INNOVATION EFFICIENCY OF HIGH-TECH INDUSTRIES IN CHINA

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Abstract

A measurement of technical innovation efficiency reflects the competitiveness of the high-tech industry for a region or a country. The high-tech industry, which appears at the forefront of technology and scientific research, provides a country with a certain competitive advantage. Many developed countries such as the USA, UK, Germany and France, have used the high-tech industry as a means to emerge on the technological frontier. Many developing countries such as China and India have developed high-tech industries, and are home to many leading product manufacturers. However, innovation efficiency is important, since it explains the efficiency of the high-tech industry in consuming resources and providing outputs. This dissertation examines the innovation efficiency of the high-tech industry in China. The Data Envelopment Analysis (DEA) method was used to study and analyse panel data. The study focused on 28 high-tech provinces of China (DMUs, DMU: Decision Making Unit), during the years 2005-2011, along with 5 industry categories and 17 industries. Different datasets were obtained to measure the input and output indices. Variables included in the inputs index included the number of full time R&D (Research and Development) personnel, internal expenditure on R&D, expenditure on new product development, and investment in fixed assets. The output index included the number of patent applications, the output value of new products, and sales revenue for new products.

The Malmquist index was calculated using static data analysis cases using Deap2 software in both cases. Several tests were employed in the analysis of the data, including the KS Test (Kolmogorov-Smirnov Test), T test (Student's t test), integral analysis, SE efficiency analysis, project analysis, total factor productivity and others. The findings indicate that the M index is unstable across the 29 provinces, and 17 industries. The Malmquist index of each DMU changes in different degrees during the 7 years. In addition, the changes have no pattern, they go from descending to rising and then declining again, or from rising to descending and then rising again. The reasons for the unstable M index were evaluated, and it becomes evident that several factors such as a total factor productivity variation, EC, TC degradation, excessive man power resources that increased the input costs. Another factor that makes the M index unstable is that many of the inputs for China were obtained from western regions, with little original research. The study also examined the STP (Science and Technology Policy) policy of the developed western countries, BRIC nations, and China, and the areas for improvement were identified. The study has made several recommendations to improve the STP policy, and for the high-tech industry to increase the innovation efficiency.

Chapter 1 INTRODUCTION

1.1. Background to the Study

Globalisation brought China into the world of modern consumerism, and the huge pent up potential of the people and its industries grew to meet the increasing demand from the world for more and more products (Tisdell, 2009). The high-tech sector comprises of contemporary technology products and services, covering robotics, integrated chips, mobile telephony, advanced digital electronics, new materials such as carbon fibres and nano-engineered materials, electro-mechanical engineering devices, etc. spanning communication, and several other fields (Spraggon & Bodolica, 2008). High-tech products are used in a number of sectors such as automotive, manufacturing communication, medical sciences, computing, robotics, consumer electronics, industrial automation, and other fields (He & Fallah 2011). Countries with high-tech industries develop a competitive advantage, and the general technology awareness of the country and its people increases (Lundvall, 2010).

This gives rise to opportunities for the knowledge economy to develop, helps to increase the intellectual capital of the country, and provides for all round growth of the economy. However, high-tech industries require innovation, the development of new concepts, effective research and development, and the addition of dynamic knowledge (Audretsch et al. 2008). The focus of this dissertation is on the efficiency of innovation in high-tech industries in China, and innovation by Chinese firms to make use of the opportunities of this sector.

1.1.1. Defining High-tech industries

The high-tech industry in China is defined as a group of companies that are engaged in one or more of the following: high-tech and high-tech product research, development, production and technical services. The dominant technology in their products must belong to the identified high-tech fields, and must include leading high-tech processing or technological breakthroughs (Zuoxing, 2010).

According to China's Statistical Yearbook on Science and Technology (NBS, 2014), the high-tech industry includes the following five parts manufacturing of medical and pharmaceutical products, manufacturing of aircraft and spacecraft, manufacturing of electronic and telecommunications equipment, manufacturing of computers and office equipment, and manufacturing of medical equipment and meters. The dissertation is going to follow a similar classification and discuss them later in detail.

1.1.2. Importance of the High-tech Industry

Since the 1980s, with the diffusion of technology brought on by globalisation, the high-tech industry has become an important area of international economic competition (Liu & Tsai, 2007). The development of the high-tech industry has promoted the growth of national economies, and the sector has become an area of focus for many countries as it adds significant value to their economies (Birch & Mykhnenko, 2009). Germany, the UK, the USA, and Japan have been acknowledged as nations with advanced high-tech industries. From 1980 onwards, countries such as Taiwan, Singapore, South Korea, have become high technology hubs, and these countries serve as crucibles of growth for high-technology sectors (Pratt, 2008).

The importance of high-tech industry is that it allows a country to move up the value chain. The process allows diffusion of advanced technology in the industries, and to move towards having more technology based firms, rather than those that are labour intensive. The reputation in the market increases, increasing revenues and firm performance (Li, 2009). Governments have realised that progress in science and technology is the basis for upgrading the structure of an industry and for economic development, and this is a critical factor in determining international competitiveness, especially for developed countries (Huang et al. 2010).

In order to strengthen a state's economic, scientific, and technological competitiveness, and to gain a strong strategic position, governments have to adjust their development strategies to encourage, support and guide the development of high technology and industry through the establishment and implementation of industrial policy. This will enable the high-tech industry to become the fastest growing and most viable industry in the modern world

(Zhongfang, 2008). Table 1-1 illustrates the advantages of the high-tech industry.

Table 1-1: Benefits of the high-tech industry

	Direct benefits	Indirect benefits
Foreign Exchange earnings	■	
FDI	■	
Employment generation	■	
Government revenue	■	
Export growth	■	
Skills upgrading		■
Testing field for wider economic reform		■
Technology transfer		■
Demonstration effect		■
Export diversification		■
Enhancing trade efficiency of domestic firms		■

Source: Shi & Ganne (2009)

1.1.3. Rationale for the study

According to a report by Oracle, while the high-tech industry presents first mover advantages to the pioneers, firms need to constantly innovate and develop new products and design concepts. The high-tech field changes rapidly, and this is seen in sectors such as mobile telephony, computing devices, robotics, automotive electronics, semiconductor devices, and others (Oracle, 2014). Resource allocation decisions must be based on market intelligence, and an ability to judge the market. With low IPR, unless firms innovate and move rapidly into new technologies, they lose out the market to competitors.

Therefore, timing the market with regular upgraded product launches becomes important, and it decides the winners and losers (Mata et al. 1995).

According to Fontana and Nesta (2007), product innovation in the high-tech industry is directly related to the success and survival of firms. The authors studied 121 high-tech firms in USA, to understand the patterns of growth and survival. Firms that developed new products and services had a survival rate of 70%, while firms that did not launch new products were either acquired or began suffering and closed down. One critique of this study concerns the fact that larger firms may acquire the profitable firms. Cockbrun and Wagner (2007) studied 356 firms and their performance after the dot.com bubble. Using patent applications to judge the level of innovation, the authors reported that firms with a larger number of patents had a greater probability of survival, while reducing the possibility of mergers and acquisitions. Firms with a number of lucrative and sought after patents had a greater chance of being acquired.

Hall et al. (2005) rejects the proposition of using patents as a sign of providing economic value. They argue that the quality, market demand and innovative capacity of the firm are the main indicators of a firm's chance for survival. Therefore, the economic performance of innovative firms becomes important, and not the number of patents they hold. Bontems and Meunier (2006) point out that for firms to become innovative, they need to become a part of the technology frontier. This means the provision of special technology parks, and assistance that nurtures and aids innovation.

The assessment of the above discussion indicates that innovation efficiency of the high-tech industry therefore depends on a number of factors. The issue of innovation in China therefore needs to be understood at greater depth. This study will help to assess if the current state of innovation in China is sustainable, if the firms will survive, and the steps needed to reach a sustainable competitive advantage in the high-tech industry.

1.1.4. China and the High-tech industry

With the advent of globalisation, and the opening of the Chinese economy, China initially became a source for low cost labour, and it served as an outsourcing hub for western firms, which needed low cost manufacturing of apparel, shoes, toys, low cost engineering and electrical products, and hardware items (Zhongfang, 2008). However, since the early 2000s, China has entered the field of high-tech products and services. As a knowledge-intensive and technology-intensive industry, China's high-tech industry has undergone rapid development over time (Liang et al. 2007). The Chinese export trade volume arising from the high-tech industry reached $5.488 trillion in 2011 (NBS, 2014).

China has become an important production base for high-tech products worldwide and has promoted the national industrial structure adjustment and product technology upgrading. These have become important forces stimulating China's economic growth, and transforming the economic growth pattern, with China having an average Gross Domestic Product (GDP) growth rate of 9.82% from 1979 to 2008 (Zhang et al., 2011).

Interestingly, the development status of the high-tech industry has a direct impact on China's international standing in the world economy. The Chinese high-tech industry is one of the fastest-growing industries in the country. Contribution to the GDP from the high-tech sector has increased steadily from 2005, and in 2013, it reached a value of ¥8843.39 billion (NBS, 2014). However, in light of the discussion from section 1.1.2, the sustainability of current innovation needs to be assessed.

1.1.5. Development of STIP in China

Science and Technology Industry Parks (STIP) are special enclaves, where new age industries are encouraged. These parks have a special status benefitting them with lower taxes, modern infrastructure, subsidised rents, availability of power and other amenities and provision of loans, all of which are needed by high technology industries. These STIPs act as knowledge and incubation centres, where new age industries are encouraged to grow. A number of countries such as the UK, Germany, Japan, the USA, Taiwan, Singapore, and other countries have set up STIPs. These areas have contributed strongly to the growth of high-tech industries (Zhang & Sonobe, 2011). With the rapid development of the high-tech industry in China, the Science and Technology Industry Parks (STIP) scheme has played a key role in promoting the transformation of science and technology into products and services, incubating high-tech enterprises and entrepreneurs and cultivating new economic development (Wang & Yan, 2009).

The Chinese government established several STIPs and new and high-tech innovation centres. From 1988 to 2012, 105 High- and New Technology Industry Development Zones (HNTIDZs) have been approved as National STIPs by the State Council. In recent years, HNTIDZs have made great strides, achieved tremendous success and found a new path for China's characteristics in developing high- and new-technology industries (NBS, 2014). Table 1-2 gives details of the growth of HNTIDZs in different areas of China.

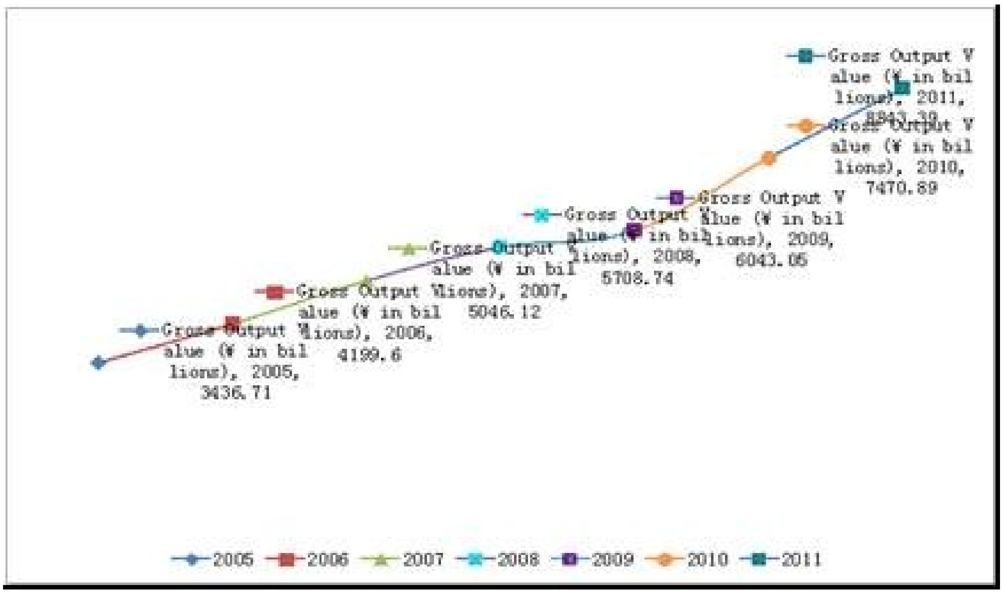
Table 1-2: State-level HNTIDZs & Geographic Distribution in China

Geographic Location	No.	%	HNTIDZs Locations
Northeast	13	12.38	Harbin, Changchun, Jilin, Daqing, Shenyang, Anshan, Dalian
North	22	20.95	Beijing Zhongguancun, Tianjin, Zhengzhou, Shijiazhuang, Taiyuan, Jinan, Baoding, Luoyang, Qingdao, Weihai, Zibo, Weifang
East	23	21.91	Shanghai, Nanjing, Suzhou, Wuxi, Changzhou, Hefei, Hangzhou, Nanchang
Coastal Area	14	13.33	Guangzhou, Shenzhen, Fuzhou, Xiamen, Zhongshan, Huizhou, Foshan, Zhuhai, Haikou
Central	9	8.57	Wuhan, Changsha, Xiangfan, Zhuzhou
Northwest	13	12.38	Lanzhou, Baoji, Xi'an, Yangling, Baotou, Wulumugi, Changji, Yinchuan, Qinghai
Southwest	11	10.48	Chengdu, Chongqing, Kunming, Mianyang, Guiyang, Guilin, Nanning
Total	105	100.00	

Source: Zeng (2014)

The rapidly growing high-tech industry has some level of statistically significant impact on China's economy. Figures 1-1 and 1-2 show the increase in China's gross output value, investment, and expenditure on R&D in high-tech industry respectively.

Figure 1-1: Rise in China's Gross Output Value in the high-tech Industry



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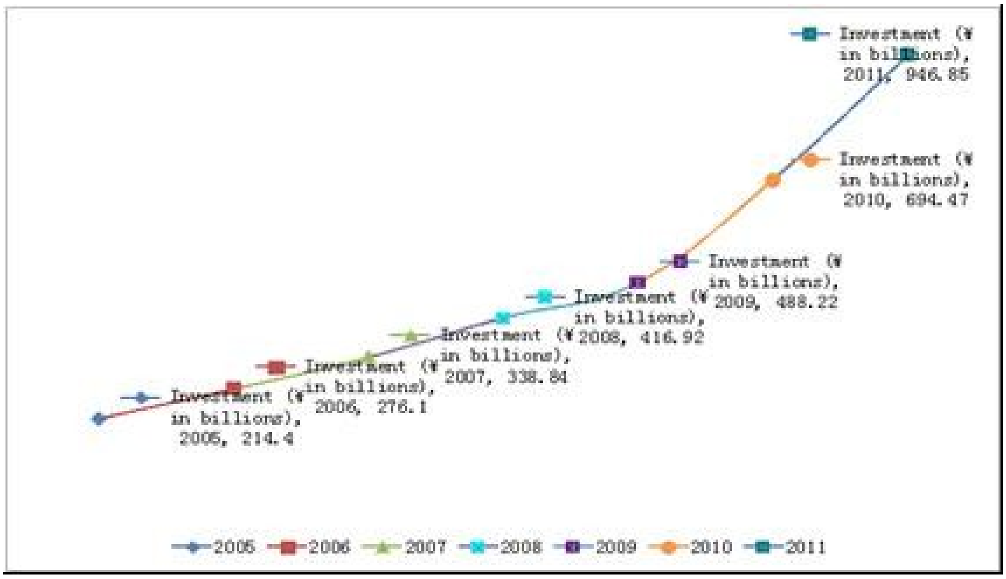
Source: NBS (2014)

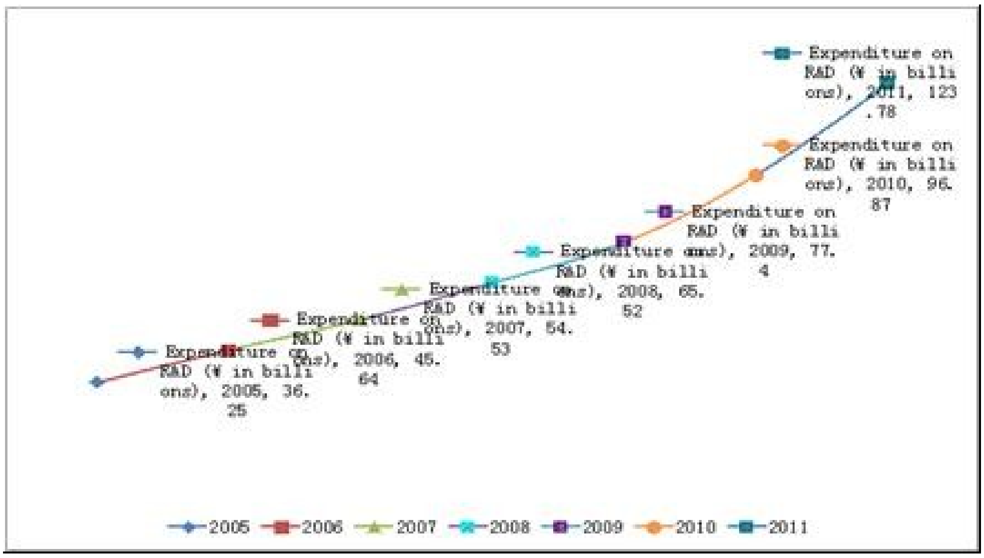
Figure 1-2: Rise in Investment in the high-tech Industry



Source: NBS (2014)

As can be seen in Figure 1-3, the investment in China's high-tech industry from 2005 to 2011 followed a growth trend similar to that of the gross output value, and reached a peak at ¥ 946.85 billion in 2011. There is a link between the growth of high-tech industry, and investment. The following figure illustrates the rise in expenditure on R&D in the high-tech industry.

Figure 1-3: Rise in expenditure on R&D in the high-tech industry



Source: NBS (2014)

The above statistics indicate steady progress in the high-tech sector in China. As per the findings in section 1.1.2, the extent of performance improvements need to be verified, since the high-tech industry is very competitive. Innovation and its quality become the deciding factors.

1.2. Important considerations for the study

The brief discussion from the previous sections has brought up some important factors. In recent years, technological innovation has been recognised as the engine for economic growth (He-Cheng, 2008). The increase in the input and output of technical innovation has become the critical factor that determines the rapid development of the high-tech industry in long term, and its influence on regional economic growth and competiveness. Thus, seizing and utilising technical innovation resources as well as ways in which the technical innovation efficiency of the high-tech industry can be enhanced have become the focus in current international competition. Consequently, improving China's high-tech industry technology innovation capacity is becoming increasingly urgent and necessary (Li, 2011).

However, the industry faces several challenges due to intense international competition, uncertainty derived from the transformation and structural adjustment of industries, and other serious challenges of the scientific and technological revolution. Since the investment scale of innovation resources is restricted by the regional economic development level and regional knowledge basis, an increase in innovation performance in output becomes an important method to enhance innovation capacity within a certain input scale for innovation resources, which request to improve technical innovation efficiency of the high-tech industry (Fang et al. 2007).

To enhance the technological innovation efficiency of the high-tech industry, a key issue that needs discussion is the way in which the technological innovation efficiency of the high-tech industry can be evaluated (Ernst & Naughton, 2007). The high-tech industry represents the comprehensive power and competitiveness of a nation. Hence, it is closely correlated to a nation's economic growth and social development. In today's intensively competitive global market, high tech industries have experienced rapid growth and played a critical role in promoting China's economic growth (He-cheng, 2008).

1.3. Areas in which further research is required

It is clear that the China's high-tech industry has grown rapidly, and the scale is expanding continuously. However, the sector faces a number of problems and these include large-scale investment, without assessing the efficiency and capacity for technological innovation. These issues reduce the ability of China to compete in the global marketplace. Under these conditions, it is important to study innovation efficiency. The subject of innovation in China has attracted attention from researchers all over the world (Suttmeier, 1997; Motohashi & Yun, 2007; Lindheimer et al., 2009). Many studies have explored innovation in China from multiple perspectives, and there have been significant achievements owing to these studies. For instance, Lai et al. (2005) used the semiconductor industry in Shanghai as a case study in his discussion on technological innovation.

Suttmeier (1997) discussed the emerging innovation networks and changing strategies for industrial technology in China. Liu et al. (2013) proposed a generic framework for analysing innovation systems and applied it comparatively with regard to China's national innovation system under central planning and after the reforms. Motohashi and Yun (2007) investigated the linkages of science and technology activities between industry and science statistically from a firm-level perspectivein China. Lindheimer et al. (2009) looked at style innovation in business and technology in China. Luan and Zhang (2011) empirically analysed patent data and related law and policies of innovation in China during the 1985 to 2009. However, the previous studies have a number of drawbacks. Based on an evaluation of literature from the prior sections, it is evident that there are a number of areas requiring further research to be conducted. Firstly, most studies focus on innovation efficiency in developed countries, while the empirical results of such studies in developed countries cannot necessarily be blanketly applied to the Chinese case. The conclusion drawn do not necessarily fit in with the specific contextual case when considering China. Secondly, the existing literature on innovation efficiency research focuses on enterprise innovation efficiency from the micro level, but does not analyse high-tech technological innovation efficiency at aggregated levels. Thirdly, these studies do not analyse the factors influencing innovation efficiency in detail. It is important to study such influencing factors in terms of policy value. As the reasons for low innovation efficiency are determined, policy suggestions for enhancing industry innovation efficiency can be suggested. Fourthly, in the area of selecting innovation output indicators, most researchers selected a measure of the sales revenue of new products as an indicator of output. These actually reflect the transformation ratio of innovation output, while the number of patent applications is the basis of innovation output.

Thus, there are a number of areas which have been identified either as lacking in the current literature base, or as needing refinement, new research and exploration at differing levels of aggregation. In particular, there has been no comprehensive and detailed analysis of factors affecting innovation efficiency in China, no aggregated study beyond the micro-level and little exploration into alternative measurements of innovation output and the ramifications of using these in models.

1.4. Research Objectives and Questions

The growth of China's high-tech industry requires large investments. With quick obsolescence, and frequent technology upgrades, the sector requires a higher efficiency for the development of products, and revenue generating mechanisms. It is clear that technological innovation is important for the long-term sustainability of the high-tech industry. Since China opened its economy, and unleashed its economic might, it has been perceived as a nation of 'sweat shops' where cheap labour is available to perform low-tech jobs (Jun & Huixin, 2010). The high-tech industry provides an opportunity for China to emerge as a hub for modern, technological growth, increase the efficiency, and help the country to compete with advanced nations. An important requirement to achieve these goals is to increase the efficiency of the high-tech industry.

Considering that this sector requires high volume of research along with funds and a highly skilled workforce, it is imperative that the efficiency of innovation must be improved (Lan & Fen-Mian, 2008). Technological innovations are achieved through a long and complex process, involving the phases of searching, selecting, implementing and capturing value (Feng & Teng, 2010). Therefore, improving the technological innovation efficiency is the key to improving the efficiency of the entire industry. The purpose and research questions of this dissertation can be distilled into the following points:

- To analyse China's high-tech technological innovation efficiency and to carry out an empirical analysis for different provinces and locations, based on panel data for China individual provinces.
- Evaluate China's high-tech technological innovation efficiency and derive data for each high-tech industry, based on the panel data for five different high-tech industries in China.
- Make recommendations to improve China's high-tech technological innovation efficiency in order to stimulate and inform policy in this important area.

1.5. Research Methodology

The research will use Data Envelopment Analysis (DEA), suggested by Charnes et al. (1978), Banker et al. (1984), and Fang and Zhang (2009). This method would be applied to analyse and evaluate high-tech technological innovation efficiency. DEA is a fractional mathematical programming method that can deal with multiple inputs and multiple outputs simultaneously (Chen et al., 2004). Secondary data will be derived from volumes of the China Statistical Yearbook on Science and Technology, and will include four input indicators and three output indicators covering 28 provinces and five high-tech industries in China from 2005 to 2011. This duration is considered, since data is available for these years. Output indicators include combining sales revenue of new products, the number of patent applications and gross value of new products. Input indicators include R&D activities of personnel equivalent to full-time equivalent, R&D Intramural expenditures, new product development expenditures and investment in fixed assets.

1.6. Structure of the Dissertation

This dissertation is organised into chapters which explore a specific area of study. Chapter 1 discusses the background, purpose, questions, methodology, importance and structure of the study. Chapter 2 reviews relevant literature on related concepts and technological efficiency in the high-tech industry. Chapter 3 introduces the research method in detail. In Chapter 4, the data analysis procedures and results for different provinces are reported. In Chapter 5, the data analysis procedures and results in 5 different high-tech industries are reported. In chapter 6, some countermeasures and suggestions on improving the innovation efficiency of China's high-tech industry are put forward. In Chapter 7, science and technology policies and the efficiency of technological innovation are compared between nations. This chapter concludes with a discussion of the results, evaluation of the contributions and limitations of the research, and suggestions for future research.

Chapter 2 LITERATURE REVIEW

2.1. Introduction

This chapter critically evaluates several important concepts related to the research question of innovation efficiency in the Chinese high-tech sector. High-tech is about technology and its application to develop new products and upgrade new processes. As seen in section 1.1.1, the high-tech industry includes five aspects: manufacturing of medical and pharmaceutical products; manufacturing of automobiles, aircraft and spacecraft; manufacturing of electronic and telecommunications equipment; manufacturing of computers and office equipment; and manufacturing of medical equipment and meters (NBS, 2014). This classification ensures that the major manufacturing, processing, and design activities are covered. However, these industries are diverse, and one could argue that innovation in pharmaceutical industries is not related to innovation in spacecraft. This argument is relevant, but by focusing on the innovation efficiency of only one sector, the dissertation would ignore the advances and opportunities available in other sectors. Rather than focusing on one sector, this chapter reviews the literature on important concepts and practices of innovation. Some of the topics discussed are the high-tech industry, the concept and measurement of efficiency, technology innovation and its application to the high-tech industry. The discussions will be focused and applied to the China and its high-tech sector. Occasional references will be made to the high-tech industry in other countries.

2.2. The high technology industry

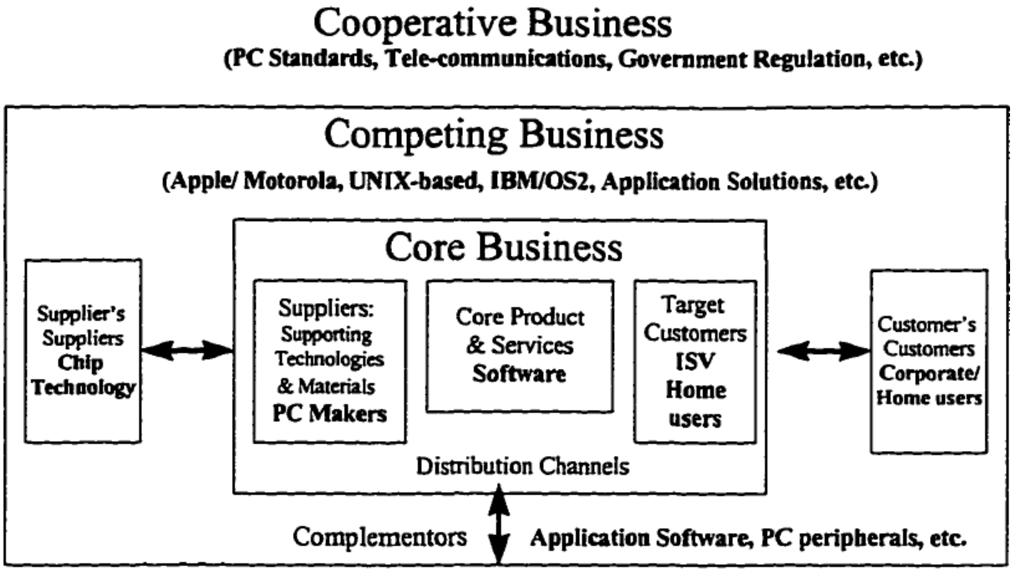
Some differences are seen in the definition and categorisation of high-tech industries, and these have an impact on the research question. One school of thought proposed by the American Electronics Association suggests that only firms that organisations with the goal of promoting high-tech use must be considered, while the U.S. Bureau of Labour Statistics argues that all firms, consumers, and outsourcing parties that use high-tech must be considered in the definition. These classifications are important, since the measurement of innovation efficiency differs across industries and consumers. This also raises the question of whether high-tech should only consider the process used for the manufacture, or the product, or the use and implementation of the technology (Kelley School of Business, 2014). This section discusses several important topics related to the subject. It is first important to discuss the value chain and how value is captured, since this will aid us in developing suitable methods to measure innovation efficiency.

2.2.1. The high-tech industry value chain

The high-tech sector operates with a complex supply chains, characterised by thin inventories, complex products, volatile product life cycles, narrow margins, and quick obsolescence. Apple with its iPhone supply chain sold 170 million units in 2014, and the typical inventory of parts supply at any given time is less than 5 days (Statista, 2015). This short inventory is one of the innovation methods used by many Chinese vendors who use the short window to procure the exact amount of parts needed, thus avoiding blocking funds in idle industry. In addition, the volatile nature of the electronics and integrated chips markets ensures that the vendors are able to get benefits of price reduction. Such practices also help the manufacturers to cater to changing customer demands (Sheffi & Rice, 2005). Therefore, understanding the value chain of high-tech industries is important in answering the research question.

The high-tech industry is configured to create value for upstream, downstream, and horizontal businesses. The high-tech industry value chain and business has three levels: a core business; competing business; and cooperative business. The core business of the firm is made up of the core products and services, suppliers, and various marketing and distribution channels, which deliver the items to the customers. The second layer is made up of the competing businesses, and these rivals offer the same or similar value proposition to the customers (Saenz et al. 2007). The value proposition is cost, quality, convenience, add-on services, brand identity, or a combination of these factors. To gain a competitive advantage, the organisation needs to innovate and improve its value proposition to the customers; otherwise, it loses its market share. Cooperative businesses are the group of shareholders, investors, government rules and regulations, and infrastructure needed for the organisation to survive and grow (Prahalad & Hamel, 1990). The following figure illustrates the business environment and value system for Microsoft.

Figure 2-1: Business environment for Microsoft



Source: Juang (2007)

Consider firms such as Apple, Intel, Microsoft and many others that are regarded as high-tech firms. The core business functions use innovation to create new products and services for new technologies and markets. Several interrelations appear in the innovations for the high-tech market. The innovation value chain in the high-tech industry is described as follows. Consider now the case of Windows, with its Windows operating system. Windows involves ongoing innovation with the development of new products such as Win XP, Win 2003, Min ME, Win 8/9/ 10, and so on. These operating systems need large amounts of computing power, and since Microsoft does not make computers and other hardware, firms such as Dell, Lenovo, HP, IBM, and others, innovate and develop more powerful computers (Niosi, 2011). The 'brain' of these devices is the processor and Chip, and Intel innovates its line of chips and processors to develop a range of processors starting with PI, II, to Quad Duo, and I7 processors. Software developers like SAP, Oracle, and others now innovate and develop very powerful software applications to make use of the large computing power. The customer at the end of the value chain has the option of using these advanced products and services for business and personal needs. Therefore, the value chain begins with innovation in one high-tech firm, and then moves rapidly through the value chain (Wang et al. 2011).

