according to types of additionality and presented in Table 5.8, Table 5.9 and Table 5.10.

For input additionality, Table 5.8 shows that firstly, the individual treatment effect tends to increase as firms' size expand, indicating that induced R&D investment in large firms, both internal and external, is significantly larger than that in other firms. Since both size and the dependent variable are in logarithm form, the marginal effect here refers to percentage change. This is inconsistent with Liu et al. (2016), who suggest that the ATET effect for smaller firms is more significant in terms of business R&D. The possible reason is that in national S&T programmes the government sometimes asks firms for matching investment to prevent the crowding-out problem. Then larger firms have to invest more since they generally receive more grants. Second, the coefficients for ownership are all negative and significant at 1 per cent level, implying that the stimulation effect for non-SOEs is much stronger, which is consistent with Liu et al. (2016). Third, as the number of programmes increases, the input additionality becomes smaller. This further supports the potential crowding-out effect of national S&T programmes which accumulates as involvement in government S&T programmes deepens. This result supports the assumption made by Zúñiga-Vicente et al. (2014), who argued that the crowding-out effect of public subsidies on private R&D investment might be stronger in firms that are frequent recipients of public subsidies than that in first-time recipients. Lastly, the value of programmes didn't affect the individual treatment effect significantly. This seemingly counterintuitive result actually supports the certification hypothesis regarding public support (Lerner 1999). The hypothesis suggests that subsidies do not necessarily lead to high growth as the marginal value of certification effect is expected to be diminishing and management cost tends to increase.

Table 5.8 Heterogeneity of inputs additionality

	Dependent variable: a_i – differences in outcome variables between two groups					
	R&D		internal R&D		external R&D	
	Coef.	P>|t|	Coef.	P>|t|	Coef.	P>|t|
Size	0.670***	0.00	0.667***	0.00	0.741***	0.00
Ownership	-0.635***	0.00	-0.619***	0.00	-1.479**	0.02
Number of programmes	-0.073***	0.00	-0.069***	0.00	-0.092*	0.07
Value of programmes	0.002	0.63	0.001	0.85	-0.003	0.72
Intercept	-5.263***	0.00	-5.246***	0.00	-5.118***	0.00
F value	43.64***	0.00	39.70***	0.00	5.02***	0.00
Number of observations	458		458		458	

Source: Author's own work.
Note: ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

As for output additionality, Table 5.9 shows that firms' size positively and significantly affects the individual treatment effect. This implies that bigger firms undertaking S&T programmes enjoy greater additionality in terms of innovation output in comparison with their control partners. It can be anticipated that larger firms have more bargaining power over the government, and therefore might be able to achieve better terms in an agreement undertaking public programmes. Secondly, SOE and non-SOEs do not show significant differences in output additionality. In addition, the number of programmes and the value of programmes have negative effects on individual output additionality. The negative coefficient of the number of programmes and government investment in the case of VNP can be partly explained by the government's preference for basic research and social benefit maximisation, which makes it harder for firms to commercialise their innovation output associated with government programmes as discussed in Section 2.2. There are two more possible reasons. Firstly, due to deeper engagement in government programmes, firms are gradually stepping away from market competition, which therefore impedes their incentive to innovate actively (Aghion et al. 2005). Secondly, in an open innovation perspective, more intensive collaboration with government and other entities implies that firms can tap into a bigger network and face higher risk of knowledge leakage and conflicts of intellectual property, thereby hampering their innovation performance.