In the case that any one of the entities such as Microsoft or Intel does not innovate, innovation does not then stop. What tends to happen is that the competing businesses step in and provide the required services. Intel initially dominated the processor and chip market. A number of other chip vendors have emerged, and these include Samsung, TI, Toshiba, Qualcomm, and many others. The vendors who innovate and develop products according to the requirements of the market survive and grow, or else other manufacturers replace them. Therefore, innovation is the key to survival and growth in the high-tech sector (Christensen et al. 2008).

The value creation process for innovation is directed at the organisation's core business process. The value generated through innovation is a perceived value, or the perception of the value among various business entities. Organisations develop innovation by cultivating the technological opportunities and trends that add to the core product values. True innovators take the lead and develop new products, becoming lead innovators. An example is Intel, which developed a number of chips and processors, forcing other firms to develop matching products. Once the innovation is ready, the firm must develop the market advantage by using sales channels, advertising, alliances, and enlarge the perceived product value (Jacobides et al. 2006).

There is a further need to collaborate with other parties to increase the perceived value. Four factors help to determine the perceived value, intra value, inter value, business environment, and technological progress. Intra value refers to the value contributed directly by the core business. These include product features, service, quality, price, and brand image. The inter value helps and guides other entities to add to the intra value. Examples include the brand name, market size, short lead time, and low cost. This helps other firms to apply the innovation in the business environment (Lepak et al. 2007). The business environment includes the infrastructure needed to support the value creation and supply in the target markets. An innovation has a limited life, and this is seen in several products such as smart phones, computers, and electronic products (Prahalad & Ramaswamy, 2004). The business environment in turn influences the technological progress. The technological progress represents the innovation and the value creation. Intel introduced 4 bit and now sells 64-bit processors through constant innovation.

2.2.2. Capturing value from innovation

Understanding the methods used to capture innovation bears an important relation to the measurement of innovation efficiency. The previous section discussed various highly popular and famous innovative products. However, many organisations err in not assessing and identifying how innovative practices and even small changes in innovation can lead to product improvement, improvement in manufacturing, design, and other organisational processes. Organisations invest a large amount of effort and funds into developing innovations, and suitable methods and frameworks are needed to capture these innovations and derive the appropriate 'rent' from their investments (Adams et al. 2006).

Teece (1986) proposed the 'profiting from innovations' framework that explains the methods and manner in which late entrants can impact innovators. The model describes the manner in which profits from an innovation are shared between innovators, imitators, customers, suppliers, and the owners. Gans and Stern (2003) proposed the 'market of ideas' model and suggested other concepts such as competitive reactions and type of appropriability. The authors speak of asset mobility, where the innovation is dispersed widely. These models find some criticism from Durand et al. (2008) who point out that the models ignore innovation features such as the number of potential application domains. Pisano (2006) brings out various other factors that are ignored while capturing innovation value; these include pricing, legal protection, barriers to imitability, and extent of profits expected.

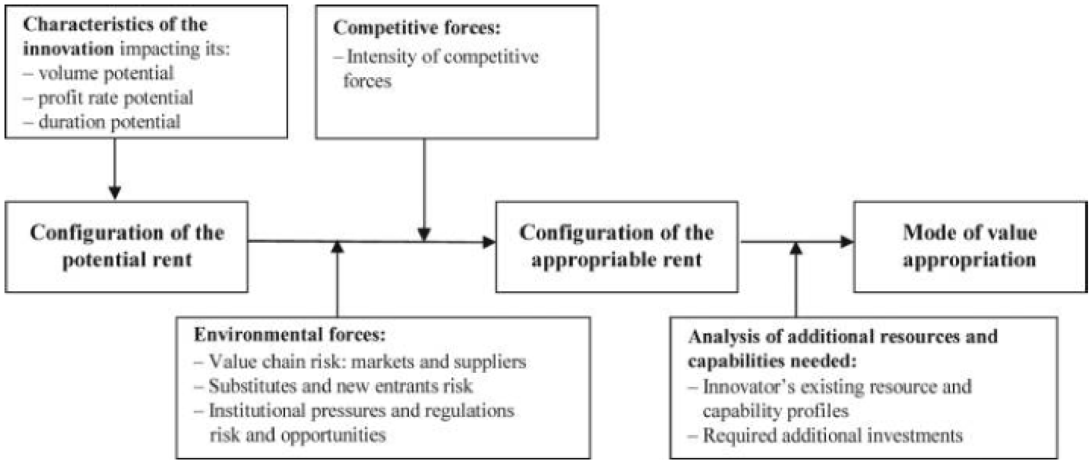
Maine and Garnsey (2006) focused on the importance of funding and availability of complementary resources to match technology and market applications. Several authors such as Colombo et al. (2006) and He et al. (2006) speak of the need for commercialisation of innovations and value appropriation. There is a need for clear commercialisation strategies, since firms invest in the innovations, and need above average profit for growth and survival. Cohen et al. (2000) speak of developing the capacity to assess future profits, since it provides the required incentive to explore the project.

While the above research sheds light on the needs and characteristics of innovation value, a certain gap is obvious, since they do not speak of specific measures needed to capture innovation value. Mu and Di Benedetto (2011) speak of the need to develop a strategic orientation for a sustained and successful commercialisation of innovations. The strategy needs to include the application domains, pricing and costing, and barriers to imitation. According to Durand et al. (2008), a larger downstream diversity may produce a larger opportunity; however, it can become complex, difficult to manage, and dilute profits. Liozu et al. (2012) point out that pricing is left to the discretion of the innovators, who can either sell the product at lower margins and higher volumes, or demand a higher premium. Apple iPhones and devices use the latter strategy, commanding a very high premium. Therefore, price premium depends on the bargaining strength of the innovator.

Duhamel et al. (2014) proposed a model for rent configuration where rent is the return derived from an activity that is more than the minimum required to attract resources to complete the activity. The rent receivable is identified by the value streams, obtained from the innovations that can be used by innovators, after due considerations of the various investments. Value is derived by an entity in the transaction as the sum of the readiness to pay of customers, minus the opportunity cost of the supplier (Porter, 1980). Resources are the various inputs given to the production process, and the capabilities as the capacity for the group of resources to carry out a task (Grant, 1991).

Going back to the model of Duhamel et al. (2014), rent is organised as per three dimensions that consider the total projected cash flows obtained from the innovation and include the duration length (L), profit margin (P), and volume (V). An index is assigned to these three dimensions with a capital letter for a strong level, along with a small letter for a weak level. This arrangement helps to derive 8 combinations for rent levels, namely, C1 (v, p, l), C2 (V, P, L), C3 (v, P, l), C4 (V, p, L), C5 (v, p, L), C6 (V, P, l), C7 (v, P, L), and C8 (V, p, l). Innovators will decide the levels of these indices. This arrangement allows potential rent configuration through different instances. The potential rent is obtained through special features of the innovation. It is possible that the potential rent can reduce or increase when the innovation is launched in the market. A number of external forces that change the bargaining position, and factors arising from regulatory forces, the competition activity, influence the appropriable rent. In addition, the nature of innovation, various controls needed for the resources, and capability for successful development influence the rent (Alegre & Chiva, 2008). Figure 2-2 illustrates the rent expected, and to develop suitable strategies for commercialisation.

Figure 2-2: Model for rent appropriation



Source: Duhamel et al. (2014)

It is essential to define the methods and strategies for different rent configuration for the indices C1 and C2 mentioned in the previous paragraphs. A point of note is that if the innovator has access to the technological, development, and business resources through internal capabilities through off-the-shelf products, the innovation is defendable. However, if the resources and capabilities must be obtained through complementors, rivals, and through alliances, then partnerships are essential. If the innovators do not have these capabilities, then he has to sell out the innovation, license it, or withdraw from the market (Schwartz et al. 2005). Figure 2-3 illustrates the strategies for various rent configurations.

Figure 2-3: Rent configurations and value capture strategies

Rent configuration	Value capture strategies
C1 (v, p, l)	Withdrawal for all type of innovations.
C2 (V, P, L)	If innovators' resource and capability position is strong, remain autonomous. Otherwise, at the start of the commercialization process, cooperate, and then license out or sell out if the innovator cannot make it "big", for both autonomous and systemic innovations
C3 (v, P, l)	If innovators' resource and capability position is strong, remain autonomous for stand-alone innovations and cooperate for systemic innovations. Otherwise, since the duration of revenue stream generation is short, it is preferable to license out or sell out quickly to competitors or complementors, since the network of complementary resources and capabilities will take time to set up
C4 (V, p, L)	If innovators' resource and capability position is strong, remain autonomous for stand-alone innovations and cooperate for systemic innovations. Otherwise, license out or sell out if one cannot make it "big", for both autonomous and systemic innovations: partners will have fewer incentives to accept cooperation relatively to C2 configuration, since the value of the configuration is lower. In case of new market creation, the innovator should develop first the commercialization process in an autonomous fashion or through cooperation to prove innovation's worth
C5 (v, p, L)	Remain autonomous for stand-alone innovations to exploit the market niche. Cooperate for systemic innovations. License out or sell out to key partners if no leadership of the network of complementors. Partners will have fewer incentives to accept cooperation relatively to C7 configuration, since the value of the configuration is lower
C6 (V, P, l)	License out or sell out quickly, for both autonomous and systemic innovations. In case of new market creation, the innovator should develop first the commercialization process in an autonomous fashion or through cooperation to prove innovation's worth
C7 (v, P, L)	Remain autonomous for stand-alone innovations to exploit the market niche. Cooperate for systemic innovations. License out or sell out to key partners if no leadership of the network of complementors
C8 (V, p, l)	Sell out quickly for both autonomous and systemic innovations. Partners will have fewer incentives to accept a license relatively to C8 configuration, since the value of the configuration is lower. In case of new market creation, the innovator should develop first the commercialization process in an autonomous fashion or through cooperation to prove innovation's worth

Source: Duhamel et al. (2014)

2.3. Measuring Innovation Efficiency

One of the most important challenges for the high-tech industry is that of measuring and quantifying innovation. The standard indicators of revenue increase, margins, market share, market penetration and others require a deeper understanding of the various issues. While a first requirement is a basic understanding and definition of innovation, explained in later sections, this section discusses, at length, the methods used to measure innovation.

Furthermore, important issues related to measuring innovation efficiency are examined.

2.3.1. Challenges in measuring Innovation Efficiency

Innovation efficiency, unlike production process efficiency, is a disorderly process. While efficiency of a production is measured as the ratio of the output to the input, this formula stops at innovation. The reason for this is that innovation is a part of the creative process with uncertain outputs, evolved solutions with R&D efforts. Some challenges emerge when business managers try to measure innovation as a standard business process like manufacturing or production. The standard key performance indicators (KPI) do not need to be refined (Cai et al. 2009).

Innovation performance and efficiency is difficult to interpret and measure. Standard KPI such as productivity index, return on investment (ROI), output per head, revenue per person, etc. can lead to perverse results, because the innovation process can take months to develop and show results. In the meantime, without results, and only development costs to show, the standard KPIs are ineffective. In addition, organisations find it difficult to relate the cause and effect of innovation, such as rise or dip in market share, improvement in profits or reduced lead times, since a number of factors help to produce these results. Another challenge is that relevant KPI are hard to convert into improvements. When KPI are interpreted and evaluated, organisations can have problems in developing common shared priorities for improvement (Bunse et al. 2010).

As an example, a R&D manager would suggest that innovation should be directed towards improving the productivity of vendors and suppliers, by developing partnerships. This can involve additional costs in training and developing vendors. The procurement manager would however, have other priorities of reducing procurement costs, and he may not agree with the drive for innovation. Another challenge is that incidental improvements sometimes do not mature into fully fledged mature systems, and they get absorbed into the production system, without receiving any acknowledgements. Innovations need not be full product releases, but small increments and improvements. When such innovations are not reported, the organisation loses out on opportunities to report, recognise, and encourage further innovation (De Felice et al. 2013). When this happens repeatedly, the staff will lose their motivation to try and innovate.

2.3.2. Methods used to measure Innovation Efficiency

It is clear from the previous section that identifying and tracking innovation is one of the major challenges. The task of measuring innovation efficiency therefore becomes more complex when one considers the wide range of industries, the processes used, and the various KPI available. Several authors have proposed measures and methods to measure the innovation efficiency, and this section presents some of these methods. A detailed discussion of models and methods is presented in chapter 3.

Cassiman and Golovko (2011) point out that while the interest in innovation is high, given the huge export potential of such products, research has focused on innovation outputs. In some cases, a small number of indicators such as number of innovations, profit and returns from the innovation, improvement in cash flows, are considered. Hogan et al. (2011) indicate that the lack of measures for innovation efficiency restricts the development of the resource-based view of the firm. Wang and Ahmed (2004) argue that given the multi-dimensional nature of innovation efficiency, it is essential to use multiple constructs, rather than just a couple of aspect of innovation. The performance of an organisation is determined by internal factors such as firm and management characteristic. Sousa et al. (2008) indicate that the structural characteristics cover the firm's strategy, which must be aligned with the external business environment. These include product development and technological, strategic, and innovation capabilities. Yam et al. (2010) indicate that any measurement of innovation efficiency must cover the innovation capability scale on three measures, financial, strategic, and achievement.

Some omission is evident in the observations, given in the preceding paragraph. All the authors assume that innovation is spontaneous, instantaneous, and time bound. Hollenstein (2003) concurs with this view and argues that innovation takes place over multiple stages that cover basic research, design, market penetration, and feedback. However, not all products and innovations have to follow these stages, and products that are already in the market already have a basic research as the basis. Evangelista and Vezzani (2010) speak of four types of innovation, namely, technological in processes, technological in products, non-technological organisational, and non-technological in marketing. These innovations are seen in the manufacturing and service sectors, and it is clear that a common method of measuring innovation efficiency, which can be applied to all these sectors, is difficult.

Teixeira (2015) proposes the 'INNOVSCALE' used to measure and quantify the innovation efficiency of high-tech firms. The author obtained data concerning 3000 firms from the Portuguese Ministry of Exports, to derive the scale. A survey instrument was designed and administered to managers from these firms. The final sample size was 2740. The instrument used questions to cover four constructs, and the Likert 5-scale instrument was used to evaluate the responses. Responses were tested for convergent validity, discriminant, and nomological validity. The four constructs for which the scale was designed are Product development capability, Innovativeness, Strategic capability, and Technological capability. The 5-point Likert scale was also used to measure various KPI of the firm. These included annual export venture financial performance, annual export venture strategic performance, and annual export venture performance achievement. The model provided positive results for its robustness, validity, and it can be considered for further research. However, the main critique is that the model relied on primary research and responses from the respondents. Secondary data of the actual firm performance was not used. Therefore, the acceptability of this 'INNOVSCALE' needs more conformation and testing with secondary data. The next section presents some conceptual frameworks to measure innovation.

2.3.3. Conceptual frameworks to measure Innovation Efficiency in high-tech firms

Discussions from the previous sections indicate have identified gaps in the literature in terms of the selection of indicators and measurement of innovation efficiency. Albaladejo and Romijn (2000) consider the measurement of innovation challenging due to its intangibility, uncertainness, and because, in some cases, it is diffused over the process. Some errors are evident in the research of authors such as Kaplan and Norton (2004) and Epstein (2007) who consider the innovation process as linear with a unique construct. It is therefore clear that innovation must be considered as a holistic process, and the measurement of innovation process must be linked with the organisation performance.

Neely et al. (2000) is of the opinion that performance measurement frameworks provide the guidelines for measuring efficiency of the innovation process. However, the researcher needs to understand and select the various measures such as internal and external, financial and non-financial metric. The authors suggested using the performance prism with five perspectives, namely, stakeholder satisfaction and contribution, strategies, processes, and capabilities. This helps firms to focus on key issues that must be addressed by the organisation. Kaplan and Norton (2005) proposed the balanced scorecard with four perspectives: financial; customer; internal processes; and innovation and learning. Lonnqvist et al. (2006) proposed 'The Navigator' framework with five perspectives, namely, process, financial, customer, human capital, and renewal and development. The 'Intangible Asset Monitor' by Bontis (2001) has three classes of intangible assets: individual competence with education and experience, the internal structure made up of management and their attitudes, and the external structure made of stakeholder relations. Three indicators help to measure the intangible assets, and these are growth and renewal, stability and efficiency.

One general assumption made by researchers is that any high-tech firm can successfully innovate. However, this is not always the case, as seen in the large number of firms that collapse and do not survive. Laforet (2011) concurs with this view and suggests that firms can innovate only if they have the inherent capability. Therefore, innovation capability is a part of the core organisation process. Yliherva (2004) considers innovation efficiency as the sum of the organisations intangible property and its capability to use this property to create innovations, by transforming knowledge into new products, processes, and systems.

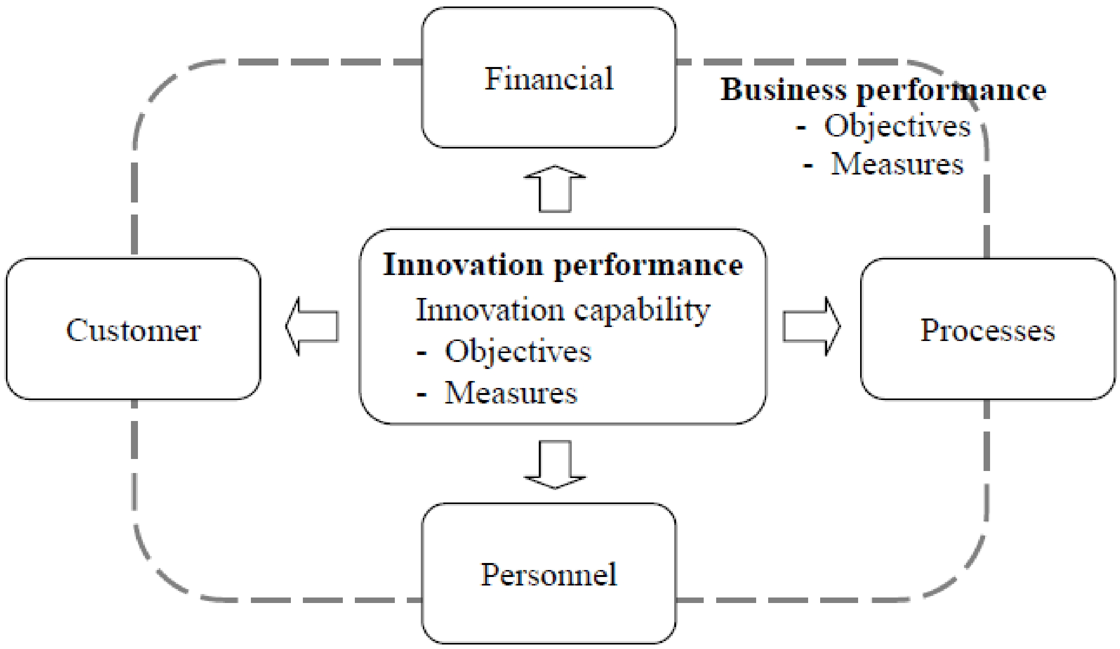
The focus of this paper is to develop measures for innovation efficiency, and this becomes a problem given the differences in organisational sizes, their products, and target markets, and the strategic direction taken. Cavusgil et al.

(2003) used five items to measure the innovation efficiency, and these are frequency of innovations, order of market entry, simultaneous entry in multiple markets, and the ability to penetrate new markets to tap the various facets of innovation capability. Considering that, these requirements are not very specific. Albaladejo and Romijn (2000) use three measures. These are assessing whether the firm has had at least one innovation in three years, the number of patents that the firm holds, and if the firm has developed an index to assess the significance of the innovation in a three-year duration. The authors further suggest that innovation efficiency must be organised into input and output measures. Tura et al. (2008) agree with this classification, since smaller firms cannot invest substantially in innovation activities. On the other hand, output measures are essential, since it is difficult to measure all innovations quantitatively.

Capaldo et al. (2003) propose a model to measure innovation efficiency. The model uses four resource sets: human resources, resources from external linkages, economic resources, and entrepreneurial resources. Each set has a number of measures to evaluate the extent of market innovation capability and the extent of innovation capability. Muller et al. (2005) propose a matrix with three categories to measure innovation efficiency. These are the leadership, capabilities, and resources. Three perspectives, namely, inputs, outputs, and processes are used to measure the capabilities. Adams et al. (2006) present a framework with seven categories to measure innovation efficiency. These are innovation strategy, project management, inputs, commercialisation, organisation and culture, knowledge management, and portfolio management. The framework uses 19 areas for measurement.

It is clear from the above discussions, that a large number of models and frameworks are available to measure innovation efficiency. Selection of the model depends on the nature of the firms under study, the products and services offered, and the target markets. A critique of the above models and frameworks is that they focus excessively on resources and capability of the organisation, what it has done, and not what it can do. Saunila and Ukko (2012) provide a conceptual framework to measure the results of innovation efficiency. The framework uses the balanced scorecard approach, and it has five perspectives, namely, financial, customer, processes, personnel, and innovation performance. The innovation performance perspective has measures for innovation capability, the activities, and results. The other perspectives help to measure the impact of innovation efficiency on the firm's business targets. The measures and objectives are specific to an organisation, and consider the organisations characteristics. The model is illustrated in the figure 2-4.

Figure 2-4: Framework to measure innovation efficiency



Source: Saunila & Ukko (2012)

The customer perspective can be used to derive measures for customer profitability, customer retention, customer satisfaction, and the market share. Process perspective helps to obtain measures for quality of products and services, flexibility of decision-making, reliability of deliveries, and effectiveness of problem solving. The personnel perspective is used to derive measures for employee satisfaction, employee retention, and employee skills. The financial perspective can be used to derive measures for benefit, profitability, and growth. The model helps to derive a number of measures, and these include the objects of innovation efficiency, measures for the objects, links between improvements needed for business performance, understanding objects of business performance perspectives, business performance metrics, and the cause-effect relationships of business performance measures (Saunila & Ukko, 2012).

2.3.4. Some observations about measuring efficiency in the high-tech industry

There is a considerable body of theoretical and empirical studies on the high-tech industry in the management, marketing, economics, and engineering fields and so on over the last forty years. However, there is a fact that needs to be taken into account when going about a review of literature on the subject of innovation measurement in high-tech industries. In the 1970s and 1980s, research into high-tech industries was mainly descriptive, generalising their characteristics (Maidique & Hayes, 1984; Quinn et al. 1990). This raised challenges in bringing in the element of objectivity into the literature review, requiring the researcher to be extremely selective in the approach with the secondary data collection. An extensive discussion on the concept and definitions of the high-tech industry is provided, so that that this research remains relevant to the topic.

Given that this research is based on the efficiency of innovation within the high-tech industry of China, it becomes critical that one gains an appreciation of the precise definition of the basic terms to have a focused overall approach to the dissertation. To explore research on this subject, a definition of the high technology industry is needed. There are many qualitative definitions of the high technology industry.

Li (2002) defines the high-tech industry as sectors with intensive technologies, such as the microelectronics information technology sector, the biotechnology sector, the new materials sector, the nuclear energy sector, and the spaceflight sector. A uniform internationally accepted standard for the extent to which the underlying technology needs to be intensive to qualify as a high-tech industry is not available. It is clear that industries should satisfy certain requirements to be classified as a high-tech industry. the first requirement is that the intensity of scientific research should be high; that is, the proportion of the cost for research and development to the output value or sales volume of the industrial sector should be high. The OECD (Hatzichronoglou, 2007) requires this proportion to reach at least 4%, while National Science Foundation stipulates that the cost for research and development shall account for at least 3.5% of the sales volume.

As a second key identifier for high-tech industries, Andersson et al. (2014) suggest that the concentration ratio of scientific and technical personnel should be high. In other words, the proportion of scientific and technical personnel to the number of workers should be high. Besides these two identifiers, other factors such as the nature of the underlying product also assume significance in certain cases.

Measurement of efficiency in the high-tech industry would thus depend on the geographic location of the enterprises. This means that the relative social development in a given geographical location must be considered when measuring the efficiency. When one speaks of the high-tech industry, the ‘what, where, and how’, become important. An industry that is considered as high-tech in China may be considered as a traditional industry elsewhere. The selection of KPIs therefore becomes distorted and confusing (Wu & Yang, 2006).

Consider the following variations in the definition of the high-tech industry. In the United Kingdom, the high technology industry is defined as a group of industries that consists of information technology, biological technology, and many other advanced science and technology industries (Gu et al. 2008). In France, economists think a new product can be categorised as a high technology industry when it is made by production line, has a high quality workforce, occupies a certain market, and becomes a new branch of industry (Foxon et al. 2005). In Australia, the high technology industry is defined as an industry with background in science and technology that has invested in research and development expenditure, mandates close involvement of researchers, and creates new products and processes (Gu et al. 2008). In the USA, high technology industries as those consuming considerable research and development funds and rapid technical progress (Peters, 2006). Finally, in China, the focus of this study, Li (2002) defines high technology industries as emerging industry groups, which are technology-intensive, are susceptible to rapid technical updates, have high added value, can conserve resources and energy in effect, and have ripple and spin-off effects for correlative industries.

Even within a particular country, different sectors may have different division standards for "high-tech industry". For instance, in the United States, each sector of the federal government greatly differs in terms of understanding of "high-tech industry". The range defined by The Federal Reserve Board is the narrowest while the range provided by Commerce Department is relatively wide. The Department of Labour provides three groups of "high-tech industries" with different ranges (Malerba, 2002): Group I has the widest range and includes 48 sectors involving 38 manufacturing sectors and 10 labour service sectors; the range of Group II is the narrowest and only includes 6 manufacturing sectors; and Group III covers 28 sectors, including 26 manufacturing sectors.

The above disparities across geographical locations and sectoral institutions / entities in the notion of what constitutes a high-tech industry, further reinforce the case for narrowing down the specific areas / industries that will form the focus of the present dissertation within the high-tech industry space. What is important to take into cognizance is that irrespective of the underlying element of detail in classifying what constitutes a high-tech industry, there exists a set of attributes specifically associated with the industry. Edquist (2005) puts forth the idea of high technology industry as a category concept that usually includes some industry categories, as against a concrete industry concept, as would be interpreted in conventional industry groups. In case of industries, a concept consists of a set of some enterprises.

The high technology industry is a set of enterprises, and not an individual enterprise. However, industry is not one-to-one correspondence with technology, and not all high technologies can become high technology industries. Whether a high technology can become an industry or not depends on two factors. According to Zhang et al. (2009), the first factor is if the technology can be applied practically or used to provide high technology products and services. The second factor is the market value of the technology, products and services. Not only is the high technology industry required to use high technologies or high technology products as inputs, its outputs should also be high technology products or services based on high technologies. Otherwise, it would be considered as a traditional industry that merely uses high technologies, not a high technology industry. This distinction is important for this research, else objections can be raised about the research data.

Some high technology industries may use both high technologies and traditional technologies in production, but their products can still be classified as high technology products. High technology industries should have the capacity of research, exploitation, and application. As such, the industries that process and assemble standardised high technology products do not belong to high technology industries category. It is in view of these necessary and sufficient conditions for an industry to qualify as a high-tech industry that the scope of industries being critically assessed for innovation efficiency in this dissertation study is based on Statistical Classification Catalogue of High-tech Industries issued by National Bureau of Statistics of the People's Republic of China (NBC, 2014).

Finally, along with the spatial differences in what constitutes a high-technology industry, there is also a temporal variability in how certain industries may or may not be classified as constituents of the high-tech industry at different points in time. The proposition here is that with the development of an economy, the range of high technology industry varies across times, even within the same country or region. When the development of an economy reaches a new stage, some new industries may become high technology industries, while the original high technology industries may be classified as more mature industries. This implies a dependency on whether an industry can be classified as a high-tech industry on the degree of development of the local economy (Zhu & Xu, 2006).

To define the scope of China's high technology industry from international experiences, corresponding methods and criteria should be chosen and established according to China's special conditions. As mentioned earlier in this chapter, this dissertation is based on Statistical Classification Catalogue of High-tech Industries issued by National Bureau of Statistics of the People's Republic of China (NBC, 2014). However, this should also be combined with international comparability in order to conveniently connect global issues.

Based on the above knowledge, the present section has argued thus far, based on existing literature on the subject, that the definition of high-tech industry is relative and dynamic; it is the entirety of enterprise groups engaging in all kinds of high-tech research, development, production, popularisation, and application. The high-tech industry is a knowledge and technology-intensive industry (Graf, 2006), with an established production process and a final product or service based on high technology. The high-tech industry typically includes a number of different sectors, and these sectors generally have large market demand. The high-tech industry has higher potential or actual economic benefits as compared to traditional industries, and its growth rate is also significantly higher. Therefore, using data from the NBC (NBC, 2014), in the "Catalogue of the High-tech Industry Statistics", the high-tech industry discussed in this dissertation includes five industries. These are manufacturing of medical and pharmaceutical products, manufacturing of aircraft and spacecraft, manufacturing of electronics and telecommunications equipment, manufacturing of computers and office equipment and finally, manufacturing of medical equipment and meters.

To conclude this section, it would be relevant to point out how research on high-tech industries in general and in China in particular has itself evolved with the evolution of the definition of what constitutes a high-tech industry. A number of studies have analysed the high-tech industry at a more detailed level, and from a micro perspective, using selected high-tech industry firms as study targets. In the 1970s and 1980s, many scholars attempted to address the issue of managing high-tech firms successfully (McCarthy et al. 1987; Eisenhardt & Schoonhoven, 1990). In the 1990s, the successful development of high-tech firms attracted much attention from academics and a number of theories were developed especially for high-tech companies, such as Gersick's Time Pacing and Eisenhardt's and Sull's Simple Rules. Zhu and Xu (2006) empirically examined the performance of strategic patterns in China's high-tech industry. They collected data from 126 Chinese high-tech companies, and found that Chinese high-tech companies with technology-strategy integration performed significantly better than those that viewed technology as a staff function, that did not significantly contribute to strategic objectives. They also observed that the Chinese Government plays an important role in Chinese high-tech companies. Warnock and Brush (1997) discussed the factors that influence the marketing of high-tech products and put forward a high-tech industry marketing mix.

2.4. Concept of Innovation Efficiency in high-tech industries

An extensive discussion was provided on capturing value from innovation and the methods used to measure innovation in high-tech industries in sections 2.2 and 2.3, respectively. The concept of efficiency is rooted into each field of industry and every aspect of social and economic life. In economics, there is no concept that is more widespread than economic efficiency. Although the concept of efficiency is broad-based, it usually involves conservation of resources or using existing resources better (Wu et al. 2005). In the history of economics, economists have put forth a range of different perspectives on the concept of efficiency at different points in time. As discussed in section 2.3.1 and 2.3.2, innovation is multi-dimensional. It is therefore important to understand the different types of innovation efficiency, specific to the high-tech industry.

2.4.1. Economic and Production Efficiency in high-tech industry innovation

Efficiency has always been associated with traditional businesses, and productivity norms, looking at the relationship between inputs and outputs. Classical economic theory has emphasised the significance of making the most of every single element that forms an input to industry, especially labour productivity and capital productivity, thus recognising the important effect efficiency has. In the area of high-tech industry, efficiency is the rational allocation of resources, which looks at how various kinds of resources in an economy are used. This provides a two-fold dimension to the concept of efficiency in high-tech industry innovation (Shi & Li, 2004).

On the one hand, efficiency means how to decrease waste as far as possible and produce the most value from a set of production factors. In a similar set of observations, efficiency is the quantity relationship between input and output, and aims to create as much innovative products as possible in the least possible time. Therefore, even in the high-tech industry, innovation must be measured as the productivity for output per unit labour time, as well as measure production efficiency by labour productivity. In other words, the high-tech industry cannot escape the laws and rules of economics. A firm that cannot innovate efficiently misses opportunities (Zuoxing, 2010).

Feiwel (2012) opines that innovation efficiency means using economic resources as effectively as possible to meet people's needs, or there does not suffer waste. When this happens, then the organisation economy is on the production possibility frontier. Viewed along a different dimension altogether, innovation efficiency relates to how resources can be allocated to the most suitable opportunities. The first kind of efficiency is called production efficiency, while the second is referred to as economic efficiency, also known as Pareto efficiency (Hargroves & Smith, 2005).

Lahiri et al. (2012) explain the concept of economic innovation efficiency as a kind of market efficiency, which involves allocating economic resources efficiently through the free movement of these factors/resources between different departments and industries. Production efficiency is a kind of organisation efficiency, which is achieved by improving internal management methods and raising production technology. The concept of economic efficiency in contemporary economic growth theory deals more with the marginal productivity associated with an incremental rise in the production resources input into the production process. With reference to the high-tech industry, it highlights the compound, dynamic characteristics of production efficiency whose meaning and range is narrower than production efficiency or efficiency.

Regardless of the difference in the understanding of innovation efficiency in the economic theory system, it is consistent with the basic understanding of efficiency, which is that efficiency is the quantity relationship between input and output, and it indicates the basic target orientation of enhancing effectiveness while reducing cost. Specifically, this dissertation studies technical efficiency and its decomposition derived from a variety of efficiency, which belongs to the relative efficiency category. In DEA, the innovation efficiency is measured by the ratio of the aggregated outputs to aggregated inputs (Chen et al. 2004). The scope of this particular study is limited to the innovation efficiency or technical efficiency dimension, rather than an overall agglomeration of production efficiency of individual units and economic efficiency for aggregated production units.

This section explained how overall efficiency of high-tech industries can be broken down into production efficiency and economic efficiency components. The main objective behind synthesising the concept of innovation efficiency in the high-tech industry is to work with a focused dataset along specific dimensions of efficiency that allows for more accurate research results within these limited boundaries. Two other parameters along which efficiency has been synthesised in prior research studies on the subject are regional and industry-specific. The next two subsections explain the rationale behind these approaches.

2.4.2. Regional Innovation Efficiency

Griffith et al. (2004) note that various inputs should be integrated to improve regional innovation efficiency for the high-tech sector. In the case of China, each province has some level of economic and administrative freedom. Therefore, the workforce and operation of the innovation process occurs within a regions, with lesser interchange of information across the regions (Li, 2009) According to Chang et al. (2012), investigating China's innovation system based on the province-level datasets is appropriate, since it allows comparison of innovation efficiency across various regions. Chi and Gennian (2004) and Peng and Bao (2006) empirically examined China's regional innovation efficiency at different points using SFA and DEA tools, and they report differences in the innovation efficiency across the regions. Therefore, regional influence has an impact on innovation efficiency in the high-tech sector.

2.4.3. Industry Innovation Efficiency

Innovation efficiency across various industries is important, since it helps to assess the extent of innovation in different countries. Lee and Shim (1995) empirically analysed American and Japanese high-tech industries' innovation efficiency, and examined the relationship between R&D investment and corporate long-term performance as well as market share. Romijn and Albaladejo (2002) and Neelankavil and Alaganar (2003) studied the high-tech industry's innovation efficiency by multiple regression analysis. The authors report that certain industries of semiconductors, chip factories, and communication sector have a higher efficiency level than aviation and pharmaceutical industries. Guan et al. (2009) and Jing (2010) constructed and measured industry innovation based on an evaluation index system. In addition, some scholars studied innovation efficiency from the perspective of enterprise. Yang and Qi (2001) studied the impact of enterprise ownership structure and nature, government investment and marketisation and other factors on enterprise innovation efficiency. Moreover, Guan and Liu (2003) also undertook research studies that evaluated the enterprise innovation efficiency.

Guan and Chen (2010) used the Super-SBM approach to evaluate the high-tech innovation efficiency of 29 Chinese manufacturing industries over a five-year period. They concluded that the innovation efficiencies among these manufacturing industries varied. Firms with higher revenues and which were larger showed higher performance, while smaller firms showed lower innovation efficiency. Firms in the manufacturing and processing of ferrous metals had higher innovation efficiency. Claudio and Andrea (2013) used data envelopment analysis (DEA) bootstrapped to examine the effects of open innovation practices on technological innovation efficiency by collecting a panel dataset from 1994 to 2005, consisting of 2472 observations from 415 Spanish manufacturing firms. This study considered indicators such as R&D spending, capital stock, and high-skilled staff, the number of product innovations, and number of patents as innovation outputs indicators. They concluded that the uncertainty of the innovation process is much greater in high-tech industries than in low-tech industries, and the open innovation strategy does make a firm more efficient in the use of their resources.

2.5. Technological Innovation Efficiency in high-tech industries

2.5.1. Technological Innovation

Kaukonen and Nieminen (1999) proposed a concept of technology innovativeness, which is related to the efficiency of technological innovation. This discussion is important, since 95% of innovations in the high-tech sector are seen in the technical areas. He explored technology innovativeness from the adaptability between R&D and industrial economy. He argued that R&D achievements are not convertible if there is no correlation between R&D activities and regional industrial economy. Technology innovation is therefore the transferability of R&D activity, and not about the input-output efficiency. Griffith et al. (2004) also highlight the concept of technological innovation and believe that in order to improve technology innovativeness of countries or regions, it is necessary to establish a technological innovation system. There is a need to integrate each innovation factor with the source of technological innovation. Several sources such as science and technology research, business activity of R&D, and industry chains must be included to make the technological innovation system efficient. Such actions help to improve the technological innovation capabilities of countries or regions.

At this point, it is critical to make a subtle distinction between invention and technological innovation. According to Gardner et al. (2007), while invention is a new concept, a new idea or an experiment at best, technological innovation takes inventions or other science and technology achievements into the production system and uses these theories to make goods needed by the market, and to create shock effects in the production system. As such, technological innovation should include the process of commercialisation and industrialisation of science and technology achievements.

Many scholars such as Mansfield et al. (1981), Freeman (1995), and Mueser (1985) have examined the concept technological innovation in the high-tech sector. Mansfield et al. (1981) believe that technological innovation is different from invention and technology samples, and is the actual and first use of technologies. This has become a common theme in the definition of technological innovation by later scholars. Quoting from the extensive research work undertaken by Myers and Marquis over forty years ago on the area of technological change and technological innovation, Bennett (2006) defines technological innovation as a process of introduction into the market of new or improved products, processes and services. Expressing the same underlying definition in a different fashion, Freeman (1995) believes technological innovation is the first commercialisation of new products, processes, systems and services. In recent years, because of the rapid development of the world economy, the decrease of natural resources and deterioration of natural environment, many scholars begun to define it from the perspective of sustainable development. Rennings (2000) points out that progress is understood as the technological innovation of enterprises. However, the sustainable utilisation of natural sources is not the main technology problem, which may have led to technical deviation. Innovation should include three changes in technologies, social and system innovation, and the inclusion of these three is a concept of ecology innovation.

In China, based on analysing and summarising the former theories and experiences, Du (2000) proposed a more complete concept for technological innovation in the high-tech sector. Du defined technological innovation as entrepreneurs capturing the market potential profit opportunities, and for business interests, reorganising production conditions and essentials, establishing more efficiency, more productivity and less expensive production and business systems to create new products, processes, and markets. It also includes obtaining new raw materials supply sources of semi-manufactured goods or establishing new organisations consisting of composite processes of science and technology, organisation, business, and finance.

In 1999, the Chinese Communist Party Central Committee and the State Council of PRC held a National Technological Innovation Conference (Yusuf & Nabeshima, 2010). The conference handed down the decision on strengthening technological innovation, developing high science and technology and achieving industrialisation. Because of this thrust to the area of technological innovation, there was unanimous focus on adoption of new modes of production and business management, improved product quality, exploitation of new products, and provision of new services. Enterprises are the subject of technological innovation. Technological innovation is an important precondition of the development of high-tech sectors. In terms of the definition of technological innovation, most scholars have reached the consensus that the above two definitions are most relevant in the Chinese context.

From the above definitions, it is seen that there was significant difference among the definitions of technological innovation from the different study perspectives. While Mansfield et al. (1981) limited technological innovation to product innovation. Bennett (2006) takes mimicry and improvement without new technology knowledge as two kinds of innovation in the lowest levels into their definition of technological innovation. Freeman (1995) inspects innovation from the economy and limits the role of standardisation as part of technological innovation. Mueser (1985) highlights the unconventional nature of technological innovation including novelty, discontinuity and success of activities.

Klemmer (1999) enhances the scope of technological innovation, by associating it with sustainable development. He holds that the process of technological innovation should consider sustainable development, and even use it as basis, but the negative effect of innovation achievements to ecology and society should not be due to technological innovation. Moreover, the negative effects of some innovation achievements are found in the process of application and washout or in improvements through further innovation. However, all of these fall under management problems in the application of technological innovation, and should not be confused with technological innovation itself. The definition of technological innovation should therefore grasp two principles. Firstly, it must have sufficient theoretical basis, which is especially important to broadening and clarifying technological innovation. Secondly, it should help to promote the development of China's socialist economy and enterprises reform, and strive to make technological innovation research have more universal meaning and functions in the reality of China's economy and life (Mendonça, 2009).

There exist debates on the definition of technological innovation, and these can be reflected upon along the following three lines.

Firstly, the determination of what exactly constitutes technology in the generic area of technological innovation is debated. On one hand, there are limitations to innovative technology in technological innovation, and non-technical innovation cannot be listed as technological innovation. As such, there are differences among technological innovation, system innovation, and organisational innovation (Fritsch & Franke, 2004) and these all belong to different categories. On the other hand, there are different perceptions regarding technology and non-technology in innovation, and this leads to the difference and debate on the concept and definition of technological innovation. This explains the rangeof technological innovation that is affected by the range of definitions of technology. This dissertation studies the technological innovation of the high technology industry, so it only discusses the innovation of high technology.

Secondly, there is a debate on whether there is a limitation on the intensity of technology change in technological innovation. The focus of debate is incremental improvement or marginal improvement, which means that it focuses on whether the growth of scale benefit because of gradual improvement in technology belongs to technological innovation or does not. Over the past decades, most Western scholars engaged in the study of technical innovation have been advocating that such incremental improvement should be viewed as separate from technological innovation (James & Mogab, 2012). This point pays attention to taking the qualitative changes of technology as standards and defining technical innovation narrowly in theory. On the contrary, other scholars pay attention to the extensible nature of the technological innovation and scope of activities. They begin with how the social coverage of innovation research and application can be increased, and think that the technology change intensity in the definition of technical innovation should be wider than it previously was.

A third issue concerns the concept and standard of success. Since all technical innovation must eventually achieve and show through the market, the unsuccessful innovations cannot be called technical innovations. In this case, the success of technological innovation could mean commercial profit or market share or technological superiority. While this point does not have a contrary argument, there is also no completely consistent view. This dissertation believes technological innovation is a whole process from exploitation of new technology to its application in the product market. As such, the success is divided into two aspects. On one hand, the patent application and authorisation indicate that the high technology has been exploited successfully. On the other hand, the achievement of economic benefits indicates that the technology has been transformed successfully (Coad & Rao, 2008).

This dissertation specialises in the efficiency of technical innovation in high technology industries. Therefore, it makes sense to carry out the research from the investment perspective and to frame technical innovation with regard to two processes. These are firstly, the process of exploitation of new knowledge and high technology in the high technology industry, and secondly, the process in which new knowledge and high technology are used to produce high technology products or change production engineering, decrease production costs, and improve product quality and service until the market value of high technology is achieved. The former process embodies the technology value of technological innovation on early R&D; the later process embodies the commercial or market value of technological innovation on later application and popularisation. These two processes are closely connected; the former can be viewed as technical preparation for the latter while the latter achieves market value for the former.

2.5.2. The two stages of Technological Innovation for the high-tech industry

Technological innovation is a whole process, which starts from the study of some applied research in research and development, after-test development, trial sales of new products and their marketing, to their finally becoming commodities, from the perspective of linear process to analysis. Thus, the technological innovation is an intimate interaction process, led by scientific and economic activities. Xu and Zhang (2008) regard technological innovation as a whole process, which includes new ideas of technology, their application to research and their experimental development, or, a combination of techniques, creation of new products, new technologies, and commercialisation.

The implementation process of high-tech industrial technological innovation refers to a series of sophisticated economic activities from research to development, from technique to production as well as from product to market based on high technology, when the concept of technological innovation is applied to the high-tech industry. However, the original products may become new products with new properties and new features once the high technology is developed and applied to them. Urel and Zebregs (2009) point out that a new technology could change the production line and transform the mode of product production, reduce production costs or enhance productivity. The newly developed high technology can be used to create new products or improve production methods. Meanwhile, new technology could be further modified and improved through feedback during the course of reforms of the production line.

In addition, consumers could also come up with new requirements for new high technology when they use new products. It is not a linear process, for the R&D of high technology, the production of new products or the improvement of production methods. However, the outputs of technological innovation achievements are of two types: technology and product, from the perspective of the whole industry. As the intermediate product, technology acts both as the result of preliminary research investment, and as the premise of late new product development and new technology transformation. Therefore, the input and output activities of high-tech industrial technological innovation can be divided into two phases, with the intermediate product as the dividing line (Glasmeier, 1988).

In the first stage, it focuses on the process of high-technology development. It develops high technology through R&D investment, and ultimately takes the form of patents and non-patent knowledge technology as the output of scientific and technological achievements and so on (Fischer, 2006). The process mainly reflects the technology development efficiency of high-tech industry technological innovation.

The second stage focuses on the high-tech transformation process. That is, using self-developed high technology, or purchasing high technology from others both at home and abroad, as well as transforming, assimilating and absorbing them. Subsequently, new products could be produced or the original product production modes improved, and ultimately come into the market in the form of products. The enterprise could also get significant economic profits by applying these high-tech achievements. This process mainly reflects the technical transformation efficiency of high-tech industrial technological innovation (Zhou, 2007).

Technological innovation also has many problems from the perspective of input-output, which is the same as the general production process. However, there are obvious distinctions between technological innovation activities and general production activities, which are mainly manifested in the expression form of input-output of technological innovation. Technological innovation is a special kind of productive activity, which includes the accumulation and breakthrough of knowledge technology, personnel training, and the realisation of economic and social benefits. In general, it covers three main aspects of innovation process in measuring technology changes. These are innovation inputs such as the investment of funds and human resources, intermediate outputs such as new inventions and new knowledge, and innovation final output such as increasing revenues and profits (Liu & Buck, 2007).

Therefore, the technological innovation of high-tech industry can be summed as an input-output system with multi-parameter inputs and outputs. To sum up, technological innovation within high-tech industries manifests itself in both phases – the first where the emphasis is on innovation in the form of new product features, development of new products, or revolutionary manufacturing techniques. The second pertains to the 'productionizing' of these innovations in the actual assembly line, which shows the relatively more tangible improvement in increased revenues, reduced costs or both. For the purposes of this study, technological innovation is viewed as a combination of the innovative developments deployed during both these phases.

2.5.3. Efficiency of Technological Innovation in the high-tech sector

The efficiency of technological innovation in the high-tech sector can be understood from the development of efficiency theory. Different formulations of efficiency can be looked at from different angles.

With the development of technological innovation in the high-tech sector of China, a number of scholars have focused on studying the efficiency of technological innovation. Research on the concept of efficiency of technological innovation has led to significant achievements, and several definitions have been given. Zeng et al. (2010) proposed a definition of the efficiency of technological innovation. They believe that the efficiency of technological innovation is an input-output concept, and that many elements of technological innovation convert into the performance of technological innovation, which belongs to research category of technological innovation system. Claudio et al. (2013) defined technological innovation efficiency as the relative capability of a firm to maximise innovation outputs given a certain quantity of innovation inputs.

In terms of measuring the efficiency of enterprise technological innovation, two contemporary measures are used. These are the ratio between new product profits accounted for by the proportion of total profit, and technological innovation of enterprises accounted for by the proportion of total enterprise investment expenditure. Kao and Liu (2011) use the relative input and output of enterprise technological innovation to measures the efficiency of enterprise technological innovation.

Increasing the input of technological innovation for high-tech sector and setting up an orderly technological innovation system is a key route to increasing technological innovation capability. However, the efficiency of technological innovation determines the utilisation of the technological innovation element. Increasing efficiency of technological innovation is equal to increasing output of technological innovation or saving inputs of technological innovation. The technological innovation system is a complex exploitation system of inputs and outputs of numerous elements and the input to output conversion occurs throughout the entire process of technological innovation (Park, 2005).

The efficiency of technological innovation is a conversion efficiency of effective economic quantity between input and output. As such, the efficiency of technological innovation determines the capability and achievement of technological innovation. However, because of the diversity of technological innovation elements and the difficulty in quantifying some elements, it is difficult to measure the absolute efficiency of technological innovation. Chi and Gennian (2004) believe that enhanced technological innovation can cause fewer inputs to create higher outputs, thus reaching relative optimums in technological innovation efficiency.

Based on the above study achievements, the understanding developed is that the efficiency of technological innovation is more a form of production efficiency, and in essence, belongs to technical efficiency. It refers to a ratio of the minimum cost and actual cost needed to make a certain amount of products, or a percentage of the actual output level with the maximal output in the same input scale, input proportion and market value, all other conditions remaining the same. Therefore, the following points need to be taken into consideration with respect to the way this dissertation perceives and treats the concept of efficiency of technological innovation. The efficiency of technological innovation in the high-tech industry is a relative efficiency. The efficiency of technological innovation is a standard measure between technological innovation output with its optimal output, based on a construction of the actual frontier of input-output innovation activities, through the horizontal comparison between different innovation subjects and the longitudinal comparison of the same innovation subject at different times. As such, this dissertation views the efficiency of technological innovation more as a relative concept rather than as an absolute measure of efficiency (Van Riel et al. 2004).

The efficiency of technological innovation is considered as a static efficiency. The efficiency of technological innovation in this dissertation measures the input-output relationship at some point, but cannot be a continuous function to measure a dynamic process at a time. The efficiency of technological innovation of a same innovation subject can be studied in different times through the longitudinal comparison. However, for the purposes of this dissertation, efficiency is viewed as a static concept, a cross-section of which is measured and assessed from a temporal viewpoint (Mohr et al. 2009).

The above arguments establish the need to isolate pure production (or technical) efficiencies from the broader subject of economic efficiency relating to allocation of limited resources across multiple production units, also referred to as allocative efficiency. It is based on the above that this dissertation limits its focus in evaluation of technological innovation efficiency to technical efficiency, and does not include considerations for economic efficiency.

2.5.4. The Efficiency of the High-tech Industry's Technological Innovation

In the late twentieth century, with the rise of high-tech industries such as information technology and biotechnology, the world industrial structure embarked upon a new round of adjustments. The high technology industry has become a locus of organisational research (Rogers et al. 2001). As such, it is of important practical significance to study the technological innovation efficiency of high-tech industry.

Production technology has been upgraded constantly due to technological innovation in the high tech industry (Blonigen & Taylor, 2000) which greatly promoted the development of the world economy. Klofsten and Jones-Evans (2000) agree with the observation that high tech firms contribute significantly to economic growth. Niosi (2011) found that technological innovation alone likely accounts for over 50 per cent of recent economic growth. More and more high-tech companies have realised that in order to sustain their customer base and seize revenue opportunities, they have to manage successive technological innovations effectively (Wu & Wang, 2005).

As the technological innovation efficiency of the high-tech industry reflects the different aspects of input and output in technological innovation, many scholars and constitutions have tried to establish a systemic index to evaluate innovation efficiency (Guan & Chen, 2010), and there have been significant achievements in academic research in this area.

Guan et al. (2003) used the Data Envelopment Analysis (DEA) model to examine the relationship between high-tech innovation capability and competitiveness at the enterprise level by analysing 182 industrial innovative firms in the high-tech science and technology industry in China. The results showed that only 16% of the enterprises operate on the best-practice frontier, and that there are some inconsistencies in organisational innovation capability and competitiveness in many enterprises. Furthermore, it also showed that decreasing returns to scale was found among about 70% of the inefficient enterprises and increasing returns to scale was found among the remaining 30% of the inefficient enterprises. Thus, the internal innovation harmonising process in these enterprises is considerably inefficient. Guan and Chen (2010) constructed a novel measurement framework for the typical innovation production process (IPP) from the system perspective associated with a relational network DEA, and applied it to a cross-region empirical study of China's high-tech innovations. The empirical innovation measurement provides in-depth evidence of China's high-tech innovation efficiency. Based on this, some policy recommendations were also made. Bai and Li (2011) analysed the influence of the local government on regional innovation efficiency of China based on the panel data of China's 30 regions during 1998–2008. The results show that regional innovation efficiency in China is low, and that the financial support from local government and financial companies and the interplay between enterprises and universities (research institutes) has had a significantly negative impact on innovation efficiency.

Xu and Cheng (2013) utilised the two-stage DEA model to assess scientific innovation and each sub-system's efficiencies of 30 Chinese provinces from 2001 to 2011, from the perspective of the science and technology development process. They concluded that organisational efficiency and degree of synergy display a positive relation. Besides, whether the science and technology organisational efficiency progresses or not depends on the extent and the direction (positive or negative) of the synergy, while the absolute value of synergy degree reflects the rising or dropping pace of organisational efficiency.

Wang and Xu (2012) used the SFA and Tobit model to calculate and evaluate innovation efficiency and impact factors of hi tech industries. Panel data of eighty-nine listed companies in high-tech sector was obtained from 2007 to 2010, covering areas such as energy saving and environmental protection, a new generation of information technology, biology, equipment manufacturing, new energy, new materials and new-energy automobiles. They concluded that the innovation efficiency of China's strategic emerging industries rose year by year. The scale of the company and subsidies had a significant positive impact on innovation efficiency, but profitability had a negative impact on innovation efficiency. There was no significant relationship between the quality of staff and innovation efficiency.

Wang et al. (2008) evaluated the high-tech innovation capability (TIC) performance of a high-tech firm quantitatively and qualitatively by adopting a fuzzy measure and non-additive fuzzy integral method. They concluded that the non-additive fuzzy integral is an effective, simple, and suitable method for identifying the primary criteria influencing. This is also true for TICs at high-tech firms, especially when the evaluation criteria are interactive and interdependent.

Xu et al. (2007) constructed a cross-country production model for evaluating the relative efficiency of aggregate R&D activities, based on the data derived from thirty countries (twenty-three OECD members and seven non-OECD economies that intensively engage in R&D). The results showed that the mean of efficiency scores was about 0.65 in the cross-country study, when environmental effects were not taken into account. After controlling for the operating environment, the mean increased to about 0.85.

Wang and Huang (2007) applied the production framework associated with the data envelopment analysis (DEA) method to evaluate the relative efficiency of R&D activities across countries. Based on quantitative analysis of data from thirty countries, the results showed that less than one-half of the countries are fully efficient in R&D activities and that more than two-thirds are at the stage of increasing returns to scale. Most countries have a more significant advantage in producing SCI cum EI publications than in generating patents. In a separate study using the DEA / Malmquist index to measure the change in R&D

efficiency among Japanese pharma firms, Hashimoto and Haneda (2008) concluded that R&D efficiency of the Japanese pharmaceutical industry has almost monotonically gotten worse from 1983 to 1992.

Liu et al. (2013) utilised the Data Envelopment Analysis (DEA) model to evaluate the relative efficiencies of thirty regional R&D investments using the First Official China Economic Census Data in 2004. The results indicate that only six provinces are globally technically efficient and that the performance of regional R&D investments in China needs to improve dramatically. This is because no province has experienced increasing returns to scale; constant returns to scale has prevailed in most provinces in the Western region, and decreasing returns to scale has prevailed in most provinces in the Eastern and Central regions. There were no direct relationships between global technical efficiency and the amount of R&D investment. The Western region had the highest average radial efficiency score, followed by the Eastern region, and then the Central region; The Eastern region has advantages in local technical efficiency, the Western region has advantages in scale efficiency, while the Central region has neither technical efficiency advantages nor scale efficiency advantages.

The patent is a very important output index of innovation efficiency and is used in every paper. This could be due to its accessibility and the general usefulness of the data. Researchers have also argued that patent data are a reliable and valid measure of innovative activity (Albert et al. 1991; Podolny and Stuart, 1995). Benner and Tushman (2002) argued that patents are useful for measuring technological innovation as they are only awarded to novel, non-obvious designs that represent advancements over existing technology. However, patent numbers cannot fully express the quality of innovation results, and they are not an ultimate goal for enterprises. Therefore, a more reasonable index is required in evaluating technological innovation. In evaluating innovation efficiency, this dissertation selects patent as one of the output indexes, and others as well. These will be discussed in detail later.

2.5.5. Decomposition of Innovation Efficiency in the high-tech industry

Efficiency can be studied from several perspectives. It can be divided into technical efficiency and technical inefficiency from the perspective of the degree of effective use of existing technologies. It also can be divided into scale efficiency and scale inefficiency from the perspective of whether the scale reaches the optimal production state or not. Furthermore, it can be divided into partial factor productivity (e.g. labour productivity, capital productivity) and total factor productivity, from the perspective of input factors impact on efficiency (Jing, 2010). This dissertation will focus on discussing innovation efficiency of China's high-tech industry from the viewpoints of technology efficiency, scale efficiency, their dynamic change and developments of these ideas.

2.5.6. Mathematical analysis of technical efficiency

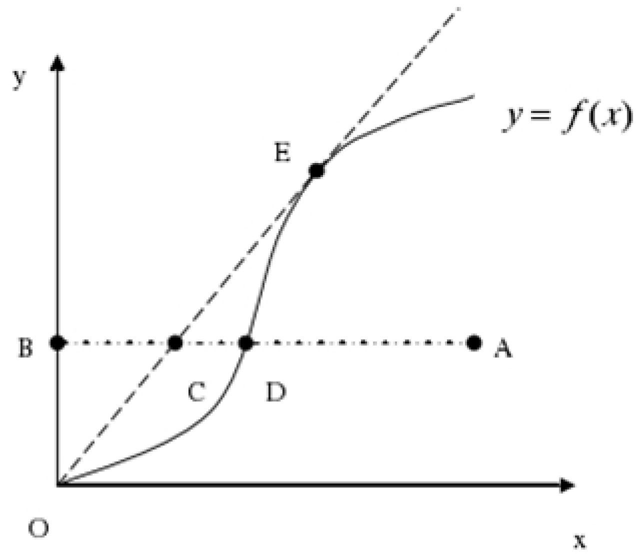
In simplistic terms, technical efficiency as a measure can be defined as the point when producer being unable to produce more products, even when the producer's technology is effective, without reducing other outputs or increasing investment (Harrison et al. 2014). While the technical efficiency measurement was first implemented nearly sixty years ago, it has since evolved considerably in terms of objectivity, measurability, and accuracy. The technical efficiency indicates the maximum output capacity with fixed investment, or the minimal input capacity consumed for a given level of production output (Coelli, 2005). It measures the distance between outputs from the evaluation unit and the maximum output. This is determined by the production frontier under the conditions of equivalent factor inputs, or at the request of the equivalent output, the distance between input consumed by evaluation unit, and the minimum input determined by the production frontier. At a technical level, whether the output or input can reach the production frontier of an evaluation unit depends on the level of technical efficiency. If technical efficiency is 1, it indicates that current technology has been given full play. When outputs or inputs do not reach the level of production frontier, the difference is due to the existing technology caused losses for failing to give full play (Guan & Chen, 2010).

The following analysis is from Emrouznejad et al. (2008), Pastor et al. (1997) and Dogramaci & Färe (1998).

Assuming production units put in *m* kind of production factors, their respective quantities are $x_1, x_2 .. x_m$. These could achieve *y* of the maximum output when production is at optimum state, under certain technical conditions. Now, there is a function relationship between $x_1, x_2 .. x_m$ and *y*. That is, $y = f(x_1, x_2 .. x_m) = f(X)$

The function relationship of inputs and maximum outputs $X = (x_1, x_2 .. x_m)^T$ describes the technical relationship between inputs and outputs. Take a simple situation as an example, when there is *x* of one kind of input factor and *y* of one kind of output, then the curve of *y=f(x)* in figure 2-5 represents the production function and the lower parts of *y=f(x)* consist of possible productive collection.

Figure 2-5: Technical Efficiency



Source: Emrouznejad et al. (2008)

As can be seen from Figure 2-5, A, D, and E are all production possibilities. Both D and E reach the maximal output within their individual inputs. The outputs of A are the same as D, while the inputs of A are much more than D. Thus, technical efficiency (TE) of A can be measured by the equation $TE_A = \frac{BD}{BA}$, where:

TE_A is the technical efficiency of A

BD is the input of D with the output of B

BA is the input of A with the output of B

Because all investigated objects could produce only so that output lies in or lower than the production function curve *y=f (x)*, the technical efficiency (TE) is therefore less than or equal to 1. The closer they are to the production function, the higher their technical efficiency (TE). Technical efficiency (TE) reaches 1 when an inspected objects lies in the production function curve. This is referred to as technological efficiency, such as in the case of D and E. A, on the other hand, falls under technological inefficiency.

The production function describes the optimal production state and is suitable for situations with one or more inputs but only one output. Thus, it is a special case of the production frontier. In fact, the Data Envelopment Analysis (DEA) method is a development of the concept of the production function, and is more suitable for measuring the efficiency of decision-making units with multi-inputs and multi-output situations (Banker & Thrall, 1992). The model of BC^2 in DEA can measure the technical efficiency of decision units.

High-tech industry innovation activity is typically a social activity with multi-inputs and multi-outputs. An entity needs to put in a variety of elements of human, material, and financial resources, etc., to get several achievements in scientific research such as patents, new products, and so on. By applying DEA to analyse China's high-tech industry innovation efficiency, the technological efficiency and technological inefficiency in individual provinces and industries can be determined. This can indicate the direction to take to improve the innovation efficiency of the relevant provinces or industries (Sher & Yang, 2005). The technological relative effectiveness of the decision-making unit obviously needs to be investigated also.

2.5.7. Scale Efficiency

Scale efficiency (SE) is a very important index that reflects whether an inspected object starts business under the most suitable investment scale or not. It is studied from the perspective of the change of input leading to the change of output, and is also called returns to scale (Banker & Thrall, 1992). Under the condition of constant technique level, when the inputs of production elements are expanded K (K>1) times from original input, that is, from $X = (x_1, x_2 .. x_m)^T$ to $kX = (kx_1, kx_2 .. kx_m)^T$, then the maximised outputs are also changed from $f(\overline{X}) = f(x_1, x_2 .. x_m)$ to $f(kX) = f(kx_1, kx_2 .. kx_m)$ correspondingly (Färe & Grosskopf, 1985).