Table 5.9 Heterogeneity of output additionality

	Dependent variable: a_i - differences in outcome variables between two groups					
	Patent application		Patent granted		VNP	
	Coef.	P>|t|	Coef.	P>|t|	Coef.	P>|t|
Size	0.614***	0.00	0.607***	0.00	0.729***	0.00
Ownership	-0.265	0.43	-0.348	0.30	-0.480	0.29
Number of programmes	-0.070***	0.00	-0.078***	0.00	-0.087**	0.03
Value of programmes	-0.016***	0.00	-0.025***	0.00	-0.067***	0.00
Intercept	-4.744***	0.00	-4.598***	0.00	-5.955***	0.00
F value	15.00***	0.00	14.66***	0.00	14.04***	0.00
Number of observations	458		458		458	

Source: Author's own work.
Note: ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

In terms of efficiency additionality, firm size affects the individual treatment effect negatively in patent-related efficiency, while it affects the VNP efficiency positively and significantly (Table 5.10). This result is consistent with our expectation as, generally, bigger firms are believed to perform worse in efficiency indicators, while the positive effect on VNP efficiency suggests that bigger firms are more powerful in commercialising their innovation outputs. It is also possible that the government provides effective procurement schemes for bigger firms with the aim of encouraging them to conduct basic research with greater social benefit. Another noteworthy observation is the negative coefficient for the number of programmes in the VNP efficiency model. This result demonstrates the negative side of undertaking national S&T programmes as firms face the difficulty of commercialisation due to the special characteristics of government-led programmes. Ownership and value of programmes do not show significant differences in terms of efficiency additionality.

Table 5.10 Heterogeneity of efficiency additionality

	Dependent variable: a_i - differences in outcome variables between two groups					
	Patent efficiency		Invention efficiency		VNP efficiency	
	Coef.	P>|t|	Coef.	P>|t|	Coef.	P>|t|
Size	-0.001**	0.02	-0.001***	0.01	1.276***	0.00
Ownership	0.002	0.17	0.001	0.27	-0.481	0.64
Number of programmes	0.000	0.65	0.000	0.20	-0.225**	0.05
Value of programmes	0.000	0.17	0.000	0.25	-0.022	0.38
Intercept	0.008**	0.05	0.007**	0.04	-10.669***	0.00
F value	2.12*	0.08	2.89**	0.02	3.33***	0.01
Number of observations	458		458		458	

Source: Author's own work.
Note: ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

5.5.2 Removing the Common Trend

One pitfall of the matching method is its dependence on the selection of pre-treatment variables. Even though this study has managed to include as many important variables as possible regarding both suitability and availability, certain unobservable factors may not be included. For example, one may argue that both treated and controlled firms may be affected by the spillover effect (Cerulli 2010). In this case, the matching estimator offers a reliable estimation of the treatment effect only if both treated and controlled firms are affected by the same amount of the spillover effect, which is not realistic. However, if the structure or distribution of the spillover effect on firms does not change over time (at least in a short period), then the DID estimation method would be able to remove this kind of time-invariant variables, and therefore provide more reliable estimates. With this consideration, we further estimate the additionality by combining the matching and DID methods. The results are summarised in Tables 5.11-5.13.

Table 5.11 PSM-DID estimation for input additionality

Outcome var.	2009-2010 Total R&D	Internal R&D	External R&D	2010-2011 Total R&D	Internal R&D	External R&D
Baseline						
Treated	9.640	9.488	6.345	9.481	9.372	5.320
Control	9.563	9.408	6.315	9.426	9.340	4.671
Diff (T-C)	0.070	0.080	0.031	0.055	0.032	0.648
Follow-up						
Treated	9.640	9.540	5.391	9.742	9.661	5.095
Control	9.080	9.000	3.873	9.402	9.321	3.740
Diff (T-C)	0.568***	0.540***	1.518***	0.34*	0.339*	1.355***
Diff-in-Diff	0.498*	0.460*	1.487***	0.285	0.307	0.707

Source: Author's own work.
Note: ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Table 5.11 shows that after controlling the potential time-invariant factors through DID, there is evidence of input additionality of S&T programmes during the period of 2009 to 2010, especially in terms of external R&D. This indicates that engaging in S&T programmes could contribute to wider collaboration of firms with other entities. This is consistent with the argument made by Feldman and Kelly (2006) who found that projects that received R&D subsidies were more likely to join new research joint ventures and connect to universities and other firms. Our results provide new evidence in the context of China. It implies that national S&T programmes might be able to reduce the transaction cost of collaborations, which is beneficial to knowledge transfer and spillover, and results in an improvement in social welfare. From this perspective, national S&T programmes might be effective in creating additionality of social returns rather than private returns. However, this effect no longer exists in the period of 2010 to 2011, which implies that the input additionality is not stable over time.