At that moment, the change in the maximised outputs could appear in the following three kinds of situation.

The first situation should be $f(kX) > kf(X)$, and is called Increasing Returns to Scale (IRS), which indicates that output is more than K times original output when inputs are expanded K times.

The second situation should be $f(kX) = kf(X)$, and is called Constant Returns to Scale (CRS), which indicates that output is expanded K times original output when inputs are expanded K times.

The third situation should be $f(kX) < kf(X)$, and is called Diminishing Returns to Scale (DRS), which indicates that output is less than K times original output when inputs are expanded K times.

The above three situations can transmit a very clear message to decision-makers. In the first situation above, there should be an increase in the depth of inputs until they reach the situation of constant returns to scale. In the third situation above, inputs should be decreased; while in the second situation above, the current situation, which is a perfect production state, should be maintained. There is no need to either increase inputs or decrease inputs. Generally, some of the reasons behind increasing returns to scale are that a larger scale makes the division of labour more sophisticated, specialisation continuously improves, etc. On the other hand, the reason behind diminishing returns is that the increase in scale exceeds reasonable limits, and this makes the functions of planning, organising, controlling, and coordination of management, as well other functions, difficult put into full play (Lee & Kang, 2007).

Compared to other industries, most of the high-tech industries have rich resources of human, material, financial, and other resources. However, it is important to study whether they carry out innovation activities under the optimal scale. Based on an analysis of the situations of returns to scale of innovation efficiency, a company can decide whether or not to increase or decrease inputs, and thus can allocate limited innovation resources in a more scientific manner in order to improve the efficient use of resources. Scale efficiency (SE) is measured by calculating the ratio of inputs in the production frontier with the inputs of constant returns to scale under the condition of the same output (Chen et al. 2007). As can be seen from figure 2-5, the ray OE indicates the production frontier with the constant returns to scale and D and A correspond to the production function. Thus, the formula expression of scale efficiency of A is as follows:

$$SE_A = \frac{BC}{BD}$$

SE_A: scale efficiency of A

BC: the input of C with the output of B

BD: the input of D with the output of B

In general, scale efficiency (SE) is less than or equal to 1. When scale efficiency is equal to 1, the inspect object is referred to as scale efficient. Otherwise, it would be scale inefficient. As such, it can be concluded from figure 2-5 that E is scale efficient while A and D are scale inefficient.

There is a kind of overall efficiency combined with technical efficiency and scale efficiency closely, which is referred to as scale, and technical efficiency (STE). Scale and technical efficiency (STE) is obtained by calculating the ratio of actual input of decision-making units to the input of the optimal scale under the condition of fix output, by assuming constant returns to scale (Cooper et al. 2007). Thus, the formula expression of scale and technical efficiency of A is as follows:

$$STE_A = \frac{BC}{BA}$$

STE_A: scale and technical efficiency of A

BC: the input of C with the output of B

BD: the input of A with the output of B

However, this formula could be combined with the formula of SE_A, TE_A and STE_A. The result is as follows:

$$STE_A = \frac{BC}{BA} = \frac{BC}{BD} \times \frac{BD}{BA} = SE_A \times TE_A$$

That is, scale and technical efficiency is equal to scale efficiency multiplied by technical efficiency. Obviously, scale and technical efficiency of a decision-making unit reaches 1 when it is both scale efficient and technical efficient, such as E in figure 2-5.

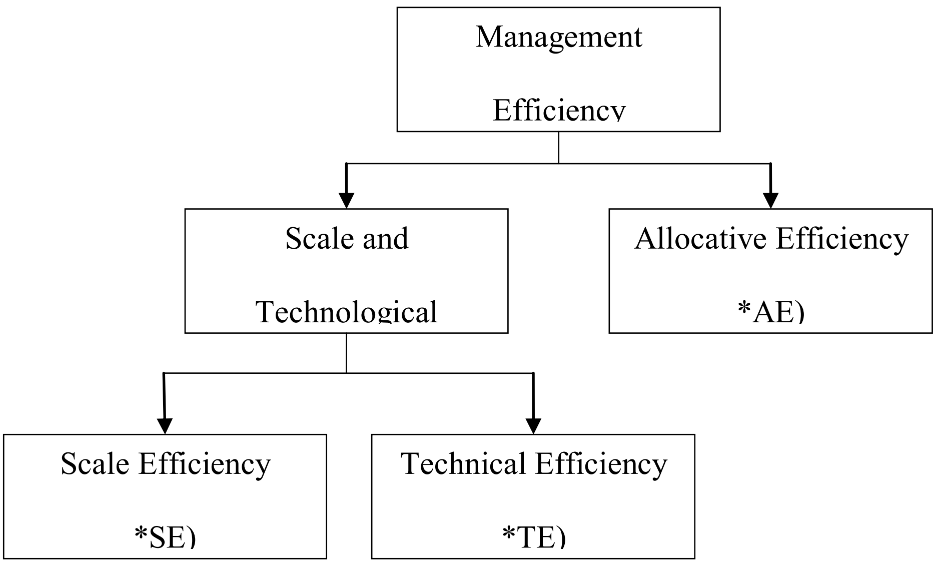
In DEA, the model C^2R measures the scale and technical efficiency of a decision-making unit. One of the basic assumptions of C^2R is that of constant returns to scale of the decision-making unit, that is, assumption of convexity. The scale and technical efficiency of decision-making unit can be calculated using the model of $C^2R$and BC^2.

Efficiency can be divided into Allocative Efficiency (AE), Management Efficiency (ME) and so on, besides technical efficiency (TE), scale efficiency (SE) and scale and technical efficiency (STE). Allocative efficiency (AE) refers to the mix of input elements with a certain output, under the conditions of a given price and technology (Ouellette & Vierstraete, 2004). It introduces the price and cost into the efficiency analysis, and this makes the efficiency evaluation more scientific and objective. The allocative efficiency of each decision-making unit can be calculated by applying the DEA model with cost, which is more suitable in the business management practice. Management efficiency (ME) is a combination of the above efficiencies, and the relationship between them is shown in figure 2-6. The organisation management level can determine whether the technical level is full play or not, whether the resources are allocated suitable or not, and whether the production scale is optimal or not.

The relationship among the above kinds of efficiency can be expressed in the following formula: Management Efficiency is equal to technical efficiency multiplied by scale efficiency multiplied by overall efficiency, which is also equal to scale and technical efficiency multiplied by allocative efficiency. That is, ME = TE * SE * AE = STE * AE.

In calculating the efficiency of resource allocation (AE), the accurate price and cost of each input and output index is required. However, it is very difficult to compute the accurate price for output in innovation activists. Therefore, this dissertation will study the innovation efficiency of the high-tech industry from the perspective of technical efficiency (TE), scale efficiency (SE), and scale and technical efficiency (STE). This is also consistent with the corresponding theoretical arguments in this direction that were presented in Section 2.3.

Figure 2-6: Decomposition of Efficiency



2.5.8. Total Factor Productivity

Total Factor Productivity (TFP) is an important concept in the theory of innovation efficiency, and it explores the source of economic growth. The theory of economic growth believes that the sources of economic growth are mainly composed of the increase in production elements and an improvement in production efficiency, while Total Factor Productivity (TFP) measures the increase in the level of production efficiency. In the theory of economic growth, productivity is divided into Partial Factor Productivity (PFP) and Total Factor Productivity (TFP), according to the contributions different production elements make to economic growth (Pengfei & Bing, 2004). Partial Factor Productivity (PFP) refers to the contribution a production element makes to total productivity. Traditional Western economists often divide the production elements into two categories: labour (L) and capital (K). Therefore, partial factor productivity mainly manifests in labour productivity and capital productivity (Lee & Heshmati, 2008). Total Factor Productivity (TFP) refers to the productivity growth induced by other production elements apart from labour and capital elements. That is, productivity growth which cannot be explained by an increase in capital and labour (Sudit, 2012).

According to Oh and Heshmati (2008), the Malmquist index is presently one of the main methods used in measuring Total Factor Productivity (TFP), and includes the parametric analysis method and non-parametric analysis method. Stochastic frontier analysis (SFA) is a typical parametric analysis method, which is generated based on the theoretical basis of the production function. Parametric analysis methods often need to set some specific functional form, to get the parameters of the model through the data fitting, and then calculate the corresponding efficiency value. However, this method is more subjective and could result in erroneous conclusions if the model is set incorrectly. Therefore, parametric analysis methods get more and more challenging, so the nonparametric analysis methods in turn contribute to measure Malmquist Index. The non-parametric analysis method has become the new method used in current international Total Factor Productivity (TFP) research.

In general, DEA, which is a non-parametric analysis method is the most popular method used. Not only can the DEA calculate Malmquist Index accurately, it can also decompose the Malmquist Index. This can provide a reliable theoretical support for determining the specific reasons behind the change in total factor productivity (TFP) of a decision-making unit. The DEA can decompose the Malmquist Index into technical change index and allocative change index, and the latter can be further divided into Technical efficiency change index and scale efficiency index. The DEA method of decomposing the Malmquist Index is based on the input-output data, which is built into the decision-making unit within a certain period. As such, it has actually a dynamic analysis to relative effectiveness of the decision-making unit through using DEA, while it is a static analysis only selecting the sectional data at one point (Diaz-Balteiro et al. 2006). This dissertation will discuss Malmquist Index and its decomposition by DEA in detail later.

2.6. Summary

This chapter began with an introduction to the high technology industry and subsequently discussed various definitions and concepts of efficiency with reference to the high-tech sector, value derived from innovation efficiency, and methods to measure innovation efficiency in the high-tech sector. Other topics discussed include technological innovation, two stages of technological innovation, efficiency of technological innovation, a decomposition of innovation efficiency, and the various definitions in the literature. Furthermore, this chapter introduced the classification of innovation efficiency and the methodology, inputs index, outputs index and conclusion in an empirical study of innovation efficiency. It is clear from the review that evaluating innovation efficiency is a complex activity and several important measures must be considered. The next chapter presents the methodology used for the research.

Chapter 3 METHODOLOGY

3.1. Introduction

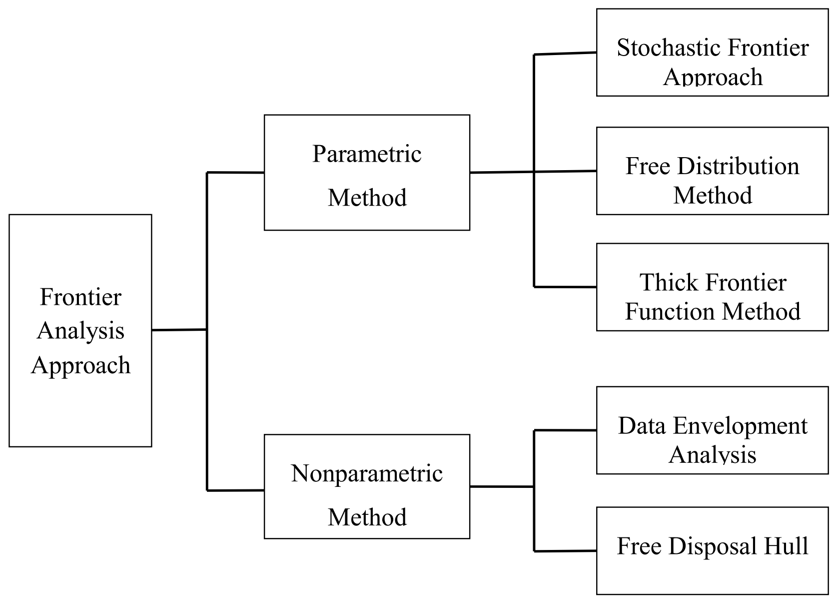
A structured and well-defined methodology is very important in academic research. The subject of evaluating the innovation efficiency in the high-tech sector is complex and involves a number of technical concepts and terms. Data Envelopment Analysis (DEA) is the chosen methodology for this research. The following sections explain important aspects of DEA and indicate the manner in which it can be used for the research.

3.2. Efficiency Measurement and an Evaluation Model

The previous chapter discussed in detail, the process of innovation in high-tech industries, and the different methods available for measurement. The qualitative nature of innovation means that it becomes difficult to define the KPIs for measurement. In addition, the complexity of high-tech industry, creativity of scientific research activities and uncertainty of the output of scientific research makes it hard to measure innovation efficiency. Several methods are available to measure innovation and the DEA method is used in this research. Measuring innovation efficiency with the DEA method means analysing input-output relation in technical innovation activities from quantitative perspective. Efficiency is a fundamental and important concept in both economics and management. As discussed in section 2.4, efficiency is often into multiple types, such as scale efficiency, technical efficiency and resource allocation efficiency.

Stochastic frontier analysis is used for economic modelling and to measure the efficiency. The efficiency measured by frontier analysis approach is not absolute efficiency, but technical efficiency. According to different production function setting ways and relevant parameter setting ways, efficiency measurement models can be classified into parametric method and nonparametric methods (Greene, 2010). Figure 3-1 illustrates the different approaches to measuring efficiency.

Figure 3-1: Approaches to the measurement of efficiency



Source: Greene (2010)

As seen in Figure 3-1, the Frontier approach has two methods, parametric and non-parametric. In this research, the non-parametric method, the DEA method is used. The parametric method involves confirming unknown parameters of the cost function through statistical methods and then calculating the ratio of the theoretical minimum cost to the actual cost. According to different assumptions of the frontier distribution function, the parametric method can be classified into stochastic frontier, free distribution method and thick frontier function method (Bauer, 1990).

The nonparametric method does not require an estimation of parameters and can be classified into data envelopment analysis (DEA) and free disposal hull. Free disposal hull is a special case of DEA. The emergence and development of the DEA provides great convenience for measuring the efficiency of different types. DEA is an effective assessment method developed on the basis of the comparative efficiency concept by a famous American operational research expert, Charns et al. (1978). Through the development for 30 years, DEA method has been relatively mature and become an important technical means in estimation practice. The DEA method is discussed is used in this research and discussed in detail in the next sections.

3.3. An Overview of the DEA Method

The DEA method (Charns et al., 1978) introduced the basic thought of single input and single output project efficiency evaluation in the evaluation of multi-input and multi-output decision-making unit efficiency. The model uses a single fractional programming model through allocating certain weights to different input and output indexes. Besides, through Charns–Cooper conversion (2C conversion), fractional programming model is transformed to linear programming model so that the efficiency of the objects investigated can be conveniently judged (Cook et al., 2014).

3.3.1. Basic Concepts

In the DEA model, the input and output data is analysed by constructing a linear programming model. This model helps to gain the comprehensive efficiency of each decision-making unit (DMU), and confirm relatively effective DMUs as per the scores. This is used to understand the cause and degree of non-DEA of other DMUs, in order to provide management information for the decision-makers. The DEA method is widely accepted as the method to measure efficiency (Ramanathan, 2003).

DEA finds use in estimation of production frontiers, for econometric studies, and the estimate the productive efficiency of decision-making units (DMU). DEA is considered as useful, since they do not assume any specific function, but they do not yield an equation for the input and output relation. DEA is used to create a function for the most efficient producers. It creates a frontier or a benchmark of the best producers, and helps to compare the performance of different functions (Tofallis, 2001). DEA functions on the basis that if an organisation has a certain level of productivity by using certain inputs, then another organisation of the same size should produce similar outputs. In such a situation, the most efficient firm becomes the benchmark and provides the means to calculate the productivity efficiency inputs and outputs. In instances when actual producers are not available, then virtual producers are used to define the benchmarks (Lovell & Schmidt, 1988).

In DEA, the most important component is the DMU. The DMU is a used to structure marketing and production decision-making in complex market environments. Important factors that define the DMU are buy class with new task, straight buy or modified re-buy; product type or materials, plan, and equipment, and purchase. The DMU is the focus in the DEA method and represents a group of homogenous multi-input and multi-output unit. Homogeneity indicates acceptance of three basic features simultaneously: same objective and task, same external environment, input and output indexes of the same type (Spekman & Gronhaug, 1986).

For the input and output, the DEA method requires discretionary, dimension independence, input negativity, output positivity etc. Input and output are a pair of concepts corresponding to investment and yield. The differences in the two are that investment and yield aim at a specific productive process, while input and output are the titles in the system science. The DMU includes entities such as public sector firms, schools, hospitals; private and non-profit organisations; private sectors such as enterprises and banks; and even countries. By selecting the appropriate DMU, the DEA method can be used for longitudinal studies, that is, observing the values at different time points of a substantive organisation as a group of DMUs. These techniques are used to study industries such as automotive, banking, electrical and electronics manufacturers, seaports, and even to calculate Olympic rankings (Cooper et al., 2007).

Axiomatic system DEA is used in multi-input and multi-output situations. It is hard to express its production possibility set and productive frontiers with graphs such as production functions. They are usually expounded in the form of vector quantities (Seiford & Thrall, 1990). Some examples of using DEA techniques and their calculations using vector analysis are as given below (Andersen & Petersen, 1993).

For a given DMU, assume there are m types of input and s types of output, X and Y mean input vector and output vector and $X \in E_{+}^{m}$, $Y \in E_{+}^{s}$. Then the production possibility set of multi-input and multi-output situations is expressed as:

$$T\left\{\left(X,Y\right)\middle| inputX \in E_{+}^{m}, outputY \in E_{+}^{s}\right\}$$

If there are n DMUs, X_j and Y_j are assumed to mean the input vector and output vector of the j[th] DMU. Then the combination (X_j, Y_j) is a production possibility.

The axiomatic system is a significant and fundamental concept in DEA method and is used to confirm the production possibility set (Allen, 1999). For different axiomatic systems, the production possibility sets will be different. Thus, the production frontier will also be different. Naturally, the comparative efficiency of DMU is diverse. Thus, it is necessary to cognize the axiomatic system in order to comprehend various DEA models. The axiomatic system met by the production possibility set T can be generalised as a number of axioms. These are commonness axiom, convexity axiom, unavailability axiom, cone axiom, contraction axiom, expansion axiom, and minimum axiom (Kersten & Vanden, 1995):

Commonness axiom: for any DMU, $(X_j, Y_j) \in T$, j=1,……, n. In other words, for basic activity, (X_j, Y_j) of input X_j and output Y_j is of course a production mode.

Convexity axiom: for any $(X, Y) \in T$, any $\left(\hat{X}, \hat{Y}\right) \in T$ and any $\alpha \in [0,1]$,

$$\alpha(X,Y) + (1-\alpha)\left(\hat{X}, \hat{Y}\right)$$
$$= \left\{\alpha X + (1-\alpha)\hat{X}, \alpha Y + (1-\alpha)\hat{Y}\right\} \in T$$

The convexity axiom is shown for two production modes (X, Y) and $\left(\hat{X}, \hat{Y}\right)$. If the input is based on the sum of α times and $(1-\alpha)$ times of X and $\hat{X}$, the output of the sum of α and $(1-\alpha)$ shows the proportions Y and $\hat{Y}$ can produce.

Unavailability axiom: This is also called the discretionary axiom. It is possible to produce with more input and less output. It is expressed with mathematical linguistics as follows: if $(X,Y)\in T$ and $\hat{X}\geq X, \hat{Y}\leq Y$, $\left(\hat{X},\hat{Y}\right)\in T$.

Cone axiom: for any $(X,Y)\in T$ and any $\alpha\geq 0$, $\alpha(X,Y)=(\alpha X,\alpha Y)\in T$.

The meaning of this axiom is as follows: input α times of X and the output α times of Y. In economics, it is also called additivity axiom.

Contraction axiom: for any $(X,Y)\in T$ and $\alpha\in(0,1]$, $\alpha(X,Y)=(\alpha X,\alpha Y)\in T$. In economics, the contraction axiom is also called the non-incremental return to scale. In other words, the scale of the production mode (X, Y) can be reduced.

Expansion axiom: For any $(X,Y)\in T$ and $\alpha\geq 1$, $\alpha(X,Y)=(\alpha X,\alpha Y)\in T$. In economics, the expansion axiom is also called the non-diminishing return to scale. In other words, the scale of the production mode (X, Y) can be increased.

Minimum axiom: The production possibility set T meets the minimum of all sets of one in axioms (1), (2) and (3) or (4A), (4B) and (4C). The significance of the minimum axiom is to confirm the production possibility set, which meets the assumptions. The production possibility set T_{C^2R} of C^2R model is jointly formed by the above (1), (2), (3), (4A) and (5), i.e.

$$T_{C^2R} = \left\{ (X,Y) \middle| X \geq \sum_{j=1}^{n} \lambda_j X_j, Y \leq \sum_{j=1}^{n} \lambda_j Y_j, \lambda_j \geq 0, J = 1,\ldots,n \right\}.$$

Besides, common production possibility sets generated due to different axiom systems in DEA method also include T_{BC^2}, T_{FG} and T_{ST}. They correspond to the BC^2 model, FG model and ST model respectively.

3.3.2. Fundamentals of DEA

The essence of the DEA method is to judge whether the DMU investigated is on the production frontier of the production possibility set. In economics, the production frontier is a kind of generalisation of the production function to multi-output. Envelope surface in the DEA method is a point set of the input-output of all effective DMUs. In fact, it is the production frontier of the production possibility set. If the DMU investigated is in the envelope surface, the DEA is effective. If not, then the DEA is ineffective (Ramanathan, 2003). Compared with production function method, the DEA method has a number of advantages, explored below.

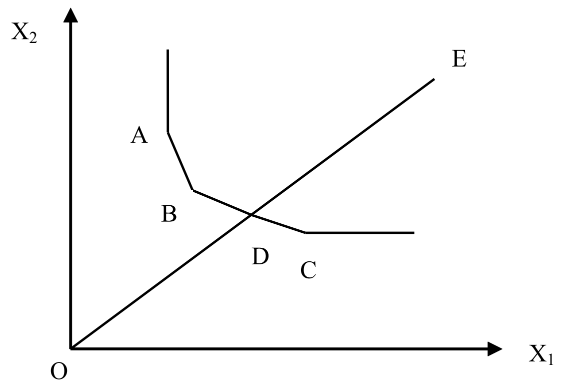
The DEA method can gain the production frontier more easily. The production frontier in the production function method can be gained through designing a specific function form. However, in the DEA method, the production frontier is composed of the envelope surface, which is composed of the points represented by the input and output data of all effective DMUs. The concept of data envelopment also originated from this. It is difficult to design a reasonable function form, which is restricted by the features of the object of study, the development phase of microeconomic subjects, the external environment etc. In western economics, economists put forward linear production functions such as the Cobb-Douglas production function (C-D production function) and the constant elasticity of substitution production function (CES production function). The DEA method only needs to apply input and output data observed in linear programming models. Due to this reason, the DEA method is considered a nonparametric statistical approach (Li & Reeves, 1999).

The DEA method has wider application scope. The production function method is applicable to a situation with one kind of or multi-inputs with one kind of output while the DEA method can investigate the sectors with multi-outputs. Besides, the production function is only used to investigate technical efficiency, while DEA method can measure more than the technical efficiency. The linear programming model can also measure scale efficiency and management efficiency through simple conversion. Thus, the DEA method can provide more decision-making information for decision-makers (Avkiran, 2001).

In practice, the production frontier in the DEA method can be more easily found, while the production frontier in the production function is just an ideal state, as the actual productive process is not always conducted under the optimal production state. Usually, the production function is obtained through fitting a group of given input element combinations and output. Thus, it is a production function in the average sense. This means actual output is above or below it. To solve this problem, the frontier production function is put forward. Although this method can indeed make all outputs below it, it inevitably needs to design the specific form of the production function (Asosheh et al. 2010).

The following examples explain the advantages of DEA method. Assume there are five homogeneous DMUs: A, B, C, D and E. All input two elements (X1, X2) and output one (Y). The points of input-output combinations of the five DMUs are drawn in figure 3-2. The broken line formed by A, B, C and D is their equal-output curve. According to production function theory, it is their production frontier, that is, envelope surface in the DEA method. Through comparing the five DMUs, from a technical perspective, A, B, C and D are effective while E is in the envelope surface. Thus, it falls under technical inefficiency. The connection line of Point E and the origin intersects with the production frontier at Point D. The input of Point D is much less than Point E. This indicates that Point E uses too many resources. In other words, compared with Point D, Point E is ineffective technically. This is also the origin of comparative efficiency in DEA. The technical efficiency of Point E can be measured with OD/OE. Only when OD/OE=1, is Point E effective technically. The DEA method constructs a linear programming model through the distance ratio of the DMU and the corresponding production frontier to evaluate comparative efficiency of each DMU (Wang et al., 2002).

Figure 3-2: Schematic diagram of DEA fundamentals



Source: Wang et al. (2002)

The above analysis shows the envelopment in DEA, which is a production frontier, composed of input-output points of DMUS with the highest production efficiency. The production frontier is subordinate to the production possibility set. The production possibility set is confirmed in accordance with certain axiomatic systems. For different axiomatic systems, the production frontier is also different. Naturally, comparative efficiency is also different.

3.4. DEA Measurement Model of Technical Efficiency and Scale Efficiency

A detailed discussion of different efficiencies was given in section 2.5, and this section describes the method to measure them. Technical efficiency, scale efficiency and comprehensive efficiency jointly decided by them are measured using the C^2R model and BC^2 model. The C^2R model assumes the return to scale is constant, and so measures the comprehensive efficiency of the DMU. The BC^2 model adds a convexity assumption: $\sum_{j=1}^{n}\lambda_j = 1$, and measures technical efficiency. Based on the two efficiencies, the scale efficiency of DMU can be calculated using a simple algebraic operation (Banker et al. 1984).

3.4.1. C^2R model

The C^2R model is used to measure the scale and technical efficiency. Each DMU processes the input factors to produce the output factors, and meet the objectives. The C^2R model, the DMU with effective DEA is used for the appropriate scale and for technical management (Li & Xu, 2008). Assume there are n DMUs and every DMU owns m types input and s types of output. For $DMU_j\left(j \in [1,\ldots,n]\right)$,

$x_{ij} = DMU_j$ input quantity for the r^{th} type of input, $y_{rj} \geq 0\left(1 \leq r \leq s\right)$

$y_{rj} = DMU_j$ input quantity for the i^{th} type of input, $x_{ij} \geq 0\left(1 \leq i \leq m\right)$

Since the status of every input index and output index in the DMU is different, assume v_i is the weight of the i^{th} input index $\left(1 \leq i \leq m\right)$ and u_r is the weight of the r^{th} output index $\left(1 \leq r \leq s\right)$. X_j in addition, Y_j mean input vector and output vector of DMU_j respectively; v and u mean weight vector of m types of input and s types of output $v \geq 0, u \geq 0$.

$$X_j = \left(x_{1j}, x_{2j}, ..., x_{mj}\right)^T, j = 1, ..., n;$$

$$Y_j = \left(y_{1j}, y_{2j}, ..., y_{mj}\right)^T, j = 1, ..., n;$$

$$v = \left(v_1, v_2, ..., v_m\right)^T;$$

$$u = \left(u_1, u_2, ..., u_s\right)^T$$

With the help of basic thought of the single input and single output project, efficiency evaluation in the field of science gives certain weights to every input-output index and determines the efficiency evaluation index number (h_j) of every MDU:

$$h_j = \frac{u^T Y_j}{v^T X_j} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}}, j = 1, 2, ...n$$

The efficiency evaluation index number (h_j) is a measure of the input ($v^T X_j$)-output ($u^T Y_j$) ratio under the weight coefficients v and u. For h_j, appropriate weight coefficients v and u can be selected all the time so that $h_j \leq 1 \left(1 \leq j \leq n\right)$ is the constraint condition. Thus, the following fractional program is obtained:

$$\begin{cases} \max \dfrac{u^T Y_{j0}}{v^T X_{j0}} \\ s.t. \dfrac{u^T Y_j}{v^T X_j} \le 1, j = 1, ..., n \\ u \ge 0, v \ge 0 \end{cases}$$

This is the initial form of the C^2R model. As it is a fractional programming problem, it is hard to calculate it. Through the Charns-Cooper conversion, C2 conversion (Charns et al., 1978), it can be transformed to an equivalent linear programming problem.

$$(P)\begin{cases} \max \mu^T Y_{j0} \\ \omega^T X_j - \mu^T Y_j \ge 0, j = 1, ..., n \\ \omega^T X_{j0} = 1 \\ \omega \ge 0, \mu \ge 0 \end{cases}$$

Where, $\omega = tv, \mu = tu$, $t = \dfrac{1}{v^T X_{j0}}$.

The linear programming problem (P) is that a weight vector can be found by comparing the target DMU DMU_{j0} and other DMUs to make the efficiency of the DMU_{j0} reach the maximum, relative to other DMUs. According to Pareto's effectiveness definition, the effectiveness of a DMU can be determined: If it is completely effective, it cannot improve any input or output when and only when other DMUs inputs or outputs do not deteriorate. Then, the definition of linear programming problem is as follows:

If the optimal solutions v^0 and u^0 of the linear programming problem (P) meet $u^{0T}Y_{j0}=1$, then the DMU_{j0} has a weak DEA effectiveness (C^2R);

If the optimal solutions v^0 and u^0 of linear programming problem (P) meet $u^{0T}Y_{j0}=1$, and $v^0>0, u^0>0$, we call DMU_{j0} DEA effectiveness (C^2R).

The dual program of the linear programming problem (P) is

$$(D)\begin{cases} \min\theta \\ s.t.\sum_{j=1}^{n} X_j\lambda_j \le \theta X_{j0} \\ \sum_{j=1}^{n} Y_j\lambda_j \ge Y_{j0} \\ \lambda_j \ge 0, j=1,\dots,n \end{cases}$$

According to the dual program (D), within the production possibility set T_{C^2R}, with the output Y_{j0} unchanged, X_{j0} should be reduced according to the same proportion θ. If it can be reduced, this shows the production activity of is DMU_{j0} ineffective. If not, then it is effective.

Based on the duality theory of linear programming, the following conclusions can be drawn:

The necessary and sufficient condition of the DMU_{j0} being weak DEA effective (C^2R) is that the optimal value of dual program (D) $\theta^0 = 1$.

The necessary and sufficient condition of the DMU_{j0} being DEA effective (C^2R)is that the optimal value of dual program (D) $\theta^0 = 1$, and that all its optimal solutions λ^0, S^{-0}, S^{+0} and θ^0 meet $S^{-0} = S^{+0} = 0$, where S^{-0} and S^{+0} are the optimal solutions of the slack variable and surplus variable respectively, under the above corresponding constraint conditions. Slack variable and surplus variable mean input redundancy and output insufficiency respectively.

Linear programming problem (P) and its dual program (D) reduce the input of DMU_{j0} under the condition where the output remains unchanged as far as possible, that is, the effectiveness of the DMU_{j0} is judged from the perspective of minimum input with output unchanged. Thus, it is also called an input-oriented C^2R model. Accordingly, DEA effectiveness can also be judged from the perspective of maximum output, with input unchanged. In this way, an output-oriented C^2R model is obtained. The DEA effectiveness gained from the two perspectives is equivalent.