Table 5.12 PSM-DID estimation for output additionality

Outcome var.	2009-2010 Patent application	2009-2010 Patents granted	2009-2010 VNP	2010-2011 Patent application	2010-2011 Patents granted	2010-2011 VNP
Baseline						
Treated	3.14	2.567	11.241	3.544	2.908	11.147
Control	3.437	2.691	11.365	3.488	2.704	10.794
Diff (T-C)	-0.297	-0.124	-0.124	0.056	0.204	0.354
Follow-up						
Treated	3.72	3.101	11.245	3.99	3.476	11.274
Control	2.948	2.374	11.02	3.135	2.866	11.315
Diff (T-C)	0.772***	0.727***	0.225	0.855***	0.61**	-0.041
Diff-in-Diff	1.068***	0.851**	0.349	0.799**	0.407	-0.394

Source: Author's own work.
Note: ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

For output additionality, Table 5.12 shows that firms with S&T programmes could be much more active in patent-related activities. This finding is consistent with Hu and Deng (2016) who found that firms which received government R&D funding file more patent applications following the receipt of government R&D grants. Bronzini and Piselli (2016) found a similar result in northern Italy. However, it is noticed that the number of patent applications is reported as a critical achievement in the annual reports of S&T programmes. Therefore, this number might be used as a criterion for the assessment of the recipients. It could thus be suspected that firms with programmes may intentionally boost patent applications in order to fulfil the criteria in the evaluation process. Although we also found that treated firms are more likely to have more granted patents, this effect disappears in the later period. Regarding VNP, no significant stimulation effects are found. This is consistent with our argument about the difficulty of commercialisation in S&T programmes.

Table 5.13 PSM-DID estimation for efficiency additionality

Outcome var.	2009-2010 Patent efficiency	2009-2010 Invention efficiency	2009-2010 VNP efficiency	2010-2011 Patent efficiency	2010-2011 Invention efficiency	2010-2011 VNP efficiency
Baseline						
Treated	0.004	0.002	8.524	0.007	0.004	7.612
Control	0.007	0.003	9.005	0.008	0.004	8.567
Diff (T-C)	-0.002*	-0.001	-0.481	-0.001	0.000	-0.955
Follow-up						
Treated	0.007	0.004	7.481	0.006	0.003	7.857
Control	0.007	0.004	8.563	0.007	0.003	8.396
Diff (T-C)	-0.001	0.000	-1.081	0.000	0.000	-0.539
Diff-in-Diff	0.002	0.001	-0.601	0.000	-0.001	0.417

Source: Author's own work.
Note: ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Lastly, there is no significant evidence supporting the existence of efficiency additionality even after we control the common trend of two groups during the two periods (See Table 5.13). This result further confirms the potential crowding-out effect as government R&D fails to raise the private return to R&D.

5.5.3 Robustness

To ensure our results are not sensitive to matching schemes, we further employ different matching algorithms to estimate the ATET effects and check the robustness of the results. Apart from the one-to-one matching method in our main results, in this section we allow the treated observations to have two (NNM2) or three nearest neighbours (NNM3). In addition, kernel matching and local linear regression (LLR) matching are adopted as well to examine the potential sensitivity.

Figure 5.7 and Table 5.14 present the matching quality of those matching schemes. It is graphically demonstrated that the difference between the two groups in each of the four matching schemes is reduced to some extent under the four matching schemes. The distributions before and after kernel matching are exactly the same, which is a result of the kernel matching algorithm itself since the matched control group is fictitiously created via weighted average firms in untreated group. The results in Table 5.14 also show that those matchings are successful as pseudo R^2 values are significantly reduced and the MBS are all very small.

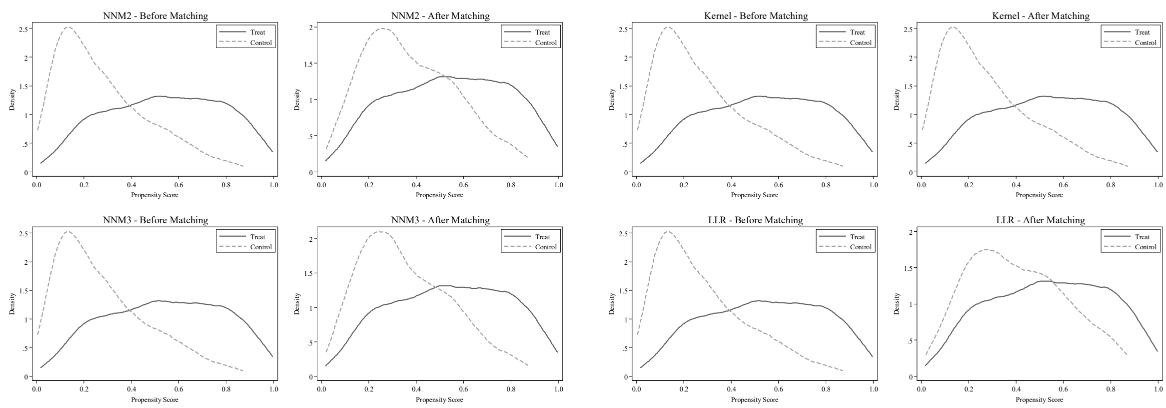


Figure 5.7 Matching qualities of different matching schemes

Table 5.14 Matching qualities of different matching schemes

	NNM-2		NNM-3		Kernel		LLR	
Sample	Ps R^2	MBS%	Ps R^2	MBS%	Ps R^2	MBS%	Ps R^2	MBS%
Unmatched	0.211^{***}	31.5	0.211^{***}	31.5	0.211^{***}	31.5	0.211^{***}	31.5
Matched	0.012	4.1	0.01	4.1	0.003	2.3	0.021	5.2

Source: Author's own work.
Note: ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

Based on these algorithms, we follow the same process discussed in section 4 to estimate the ATET effect and the results are listed in Table 5.15. After comparing results in Table 5.15 with those in Table 5.5, we found that our conclusions drawn in Section 4 are not sensitive to matching schemes, indicating the robustness of our results.

Table 5.15 Additionalities under different matching schemes

		NNM2		NNM3		Kernel		LLR	
Variable	Sample	D	t	D	T	D	t	D	t
R&D expenditure	U	1.1349	11.58^{***}	1.1349	11.58^{***}	1.1349	11.58^{***}	1.1349	11.58^{***}
	ATET	0.0041	0.03	0.0197	0.15	0.0356	0.29	-0.0063	-0.04
Internal R&D	U	1.1025	10.88^{***}	1.1025	10.88^{***}	1.1025	10.88^{***}	1.1025	10.88^{***}
	ATET	0.0097	0.07	0.0276	0.21	0.0434	0.35	-0.0017	-0.01
External R&D	U	2.0255	7.98^{***}	2.0255	7.98^{***}	2.0255	7.98^{***}	2.0255	7.98^{***}
	ATET	0.1894	0.53	0.1604	0.47	0.1614	0.50	0.1475	0.37
Patent application	U	1.2652	9.19^{***}	1.2652	9.19^{***}	1.2652	9.19^{***}	1.2652	9.19^{***}
	ATET	0.1377	0.67	0.0935	0.48	0.0826	0.47	0.0250	0.10
Patent granted	U	1.2474	8.73^{***}	1.2474	8.73^{***}	1.2474	8.73^{***}	1.2474	8.73^{***}
	ATET	0.0850	0.42	0.0976	0.49	0.1106	0.61	0.0485	0.20
VNP	U	0.5852	2.74^{***}	0.5852	2.74^{***}	0.5852	2.74^{***}	0.5852	2.74^{***}
	ATET	-0.2529	-0.84	-0.1948	-0.68	-0.1299	-0.49	-0.1480	-0.47
Patent efficiency	U	-0.0016	-2.02^{**}	-0.0016	-2.02^{**}	-0.0016	-2.02^{**}	-0.0016	-2.02^{**}
	ATET	-0.0007	-0.51	-0.0008	-0.61	-0.0009	-0.85	-0.0009	-0.64
Invention efficiency	U	-0.0003	-0.54	-0.0003	-0.54	-0.0003	-0.54	-0.0003	-0.54
	ATET	-0.0002	-0.21	-0.0003	-0.39	-0.0003	-0.51	-0.0004	-0.39
VNP efficiency	U	-1.7507	-2.15^{**}	-1.7507	-2.15^{**}	-1.7507	-2.15^{**}	-1.7507	-2.15^{**}
	ATET	-0.4122	-0.63	-0.3225	-0.53	-0.8254	-0.81	-0.9002	-1.16