3.4.2. BC^2 model

The BC^2 model is built with the assumption of the variable return to scale for a DMU (Yuan et al. 2013). The technical efficiency model is decomposed into pure technical efficiency and scale efficiency. Pure technical efficiency highlights the production efficiency, set by the managers using a constant scale. The scale efficiency gives the production efficiency, set by the scale factors. The technical efficiency provides the comprehensive technical efficiency for the resource allocation and its utilisation by the DMU. There is an important assumption to be taken into consideration when judging DMU effectiveness with the C^2R model: the cone axiom. In other words, the DMU investigated can expand output scale through an increase in input proportion. As such, the C^2R model measures both technical efficiency and scale efficiency. However, technically one cannot judge whether scale inefficiency or technical inefficiency leads to non-DEA effectiveness. In addition, the cone assumption is very harsh and there is a large gap with actual conditions. Banker et al. (1984) added the convexity assumption on the basis of the production possibility set T_{C^2R}:

$\sum_{j=1}^{n} \lambda_j = 1$. This adequately solves for mixed technical efficiency and scale efficiency. The BC^2 model is especially used to investigate the technical efficiency of the DMU appearing under such a background. The production possibility set of the BC^2 model is:

$$T_{BC^2} = \left\{ (X,Y) \middle| X \geq \sum_{j=1}^{n} \lambda_j X_j, Y \leq \sum_{j=1}^{n} \lambda_j Y_j, \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0, j = 1, \ldots, n \right\}$$

The input-oriented BC^2 model and its dual program are:

$$\left(P_{BC^2}^I\right) \begin{cases} \max\left(\mu^T Y_{j0} - \mu_0\right) \\ \omega^T X_j - \mu^T Y_j + \mu_0 \geq 0, j = 1, \ldots, n \\ \omega^T X_{j0} = 1 \\ \omega \geq 0, \mu \geq 0 \end{cases}$$

and $$\left(D_{BC^2}^I\right) \begin{cases} \min \theta \\ s.t. \sum_{j=1}^{n} X_j \lambda_j \leq \theta X_{j0} \\ \sum_{j=1}^{n} Y_j \lambda_j \geq Y_{j0} \\ \sum_{j=1}^{n} \lambda_j = 1 \lambda_j \geq 0, j = 1, \ldots, n \end{cases}$$

For the BC^2 model, the same definition applies:

If the optimal solutions ω^0, μ^0 and μ_0^0 of the linear programming problem ($P_{BC^2}^I$) meet $u^0 Y_{j0} - \mu_0^0 = 1$, then the DMU_{j0} has a weak DEA effectiveness (BC^2).

If the optimal solutions ω^0, μ^0 and μ_0^0 of linear programming problem ($P_{BC^2}^I$)

meet $u^0 Y_{j0} - \mu_0^0 = 1$, and $\omega^0 \rangle 0$, $\mu^0 \rangle 0$, we call DMU_{j0} DEA effectiveness (BC^2).

Similarly, in accordance with the duality theory of linear programming, similar conclusions can be drawn:

The necessary and sufficient condition of the DMU_{j0} being weak DEA effective (BC^2) is that the optimal value of dual program ($D_{BC^2}^I$) $\theta^0 = 1$.

The necessary and sufficient condition of DMU_{j0} being DEA effective (BC^2) is that the optimal value of dual program ($D_{BC^2}^I$) $\theta^0 = 1$, and that all its optimal solutions λ^0, S^{-0}, S^{+0} and θ^0 meet $S^{-0} = S^{+0} = 0$.

The C^2R model and BC^2 model can convey important decision-making information to decision-makers and have a very specific economic significance. An analysis of the return to scale can be carried out for the unit investigated:

When $\sum_{j=1}^{n} \lambda_j^0 = 1$, DMU_{j0} exhibits unchanged return to scale. This means the unit investigated should adopt a stable development strategy;

When the $\sum_{j=1}^{n}\lambda_j^0 \langle 1$, DMU_{j0} exhibits incremental return to scale. This means that the input scale can be further expanded;

When $\sum_{j=1}^{n}\lambda_j^0 \langle 1$, DMU_{j0} exhibits diminishing return to scale. This means the input should be reduced and the redundant resources shifted to other fields.

Next, a projection analysis can be conducted for DMU_{j0} with non-DEA effectiveness through the optimal solutions:

$$\hat{X}_{j0} = \theta X_{j0} - S^{-0} = \sum_{j=1}^{n}\lambda_j X_j$$

$$\hat{Y}_{j0} = Y_{j0} + S^{+0} = \sum_{j=1}^{n}\lambda_j Y_j$$

It can be proved that the projection $\left(\hat{X}_{j0}, \hat{Y}_{j0}\right)$ of DMU_{j0} on the production frontier is DEA effective. The reduced value of the input and the added value of the output are:

$$\Delta X_{j0} = X_{j0} - \hat{X}_{j0}$$

$$\Delta Y_{j0} = \hat{Y}_{j0} - Y_{j0}$$

3.5. DEA measurement Model of Malmquist Index

The Malmquist index was proposed by Swedish economist and statistician Malmquist in 1953, and was used to analyse consumption change in different periods (Malmquist, 1953). The index scales consumption bundles up or down, in a radial fashion to some arbitrarily selected indifference surface. In this context, Malmquist's scaling factor turns out to be the input-distance function, proposed by Shephard (1953). Malmquist quantity indexes for pairs of consumption bundles can be constructed from ratios of corresponding pairs of input distance functions.

Caves et al. (1982) constructed a Malmquist productivity index and used it to analyse production efficiency on the basis of the distance function. However, since a scientific distance function measurement method was not developed, their research remained as a theoretical analysis. This method was not widely applied until 1989 when Fare et al. applied the DEA method to measure the distance function.

Fare et al. (1998) decomposed the Malmquist productivity index into efficiency change (EC) and technical change (TC) (including pure technical efficiency PTC and scale efficiency SC). Their research provided significant guidance for determining the relationship among the change in DMU productivity, technical advance and management level. This decomposition method then became an important tool to study economic growth and total factor productivity.

3.5.1. The Malmquist Distance Function

The distance function refers to the function between a production point and the production frontier (Shephard, 1953). It can be classified into input-oriented and output-oriented distance functions. The input-oriented distance function refers to the proportion of compressing input vectors to the production frontier with a given output. The output-oriented distance function refers to the largest range of increasing output vectors with a given input. The essence of the two definitions is the same. This dissertation selects the output-oriented distance function. The distance function is closely related to the production possibility set. The production possibility set is the set composed of all possible production activities under certain technical conditions. There are different production possibility sets in different periods. As such, there are also different production frontiers. According to the definition, the distance function may be expressed in diverse ways. The significance is also different. Take the period t and t+1 for example.

Under constant returns to scale (CRS), the distance function has four types of expressions (Banker et al., 2004):

(1) $D^t\left(X^t, Y^t \middle| C, S\right) = \inf\left\{\theta : \left(X^t, Y^t / \theta\right) \in S^t\right\}$ means the distance between the

production point $\left(X^t, Y^t\right)$ during t and the current production frontier;

(2) $D^t\left(X^{t+1}, Y^{t+1} \middle| C, S\right) = \inf\left\{\theta : \left(X^{t+1}, Y^{t+1} / \theta\right) \in S^t\right\}$ means the production technology during t, that is, the distance between the production point $\left(X^{t+1}, Y^{t+1}\right)$ during t+1 and the production frontier during t, with the data during t used as the reference set;

(3) $D^{t+1}\left(X^{t+1}, Y^{t+1} \middle| C, S\right) = \inf\left\{\theta : \left(X^{t+1}, Y^{t+1} / \theta\right) \in S^{t+1}\right\}$ means the distance between the production point $\left(X^{t+1}, Y^{t+1}\right)$ during t+1 and the current production frontier;

(4) $D^{t+1}\left(X^t, Y^t \middle| C, S\right) = \inf\left\{\theta : \left(X^t, Y^t / \theta\right) \in S^{t+1}\right\}$ means the production technology during t+1, that is, the distance between the production point $\left(X^t, Y^t\right)$ during t and the production frontier during t+1 with the data during t+1 as the reference set.

Where X^t, X^{t+1}, Y^t and Y^{t+1} mean input and output vectors during t and t+1 respectively; S^t and S^{t+1} mean the production possibility sets in respective periods; and θ is the largest range of increasing output vectors. For the above four distance functions, due to different referenced production possibility sets, the value ranges are also different. (1) and (3) investigate the distance between current production point and the production frontier. As such, $0 \langle D^t\left(X^t, Y^t\right) \leq 1$, $0 \langle D^{t+1}\left(X^{t+1}, Y^{t+1}\right) \leq 1$. Regarding (2) and (4), since they do not refer to the current production possibility set, their distance functions may be greater than

1.

3.5.2. Malmquist Index and Its Decomposition

Under the condition of CRS and free disposal of elements ((C, S)), Fare et al. (1994) defined Malmquist index as follows:

$$M_t = \frac{D^t\left(X^{t+1}, Y^{t+1} \middle| C, S\right)}{D^t\left(X^t, Y^t \middle| C, S\right)} ,$$

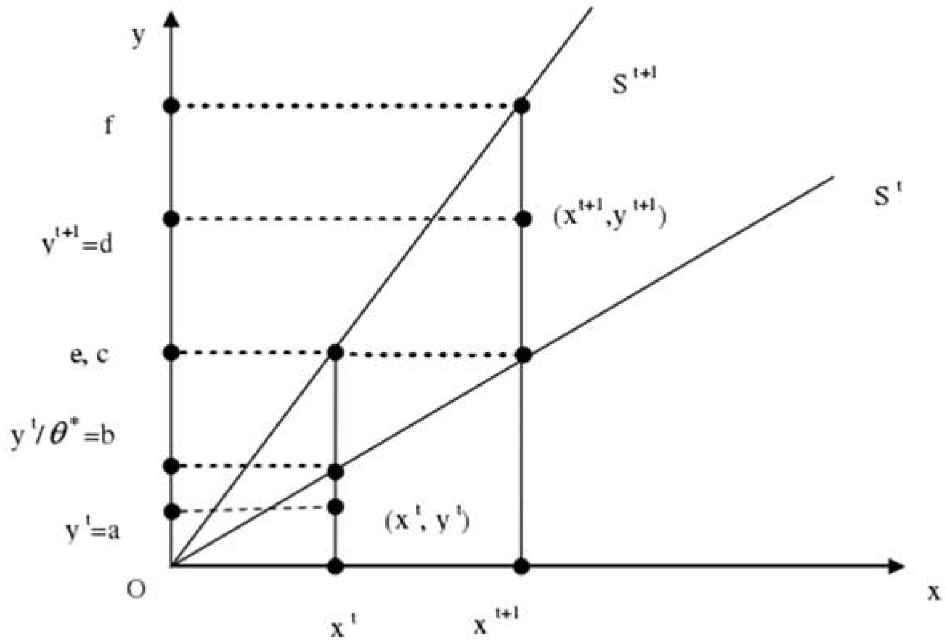
$$M_{t+1} = \frac{D^{t+1}\left(X^{t+1}, Y^{t+1} \middle| C, S\right)}{D^{t+1}\left(X^t, Y^t \middle| C, S\right)} 。$$

M_t in addition, M_{t+1} mean the specific values of two production points and production frontiers under the technology during t and t+1, and reflect the changes in the production efficiency during t and t+1. Take a single input (x) and single output (y) for example see Figure 3-3 $\left(X^t, Y^t\right)$ and $\left(X^{t+1}, Y^{t+1}\right)$ mean the production points during t and t+1; and S^t and S^{t+1} mean the production possibility sets during t and t+1. The four distance functions can be expressed as:

$$D^t\left(X^{t+1}, Y^{t+1} \middle| C, S\right) = \frac{Od}{Oe} ; \quad D^t\left(X^t, Y^t \middle| C, S\right) = \frac{Oa}{Ob}$$

$$D^{t+1}\left(X^{t+1}, Y^{t+1} \middle| C, S\right) = \frac{Od}{Of} ; \quad D^{t+!}\left(X^t, Y^t \middle| C, S\right) = \frac{Oa}{Oc}$$

Figure 3-3: Output based Malmquist Index



Source: Fare et al. (1994)

To avoid randomness in selecting a reference time for production technology, Fare et al. (1994) took the geometric mean of the two according to Fisher's ideal index (1922), as the efficiency evolution indexes during the two periods.

Thus, the Malmquist index is transformed to:

$$M_{t,t+1} = \left[\frac{D^t\left(X^{t+1}, Y^{t+1} \middle| C, S\right)}{D^t\left(X^t, Y^t \middle| C, S\right)} \times \frac{D^{t+1}\left(X^{t+1}, Y^{t+1} \middle| C, S\right)}{D^{t+1}\left(X^t, Y^t \middle| C, S\right)} \right]^{\frac{1}{2}}$$

$$= \left[\frac{Od}{Oe} \times \frac{Ob}{Oa} \times \frac{Od}{Of} \times \frac{Oc}{Oa} \right]^{\frac{1}{2}}$$

In order to look for the cause of change in total factor productivity, Fare et al. (1998) decomposed this index into two parts: comprehensive Efficiency Change (EC) index and Technical Change (TC) index, where,

$$EC = \frac{D^{t+1}\left(X^{t+1},Y^{t+1}\left|C,S\right.\right)}{D^{t+1}\left(X^{t},Y^{t}\left|C,S\right.\right)} = \frac{Od}{Oe}\times\frac{Ob}{Oa};$$

$$TC = \left[\frac{D^{t}\left(X^{t+1},Y^{t+1}\left|C,S\right.\right)}{D^{t+1}\left(X^{t+1},Y^{t+!}\left|C,S\right.\right)}\times\frac{D^{t}\left(X^{t},Y^{t}\left|C,S\right.\right)}{D^{t+1}\left(X^{t},Y^{t}\left|C,S\right.\right)}\right]^{\frac{1}{2}}$$

$$= \left[\frac{Od}{Oe}\times\frac{Of}{Od}\times\frac{Oa}{Ob}\times\frac{Oc}{Oa}\right]^{\frac{1}{2}} = \left[\frac{Of}{Oe}\times\frac{Oc}{Ob}\right]^{\frac{1}{2}}$$

Then,

$$M_{t,t+!} = \frac{D^{t+!}\left(X^{t+1},Y^{t+1}\left|C,S\right.\right)}{D^{t}\left(X^{t},Y^{t}\left|C,S\right.\right)}\times\left[\frac{D^{t}\left(X^{t+1},Y^{t+1}\left|C,S\right.\right)}{D^{t+1}\left(X^{t+1},Y^{t+1}\left|C,S\right.\right)}\times\frac{D^{t}\left(X^{t},Y^{t}\left|C,S\right.\right)}{D^{t+1}\left(X^{t},Y^{t}\left|C,S\right.\right)}\right]^{\frac{1}{2}}$$

$$= \frac{Od}{Of}\times\frac{Ob}{Oa}\times\left[\frac{Of}{Oe}\times\frac{Oc}{Ob}\right]^{\frac{1}{2}}$$

Coelli et al. (2005) argue that the comprehensive efficiency change index describes catching-up degree of the production frontier from t to t+1, also called the “catching-up effect”. It measures whether the DMU further approaches current production frontier for production. To some extent, it also reflects the change of the organisational management level of the DMU. When EC＞1, this indicates an improvement in the comprehensive efficiency of the DMU. Conversely, when EC<1, it shows a decline in efficiency. When EC=1, this shows that the comprehensive efficiency of the DMU remains unchanged.

Färe et al. (1997) point out that the technical change index describes the shift in the production frontier of the DMU during the two periods, also called the "frontier shift effect". It measures whether the technology of DMU advances. Like the comprehensive efficiency change index, when TC＞1, this indicates an improvement in the comprehensive efficiency of the DMU. Conversely, when TC<1, it shows a decline in efficiency. When TC=1, this indicates that the technical efficiency of DMU remains unchanged. In the theory of total factor productivity, technical progress is divided into two situations: embodied technical progress and non-embodied technical progress. If technical progress is in an input factor, it is called embodied technical progress. If it is not in an embodied technical progress (i.e. unrelated to input factor), it is called non-embodied technical progress.

As mentioned above, the Malmquist index and its decomposition are analysed under the condition of CRS. Considering that the actual economic system operates under the condition of VRS, Färe et al. (1997) further decomposed EC into pure technical efficiency (PTE) and scale efficiency (SE). In this way, the Malmquist index can finally be decomposed into comprehensive efficiency change, pure technical efficiency (PTE) change, scale efficiency (SE) change and technical change (TC). At this moment, the Malmquist index can be decomposed into:

$$M_{t,t+1} = \left[\frac{D^t\left(X^{t+1},Y^{t+1}|C,S\right)}{D^{t+1}\left(X^{t+1},Y^{t+1}|C,S\right)} \times \frac{D^t\left(X^t,Y^t|C,S\right)}{D^{t+1}\left(X^t,Y^t|C,S\right)} \right]^{\frac{1}{2}} \times \frac{D^{t+1}\left(X^{t+1},Y^{t+1}|V,S\right)}{D^t\left(X^t,Y^t|V,S\right)} \times \frac{S^t\left(X^t,Y^t\right)}{S^{t+1}\left(X^{t+1},Y^{t+1}\right)}$$

Where, $D^t\left(X^t,Y^t|V,S\right)$ and $D^{t+1}\left(X^{t+1},Y^{t+1}|V,S\right)$ mean output distance functions of DMU under VRS, during t and t+1. In fact, the ratio of the two is PET. $S^{t}\left(X^{t}, Y^{t}\right)$ and $S^{t+1}\left(X^{t+1}, Y^{t+1}\right)$ mean the scale efficiencies during the two periods. When the actual production point is (X, Y), the formula is:

$$S(X,Y)=\frac{D\left(X,Y|V,S\right)}{D\left(X,Y|C,S\right)}$$

The Malmquist index and the decomposed EC, PTE, SE and TC have common standards of judgment in terms of the numerical value: when the index is greater than 1, this means the corresponding efficiency improves; conversely, the efficiency declines. When the index is equal to 1, this means the efficiency is not changed. When the index is lower than 1, this means the DMU should be directed towards efficiency improvement in the future.

3.5.3. DEA Measurement Model of Malmquist Index

According to the definition, the distance function is actually the comprehensive efficiency of DMU. As such, a study of the distance function can be transformed to a study of the efficiency function (Chen & Ali, 2004). The efficiency function also has different definitions due to different reference times. For example, $F^{t}\left(X^{t}, Y^{t}\right)$ means the efficiency of the production point $\left(X^{t}, Y^{t}\right)$ of current DMU at the state of the system technology during t. Then, $D^{t}\left(X^{t}, Y^{t}\right)=F^{t}\left(X^{t}, Y^{t}\right)$. Similarly, the other three distance functions $D^{t}\left(X^{t+1},Y^{t+1}\right)$, $D^{t+1}\left(X^{t+1},Y^{t+1}\right)$ and $D^{t+1}\left(X^{t},Y^{t}\right)$ are equivalent to efficiency functions $F^{t}\left(X^{t+1},Y^{t+1}\right)$, $F^{t+1}\left(X^{t+1},Y^{t+1}\right)$ and $F^{t+1}\left(X^{t},Y^{t}\right)$ respectively.

The parametric method and non-parametric method can be used to measure the Malmquist index. The DEA method adopted in this paper is a typical non-parametric method. Under the condition of CRS, the above four distance functions are solved through the following four DEA models. Take the k[th] DMU for example:

$$(1)D^{t}\left(X^{t},Y^{t}\right)=\min\theta \quad (2)D^{t}\left(X^{t+1},Y^{t+1}\right)=\min\theta$$

$$s.t.\begin{cases}\sum_{j=1}^{n}X_j^t\lambda_j\le\theta X_k^t\\ \sum_{j=1}^{n}Y_j^t\lambda_j\ge Y_k^t\\ \lambda_j\ge 0, j=1,\dots,n\end{cases} \quad s.t.\begin{cases}\sum_{j=1}^{n}X_j^{t+1}\lambda_j\le\theta X_k^t\\ \sum_{j=1}^{n}Y_j^{t+1}\lambda_j\ge Y_k^t\\ \lambda_j\ge 0, j=1,\dots,n\end{cases}$$

$$(3)D^{t+1}\left(X^{t+1},Y^{t+1}\right)=\min\theta \quad (4)D^{t+1}\left(X^{t},Y^{t}\right)=\min\theta$$

$$s.t.\begin{cases}\sum_{j=1}^{n}X_j^{t+1}\lambda_j\le\theta X_k^{t+!}\\ \sum_{j=1}^{n}Y_j^{t+1}\lambda_j\ge Y_k^{t+1}\\ \lambda_j\ge 0, j=1,\dots,n\end{cases} \quad s.t.\begin{cases}\sum_{j=1}^{n}X_j^{t}\lambda_j\le\theta X_k^{t+1}\\ \sum_{j=1}^{n}Y_j^{t}\lambda_j\ge Y_k^{t+1}\\ \lambda_j\ge 0, j=1,\dots,n\end{cases}$$

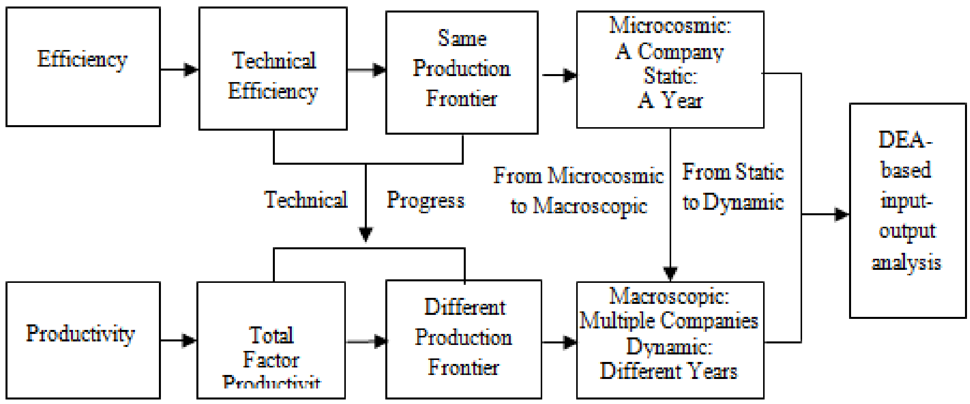
If a constraint condition $\sum_{j=1}^{n}\lambda_j=1$ is added in Model (1) and Model (3), PET of each DMU under VRS condition, then the corresponding scale efficiency can be gained through the comprehensive efficiency gained from C^2R model dividing PET.

3.6. Innovation Activity Efficiency Vs. Total Factor Productivity

3.6.1. Difference

Technical efficiency refers to the technical efficiency of a province/industry in a year under the same production frontier (Zhang et al., 2003). It is a static and microcosmic measurement. The measurement result is a group of limited values between 0 and 1. It measures absolute efficiency, but comparative efficiency. Total factor productivity refers to a dynamic change in the productivity of multiple provinces/industries in different years under different production frontiers. It is a dynamic and macroscopic measurement. The measurement result is often the change rate expressed with the index. Technical efficiency and total factor productivity have close relations. The same production frontier is transited to different production frontiers through technical progress and static technical efficiency is transited to dynamic total factor productivity measurement, which realises microcosmic-macroscopic and static-dynamic deep system research, as shown in Figure 3-4.

Figure 3-4: Relation between Technical Efficiency and Total Factor Productivity



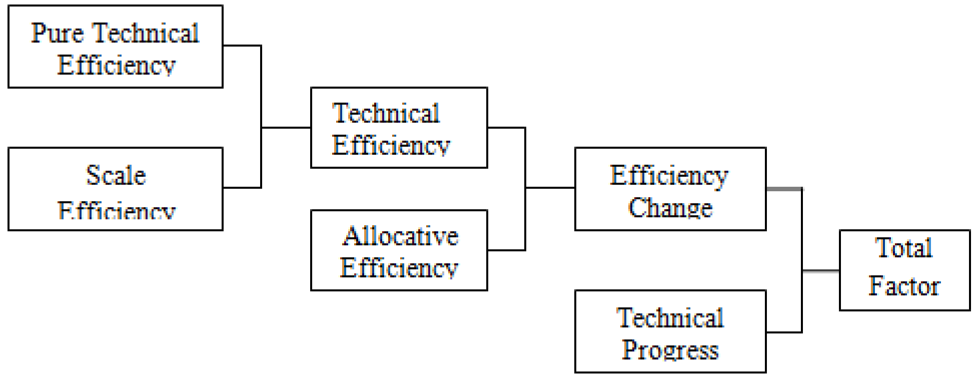
Technical efficiency measures the efficiency of multiple DMU for any year, while total factor productivity measures changes in the total output relative to total input and changes in total factor productivity of multiple provinces/industries in multiple periods (Favero & Papi, 1995). This is the largest difference with efficiency (or technical efficiency). Technical efficiency is static and measures the efficiency and differences in different provinces/industries in a year. Total factor productivity is dynamic and measures relative changes in the efficiency and technology of various provinces/industries in different periods (years). Total factor productivity focuses on individuals and industries. It is dynamic and macroscopic. Technical efficiency involves individuals, enterprises. It is static and microcosmic. The differences between innovative activity efficiency and total factor productivity are obvious, but at the same time, both of them are also closely related. This is not just reflected in the theoretical connotations and theoretical evolution, but also in the research methods (Zhang et al., 2011).

3.6.2. Relationship

Theoretically, innovation efficiency and total factor productivity have close relations. Under the condition of unchanged VRS, in view of technical progress, the changes in total factor productivity can be decomposed into efficiency change and technical progress. Here, efficiency change is not totally the same as that studied in this dissertation. This is because efficiency change can be classified into technical efficiency change and allocative efficiency change (Gang et al., 2003).

Since allocative efficiency involves the input-output factor price problem, this dissertation adopts a nonparametric method without consideration of factor price (Barros & Mascarenhas, 2005). The efficiency used in this dissertation therefore refers to technical efficiency rather than allocative efficiency. Through the above decomposition process, total factor productivity and technical efficiency can be connected. It can be seen that total factor productivity and technical efficiency are closely related. They are two indispensable layers in research.

Figure 3-5: Decomposition of Technical Efficiency and Total Factor Productivity



Under a deterministic frontier, the DEA analysis develops rapidly, and Shephard (1970) came up with distance function. With regard to total factor productivity, Solow (1957) studied technical progress in detail and put forward the Solow model. The model is mainly based on Divisia index.

Total factor productivity and technical efficiency develop under their own theoretical frameworks and have no intersection. Fare et al. (1994) associated total factor productivity with technical efficiency through the Malmquist productivity index. Since then, total factor productivity and technical efficiency have not been completely independent fields and have been put together for comparative study. According to the research methods used in this dissertation, trust company efficiency and total factor productivity are measured through the input-output method in technical economy.

3.7. Suitability of DEA research in the Chinese context

As seen from the discussions in the previous sections, DEA finds use in a large cross section of industries. Studies using DEA are carried out for ports, electrical equipment industries, hospitals, construction, and a number of other sectors. This research is to study the innovation efficiency for Chinese high-tech sector. The five sectors chosen to be studied were selected in Chapter 1.

DEA is not restricted to any one sector or stream. If the correct input data is available, it can be used to study the efficiency of any country and its industries. The data for this research is available in the Chinese Statistical Handbook, and data on innovation efficiency is available for a number of years. Therefore, applying the DEA principles to the selected data sets will help to complete the research.

3.8. Summary

This chapter comprehensively evaluated the DEA measurement method and is the most important link in empirical analysis. It is clear scientific research performance is decomposed into technical efficiency, scale efficiency, comprehensive efficiency and total factor productivity. Subsequently, basic concepts, fundamentals and the development course of DEA method are presented in detail. On this basis, the model and model, used to measure comprehensive efficiency, technical efficiency and scale efficiency were introduced. Furthermore, this chapter explains how to apply the two models to calculate Malmquist index, which is used to measure total factor productivity. The DEA method based on nonparametric method for empirical analysis with the C^2R model will be used in this dissertation. In measuring technical efficiency, the traditional DEA and the DEA model based on directional distance function are used. In measuring total factor productivity, the DEA-based Malmquist productivity index model is used. The two have certain similarities in terms of the research method. In terms of practical significance, if the research shows that low total factor productivity of high-tech industries is caused by the frontier's technical level, then corresponding national policies can guide continuous technical innovation of high-tech industries, improve the frontier production function, and promote technical progress.

From the perspective of technical efficiency, if high-tech industries have high technical levels but a large gap still exists between the output and production frontier, then this is caused by low technical efficiency. Now, the countermeasures that can be implemented include enhancing management levels and perfecting governance mechanisms in order to boost technical efficiency. It can be seen that total factor productivity and technical efficiency have different meanings from a political perspective. Nevertheless, reforms are needed to promote technical progress of high-tech industries and systems are needed to improve the utilisation rate of existing resources.

Chapter 4 EMPIRICAL ANALYSIS OF INNOVATION EFFICIENCY OF CHINA'S HIGH-TECH INDUSTRIES USING PROVINCIAL PANEL DATA

4.1. Introduction

This chapter uses data from the Chinese Statistical Yearbook, analyses the data, and presents the findings for the research. Objectives of the research will be answered mainly from the findings of this chapter.

A number of tests are carried out and these include integral analysis, analysis of the static technical efficiency. CRSTE, VRSTE, and SE efficiency analyses are presented along with the projection analysis. These tests are further reinforced with the Malmquist based dynamic measurement and evaluation of innovation efficiency of China's high-tech industry. The last series of tests provide the analysis of the total factor productivity, where the characteristics of the Malmquist index are analysed along with causes for the unstable Malmquist index, followed by an analysis of the PTE and SE changes, the M Mean Change, and the trend of 28 DMUs is considered for 2005-2011. This is followed by a regional comparison of the Malmquist index for the study period and a section discussing and analysing the findings.

The chapter is organised as follows. First 28 DMUs and the input/ output indexes are confirmed for the study. Next, data for analysis are extracted are screened and analysed. The next series of steps is the analysis of this data, including the tests described above. A static analysis and evaluation is carried out to assess the innovation efficiency of the DMUs.

4.2. DMU, Index System and Data

4.2.1. Confirmation of DMU

The development of high-tech technical industries in various provinces such as the autonomous regions/municipalities, directly under the Central Government of China shows variations, due to their location and history. To meet the homogeneity requirement for DMU in DEA method, screening is used to ensure the correct DMUs are included in the research. For example, the main industry in Tibet is tourism. However, the development yearbook of China's high-tech technical industries excludes the data about Tibet. Relative to other provinces, two autonomous regions, Qinghai and Xinjiang have less development. Overall, provinces in the eastern China are more developed (Lu & Lo, 2007). The above justification is used to select the 28 DMUs for the research.

The research will consider panel data for 2005-2011 for the following reasons. China's space programme in 2005 showed that China had become the third largest technological power in the world. In this year, China passed the National Outline for Medium and Long Term S&T Development, analysed the situation of China's scientific and technical development, specified guidelines and set strategic targets. The scientific and technical development plan for the next 15 years was deployed. In the plan, tasks and key points of scientific and technical development were proposed, policy measures of scientific and technical system reforms were developed, the state innovation system construction and scientific and technical guarantee implemented (Qingwang & Junxue, 2005).