Source: Author's own work.
Note: U for unmatched, D for difference, and t for t-statistics. ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

We also test various kernel types in order to examine the robustness of our findings. The default kernel type is Epanechnikov which has a parabolic-shaped distribution. We also use two alternative types of kernel distribution, namely, Gaussian and biweight kernel to repeat the same exercise in order to test the robustness. The Gaussian kernel function has a much flatter peak and fatter tails, while biweight kernel function has a sharper peak and lighter tails, both in comparison with the Epanechnikov kernel type. The results demonstrate that our estimation is consistent and the conclusions drawn are robust (See Table 5.16). We also tried many other model specifications by changing the covariates for estimation, and the results remain consistent with the findings in section 4[15].

Table 5.16 PSM-DID with other kernel types

Outcome var.	DID-Gaussian		DID-biweight	
	2009-2010	2010-2011	2009-2010	2010-2011
R&D expenditure	0.400	0.273	0.505**	0.276
Internal R&D	0.365	0.295	0.47*	0.298
External R&D	1.402**	0.619	1.507***	0.722
Patent application	0.941***	0.767**	1.089***	0.8**
Patent granted	0.718**	0.446	0.854**	0.383
VNP	0.276	-0.343	0.372	-0.400
Patent efficiency	0.001	0.000	0.002	0.001
Invention efficiency	0.001	0.001	-0.001	0.000
VNP efficiency	-0.379	0.692	-0.631	0.416

Source: Author's own work.
Note: ***, ** and * indicate significance at 1%, 5% and 10%, respectively.

5.6 Conclusion

This chapter assesses the effectiveness of China's national S&T programmes in promoting firms' innovation capability. Unlike previous studies, this study sheds light on the additionality of efficiency performance aside from popular investigation of input and output additionality. This study also emphasizes the underlying indirect support from government S&T programmes in addition to the popular assessment of the effect of direct subsidies, since the certification effects are expected to be stronger in China as the country is transitioning from a planned economy to a mixed market economy (Lerner 1999; Boeing et al. 2016).

Based on a survey of 443 innovative firms in China, this study firstly investigates the determinants of winning S&T programmes. It is found that the firms' knowledge stock and knowledge infrastructure are dominant factors affecting the selection of national S&T programmes, which conforms to China's innovation policy of "picking the winners" strategy. The government's preference to allocate programmes to SOEs has not changed much. This

[15] The results for different settings of covariates are omitted due to limited space and are available upon request.

study finds that small and large firms are more likely to receive public support than medium-sized firms. Certain inertia in public support is observed, while collaboration with universities is emphasised in the selection process. Overall, the determinants of obtaining S&T programmes are highly consistent with the information provided in the application forms as well as the findings by existing studies on China.