During the selected years, China showed good achievements in intellectual property creation and protection, and developed many innovation solutions. The year 2005 has a symbolic significance in the development history of China's high-tech industries (Zhang & Gong, 2005). The year 2006 was the first year of the 11th Five-year Plan. It is especially important to analyse the changes in innovation efficiency of China's high-tech industries by taking the final year of the 10th Five-year Plan – 2005 as the benchmark year. We select the first three years and the following 3 years of 2008 financial crisis or a total of 7 years as the research sample for contrastive analysis of changes in innovation efficiency of China's high-tech industries before and after financial crisis. This approach will provide policy suggestions to improve the innovation efficiency of China's future high-tech industries.

4.2.2. Screening Input/ Output Indexes

The analysis on innovation activities of high technology industries shows that as many as 84 input/ output indexes used to study innovation efficiency of a country (Saisana & Dionisis, 2013). Obviously, not all indexes can be included in this research, and therefore, a screening is used to select the indices. Index selection plays a decisive role for analysis data. The screening is done as per the following factors. Strong linear dependence among data should be avoided, the number of DMUs should be greater than twice of the sum of input and output indexes.

4.2.3. Screening Input Indexes

Tseng and Lee (2009) speak of the importance of considering the number of full time human resources for DEA innovation efficiency studies. Since government provides grants for research, the number of people who are funded through such programmes becomes a crucial index. In the aspect of resources, the number of staff engaged in scientific research and the numbers of technical innovation teams form the first input index. However, in view of actual development conditions in high technology industries in each province and data availability, this dissertation selects the number (X_1) of resources as the index of human resources. Full-time resources are teams whose time for scientific research activities accounts for at least 90% of annual working time in the reporting period and others are non-full-time resources. Non-full-time resources can be converted to full-time resources based on their actual working time.

Sharma & Thomas (2008) highlight the importance of the expenditure made on R&D in the innovation efficiency studies. Countries and organisation that have a higher budget for R&D have a higher level of efficiency. In the aspect of

R&D fund input, two indexes are considered: expenditure on R&D (X_2) and expenditure on New Products Development (X_3). The two indexes also indirectly reflect the degree of valuing innovation activities for development of high-tech industries and development conditions in each province.

Fu (2008) argues about the importance of investment in infrastructure, equipment, and other areas, for innovation studies. Hence, this forms another index. In the aspect of material capital input, the index which can mostly reflect material capital input of high-tech industries is Investment in Fixed Assets (X_4).

4.2.4. Screening output indexes

According to Bian and Yang (2010), the output indices are very important, since they highlight the extent of innovation efficiency in a country or an industry. For innovation activity output of high-tech industries, it is necessary to pay attention to the result quality during index selection in order to reflect basic requirements of the performance concept. This dissertation selects three output indexes. These are Patent Applications (Y_1), Gross value of New Products (Y_2) and Scales Revenue of New Products (Y_3). The three indexes indicate an ability to transform science and technology input into actual productivity and income.

4.2.5. Data Collection and Screening

The data was obtained mainly from the *China Statistics Yearbook on High Technology Industry,* which is jointly written by the State Statistics Bureau, National Development and Reform Commission and the Ministry of Science and Technology and is published by China Statistical Publishing House (NBS, (2014). This dissertation carries out static analysis for the DMU data from 2005-2011 and mainly analyses the data in 2011, since the publication had complete data for these years. Dynamic analysis is also based on the data from 2005 to 2011.

Grosskopf (1996) argues that test statistics method selection is important for DEA analysis. In view of the key role of input and output indexes in technical efficiency measurement, this dissertation introduces the KS test and T test to confirm input and output indexes.

4.2.6. The K-S Test

Kolmogorov-Smirnov or K-S test is a non-parametric test, used to analyse the extent of equality of one-sided probability distributions. The results are used to compare sample data with a one-sample K-S test curve. It presents a reliable method of comparing two samples. The test is based on the principle that the empirical distribution is a theoretical distribution consistent estimate. It is used to describe the similarity or differences of two independent statistical samples. This test is used in this research to analyse and test the sample data (Corder & Foreman, 2014).

Assume $X_1,...,X_m \overset{iid}{\sim} F(x)$, $Y_1,...,Y_n \overset{iid}{\sim} G(x)$ and whole samples are independent; $F(x)$ and $G(x)$ are continuous distribution functions. The null and alternative hypotheses for KS test are (Taylor & Emerson, 2011):

$$H_0 : F(x) \equiv G(x)$$

$$H_1 : F(x) \neq G(x)$$

According to the Glivenko–Cantelli theorem (Vaart, 1998), it is feasible to adopt empirical distribution functions to approximate theoretical distribution functions.

Using the K-S test (Simar & Wilson, 2008) $D = \max_{i,j}\left\{\left|F_m\left(X_{(i)}\right) - G_n\left(Y_{(j)}\right)\right|\right\}$ to test the above assumption, where $F(x)$ and $G(x)$ mean empirical distribution functions of Sample X and Sample Y; $X_{(i)}$ and $Y_{(j)}$ mean order statistics of

Sample X and Sample Y; and m and n mean the number of samples. The rejection region of H_0 helps it take the maximum value. The significance level of the statistics D can be expressed by the reliability distribution function Q_{ke}:

$$pro(D) = Q_{ke}(\lambda) = 2\sum_{j=1}^{\sim}(-1)^{j-1} e^{-2j^2\lambda^2}$$

Where $\lambda = \left|\sqrt{N_e} + 0.12 + \frac{0.11}{\sqrt{N_e}}\right| D$， $N_e = \frac{mn}{m+n}$

According to Banker et al. (2004), if the two independent samples are very similar, when statistics distance is $D \to 0$, $p \to 1$, and vice versa. Thus, the K-S test can serve as the statistics of the nonlinearity test. The test assessment is nonlinear correlation of surrogate data generated through phase method is eliminated and reorganised data and original data are used for KS test. The rejection region is 0.05. If the significance level $p > 0.05$, this shows original data have linear features; if the significance level $p < 0.05$, this indicates original data has nonlinear features.

4.2.7. T test

The T test also called the t student distribution is used to evaluate if two data sets are different. It is used when the test follows a normal distribution curve, when the scaling term is known. When the scaling is not known, and it is replaced and an estimate is used, then it follows the student t distribution. It is actually a significance test of mathematical expectation when the normal population variance is unknown (Rice, 2006).

Assume that in the test, the totality obeys normal distribution (Edgell & Noon, 1984). Therefore, $N(\mu, \delta^2)$; $\xi = (\xi_1, \xi_2, ..., \xi_n)$ is a random sample with the capacity of n; sample mean is $\bar{\xi}$; the population variance in U test is known. However, in normal conditions, it is hard to meet this requirement. A very natural idea is that an unbiased estimator S^2 of δ^2 is used to replace it. The test statistics $T = \frac{\xi - \mu_0}{S}\sqrt{n}$ obeys the t distribution with a degree of freedom of n-1. The above test is called the T test. The T test can test the assumption that the significance level of mathematical expectation μ is α:

According to O'Mahony (1986), the rejection region of null hypothesis $H_0 : \mu \le \mu_0$ is $\bar{\xi} \ge \mu_0 + t_\alpha \frac{S}{\sqrt{n}}$; when null hypothesis $H_0 : \mu \ge \mu_0$,the rejection region is $\bar{\xi} \le \mu_0 - t_\alpha \frac{S}{\sqrt{n}}$; when null hypothesis $H_0 : \mu = \mu_0$, the rejection region is

$$\left|\bar{\xi}-\mu_0\right| \geq t_{\alpha/2}\frac{S}{\sqrt{n}}.$$

The above tests are called T tests. The critical value $t_{\alpha/2}$ is α quantile on t distribution with freedom degree of n-1. The specific value can be obtained from the t-distribution table.

The KS test results and T test results of input-output indexes as well as the statistical description are shown in Table 4-1 and Table 4-2 (Pastor et al., 1999; Banker & Natarajan, 2011).

Table 4-1: KS Test Results and T Test Results of Input-Output Indexes

Index type	**Index to be tested**	**KS test**	**T test**
Input index	Converted full-time quantity of R&D activity personnel (number of personnel/year)	4.472***	4.839***
	Internal expenditure of R&D funds (10 thousand Yuan))	4.383***	7.308***
	Expenditure on new products development (10 thousand Yuan)	4.311***	7.221***
	Investment in Fixed Assets (100 million Yuan)	3.083***	6.578***
Output index	Patent applications	5.109***	6.830***
	Output value of new products (10 thousand Yuan)	4.212***	7.040***
	Sales revenue of new products (10 thousand Yuan)	4.242***	10.881***

Table Note: *, ** and *** mean significance at the levels of 10%, 5% and 1% respectively.

Table 4-2: Statistical Description of Input-Output Indexes

Index type	Index	Mean	Median	Maximum	Minimum	Std.Dev	Observations
Input index	Converted full-time quantity of R&D activity personnel (number of personnel/year)	10409	4907.5	167069	12	22154	196
	Internal expenditure of R&D funds (10 thousand Yuan)	211797	71978	3322460	280	434165	196
	Expenditure on new products development (10 thousand Yuan)	246962	74270	4016820	536	491129	196
	Investment in Fixed Assets (100 million Yuan)	141.53	83.77	1536.42	1.06	182.09	196
Output index	Patent applications	1551	349	36742	1	4487	196
	Output value of new products (10 thousand Yuan)	3733925	675310	52689299	150	7152975	196
	Sales revenue of new products (10 thousand Yuan)	3733189	625671.5	52322794	150	7238196	196

4.3. Static Analysis and Evaluation of Innovation Efficiency of DMUs

Static analysis with the DEA method is the analysis of the comparative efficiency of a DMU for a specific period rather than time series (Cook & Seiford, 2007). This section presents the static measurement and evaluation of innovation efficiency of China's high-tech industry.

4.3.1. Integral Analysis of Technical Innovation Efficiency of DMUs

The DEA method uses two models to evaluate DMU comparative efficiency, the input-oriented efficiency measurement model, and the output-oriented efficiency measurement model (Casu & Molyneux, 2003). The efficiency values obtained through the two models may differ, but they are the same under the situation of weak effectiveness and effectiveness. The input-oriented model focuses on input factor minimisation, while the output-oriented model focuses on output maximisation. Since the technological innovation input indexes (converted full-time quantity of R&D activity personnel, internal expenditure of R&D funds, expenditure on new products development and investment in fixed assets) are rigid to an extent, this dissertation selects the output-oriented DEA model. Furthermore, since the science and technology input scale of a province could be changed in certain periods and there is an internal impulse, which continuously expands, the output-oriented DEA model with varied scale was selected (Barros & Athanassiou, 2004).

This dissertation uses the Deap 2.1 software to measure and calculate the technical innovation efficiency STE scores of high-tech industries of each province from 2005 to 2011, and conducts a contrastive analysis of STE, also called comprehensive efficiency of each province in the same year. It mainly focuses on the provinces on the production frontier (Coelli et al., 2005). The measurement results are shown in Table 4-3.

Table 4-3: STE of CRSTE under CRS during 2005-2011

Province	2005	2006	2007	2008	2009	2010	2011	Years on frontier
Beijing	0.547	0.756	1.000	0.547	1.000	1.000	1.000	4
Tianjin	1.000	1.000	1.000	1.000	1.000	1.000	1.000	7
Hebei	0.156	0.517	0.215	0.156	0.305	0.462	0.344	0
Shanxi	0.499	1.000	1.000	0.499	1.000	1.000	0.529	4
Inner Mongolia	0.333	0.233	0.057	0.333	0.337	0.680	0.367	0
Liaoning	0.432	0.493	0.494	0.432	0.382	0.550	0.496	0
Jilin	0.343	0.490	0.425	0.343	0.327	0.694	0.364	0
Heilongjiang	0.248	0.350	0.131	0.248	0.188	0.233	0.408	0
Shanghai	1.000	0.800	0.712	1.000	0.741	0.674	0.693	2
Jiangsu	0.216	0.249	0.321	0.216	0.455	0.650	0.870	0
Zhejiang	0.405	0.427	0.315	0.405	0.675	0.844	0.757	0
Anhui	0.207	0.323	0.257	0.207	0.606	0.831	0.734	0
Fujian	0.812	0.671	0.752	0.812	0.688	0.811	1.000	1
Jiangxi	0.226	0.289	0.176	0.226	0.315	0.392	0.253	0
Shandong	0.452	0.584	0.464	0.452	0.473	0.696	0.706	0
Henan	0.233	0.679	0.264	0.233	0.457	1.000	0.858	1
Hubei	0.497	0.417	0.237	0.497	0.290	0.507	0.369	0

Province	2005	2006	2007	2008	2009	2010	2011	Years on frontier
Hunan	0.169	0.534	0.219	0.169	0.657	1.000	1.000	2
Guangdong	1.000	1.000	0.836	1.000	1.000	1.000	1.000	6
Guangxi	0.277	0.476	0.170	0.277	0.460	0.621	0.326	0
Hainan	0.180	0.789	1.000	0.180	0.738	0.670	0.951	1
Chongqing	0.266	0.672	0.327	0.266	0.781	0.930	1.000	1
Sichuan	0.259	0.330	0.307	0.259	0.428	0.666	0.411	0
Guizhou	0.507	0.573	0.327	0.507	0.711	0.709	0.792	0
Yunnan	1.000	1.000	1.000	1.000	1.000	0.882	0.668	5
Shaanxi	0.440	0.254	0.216	0.440	0.239	0.347	0.314	0
Gansu	0.348	1.000	0.339	0.348	0.482	0.806	0.735	1
Ningxia	0.643	0.484	0.510	0.643	0.563	1.000	0.810	1
Means	0.453	0.585	0.467	0.453	0.582	0.738	0.670	0
Number of frontiers	4	4	5	4	5	7	6	

According to DEA measurement results, Table 4-3 describes STE scores of each province and the mean of the seven years from 2005 to 2011. SET measures total efficiency of DMU, and the proportion of innovation in the high-tech technology industry for each province to the largest possible output, under the current technical level. It can be seen from Table 4-3 that all technical efficiency values are between 0 and 1. Efficiency values measured by the DEA model are a group of limited values. If the efficiency value is 1, this means that the province is on the production frontier and is effective technically (Wang et al., 2013). Please refer to section 7.2 for an analysis and discussion of the findings.

4.3.2. Analysis of STE of Provincial High-tech Industry in 2011

The above analysis is aimed at determining the technical innovation efficiency of the high-tech industry from 2005 to 2011. The emphasis is the STE of each province. Since the efficiency has no comparative significance in different years, this section will focus on the STE of each province in 2011 and decompose the STE into pure technical efficiency (PTE) and scale efficiency (SE) for analysis, to compare the differences and sources of innovation efficiency of the different provinces (Zou et al., 2013).

Table 4-4: Measurement Results of the Comparative Efficiency of Innovation Efficiency of the High-tech Industry for 28 Provinces in 2011

Province	crste	vrste	SE	Scale state
Beijing	1.000	1.000	1.000	——
Tianjin	1.000	1.000	1.000	——
Hebei	0.344	0.351	0.979	irs
Shanxi	0.529	0.637	0.830	irs
Inner Mongolia	0.367	1.000	0.367	irs
Liaoning	0.496	0.515	0.964	irs
Jilin	0.364	0.395	0.920	irs
Heilongjiang	0.408	0.419	0.974	irs
Shanghai	0.693	0.694	0.999	irs
Jiangsu	0.870	1.000	0.870	drs
Zhejiang	0.757	0.757	0.999	——
Anhui	0.734	0.734	1.000	——
Fujian	1.000	1.000	1.000	——
Jiangxi	0.253	0.265	0.952	irs

Province	crste	vrste	SE	Scale state
Shandong	0.706	0.846	0.835	drs
Henan	0.858	1.000	0.858	drs
Hubei	0.369	0.371	0.994	irs
Hunan	1.000	1.000	1.000	——
Guangdong	1.000	1.000	1.000	——
Guangxi	0.326	0.383	0.850	irs
Hainan	0.951	1.000	0.951	irs
Chongqing	1.000	1.000	1.000	——
Sichuan	0.411	0.412	0.996	irs
Guizhou	0.792	0.907	0.873	irs
Yunnan	0.668	0.721	0.928	irs
Shaanxi	0.314	0.319	0.986	irs
Gansu	0.735	0.876	0.848	irs
Ningxia	0.810	1.000	0.810	irs
Means	0.670	0.736	0.921	
Number of frontiers	6	11	7	

Table Note:
irs means increasing returns to scale
drs means decreasing returns to scale
—— means constant returns to scale
crste = technical efficiency from CRS DEA
vrste = technical efficiency from VRS DEA
scale = scale efficiency = crste/vrste
Note also that all subsequent tables refer to VRS results

Analysis and discussion of the results is given in section ‘7.2.1.2 Discussion of CRSTE Efficiency Analysis’ and section ‘7.2.1.3 Discussion of VRSTE Efficiency Analysis’.

4.3.3. SE Efficiency Analysis

SE measures if each province carries out technical innovation activities at the most proper input scale under certain technical level, i.e. the distance between the production frontier under CRS and the production frontier under VRS. This gives rise to three instances, increasing returns to scale (IRS), decreasing returns to scale (DRS) and constant returns to scale (CRS). CRS is the most ideal production state, while IRS and DRS belong to SE inefficiency. For increasing or decreasing DMUs, improvement is needed to reach the ideal state (Zhang et al., 2015). Results from the findings are given in Table 4-4.

A number of factors cause increasing or decreasing returns to scale in the provinces. Table 4-5 and Table 4-6 show specific indexes and the data of non-DEA effectiveness of different provinces from the perspective of slack variables and surplus variables. In line with the basic theories of linear programming, the values of slack variables show the decrease in the input factor amount investigated under the condition where the output remains unchanged, compared with other DMUs (Zhang et al., 2011). Therefore, S_1^{-0}, S_2^{-0}, S_3^{-0} and S_4^{-0} correspond to the decreased amount of four input factors: X_1, X_2, X_3 and X_4. Similarly, the values of surplus variables show the increased amount of the output under the condition where the input remains unchanged compared with other DMUs. S_1^{+0}, S_2^{+0} and S_3^{+0} correspond to the increased amount of 3 output factors: Y_1, Y_2 and Y_3 (Zhang et al., 2011). Table 4-5 gives a summary of Input Slacks C^2R.

Table 4-5: Summary of Input Slack (C^2R)

Province	S_1^{-0}	S_2^{-0}	S_3^{-0}	S_4^{-0}
Beijing	0.000	0.000	0.000	0.000
Tianjin	0.000	0.000	0.000	0.000
Hebei	73.210	4316.002	0.000	0.000
Shanxi	77.008	0.000	0.000	0.000
Inner Mongolia	0.000	0.000	0.000	0.000
Liaoning	0.000	90493.397	48398.519	23.362
Jilin	0.000	0.000	0.000	0.000
Heilongjiang	0.000	8687.378	0.000	0.000
Shanghai	1127.661	0.000	115225.262	0.000
Jiangsu	0.000	0.000	0.000	0.000
Zhejiang	6446.728	28191.333	0.000	0.000
Anhui	0.000	0.000	5214.160	117.652
Fujian	0.000	0.000	0.000	0.000
Jiangxi	0.000	919.542	0.000	0.000
Shandong	0.000	67131.218	0.000	89.186
Henan	0.000	0.000	0.000	0.000
Hubei	0.000	7108.678	0.000	0.000
Hunan	0.000	0.000	0.000	0.000
Guangdong	0.000	0.000	0.000	0.000
Guangxi	0.000	489.942	0.000	0.000
Hainan	0.000	0.000	0.000	0.000
Chongqing	0.000	0.000	0.000	0.000
Sichuan	0.000	0.000	32251.094	78.640
Guizhou	0.000	0.000	0.000	0.000
Yunnan	109.156	2775.112	0.000	0.000
Shaanxi	0.000	19337.261	0.000	0.000
Gansu	0.000	2230.228	0.000	0.000
Ningxia	0.000	0.000	0.000	0.000
Means	279.777	8274.289	7181.751	11.030

Refining the results from Table 4-5, causes for non-DEA effectiveness of SE of 16 provinces from the output perspective are given in Table 4-6. Overall, 3 output indexes [Scales Revenue of New Products (Y_3), Gross value of New Products (Y_2) and Patent Applications (Y_1)] influence non-DEA effectiveness.

They have 14 surplus variables, 13 surplus variables and 1 surplus variable greater than 0. Horizontally, among 16 DMUs with non-DEA effectiveness, there are 12 provinces with 2 surplus variables greater than 0, accounting for 75%. There are only 4 provinces with 1 surplus variable greater than 0, accounting for 25%. The major cause for non-DEA effectiveness of SE for 16 provinces is that their output levels are low. This provides an important basis for improving the innovation efficiency of China's high-tech industry (Hong, 2012).

Table 4-6: Summary of Output Deficiency (C^2R)

Province	S_1^{+0}	S_2^{+0}	S_3^{+0}
Beijing	0.000	0.000	0.000
Tianjin	0.000	0.000	0.000
Hebei	0.000	700068.663	671217.776
Shanxi	0.000	216641.106	221067.071
Inner Mongolia	0.000	0.000	0.000
Liaoning	262.811	171148.120	0.000
Jilin	0.000	247966.798	203331.394
Heilongjiang	0.000	643012.130	681741.023
Shanghai	0.000	95860.623	0.000
Jiangsu	0.000	0.000	0.000
Zhejiang	0.000	0.000	237090.316
Anhui	0.000	1371808.929	1573637.962
Fujian	0.000	0.000	0.000
Jiangxi	0.000	0.000	46545.895
Shandong	0.000	0.000	0.000
Henan	0.000	0.000	0.000
Hubei	0.000	733433.047	773176.424
Hunan	0.000	0.000	0.000
Guangdong	0.000	0.000	0.000
Guangxi	0.000	0.000	3524.496
Hainan	0.000	0.000	0.000
Chongqing	0.000	0.000	0.000

Province	S_1^{+0}	S_2^{+0}	S_3^{+0}
Sichuan	0.000	447652.510	443411.959
Guizhou	0.000	105927.619	130150.906
Yunnan	0.000	96716.474	124734.830
Shaanxi	0.000	192470.403	137730.470
Gansu	0.000	62677.839	56434.092
Ningxia	0.000	0.000	0.000
Means	9.386	181620.866	189421.236

4.3.4. Projection Analysis

According to Zhong et al. (2011), when there is an increasing scale, more input can be added in an appropriate manner. When there is decreasing scale, input should be reduced or the output level should be increased. However, both an increasing scale and decreasing scale reflect scale inefficiency. The DEA model can show when input and output efficiency is not optimal, or when there is a need to reduce certain input with unchanged output, or a need to increase the output with certain input. In order to determine the ways in which input can be reduced and output increased, the projection theory will be needed for analysis.

According to Wang et al. (2013), the projection theory is an important link for the DEA method and further analyses the DMU of scale inefficiency. The functions of the projection analysis are as follows. It can calculate the decreased amount of each input factor and increased amount of each output; secondly, it can confirm the ideal values of each input factor and output factor; thirdly, it can calculate the decrease and increase of proportions of input indexes and output indexes. The projection analysis can also help decision-makers to discover the main influencing factors to provide an important basis for allocating scientific research in a more methodical manner.

The above three aspects are closely related. The decreased value of the input gained according to the project formula is $\Delta X_{j0} = X_{j0} - \hat{X}_{j0}$, and the increased value of the output is $\Delta Y_{j0} = \hat{Y}_{j0} - Y_{j0}$. Projection $\left(\hat{X}_{j0}, \hat{Y}_{j0}\right)$ shows the ideal values of each input factor and output factor. The decreased input proportion and increased output proportion can be gained through decreased input value and increased output value dividing the original data of corresponding indexes (Zhou et al., 2014). Results of the 5 Input Reduction Proportion of Scale Inefficiency DMU (%) are given in Table 4-7. Results of the Output Increase Proportion of Scale Inefficiency DMU (%) are given in Table 4-8. Data from the two tables clearly shows the main reduction factors of the input and main increase factors of the output for the 16 provinces.

Table 4-7: Input Reduction Proportion of Scale Inefficiency DMU (%)

Province	X_1	X_2	X_3	X_4
Beijing	0.00%	0.00%	0.00%	0.00%
Tianjin	0.00%	0.00%	0.00%	0.00%
Hebei	66.18%	70.60%	64.89%	64.89%
Shanxi	41.81%	36.25%	36.25%	36.25%
Inner Mongolia	0.00%	0.00%	0.00%	0.00%
Liaoning	48.53%	74.23%	63.88%	57.66%
Jilin	60.46%	60.46%	60.46%	60.46%
Heilongjiang	58.07%	65.42%	58.07%	58.07%
Shanghai	37.77%	30.56%	46.25%	30.56%
Jiangsu	0.00%	0.00%	0.00%	0.00%

Province	X_1	X_2	X_3	X_4
Zhejiang	46.70%	30.32%	24.26%	24.26%
Anhui	26.58%	26.58%	29.96%	86.12%
Fujian	0.00%	0.00%	0.00%	0.00%
Jiangxi	73.47%	74.39%	73.47%	73.47%
Shandong	15.37%	25.96%	15.37%	32.94%
Henan	0.00%	0.00%	0.00%	0.00%
Hubei	62.92%	65.24%	62.92%	62.92%
Hunan	0.00%	0.00%	0.00%	0.00%
Guangdong	0.00%	0.00%	0.00%	0.00%
Guangxi	61.69%	63.53%	61.69%	61.69%
Hainan	0.00%	0.00%	0.00%	0.00%
Chongqing	0.00%	0.00%	0.00%	0.00%
Sichuan	58.76%	58.76%	71.89%	82.18%
Guizhou	9.34%	9.34%	9.34%	9.34%
Yunnan	35.63%	40.10%	27.93%	27.93%
Shaanxi	68.11%	73.99%	68.11%	68.12%
Gansu	13.28%	27.40%	13.28%	13.28%
Ningxia	0.00%	0.00%	0.00%	0.00%

Table 4-8 presents the results of the output increase proportion of scale inefficiency for the provinces.

Table 4-8: Output Increase Proportion of Scale Inefficiency DMU (%)

Province	Y_1	Y_2	Y_3
Beijing	0.00%	0.00%	0.00%
Tianjin	0.00%	0.00%	0.00%
Hebei	0.00%	133.91%	131.81%
Shanxi	0.00%	100.04%	113.86%
Inner Mongolia	0.00%	0.00%	0.00%
Liaoning	35.23%	9.53%	0.00%
Jilin	0.00%	57.68%	45.24%
Heilongjiang	0.00%	181.48%	235.88%
Shanghai	0.00%	1.41%	0.00%

Province	Y_1	Y_2	Y_3
Jiangsu	0.00%	0.00%	0.00%
Zhejiang	0.00%	0.00%	3.64%
Anhui	0.00%	74.19%	102.04%
Fujian	0.00%	0.00%	0.00%
Jiangxi	0.00%	0.00%	4.76%
Shandong	0.00%	0.00%	0.00%
Henan	0.00%	0.00%	0.00%
Hubei	0.00%	35.52%	39.63%
Hunan	0.00%	0.00%	0.00%
Guangdong	0.00%	0.00%	0.00%
Guangxi	0.00%	0.00%	2.77%
Hainan	0.00%	0.00%	0.00%
Chongqing	0.00%	0.00%	0.00%
Sichuan	0.00%	44.42%	46.04%
Guizhou	0.00%	62.88%	96.84%
Yunnan	0.00%	33.05%	50.13%
Shaanxi	0.00%	13.40%	9.45%
Gansu	0.00%	43.16%	38.87%
Ningxia	0.00%	0.00%	0.00%

4.4. Malmquist-Based Dynamic Measurement and Evaluation of Innovation Efficiency of China's High-tech Industry

Unlike the static analysis where only the data in a given period is selected for analysis, in dynamic analysis, the data of the DMU in a time series is selected. The technical efficiency measured with the DEA method is static. It is a group of comparative efficiency values rather than absolute efficiency values (Bai et al., 2015).

The efficiency value of 2011 cannot be compared with that of 2010. Only the efficiency values in the same period can be analysed horizontally. The changes in technical innovation efficiency of ineffective provinces in different periods cannot be discussed. Technical innovation efficiency measured and calculated on the basis of Malmquist productivity index is dynamic. It measures the changes in technical innovation efficiency. The changes in the technical innovation efficiency of different provinces and regions in different years can be compared. Relevant efficiency change rules and causes can be determined through dynamic analysis, in order to provide more information for decision-makers (Qian-xiao & Wen, 2012).

The DEA method realises dynamic analysis of comparative efficiency of DMU through the Malmquist index decomposition. The technical innovation efficiency study measured and calculated based on the Malmquist productivity index is the updated version of static measurement study of the technical innovation efficiency of the high-tech industry. When looked at from this perspective, this chapter has a certain logical relationship with the last chapter. This dissertation selects the years from 2005 to 2011. The DMU and index system are the same with those in the above static analysis (Wang & Zhang, 2012). According to four formulas of "DEA measurement models of Malmquist index", the Malmquist index of the above 28 DMUs, comprehensive efficiency change (EC) index, technical the software DEAP2.1 calculates change (TC) index (Wei et al., 2013). The results are shown in Table 4-9. In an empirical study, the dynamic measurement of efficiency usually adopts the index method.

This section will measure the technical innovation efficiency changes of the high-tech industry for each province on the basis of the Malmquist index model and decomposed innovation efficiency decomposed into technical change index and technical efficiency change index, so as to trace the root of technical innovation changes. The analysis is carried out on different levels – on China as a whole, then on a regional basis, and subsequently on an individual basis; i.e. the first empirical analysis is on changes in the technical innovation efficiency China's high-tech industry as a whole. Subsequently, an analysis of the differences in technical innovation efficiency changes of the provincial high-tech industry is done. The final analysis is of the technical innovation efficiency changes of the high-tech industry in the east, middle part and the west.

4.5. An analysis of total factor productivity

4.5.1. Characteristics of the Malmquist Index Change

The Malmquist index measures a number of dependent and independent variables. A change in any of these variables creates an unstable index. As explained in section 3.5, the Malmquist index M is a bilateral index that helps to compare the production technology of two regions or sectors and the total productivity factor TFP. Two important elements are the technical efficiency change EC and the technological progress TC. Technical efficiency change EC can be decomposed into pure technical efficiency PEC and scale efficiency

SEC. When EC = 1, then the adjacent TC is not changed. EC < 1 suggests a reduced technical efficiency, while EC > 1 means a greater technical efficiency. When M > 1, then it means that, the index has a positive role for the growth of TFP (Song & Zhang, 2013).

Table 4-9 presents results of changes in the M, EC, and TC indices for the study period. It is clear the Malmquist index is unstable and there are several reasons for the unstable index. During the period from 2005-2011, the average of the technical innovation efficiency - Malmquist index of high-tech industry from 2006-2007 was the largest (1.128); the average during 2008-2009 was the smallest (0.921). The average of the Malmquist index was less than 1 during the periods 2009-2010 and 2010-2011, following the rise in 2008-2009. A detailed analysis and discussion is given in section '7.2.2 Causes for the unstable Malmquist Index'.

Table 4-9: Results of M, EC and TC Index Changes during 2005-2011

	2005-2006			2006-2007			2007-2008			2008-2009			2009-2010			2010-2011		
Region	**M**	**EC**	**TC**	**M**	**EC**	**TC**	**M**	**EC**	**TC**	**M**	**EC**	**TC**	**M**	**EC**	**TC**	**M**	**EC**	**TC**
Beijing	1.586	1.383	1.147	2.825	1.322	2.137	0.876	1	0.876	0.971	1	0.971	0.591	1	0.591	0.806	1	0.806
Tianjin	0.985	1.000	0.985	0.663	1	0.663	0.745	0.89	0.837	1.269	1.007	1.269	0.713	1	0.713	0.908	1	0.908
Hebei	1.331	3.312	0.402	0.872	0.416	2.094	1.51	3.446	0.438	0.699	0.97	0.699	0.998	1.513	0.66	0.918	0.743	1.235
Shanxi	1.329	2.004	0.663	2.642	1	2.642	0.438	1	0.438	1.052	1	1.052	0.697	1	0.697	0.762	0.529	1.44
Inner Mongolia	0.372	0.699	0.533	0.233	0.247	0.944	2.829	7.171	0.394	1.47	0.816	1.47	1.333	2.019	0.66	0.725	0.54	1.341
Liaoning	0.704	1.142	0.616	1.088	1.003	1.086	1.101	1.453	0.757	0.577	0.993	0.577	1.218	1.442	0.845	0.815	0.902	0.904
Jilin	0.628	1.43	0.44	1.815	0.869	2.089	0.985	1.987	0.496	0.461	0.806	0.461	1.525	2.122	0.719	0.754	0.524	1.439
Heilongjiang	1.095	1.41	0.776	0.811	0.376	2.16	1.161	1.976	0.588	0.821	0.998	0.821	1.009	1.239	0.814	1.816	1.75	1.038
Shanghai	0.898	0.800	1.122	0.862	0.891	0.967	1.104	1.274	0.866	0.741	1.099	0.741	0.712	0.91	0.782	0.96	1.028	0.933
Jiangsu	0.853	1.15	0.742	1.361	1.29	1.055	1.391	1.743	0.798	0.813	0.813	0.813	1.142	1.429	0.799	1.167	1.337	0.873
Zhejiang	1.346	1.054	1.276	1.328	0.738	1.798	1.104	1.86	0.594	1.219	1.011	1.219	1.021	1.25	0.817	0.944	0.897	1.053
Anhui	1.151	1.555	0.74	0.769	0.796	0.966	0.84	1.475	0.569	2.326	0.857	2.326	0.868	1.371	0.633	1.121	0.883	1.269
Fujian	0.841	0.826	1.019	0.899	1.121	0.802	1.042	1.33	0.784	0.608	0.992	0.608	1.02	1.178	0.865	0.909	1.234	0.737
Jiangxi	0.618	1.282	0.483	0.994	0.607	1.637	1.006	1.555	0.647	1.555	0.966	1.555	0.89	1.245	0.715	0.907	0.645	1.407
Shandong	0.851	1.291	0.659	1.07	0.797	1.344	0.945	0.926	1.021	1.125	0.808	1.125	1.161	1.471	0.789	0.989	1.015	0.974
Henan	1.263	2.915	0.433	0.844	0.39	2.166	1.294	3.209	0.403	0.893	0.73	0.893	1.348	2.189	0.616	1.161	0.858	1.354
Hubei	0.637	0.84	0.758	1.199	0.567	2.116	0.985	1.808	0.545	0.854	1.027	0.854	1.334	1.745	0.764	0.803	0.727	1.104
Hunan	2	3.168	0.631	0.66	0.409	1.612	1.12	2.454	0.456	1.624	1.003	1.624	1.128	1.523	0.741	1.209	1	1.209
Guangdong	1.352	1	1.352	1.442	0.836	1.725	0.948	1.155	0.82	1.303	1.035	1.303	0.948	1	0.948	0.886	1	0.886
Guangxi	0.688	1.717	0.401	0.982	0.357	2.749	1.303	3.966	0.329	1.029	0.791	1.029	0.881	1.35	0.653	0.688	0.525	1.31
Hainan	1.184	4.417	0.268	5.024	1.268	3.962	0.099	0.35	0.282	2.527	2.105	2.527	0.755	0.908	0.832	1.636	1.419	1.153
Chongqing	1.456	2.526	0.577	0.735	0.486	1.512	1.517	1.897	0.8	1.462	1.046	1.462	0.845	1.192	0.709	1.704	1.075	1.585
Sichuan	0.996	1.273	0.783	1.131	0.93	1.216	1.005	1.174	0.856	1.268	1.011	1.268	1.165	1.558	0.748	0.714	0.617	1.158

Guizhou	1.258	1.129	1.115	1.598	0.571	2.799	1.292	3.058	0.423	0.688	0.947	0.688	0.791	0.998	0.792	1.349	1.116	1.209
Yunnan	0.327	1	0.327	3.391	1	3.391	0.257	0.712	0.361	2.094	1.143	2.094	0.562	0.882	0.637	0.802	0.758	1.059
Shaanxi	0.689	0.576	1.195	1.341	0.853	1.572	1.001	1.589	0.63	0.78	1.013	0.78	1.139	1.451	0.785	0.989	0.906	1.091
Gansu	1.666	2.871	0.58	0.456	0.339	1.342	0.662	1.014	0.653	1.601	0.914	1.601	1.23	1.671	0.736	1.006	0.913	1.102
Ningxia	0.677	0.752	0.9	1.209	1.055	1.146	0.78	1.056	0.738	1.15	0.986	1.15	1.372	1.777	0.772	0.733	0.81	0.906
Means	0.947	1.379	0.686	1.128	0.699	1.614	0.921	1.564	0.589	1.079	0.977	1.079	0.982	1.328	0.739	0.97	0.879	1.104
>1or=1	13	22	7	15	9	23	16	25	1	16	13	16	15	24	0	9	12	19

4.5.2. Analysis of PTE and SE Changes

The EC index is calculated under the condition of CRS. Decomposing it into PTE change and SE change aims to distinguish the two in order to determine the special factors, which lead EC changes, as this is beneficial to decision-makers. PET change and SE change are the specific values of PTE and SE in two periods. The PTE in two periods is calculated according to (1) and (3) in DEA measurement models of Malmquist index and the constraint condition $\sum_{j=1}^{n} \lambda_j = 1$. The BC^2 model is also adopted. The SE in the two periods is calculated through the SEs obtained by the C^2R model dividing their respective PTEs (Fang et al., 2013). We apply DEAP2.1 software to calculate the PTE change and SE change of 28 DMUs during 2005-2011, as shown in Table 4-10. Please refer section '6.3.1 Discussion of PTE and SE Changes'.

Table 4-10: PTE and SE Changes During 2005-2011

	2005-2006			**2006-2007**			**2007-2008**			**2008-2009**			**2009-2010**			**2010-2011**		
Region	**EC**	**PTE**	**SE**	**EC**	**PTE**	**SE**	**EC**	**PTE**	**SE**	**EC**	**PTE**	**SE**	**EC**	**PTE**	**SE**	**EC**	**PTE**	**SE**
Beijing	1.383	1.427	0.969	1.322	1.277	1.035	1	1	1	1	1	1	1	1	1	1	1	1
Tianjin	1	1	1	1	1	1	0.89	0.896	0.993	1.007	1.116	1.007	1	1	1	1	1	1
Hebei	3.312	3.273	1.012	0.416	0.39	1.068	3.446	3.54	0.973	0.97	0.424	0.97	1.513	1.443	1.049	0.743	0.733	1.014
Shanxi	2.004	1.516	1.321	1	1	1	1	1	1	1	1	1	1	1	1	0.529	0.637	0.83
Inner Mongolia	0.699	0.964	0.725	0.247	1.237	0.2	7.171	1	7.171	0.816	1	0.816	2.019	1	2.019	0.54	1	0.54
Liaoning	1.142	0.866	1.32	1.003	0.936	1.071	1.453	1.476	0.985	0.993	0.535	0.993	1.442	1.438	1.003	0.902	0.902	1
Jilin	1.43	1.402	1.02	0.869	0.961	0.904	1.987	1.773	1.12	0.806	0.479	0.806	2.122	1.886	1.125	0.524	0.516	1.015
Heilongjiang	1.41	1.336	1.055	0.376	0.379	0.992	1.976	2.066	0.956	0.998	0.727	0.998	1.239	1.334	0.929	1.75	1.575	1.111
Shanghai	0.8	1	0.8	0.891	0.91	0.979	1.274	1.099	1.16	1.099	0.742	1.099	0.91	0.909	1.001	1.028	1.03	0.999
Jiangsu	1.15	0.676	1.702	1.29	1.447	0.891	1.743	2.607	0.669	0.813	1	0.813	1.429	0.891	1.603	1.337	1.122	1.192
Zhejiang	1.054	1.062	0.993	0.738	1.239	0.596	1.86	1.088	1.71	1.011	1.14	1.011	1.25	1.254	0.997	0.897	0.893	1.004
Anhui	1.555	1.234	1.261	0.796	0.78	1.02	1.475	1.534	0.961	0.857	1.868	0.857	1.371	1.122	1.222	0.883	0.88	1.004
Fujian	0.826	0.834	0.99	1.121	1.101	1.018	1.33	1.329	1.001	0.992	0.693	0.992	1.178	1.171	1.006	1.234	1.232	1.001
Jiangxi	1.282	1.253	1.023	0.607	0.57	1.066	1.555	1.638	0.949	0.966	1.191	0.966	1.245	1.159	1.074	0.645	0.666	0.968
Shandong	1.291	0.733	1.761	0.797	1.24	0.642	0.926	0.594	1.557	0.808	1.36	0.808	1.471	1.228	1.197	1.015	1.174	0.864
Henan	2.915	3.198	0.911	0.39	0.534	0.729	3.209	2.023	1.586	0.73	0.737	0.73	2.189	1.593	1.374	0.858	1	0.858
Hubei	0.84	0.532	1.578	0.567	0.707	0.802	1.808	1.47	1.23	1.027	0.661	1.027	1.745	1.764	0.989	0.727	0.721	1.009
Hunan	3.168	2.794	1.134	0.409	0.351	1.167	2.454	2.453	1	1.003	1.22	1.003	1.523	1.487	1.024	1	1	1
Guangdong	1	1	1	0.836	1	0.836	1.155	1	1.155	1.035	1	1.035	1	1	1	1	1	1
Guangxi	1.717	1.394	1.231	0.357	0.486	0.735	3.966	3.136	1.264	0.791	0.862	0.791	1.35	1.189	1.135	0.525	0.511	1.026
Hainan	4.417	1	4.417	1.268	1	1.268	0.35	1	0.35	2.105	1	2.105	0.908	1	0.908	1.419	1	1.419

Chongqing	2.526	2.169	1.164	0.486	0.465	1.045	1.897	1.984	0.956	1.046	1.203	1.046	1.192	1.241	0.96	1.075	1.026	1.047
Sichuan	1.273	1.258	1.012	0.93	1.161	0.801	1.174	0.922	1.273	1.011	1.174	1.011	1.558	1.559	0.999	0.617	0.618	0.998
Guizhou	1.129	1.015	1.112	0.571	0.735	0.776	3.058	2.322	1.317	0.947	0.75	0.947	0.998	1.006	0.992	1.116	1.201	0.93
Yunnan	1	1	1	1	1	1	0.712	0.813	0.875	1.143	1.23	1.143	0.882	1	0.882	0.758	0.721	1.051
Shaanxi	0.576	0.611	0.943	0.853	1.073	0.795	1.589	1.214	1.309	1.013	0.686	1.013	1.451	1.471	0.986	0.906	0.894	1.014
Gansu	2.871	1.561	1.839	0.339	0.392	0.866	1.014	1.19	0.852	0.914	1.533	0.914	1.671	1.398	1.195	0.913	0.867	1.053
Ningxia	0.752	0.564	1.333	1.055	1.599	0.66	1.056	1.046	1.01	0.986	1.059	0.986	1.777	1	1.777	0.81	1	0.81
Means	1.379	1.166	1.182	0.699	0.818	0.855	1.564	1.401	1.116	0.977	0.926	0.977	1.328	1.208	1.099	0.879	0.897	0.98
>1or=1	22	19	21	9	14	12	25	24	17	13	17	13	24	26	9	12	15	19

4.5.3. Analysis of the M Mean Change and the Trend of 28 DMUs

Technical innovation efficiency change and technical progress variation trends are basically consistent. The technical progress index and technical efficiency variability index present reverse waves (Song & Cui, 2014). Table 4-11 gives an analysis of the M Mean change and the trend for 28 DMUs for the study period. Please refer to section '7.2.2.2 Discussion of the M Mean Change and the Trend of 28 DMUs'.

Table 4-11: Malmquist Index Summary of Firm Means from 2005-2011

Year	Malmquist index	TE change	technical change	PTE change	SE change
2005-2006	0.947	1.379	0.686	1.166	1.182
2006-2007	1.128	0.699	1.614	0.818	0.855
2007-2008	0.921	1.564	0.589	1.401	1.116
2008-2009	1.079	0.905	1.193	0.926	0.977
2009-2010	0.982	1.328	0.739	1.208	1.099
2010-2011	0.970	0.879	1.104	0.897	0.98
Mean	1.002	1.081	0.927	1.050	1.029

4.5.4. Regional Comparison of the Malmquist Index from 2005-2011

For this analysis, the 28 DMUs are divided into three parts, eastern region, central region and western region, according to geographical distribution of the 28 provinces (Zhang et al., 2011). Table 4-12 compares the M index for all regions during the study period. Please refer to section '7.2.2.3 Regional Comparison of the Malmquist Index' for the analysis and discussion of the result.

Table 4-12: Comparison of Malmquist Index in Each Region

Region	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011
East	1.085	1.585	0.988	1.077	0.934	0.994
Number of improved units	5	7	6	5	5	2
Number of declining units	6	4	5	6	6	9
Central	1.090	1.217	0.979	1.198	1.100	1.067
Number of improved units	5	3	4	4	5	4
Number of declining units	3	5	4	4	3	4
West	0.903	1.231	1.183	1.282	1.035	0.968
Number of improved units	3	5	6	7	5	3
Number of declining units	6	4	3	2	4	6

The mean Malmquist index from 2005-2011 in the east, central and western regions and the analysis of the results of decomposition index changes are shown in Table 4-13.

Table 4-13: Mean Malmquist Index and the Decomposition Index in the East, Middle Region and the West

Region	Malmquist index	effch	tech	pech	sech
East	1.004	1.087	0.923	1.039	1.046
Number of improved units	7	8	2	6	7
Number of unchanged units	0	2	0	3	4
Number of declining units	4	1	9	2	0
Middle region	1.032	1.105	0.934	1.081	1.022
Number of improved units	4	7	0	6	6
Number of unchanged units	0	0	0	0	0
Number of declining units	4	1	8	2	2
West	0.974	1.052	0.926	1.036	1.015
Number of improved units	3	2	2	6	5
Number of unchanged units	0	0	0	1	0
Number of declining units	6	7	7	2	4

According to Table 4-13, the average annual growth rate of the Malmquist index in the central region was the highest, reaching 3.2%; the east experienced a low growth rate, with a growth rate of only 0.4%. The annual growth rate of 7 provinces was negative. The middle region can therefore be observed to have had a rising trend. General provinces show growth. Only the western region exhibited negative growth (-2.6%). 6 provinces show the downtrend in terms of the Malmquist index of technical innovation efficiency. The technical efficiency index effect of the three regions however showed a general increase. The annual average growth rate in the central region was the highest, reaching 10.5%, while annual average growth rate in the west is lowest at 5.3%. Among the 9 provinces, 7 provinces presented a downtrend. The technical progress index of the three regions declined, with the most serious decline occurring in the eastern region, with an annual average decrease rate of 7.7%. Most provinces were in the declining stage. The technical progress indexes of 8 provinces in the middle region were less than 1. For PTE and SE, the three regions showed positive growth, although the growth in the west was relatively slow, at only 1.5% (Wang et al., 2013).

According to Table 4-14, among the 28 provinces, the mean of Malmquist index change of technical innovation efficiency of 14 of the provinces was greater than 1. To be more specific, Chongqing had the largest Malmquist index change (1.227), followed by Hunan (1.218). Yunnan has the smallest change (0.804). The annual average growth rate of the M index in Beijing, Zhejiang, Henan, Hunan, Guangdong, Hainan, Chongqing and Guizhou was above 10%. The annual average growth rate of Chongqing in particular reached 22.7%. The M growth of Hebei, Shandong and Sichuan was relatively slow, with an annual growth rate of about 2%. The Malmquist index changes can be classified into EC (effeminacy change) and TC (technical change). The M of Tianjin, Inner Mongolia, Liaoning, Shanghai, Fujian and Yunnan was below 0.9, but the causes of this negative growth differed. The negative growth in Tianjin, Shanghai and Fujian was mainly caused by a decline in TC; The TC of Inner Mongolia was also low, and the EC was not stable either. The TC and EC of Yunnan were not very good, and this can affect M growth. The technical innovation efficiency of Shanxi, Shaanxi and Gansu is between 0.96 and 1.0. The technical innovation efficiency of these provinces falls behind slightly. For Shanxi and Gansu, this is due to a decline in the technical frontier and insufficient innovation ability; for Shaanxi, this is due to a decrease in SE (Zhang et al., 2011).

Technical efficiency change can be decomposed into PTE change and SE change under VRS (Wang et al., 2012). The data show that the change mean of PTE for the 28 provinces is 1.050, and the change mean of PTE for 22 provinces is equal to or greater than 1. In accordance with input indexes selected in this dissertation, the mean of the PTE is greater than 1. This indicates that each province in China pays attention to the input in scientific research so that PTE is on the rise. However, looking at it from the angle of absolute value, the change mean of PTE just exceeds 1. This drags technical efficiency change to some extent. The change mean of SE for the 28 provinces is only 1.029. The Change mean of SE in 6 provinces is less than 1. This reflects an ineffective technical innovation input scale. As such, more importance should be attached to these provinces, and the input in scientific research innovation in the high-tech industry should be increased in order to increase SE.

Table 4-14: The Mean Change Trend of The Malmquist Index and the Decomposition Index of Technical Innovation Efficiency of Each DMU from 2005-2011

Province	M	EC	TC	PTE	SE
Beijing	1.104	1.106	0.999	1.105	1.000
Tianjin	0.858	1.000	0.858	1.000	1.000
Hebei	1.020	1.140	0.894	1.125	1.014
Shanxi	0.975	1.010	0.966	0.994	1.015
Inner Mongolia	0.839	1.016	0.825	1.030	0.987
Liaoning	0.886	1.024	0.865	0.969	1.056
Jilin	0.917	1.010	0.909	1.018	0.992
Heilongjiang	1.076	1.087	0.990	1.081	1.005
Shanghai	0.870	0.941	0.924	0.941	1.000
Jiangsu	1.098	1.261	0.871	1.169	1.079
Zhejiang	1.150	1.110	1.036	1.106	1.004
Anhui	1.091	1.234	0.884	1.182	1.045
Fujian	0.873	1.035	0.844	1.034	1.001
Jiangxi	0.959	1.019	0.941	1.012	1.006
Shandong	1.018	1.077	0.945	1.010	1.067
Henan	1.116	1.243	0.898	1.263	0.984
Hubei	0.940	0.951	0.988	0.880	1.081
Hunan	1.218	1.345	0.906	1.278	1.053
Guangdong	1.124	1.000	1.124	1.000	1.000
Guangxi	0.905	1.027	0.881	1.018	1.009
Hainan	1.107	1.321	0.837	1.000	1.321
Chongqing	1.227	1.247	0.984	1.206	1.034
Sichuan	1.030	1.080	0.954	1.073	1.007
Guizhou	1.114	1.077	1.034	1.078	0.999
Yunnan	0.804	0.935	0.859	0.947	0.988
Shaanxi	0.966	0.945	1.022	0.946	0.999

Province	M	EC	TC	PTE	SE
Gansu	0.999	1.133	0.882	1.052	1.077
Ningxia	0.951	1.039	0.915	1.000	1.039
Means	1.002	1.081	0.927	1.050	1.029

Table Note: All Malmquist index averages are geometric means.

4.6. Conclusion

This chapter has examined the performance of the 28 regions using macroscopic and dynamic research of the Malmquist index of technical innovation efficiency from DEA-based microcosmic and static technical efficiency research. The technical innovation efficiency measurement and change problems from the perspective of empirical analysis were studied for the 28 regions. It is clear that the high-tech regions showed a rise in the Malmquist index during the study period. However, in some regions, instability in observed in the index. These and observations from the results indicate variation among different regions of the high-tech industry. While the financial meltdown and recession has some impact on the industry, is clear that the nature of industries also has an impact on the Malmquist index. The next chapter evaluates the index for different industrial sectors of the high-tech industry in China.

Chapter 5 INDUSTRY-BASED EMPIRICAL ANALYSIS OF INNOVATION EFFICIENCY OF CHINESE HIGH-TECH INDUSTRY

5.1. Introduction

Chapter 4 presented the data and analysis of 28 DMUs from different regions of China. The innovation of the high-tech industry was analysed using panel data. It is important to understand the innovation efficiency of specific industrial sectors, since there can be variation among different types of industries. In other words, it is possible that the innovation efficiency of the Electronic and communication device-manufacturing sector would be different from that of Pharmaceutical industry. This perspective of the research is important, since this approach helps to analyse the extent of innovation efficiency in different industries. The method used to carry out these studies is similar to that followed in chapter 5, where different regions were studied. As stated in chapter 3, the period for the data analysis remains 2008-2011. Four steps are used and these are, firstly, confirm the specific DMU and rational input-output index system and data; secondly, describe the data from 2005-2011 and carry out a static analysis of the data in 2011; thirdly, select the data for the period for dynamic analysis, and finally, propose several suggestions according to the conclusions of the static analysis and the dynamic analysis.

5.2. DMU, Index System and Data

5.2.1. Confirmation of DMU

Wang and Wei (2010) classified China's high-tech industries into five industry groups and 17 industries. The China Statistics Yearbook on High Technology Industry jointly considered these categories and these will be used in this chapter. Details of these industries are in table 5-1 as below.

Table 5-1: Selection of DMUs

Industry category	Industries included
Pharmaceutical industry	Chemicals manufacturing
	Chinese patent medicine manufacturing,
	biological product manufacturing
Aerospace vehicle manufacturing	Aircraft manufacturing and repair
	Spacecraft manufacturing
Electronic and communication device manufacturing	Communication equipment manufacturing
	Radar and corollary equipment manufacturing
	Radio and television equipment manufacturing
	Electronic device manufacturing,
	Electronic component manufacturing
	Domestic audio-visual equipment manufacturing
	Other electronic equipment manufacturing
Electronic computer and office equipment manufacturing industry	Complete electronic computer manufacturing
	Computer peripheral equipment manufacturing
	Office equipment manufacturing
Medical equipment and instrument manufacturing industry	Medical equipment and apparatus manufacturing
	Instrument manufacturing

5.2.2. Screening Input-Output Indexes

Among the indices of innovation activities of high-tech industry, a number of researchers (Guan & Chen, 2010) use the technological development evaluation index system. This index was initially established by OECD, MD and World Bank, and then by China Research Society for Technical Index. Although these index systems have are strongly backed by authority, they are partial to the evaluation of comprehensive strength and the competitiveness of science and technology in each country at a macroscopic level. Thus, they cannot be wholly applied to the evaluation and comparison of each industry at a microcosmic level; neither can they reflect a scientific development perspective (Liu et al., 2010).

Some researchers have studied the problem of assessing innovation for specific industries such as ports, hospitals, and other industries (He-Cheng, 2008; Fang & Zhang, 2009). Research that compares data across various sectors, and integrated with the key regions of China is not available. This chapter will fill the gap and provide an analysis of five high-tech industrial sectors. Some are representative to an extent, such as the scientific and technological progress evaluation system established by Zhu et al. (2006); the scientific and technical evaluation index system established by Guan and Chen (2010) through document accumulation analysis; and the scientific and technical evaluation index system established by Jing (2010) based on China's scientific and technical system reform. The industrial scientific and technical innovation efficiency indexes should pay attention to development reality of China's high-tech industry.

Based on the analysis of the literature above, the technical input and technical output are selected to reflect scientific and technical strength of the high-tech industry. In order to measure technical input, three major indices were selected: human capital, R&D input and investment in fixed assets. In measuring technical output, the indices used include number of granted patents, gross output of high technology and sales revenue of high-tech products. As noted in Chapter 4, in selecting indices to measure industrial technical innovation efficiency, the following two factors are considered, Strong linear dependence among data should be avoided, and the number of DMUs should be greater than twice of the sum of input and output indexes (Yanbing, 2008).

5.2.3. Screening input indexes

In measuring human resources, the number of staff engaged in scientific research and the number of technical innovation teams are used as input indexes. The criteria to be used in determining the personnel to be included in these indices are the same as in the previous chapter.

In measuring R&D fund input, two indexes are used: Expenditure on R&D (X_2) (MD, World Bank) and Expenditure on New Products Development (X_3) (OECD, China Research Society for Technical Index. The two indexes also indirectly reflect the degree of value placed on innovation activities for development of high-tech industries and the development conditions in each industry (Tseng & Lee, 2009).

According to Sharma and Thomas (2008), in measuring material capital input, the index which mostly suitably reflects material capital input of high-tech industries is Investment in Fixed Assets (X_4).

5.2.4. Screening output indexes

In measuring the innovation activity output of high-tech industries, it is necessary to pay attention to result quality during index selection in order to reflect the basic requirements of the performance concept (Johnes & Li, 2008). The following output indexes are selected: Patent Applications (Y_1) (MD, World Bank), Gross value of New Products (Y_2) (China Research Society for Technical Index) and Scales Revenue of New Products (Y_3) (China Research Society for Technical Index). The three indexes indicate the ability to transform science and technology input into actual productivity and income.

5.2.5. Data Collection and Screening

The data in this chapter are the relevant index data of 17 DMUs from 2005-2011 selected from China Statistics Yearbook on High Technology Industry. In most studies, the selection of test statistics has a direct influence on the evaluation of results. In view of the key role input and output indexes play in technical efficiency measurement, this dissertation utilises original data for data processing and introduces the KS test and the T test to confirm input and output indexes (Chang & Hu, 2010). Before the index test, a statistical description of the index data is first conducted, as shown in Table 5-2, while the results of the KS test and the T test are shown in table 5-3.

Table 5-2: A Statistical Description of the Input-Output Index

Index type	Index	Mean	Median	Maximum	Minimum	Std.Dev	Observations
Input index	Converted full-time quantity of R&D activity personnel (number of personnel/year)	17031.17	56343.5	112346	341	20414.93	119
	Expenditure of R&D funds (10thousand Yuan)	417130.22	1773238.5	3532317	14160	557238.49	119
	Expenditure on new products development (10thousand Yuan)	486962.86	2259994	4494800	25188	620855.20	119
	Investment in Fixed Assets	263.59	1011	2016	6	320.01	119

	(100 million Yuan)						
Output index	Patent applications	2540.45	11880	23751	9	3961.77	119
	Output value of new products (10thousand Yuan)	7308749.65	22749258	45463632	34884	9446791.61	119
	Sales revenue of new products (10thousand Yuan)	7328799.4	23115233.5	46192610	37857	9742343.48	119

Table 5-3: KS Test Results and T Test Results of Input/ Output Indexes

Index type	Index to be tested	KS test	T test
Input index	Converted full-time quantity of R&D activity personnel (number of personnel/year)	2.280***	9.101***
	Expenditure of R&D funds (10000 Yuan)	2.561***	8.166***
	Expenditure on new products development (10000 Yuan)	2.493***	8.556***
	Investment in Fixed Assets (100 million Yuan)	2.293***	8.986***
Output index	Patent applications	2.852***	6.995***
	Output value of new products (10000 Yuan)	2.407***	8.440***
	Sales revenue of new products (10000 Yuan)	2.478***	8.206***

Table Note: *, ** and *** mean significance at the levels of 10%, 5% and 1% respectively.

5.3. The Industry-Based Static Analysis and an Evaluation of the Innovation Efficiency of the High-tech Industry

Static analysis with DEA method refers to an investigation of the comparative efficiency of scientific research performance in a period rather than time series DMU (Cullinane & Wang, 2010). This section will carry out static measurement and evaluation of innovation efficiency of China's high-tech industry from the perspective of an empirical study on the basis of Chapter 3.

5.3.1. *Integral Analysis of Technical Innovation Efficiency of High-Tech Industry*

When the DEA method is adopted for static measurement of technical efficiency of input/output of the 17 industries in a year, the results measured with the input-oriented efficiency measurement model are the same as the results measured output -oriented efficiency measurement model. Considering that the science and technology input of each industry is rigid to an extent, the output oriented model is selected for measurement (Hu & Mathews, 2008).

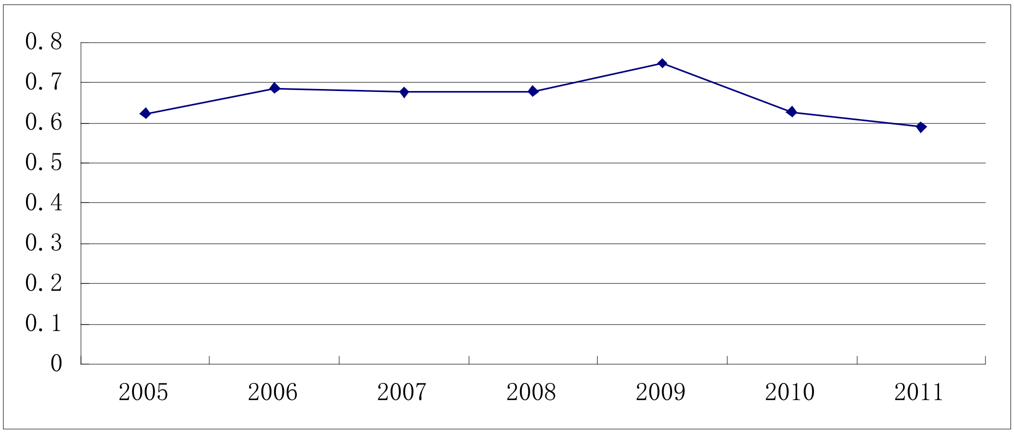
The Selection of CRS (C^2R, no consideration of RS model) or VRS (BC^2, consideration of RS model) mainly depends on scale changes. Considering that the output scale efficiency will change continuously due to continuous expansion of the input, VRS is selected. Based on the above, the output-oriented DEA model with varied scale is selected (Yu & Lin, 2008). This dissertation adopts Deap2.1 software to measure and calculate technical innovation efficiency STE scores of high-tech industries in each industry from 2005 to 2011, conducts contrastive analysis of STE (also called comprehensive efficiency) of each province in the same year and mainly focuses on the provinces on the production frontier. The measurement results are shown in Table 5-4.