By combining the propensity score matching technique with the difference-in-difference method, the additionality of national S&T programmes is estimated, particularly in terms of private return. The results show that the significant difference between treated and controlled groups disappears after matching. Therefore, the effectiveness of S&T programmes in promoting firms' innovation capability might be overestimated. In addition, the negative additionality in R&D investment and efficiency performance indicates that there are potential crowding-out effects and problems with resource misallocation and dissipation when undertaking national S&T programmes. Moreover, the investigation of the heterogeneity of individual treatment effects shows that the stimulation effect of national S&T programmes is greater for large firms, while larger firms are also less stimulated in efficiency performance. Non-SOEs are stimulated to a greater extent in terms of innovation input, while there is no significant difference between SOEs and non-SOEs in other dimensions. It is also found that, as engagement in national S&T programmes deepens, the potential crowding-out effect accumulates and firms' performance worsens. In addition, after removing the time-invariant factors, there is significant positive additionality in terms of external R&D expenditure and patent-related activities, while product-related outcomes did not show significant improvement. Efficiency additionality is consistently insignificant even if the common trend is controlled. Various matching schemes and different model specifications support the robustness of the results and hence the conclusions.

The policy implications derived from this analysis are manifold. First, after comparing the results in this study with those from other studies, we found that the selection criteria are quite similar across different supporting programmes, which might cause some problems. The government should set pertinent selection criteria in line with the aims of various supporting schemes and closely monitor the implementation process. Secondly, the economic justification for national S&T programmes remains questionable as our analysis did not show significant and consistent effects of these programmes on firms' internal R&D investment, product-related output, and efficiency improvement. The authority should pay more attention to raising the private return through facilitating the commercialisation of programme-related products, which may significantly reduce crowding-out effects and improve efficiency. Thirdly, an increase in the amount of government grants does not necessarily increase the additionality effects. On the contrary, deeper engagement in public programmes could reduce the additionality effects. Therefore, S&T programmes should aim to gain more benefit from the certification effects rather than disregarding the efficiency of utilisation and pursuing mass investment.

There are certain limitations in this analysis. Firstly, we were not able to assess the effect of these programmes on social welfare (Lerner 1999). Thus, insignificant results regarding some of those additionalities do not necessarily mean the national S&T programmes are not effective, as their major goal may be to achieve an optimal R&D level and therefore maximize the social benefit. Secondly, this study focuses on national S&T programmes only and hardly touches upon the effect of alternative programme designs. For example, it is argued that policy instruments like tax credits may give more discretion to the firms and therefore are more effective in promoting private innovation activities (Marino et al. 2016). Innovative design in financial products also can contribute considerably to firms' technological innovation. Thirdly, the relatively short time span of our sample prevents us from further investigating the potential lag effects of government S&T programmes, which might be more realistic as these programmes focus on long-term goals. Guo et al. (2017) found that the short-term effects of government-subsidised R&D programmes are stronger than the long-term ones. Boeing (2016) also pointed out the crowding-out effect happens instantaneously, while in later periods it becomes neutral. Thus, it would be ideal to construct a comparison between short-term and long-term effects if more data become available in the future.

CHAPTER 6 – CONCLUSIONS AND POLICY IMPLICATIONS

After decades of economic reform and upgrading from a low-income country to a middle-income country, China now faces the inevitable challenges associated with transforming from imitation to innovation. Indigenous innovation is indispensable to achieve more sustainable growth and avoid the so-called "middle-income trap", especially after enjoying the lower-hanging fruit of technology imports. As the announcement of the *National Medium- and Long-term Science and Technology Development Plan* in 2006, building an innovation-driven economy has been raised to an unprecedented and strategic level for the current stage of development of China. As enterprises become the major player in innovation activities, their propensity to innovate and their interactions with other entities in the RIS are yet to be subject to in-depth exploration. This thesis provides new insights into the understanding of China's innovation development by examining the changing role of China in international innovation as well as the innovative behaviour of Chinese manufacturing firms. Our results are informative and constructive for policymakers who wish to draw relevant conclusions for implementing effective stimulus to encourage firms to innovate and therefore contribute to sustainable growth. This chapter summarises the major findings of the core chapters and discusses associated policy implications.

6.1 Summary of the Major Findings

This thesis examined the determinants of firms' innovative behaviour relating to a resource-based view and regional innovation system (RIS). Specifically, the impacts of academic collaboration and government intervention on firms' innovation performance are investigated in detail. Beginning with a historical analysis of China's changing role regarding innovation, this study explored the extent to which the network of product-embodied R&D in China has changed and how each industrial sector has responded during this transition from being resource-driven to innovation-driven. This study finds that, in accordance with the expansion of the R&D sector as well as the extension of economic linkages with other countries, China is transforming from a technology absorber to a neutral player who is also a significant knowledge producer. However, although China's dependence on foreign technology is significantly reduced, there is still a long way for China to go if it is to become a pure technology creator, once compared with developed countries in terms of the technology multiplier. The domestic innovation system has become much better connected over time. This coincided with the deepening of globalisation, which requires integration of technology in different industries and infusion of knowledge in a diverse of areas. Specifically, three industries have become the most important R&D sources. This renders the network more polycentric, which is a structure more beneficial to technology diffusion. At the same time, the network is grown more evenly distributed in terms of inward linkages, implying that most of the sectors benefited from the intersectoral technology diffusion.

In order to promote indigenous innovation and reduce dependence on foreign technology, business enterprises are particularly important for building an innovative country. Given the systematic nature of the innovation process, it is argued that firms' innovative behaviour is not only affected by their internal resources but also by the regional system in which they are embedded. This study finds that, from the view of internal resources, Chinese innovative firms are generally old, large, exporters, and state-owned. Firms with higher efficiency or a superior level of human resources are more likely to participate in innovation. A better knowledge base, long-term planning and extra subsidies all contribute to raising the probability of engaging in innovation. A high level of liability or debt burden is detrimental to innovation participation, especially at the R&D stage and for mature innovators. It is observed that competition has an inverted U-shaped relationship with innovative behaviour, regardless of measurement type. From the view of the local environment, regional financial development increased the probability of R&D investment but reduced that of producing new products. FDI crowded out innovative activities conducted by local firms, while environmental protection stimulated firms to innovate. Both government support and IPRs have a significantly positive effect on innovation, no matter how innovation is identified. Network completeness negatively affected firms' innovation participation. It is also found that high-tech industries not only invest in R&D more intensively, but also more frequently. SOEs still dominate innovation activity in comparison with other firms.

In addition to an analysis of firms' innovative behaviour in regional innovation systems, a specific investigation of the interaction between firms and universities was performed, as university-industry collaboration is argued to be one of the most effective means to compensate for limited internal R&D capabilities, especially in China. The present study finds that the extensive margin of collaboration is negative, implying that collaboration requires firms to bear greater costs in building absorptive capability and coordination, thereby harming the efficiency performance. Meanwhile, results in terms of the intensive margin show that the frequency of collaboration positively affects firms' innovation efficiency, while the intensity of collaboration is observed to have a U-shaped relationship with innovation efficiency, particularly in the commercialisation stage. It implies that, once firms start to collaborate, they experience benefits as experience accumulates. There is no evidence to support the idea that collaboration works differently across the two innovation stages. In contrast, the regional moderators are found to play different roles in the two stages. The higher level of IPR reduces the contribution of collaboration to R&D efficiency, while local university quality magnifies the impact of collaboration on R&D efficiency. A higher level of regional openness is detrimental to utilising the benefits of collaboration, particularly in commercialisation stage.

Since 2003, China has witnessed a dramatic return to "techno-industrial policy" which involves direct government intervention in shaping specific industrial sectors. This shift has encouraged a new round of discussion and debate about the effectiveness of government interventions in fostering innovation. The findings in this study suggest that the effectiveness of S&T programmes in promoting firms' innovation capability might be overestimated. These findings also imply potential crowding-out effects and suspicious problems in terms of resource misallocation and dissipation associated with S&T programmes. At the individual level, larger firms are generally more stimulated by national S&T programmes, particularly in terms of input and output additionality rather than efficiency additionality. There is no significant difference between SOEs and non-SOEs, except in input additionality, which is stronger for non-SOEs. It is also found that, as engagement in national S&T programmes deepens, the potential crowding-out effect will accumulate and firms' performance worsens. After removing the common trend, there is positive and significant additionality in terms of firms' R&D investment during the period of 2009 to 2010, especially in terms of external R&D expenditure. Significant additionality concerning patent-related activities is observed as well, while product-related outcomes didn't show any improvements. Efficiency additionality is consistently insignificant even when the time-invariant factors are considered.

6.2 Policy Implications

This study suggests some important policy implications for China, especially during the transition to an innovation-driven economy. First, although the dependence on foreign technology has been reduced significantly as the R&D sector expanded, there is still a considerable way to go if China is to become a pure technology provider. Therefore, the way in which foreign knowledge spillovers can be utilized, as well as strategies to enhance indigenous innovation harmoniously, should be the priorities for the current stage. Furthermore, intersectoral interactions have become increasingly important in supporting the innovation-driven growth of China. Thus, the government should make greater efforts to reduce the barriers and lower the transaction costs for integrating the upstream and downstream sectors and encourage collaboration across sectors.

Secondly, firms' innovative behaviour is not only affected by internal resources but also by the systems in which they are embedded. Therefore, the key policy implications of this study are centred on ways in which the government can utilize these contextual factors in order to leverage influence or to complement firms' internal resources. Specifically, firms' R&D activities are inhibited by a lack of financial resources as well as the fear of knowledge leakage if they obtain finance from external sources. Therefore, when promoting the regional financial development to release firms from financial constraint, the local authority should implement stringent protection of intellectual property rights as well. Otherwise, the commercialisation process will be negatively affected. In addition, the government should manage the level of competition at a reasonable extent to maximise its stimulation effect on innovation, as competition that is too fierce will destroy firms' incentive to innovate. Moreover, SOEs are found to play an important role in innovation, which may be driven by government policies or inherited from the former central planning system. In order to achieve more sustainable and efficient development as well as fully explore the potential of the private sector, pertinent policies are required to encourage or support non-SOEs to participate in innovation more intensively and frequently.

Thirdly, a positive intensive margin indicates that firms' efficiency in terms of innovation can be improved via collaboration. However, a negative extensive margin implies that firms bear certain coordination costs before they can benefit from collaboration. Therefore, the local authority should target smoothing of the early stage of collaboration by providing financial incentives in order to reduce the costs associated with building trust between collaborating parties. Additionally, absorptive capabilities also play an important role in successful collaboration. Therefore, it might be effective to establish some information sharing centres or common technology platforms to accelerate the deepening of collaboration processes. Moreover, regional moderators provide the local government with handy leverage tools for adjusting the inconsistent performance of the two innovation stages in terms of efficiency. Particularly, the quality of local universities is important for successful collaboration in improving R&D efficiency. Thus, reinforcing local tertiary institutions might be an indirect but effective way to improve firms' R&D performance.

Fourthly, this study suggests that the economic justification for government intervention, particularly the national S&T programmes, remains questionable as our analysis did not find any significant and consistent contribution from public support on firms' innovation performance. Therefore, the authority should pay more attention to raising the private return through facilitating the commercialisation of firms' innovation, which might be beneficial to reducing the crowding-out effects and improving the efficiency of resource utilisation. The similarity in terms of selection criteria across different supporting programmes might cause some problems. The government should set relevant selection criteria in line with the aims of various supporting schemes and closely monitor the implementation process to minimise the misallocation and dissipation of research funds. The results also revealed that a greater volume of government grants does not guarantee additionality effects. Thus, government intervention should focus on highlighting the certification effects rather than providing massive investment, which exhibits decreasing efficiency.

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