Table 5-4: STE of CRSTE under CRS during 2005-2011

Industry	2005	2006	2007	2008	2009	2010	2011	Years on frontier
Chemicals manufacturing	0.436	0.466	0.427	0.419	0.635	0.466	0.379	0
Chinese patent medicine manufacturing	1.000	0.964	0.707	0.960	1.000	0.657	0.580	2
Biological product manufacturing	0.749	0.485	0.494	0.389	0.494	0.390	0.354	0
Aircraft manufacturing and repair	0.302	0.323	0.315	0.377	0.312	0.289	0.323	0
Spacecraft manufacturing	0.082	0.125	0.127	0.173	0.230	0.182	0.144	0
Communication equipment manufacturing	1.000	1.000	1.000	1.000	1.000	0.823	1.000	6
Radar and corollary equipment manufacturing	0.208	0.350	0.329	0.211	0.324	0.314	0.386	0
Radio and television equipment manufacturing	0.686	0.816	1.000	1.000	1.000	1.000	1.000	5
Electronic device manufacturing,	0.386	0.549	0.632	0.622	0.849	0.710	0.488	0
Electronic component manufacturing	0.367	0.316	0.378	0.376	0.723	0.507	0.484	0
Domestic audio-visual equipment manufacturing	1.000	1.000	1.000	0.953	1.000	1.000	1.000	6
Other electronic equipment manufacturing	0.486	0.525	0.741	0.570	0.867	0.538	0.423	0
Complete electronic computer manufacturing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	7
Computer peripheral equipment manufacturing	0.692	1.000	0.921	1.000	1.000	1.000	1.000	5
Office equipment manufacturing	0.778	1.000	0.874	0.715	0.525	1.000	0.594	2
Medical equipment and apparatus manufacturing	1.000	1.000	1.000	1.000	0.843	0.319	0.344	4
Instrument manufacturing	0.412	0.764	0.552	0.758	0.908	0.464	0.538	0
Mean	0.623	0.687	0.676	0.678	0.748	0.627	0.590	0
Number of frontiers	5	6	5	5	6	5	5	

The DEA measurement results in Table 5-4 describe the STE scores of each industry and the means of the seven years from 2005 to 2011. According to Tiemann and Schreyögg (2008), STE measures the total efficiency of the DMU and reflects the proportion of innovation in each industry in the high-tech technology industry to the largest possible output under the current technical level, as shown in Figure 5-1. According to the STE, the proportion of actual output from 2005-2009 gradually rises and reaches the highest point in 2009. However, this proportion reduces in 2009-2011. The following graph gives the trend in mean of STE for 2005-2011.

Figure 5-1: The Means of STE from 2005 to 2011



5.3.2. Industry-based STE Analysis in 2011

This section will focus on the STE of each industry in 2011 and decompose the STE into PTE and SE for analysis, to compare the differences and sources of innovation efficiency for the different industries. This section analyses the innovation efficiency of 17 industries. Since the output is mainly influenced by the input, Deap2.1 and input-orientated VRS multi-stage DEA model are used for measurement. The results are given in table 5-5 below:

Table 5-5: Measurement Results of Comparative Efficiency of Innovation Efficiency of 17 Industries in 2011

Industry	Crste	vrste	SE	Scale state
Chemicals manufacturing	0.379	0.384	0.989	irs
Chinese patent medicine manufacturing	0.580	0.637	0.910	irs
Biological product manufacturing	0.354	0.588	0.602	irs
Aircraft manufacturing and repair	0.323	0.372	0.869	irs
Spacecraft manufacturing	0.144	0.691	0.208	irs
Communication equipment manufacturing	1.000	1.000	1.000	——
Radar and corollary equipment manufacturing	0.386	1.000	0.386	irs
Radio and television equipment manufacturing	1.000	1.000	1.000	——
Electronic device manufacturing,	0.488	0.963	0.507	drs
Electronic component manufacturing	0.484	0.808	0.599	drs
Domestic audio-visual equipment manufacturing	1.000	1.000	1.000	——
Other electronic equipment manufacturing	0.423	0.592	0.716	irs
Complete electronic computer manufacturing	1.000	1.000	1.000	——
Computer peripheral equipment manufacturing	1.000	1.000	1.000	——
Office equipment manufacturing	0.594	1.000	0.594	irs
Medical equipment and apparatus manufacturing	0.344	0.489	0.703	irs
Instrument manufacturing	0.538	1.000	0.538	drs
Mean	0.590	0.795	0.742	
Number of frontiers	5	8	5	

Table Note:

irs means increasing returns to scale

drs means decreasing returns to scale

—— means constant returns to scale

crste = technical efficiency from CRS DEA

vrste = technical efficiency from VRS DEA

scale = scale efficiency = crste/vrste

Note also that all subsequent tables refer to VRS results

5.3.3. Industry-based CRSTE Efficiency Analysis in 2011

CRSTE here refers to the efficiency studied in this dissertation. In 2011, the CRSTE of technical innovation for China's high-tech industry was low, with a mean of only 0.590. The maximum value of CRSTE was 1 and the minimum value was 0.144. It can be seen from the table that only the CRSTE of communication equipment manufacturing, radio and television equipment manufacturing, complete electronic computer manufacturing and computer peripheral equipment manufacturing were 1. Only these industries are in the state of DEA effectiveness. Other industries are in a state of DEA inefficiency. In the 12 industries with non-DEA effectiveness, the STE value was low. Office equipment manufacturing ranks top, with a CRSTE value of 0.594. Spacecraft manufacturing had the lowest value (0.144). The efficiency value of 11 industries was lower than the mean of 0.590. In particular, non-DEA effective DMUs, which are lower than the mean, indicate that China's fundamental research is weak (Saranga & Moser, 2010).

The relations of some industries such as complete electronic computer manufacturing, electronic device manufacturing and electronic component manufacturing show that China's high technology is mainly from import and technical cooperation; and that the mastery degree of the core technology is low. In a sense, this indicates that the technical innovation efficiency of China's high-tech industry is generally in a state of inefficiency (Zhu & Xu, 2006).

As noted in chapter four, the main reasons for non-DEA effectiveness of CRSTE include technical efficiency value and scale efficiency value. According to Table 5-5, the main cause of non-DEA effectiveness of CRSTE is non-DEA effectiveness of SE, i.e. scale inefficiency, for the change direction of the two is basically consistent. Non-DEA effectiveness of CRSTE in radar and corollary equipment manufacturing, office equipment manufacturing and instrument manufacturing are completely caused by scale inefficiency, while non-DEA effectiveness of CRSTE in other industries is jointly caused by technical inefficiency and scale inefficiency. Table 5-5 further shows that the causes for scale inefficiency are different. Some are due to increasing return to scale while some are due to decreasing return to scale (Yuan & Tian, 2012).

5.3.4. Industry-based VRSTE Efficiency Analysis in 2011

PTE calculated under VRS is VRSTE. PTE calculated under VRS is the gap between the inefficient unit and the unit on the production frontier, i.e. the largest output of DMU with a given input combination (Ping et al., 2009). Low PTE is one of the major causes of the low mean of the CRSTE for China's high-tech industry. It can be seen from Table 5-5 that the mean is 0.795. The PTE of 7 out of the 17 industries is equal to 1, on the production frontier. Thus, these industries realise their optimal resource allocation, accounting for about 47.06%. This is because these industries increased the force of resource integration and improved their comprehensive competitive power. This in turn led to an improvement of their PTE. However, 9 industries are not on the production frontier. The mean of the PTE in 17 industries was below 0.795. Among the 9 DMUs with non-DEA effectiveness of PTE, electronic device manufacturing had the highest efficiency, reaching 0.963, followed by electronic component manufacturing (0.808). Many industries had low efficiency and the efficiency of chemicals manufacturing, aircraft manufacturing and repair as well as medical equipment and apparatus manufacturing were below 0.500. Aircraft manufacturing and repair had the lowest efficiency (0.372).

5.3.5. Industry-based SE Analysis in 2011

SE is RS state of system activities and means the distance between the effective production frontier under CRS and the effective production frontier under VRS (Guan & Chen, 2010). For increasing or decreasing DMUs, improvement is needed to reach the ideal state. It can be seen from Table 5-5 that the mean of SE is 0.742. Among the 17 industries, 5 provinces are on the production frontier, including computer peripheral equipment manufacturing, complete electronic computer manufacturing, radio and television equipment manufacturing, communication equipment manufacturing and domestic audio-visual equipment manufacturing.

These seven industries have high technical innovation scales in the high-tech industry, good development and leading operation management mechanisms for scientific research innovation and human capital structures. They are the bellwethers driving development of China's high-tech industry. In terms of the scale state, among the 17 industries, the RS of 9 industries is increasing, accounting for 52.94%. At the same time, RS of computer peripheral equipment manufacturing, complete electronic computer manufacturing, radio and television equipment manufacturing, communication equipment manufacturing and domestic audio-visual equipment manufacturing is constant, accounting for 29.41%; while the RS of electronic device manufacturing, electronic component manufacturing and instrument manufacturing is decreasing, accounting for 17.65%.

A number of factors cause increasing or decreasing returns to scale in the 12 industries (Avkiran & Rowlands, 2008). Table 5-6 and 5-7 show specific indexes and the data of non-DEA effectiveness for different industries from the perspectives of slack variable and surplus variable. In line with the basic theories of linear programming, the values of slack variables show the decreased amount of the input factor investigated under the condition where the output remains unchanged compared with other DMUs. S_1^{-0}, S_2^{-0}, S_3^{-0} and S_4^{-0} correspond to the decreased amount of four input factors: X_1, X_2, X_3 and X_4. Similarly, the values of surplus variables show the increased amount of the output under the condition where the input remains unchanged compared with other DMUs. S_1^{+0}, S_2^{+0} and S_3^{+0} correspond to the increased amount of 3 output factors: Y_1, Y_2 and Y_3.

Table 5-6: Summary of Input Slacks (C^2R)

Industry	S_1^{-0}	S_2^{-0}	S_3^{-0}	S_4^{-0}
Chemicals manufacturing	4693.139	63203.859	0.000	188.855
Chinese patent medicine manufacturing,	3190.048	29116.111	0.000	210.111
biological product manufacturing	0.000	7607.141	0.000	246.229
Aircraft manufacturing and repair	0.000	174111.734	59634.578	0.000
Spacecraft manufacturing	0.000	47247.700	0.000	9.482
Communication equipment manufacturing	0.000	0.000	0.000	0.000
Radar and corollary equipment manufacturing	0.000	0.000	0.000	0.000
Radio and television equipment manufacturing	0.000	0.000	0.000	0.000
Electronic device manufacturing,	0.000	0.000	106407.549	1583.053
Electronic component manufacturing	13722.125	30784.158	0.000	253.829
Domestic audio-visual equipment manufacturing	0.000	0.000	0.000	0.000
Other electronic equipment manufacturing	0.000	12989.315	28623.001	237.761
Complete electronic computer manufacturing	0.000	0.000	0.000	0.000
Computer peripheral equipment manufacturing	0.000	0.000	0.000	0.000
Office equipment manufacturing	0.000	0.000	0.000	0.000
Medical equipment and apparatus manufacturing	0.000	22092.192	1061.300	93.201
Instrument manufacturing	0.000	0.000	0.000	0.000
Mean	1270.901	22773.659	11513.319	166.031

The output slacks for different high-tech industries is given in Table 5-7. It explains the causes of non-DEA effectiveness of SE of 9 industries from the output perspective.

Table 5-7: Summary of Output Slacks C^2R

Industry	S_1^{+0}	S_2^{+0}	S_3^{+0}
Chemicals manufacturing	0.000	0.000	1908415.904
Chinese patent medicine manufacturing	0.000	0.000	501199.511
biological product manufacturing	39.147	0.000	167088.533
Aircraft manufacturing and repair	0.000	24192.090	0.000
Spacecraft manufacturing	73.086	500292.535	406891.547
Communication equipment manufacturing	0.000	0.000	0.000
Radar and corollary equipment manufacturing	0.000	0.000	0.000
Radio and television equipment manufacturing	0.000	0.000	0.000
Electronic device manufacturing,	0.000	0.000	1992022.625
Electronic component manufacturing	0.000	0.000	2897302.650
Domestic audio-visual equipment manufacturing	0.000	0.000	0.000
Other electronic equipment manufacturing	0.000	0.000	370420.281
Complete electronic computer manufacturing	0.000	0.000	0.000
Computer peripheral equipment manufacturing	0.000	0.000	0.000
Office equipment manufacturing	0.000	0.000	0.000
Medical equipment and apparatus manufacturing	0.000	185444.800	181735.267
Instrument manufacturing	0.000	0.000	0.000
Mean	6.602	41760.554	495592.725

5.3.6. Projection Analysis

Table 5-8 and Table 5-9 show decreased input proportion and increased output proportion of 9 non-DEA effective DMUs. Moreover, these tables clearly show main reduction factors of the input and the main increase factors of the output for the 9 industries. Take electronic device manufacturing for example. In terms of the input, the decreased proportions of X_1, X_2 and X_3 differ little (3.68%, 3.68% and 9.64%). For X_4, the proportion is as high as 82.2%. In terms of the output, there are great differences. The index (Scales Revenue of New Products) (Y_3) is 11.2%. It can thus be seen that X_4 and Y_3 are the main factors leading to non-DEA effectiveness of this industry. X_4 can still reduce by 82.2%, i.e. reducing to 35.907 billion Yuan from 201.623 billion Yuan. Y_3 can increase about 11.2%, increasing to 198.505316 billion Yuan from 178.58509 billion Yuan. The analysis for other units is also similar (Tone & Tsutsui, 2009).

It can be seen from Table 5-9 that four input indexes of 9 non-DEA effective DMUs need to decrease to different degrees. Among the four indexes X_1, X_2, X_3 and X_4, aircraft manufacturing and repair declined the most, reaching 62.8%, 76.7%, 68.0% and 62.8% respectively. This is closely related to the result that the comprehensive efficiency of the industry is the smallest. Decrease differences for some industries are large. Take electronic device manufacturing for example. The decrease range of X_1, X_2 and X_3 is the smallest, reaching 3.68%, 3.68%, and 9.64% respectively. However, X_4 is as high as 82.2%. For some industries such as chemicals manufacturing and spacecraft manufacturing, the decrease proportions of the four indexes differ little. X_1, X_2, X_3 and X_4 of chemicals manufacturing are 72.3%, 67.9%, 61.6% and 80.5% respectively. X_1, X_2, X_3 and X_4 of spacecraft manufacturing are 30.9%, 57.2%, 30.9% and 44.9% respectively (Adler & Yazhemsky, 2010).

In contrast with the situation where input indexes reduce to different degrees, the increase range of the output indexes differs a lot, including slight increase, large increase and no increase. For the index Y_1, the increase range of spacecraft manufacturing is largest, reaching 25.3%. 15 DMUs need no increase. The original data of patent application number for spacecraft manufacturing is 289, while the ideal number is 362. For the index Y_2, 14 DMUs need no increase. Spacecraft manufacturing still has the largest increase range, reaching 140.3%. The numerical value of original data Output Value of New Products (Y_2) of this industry is 3.56494 billion Yuan, increasing to 8.567865 billion Yuan. For the index Y_3, only 8 DMUs need no increase. Spacecraft manufacturing still has the largest increase range, reaching 112.9%. The numerical value of the original data sales revenue of new products (Y_3) is 3.60362 billion Yuan, increasing to7.672535 billion Yuan (Chu et al., 2010).

Table 5-8: Input Reduction Proportion of Scale Inefficiency DMU (%)

Industry	X_1	X_2	X_3	X_4
Chemicals manufacturing	72.3%	67.9%	61.6%	80.5%
Chinese patent medicine manufacturing,	59.3%	47.7%	36.3%	79.8%
biological product manufacturing	41.2%	45.5%	41.7%	91.6%
Aircraft manufacturing and repair	62.8%	76.7%	68.0%	62.8%
Spacecraft manufacturing	30.9%	57.2%	30.9%	44.9%
Communication equipment manufacturing	0.00%	0.00%	0.00%	0.00%
Radar and corollary equipment manufacturing	0.00%	0.00%	0.00%	0.00%
Radio and television equipment manufacturing	0.00%	0.00%	0.00%	0.00%
Electronic device manufacturing,	3.68%	3.68%	9.64%	82.2%

Industry	X_1	X_2	X_3	X_4
Electronic component manufacturing	43.4%	22.1%	19.2%	40.8%
Domestic audio-visual equipment manufacturing	0.00%	0.00%	0.00%	0.00%
Other electronic equipment manufacturing	40.8%	47.8%	50.9%	86.8%
Complete electronic computer manufacturing	0.00%	0.00%	0.00%	0.00%
Computer peripheral equipment manufacturing	0.00%	0.00%	0.00%	0.00%
Office equipment manufacturing	0.00%	0.00%	0.00%	0.00%
Medical equipment and apparatus manufacturing	51.1%	61.8%	51.5%	79.2%
Instrument manufacturing	0.00%	0.00%	0.00%	0.00%

Table 5-9: Output Reduction Proportion of Scale Inefficiency DMU (%)

Industry	Y_1	Y_2	Y_3
Chemicals manufacturing	0.00%	0.00%	17.6%
Chinese patent medicine manufacturing,	0.00%	0.00%	14.5%
biological product manufacturing	7.47%	0.00%	81.6%
Aircraft manufacturing and repair	0.00%	5.27%	0.00%
Spacecraft manufacturing	25.3%	140.3%	112.9%
Communication equipment manufacturing	0.00%	0.00%	0.00%
Radar and corollary equipment manufacturing	0.00%	0.00%	0.00%
Radio and television equipment manufacturing	0.00%	0.00%	0.00%
Electronic device manufacturing,	0.00%	0.00%	11.2%
Electronic component manufacturing	0.00%	0.00%	17.1%
Domestic audio-visual equipment manufacturing	0.00%	0.00%	18.4%
Other electronic equipment manufacturing	0.00%	0.00%	0.00%
Complete electronic computer manufacturing	0.00%	0.00%	0.00%
Computer peripheral equipment manufacturing	0.00%	0.00%	0.00%
Office equipment manufacturing	0.00%	0.00%	0.00%
Medical equipment and apparatus manufacturing	0.00%	20.2%	21.1%

Instrument manufacturing	0.00%	0.00%	0.00%

5.4. Malmquist-based Dynamic Measurement and Evaluation of Industrial Technical Innovation Efficiency

The Malmquist productivity index is mainly used to study and judge the relationship between DMU productivity change and technical progress & management level. It is a significant basis for analysing technical innovation efficiency (Kao, 2010). In contrast with static analysis in which only the data in a period are selected for analysis, the data of the DMU in a time series are selected in dynamic analysis. Technical innovation efficiency measured through a Malmquist-based productivity index is dynamic. It measures the changes in technical innovation efficiency and the changes in technical innovation efficiency in different years and different industries can be compared.

Relevant efficiency change rules and causes can be found out through dynamic analysis to provide more information for decision-makers. The DEA method realises dynamic analysis of relative efficiency of DMU through Malmquist index decomposition. The technical innovation efficiency study measured and calculated on the basis of the Malmquist productivity index is the updated version of static measurement study of technical innovation efficiency of high-tech industry (Odeck, 2009).

The DMU and index system are the same as those in the above static analysis. According to four formulas of “DEA measurement models of Malmquist index”, Malmquist index of the above 17 DMUs, comprehensive efficiency change (EC) index, technical change (TC) index are calculated using the software Deap2.1.

In empirical studies, the index method is adopted for the dynamic measurement of efficiency. This section will measure technical innovation efficiency changes of the high-tech industry in each industry on the basis of Malmquist index model and decompose innovation efficiency (decomposed into technical change index and technical efficiency change index) so as to trace the root of technical innovation changes (Emrouznejad & Thanassoulis, 2010). As in the previous chapter, the analysis will be carried out on different levels –China as a whole, then on a regional basis, and subsequently on an individual basis.

5.4.1. Characteristics of Changes in Malmquist Index

It can be seen from Table 5-10 that during 2005-2011, the average value of the technical innovation efficiency - Malmquist index of the high-tech industry was the largest (1.163) in 2009/2010 and the smallest (0.9541) in 2008/2008. The average of the Malmquist index is 1.045.

The largest feature of total factor productivity of the 17 industries is not stable enough, and the fluctuation is large. These are mainly reflected in two aspects. From the perspective of DMU, the Malmquist index of each DMU changes to different degrees during the 7 years. In addition, the changes have no pattern, from descending to rising and then declining again, or from rising to descending and then rising again. There are multiple instances of these occurrences (Asmild et al., 2004).

Considering the time perspective, the number of DMUs with a Malmquist index greater than 1 is smallest (only 8) in 2008-2009 and reaches the largest (13) in 2009-2010. Their large fluctuation in total factor productivity fully indicates they are still in rapid development. All kinds of input and output factors often have large fluctuations. This point can be clearly shown from the original data. It is clear from the data that the Malmquist Index is unstable. The reasons for an unstable index are discussed in section '7.2.2 Discussion of causes for unstable Malmquist Index'.

Table 5-10: M, EC and TC Index Changes from 2005-2011

	2005-2006			2006-2007			2007-2008			2008-2009			2009-2010			2010-2011			MEAN		
Industry	**M**	**EC**	**TC**	**M**	**EC**	**TC**	**M**	**EC**	**TC**	**M**	**EC**	**TC**	**M**	**EC**	**TC**	**M**	**EC**	**TC**	**M**	**EC**	**TC**
Chemicals manufacturing	0.854	1.070	0.798	1.024	0.917	1.117	0.990	0.980	1.010	1.149	1.516	0.758	1.031	0.734	1.404	0.834	0.814	1.024	0.980	1.005	1.019
Chinese patent medicine manufacturing,	0.713	0.964	0.739	0.962	0.734	1.311	1.211	1.357	0.892	0.878	1.042	0.843	1.104	0.657	1.681	0.888	0.883	1.006	0.959	0.940	1.079
biological product manufacturing	0.457	0.648	0.706	1.337	1.019	1.313	0.804	0.786	1.022	0.987	1.272	0.776	1.098	0.788	1.393	1.073	0.909	1.181	0.959	0.904	1.065
Aircraft manufacturing and repair	0.978	1.071	0.913	1.044	0.974	1.073	1.163	1.196	0.972	0.730	0.828	0.881	1.157	0.927	1.248	1.013	1.116	0.908	1.014	1.019	0.999
Spacecraft manufacturing	1.940	1.532	1.266	1.503	1.013	1.483	1.057	1.368	0.773	1.376	1.325	1.039	1.220	0.792	1.541	0.858	0.791	1.084	1.326	1.137	1.198
Communication equipment manufacturing	1.307	1.000	1.307	1.112	1.000	1.112	0.797	1.000	0.797	1.090	1.000	1.090	0.960	0.823	1.167	0.929	1.216	0.764	1.033	1.007	1.040
Radar and corollary equipment manufacturing	1.510	1.685	0.896	0.845	0.941	0.898	0.625	0.641	0.975	1.359	1.535	0.885	1.237	0.970	1.276	1.166	1.229	0.949	1.124	1.167	0.980
Radio and television equipment manufacturing	1.351	1.189	1.136	2.068	1.225	1.687	0.793	1.000	0.793	0.917	1.000	0.917	2.342	1.000	2.342	1.064	1.000	1.064	1.423	1.069	1.323
Electronic device manufacturing,	1.188	1.420	0.837	1.182	1.151	1.027	1.199	0.984	1.218	1.113	1.366	0.814	1.113	0.836	1.332	0.966	0.687	1.405	1.127	1.074	1.106
Electronic	0.671	0.860	0.780	1.258	1.196	1.052	1.203	0.996	1.208	1.464	1.922	0.761	1.050	0.702	1.497	0.949	0.953	0.996	1.099	1.105	1.049

component manufacturing																					
Domestic audio-visual equipment manufacturing	1.106	1.000	1.106	0.873	1.000	0.873	0.815	0.953	0.856	1.156	1.050	1.101	0.812	1.000	0.812	1.205	1.000	1.205	0.995	1.001	0.992
Other electronic equipment manufacturing	0.802	1.079	0.743	1.831	1.411	1.298	0.756	0.770	0.982	1.245	1.519	0.820	1.007	0.621	1.622	0.947	0.788	1.203	1.098	1.031	1.111
Complete electronic computer manufacturing	1.176	1.000	1.176	0.689	1.000	0.689	1.365	1.000	1.365	0.660	1.000	0.660	1.143	1.000	1.143	1.246	1.000	1.246	1.047	1.000	1.047
Computer peripheral equipment manufacturing	1.261	1.446	0.872	0.836	0.921	0.908	1.293	1.086	1.191	0.899	1.000	0.899	1.209	1.000	1.209	1.166	1.000	1.166	1.111	1.076	1.041
Office equipment manufacturing	1.422	1.286	1.105	0.587	0.874	0.671	0.934	0.818	1.142	0.457	0.734	0.623	2.563	1.906	1.345	0.625	0.594	1.052	1.098	1.035	0.990
Medical equipment and apparatus manufacturing	0.752	1.000	0.752	1.329	1.000	1.329	1.156	1.000	1.156	0.524	0.843	0.622	0.845	0.378	2.234	1.177	1.078	1.092	0.964	0.883	1.198
Instrument manufacturing	1.500	1.852	0.810	1.102	0.723	1.524	1.243	1.373	0.905	0.994	1.198	0.830	0.929	0.511	1.819	1.189	1.160	1.025	1.160	1.136	1.152
Mean	1.052	1.145	0.919	1.096	0.993	1.104	0.999	0.998	1.001	0.954	1.148	0.831	1.163	0.813	1.430	1.003	0.937	1.071	1.045	1.006	1.059
Years greater than or equal to 1	10	14	6	11	10	12	9	9	8	8	14	3	13	5	16	9	9	13	12	14	13

5.4.2. Analysis of PTE and SE Changes

The method used in section 4.5.2 for PTE and SE analysis, is applied here. The results are shown in Table 5-11. The analysis and discussion are given in section '7.2.2 Discussion of causes for unstable Malmquist Index' .

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Table 5-11: PTE and SE Changes from 2005-2011

	2005-2006			2006-2007			2007-2008			2008-2009			2009-2010			2010-2011		
Industry	EC	PTE	SE	EC	PTE	SE	EC	PTE	SE	EC	PTE	SE	EC	PTE	SE	EC	PTE	SE
Chemicals manufacturing	1.070	1.088	0.983	0.917	0.902	1.017	0.980	0.997	0.983	1.516	1.489	1.018	0.734	0.744	0.986	0.814	0.810	1.004
Chinese patent medicine manufacturing,	0.964	0.994	0.970	0.734	0.713	1.030	1.357	1.412	0.961	1.042	1.000	1.042	0.657	0.675	0.974	0.883	0.944	0.935
biological product manufacturing	0.648	0.953	0.680	1.019	0.647	1.574	0.786	1.215	0.647	1.272	0.890	1.429	0.788	0.704	1.119	0.909	1.253	0.726
Aircraft manufacturing and repair	1.071	1.012	1.058	0.974	0.871	1.118	1.196	1.197	0.999	0.828	0.855	0.969	0.927	0.897	1.034	1.116	1.280	0.873
Spacecraft manufacturing	1.532	1.000	1.532	1.013	1.000	1.013	1.368	0.897	1.524	1.325	1.114	1.189	0.792	0.809	0.978	0.791	0.854	0.927
Communication equipment manufacturing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.823	1.000	0.823	1.216	1.000	1.216
Radar and corollary equipment manufacturing	1.685	1.000	1.685	0.941	1.000	0.941	0.641	1.000	0.641	1.535	1.000	1.535	0.970	0.992	0.977	1.229	1.008	1.220
Radio and television equipment manufacturing	1.189	1.000	1.189	1.225	1.000	1.225	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Electronic device manufacturing,	1.420	1.410	1.007	1.151	1.172	0.982	0.984	1.129	0.871	1.366	1.251	1.092	0.836	1.054	0.793	0.687	1.003	0.685
Electronic component manufacturing	0.860	0.852	1.009	1.196	1.209	0.989	0.996	1.091	0.913	1.922	1.744	1.102	0.702	0.699	1.003	0.953	1.589	0.600
Domestic audio-visual equipment manufacturing	1.000	1.000	1.000	1.000	1.000	1.000	0.953	0.962	0.991	1.050	1.040	1.009	1.000	1.000	1.000	1.000	1.000	1.000
Other electronic equipment manufacturing	1.079	0.804	1.342	1.411	1.098	1.286	0.770	0.687	1.120	1.519	1.432	1.061	0.621	0.670	0.926	0.788	1.017	0.775
Complete electronic computer manufacturing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Computer peripheral equipment manufacturing	1.446	1.436	1.007	0.921	0.930	0.990	1.086	1.075	1.010	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Office equipment manufacturing	1.286	1.000	1.286	0.874	1.000	0.874	0.818	1.000	0.818	0.734	1.000	0.734	1.906	1.000	1.906	0.594	1.000	0.594
Medical equipment and apparatus manufacturing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.843	0.858	0.982	0.378	0.396	0.954	1.078	1.438	0.750
Instrument manufacturing	1.852	1.857	0.997	0.723	0.829	0.872	1.373	1.549	0.886	1.198	1.010	1.186	0.511	0.635	0.805	1.160	1.576	0.736

Mean	1.145	1.060	1.080	0.993	0.952	1.043	0.998	1.055	0.945	1.148	1.077	1.066	0.813	0.816	0.997	0.937	1.083	0.865
Years greater than or equal to 1	13	12	13	10	11	11	8	12	7	13	13	13	5	7	8	8	13	7

5.4.3. Analysis of M mean change and the trend of 17 DMUs

Table 5-12 shows the Malmquist index changes of innovation efficiency and the decomposition results of China's 17 high-tech industries from 2005-2011 (Haibo & Shujia, 2009). In recent years, the Malmquist index of innovation efficiency of the high-tech industry increased by 4.5% on average; the growth rate reached the highest (16.3%) in 2010 and reached the lowest (-4.6%) in 2009; the mean of technical efficiency was 1.059, up 5.9%. It becomes the main driving force of the rise in technical innovation efficiency. The mean of PTE change was 1.007, up 0.7%.

The mean of SE change was 0.999, up 0.1%. The mean of technical progress index was 1.006, down 0.6%. This indicates that the optimal frontier of technical innovation did not change much from 2005-2011; the improvement in technical progress and innovation ability was limited, and this restrained the rise in technical innovation efficiency to some extent. From 2005-2011, technical innovation efficiency slightly rose (4.5%) due to an improvement in technical efficiency (5.9 %). Technical innovation efficiency change and technical progress variation trend are basically consistent. The technical progress index and technical efficiency variability index indicate a reverse wave (Zhang & Choi, 2013). Discussion of the results is given in section

Table 5-12: MALMQUIST Index Summary of Annual Means in 2005-2011

Year	Malmquist index	Effch TE change	Tech technical change	Pech PTE change	Sech SE change
2005-2006	1.052	1.145	0.919	1.060	1.080
2006-2007	1.096	0.993	1.104	0.952	1.043
2007-2008	0.999	0.998	1.001	1.055	0.945
2008-2009	0.954	1.148	0.831	1.077	1.066
2009-2010	1.163	0.813	1.430	0.816	0.997
2010-2011	1.003	0.937	1.071	1.083	0.865
Mean	1.042	0.999	1.044	1.002	0.996

5.4.4. Industrial Comparison of Malmquist Index from 2005-2011

In accordance with product relations in the 17 industries, the 17 DMUs are classified into 5 industrial groups: pharmaceutical industry, aerospace vehicle manufacturing, electronic and communication device manufacturing, electronic computer and office equipment manufacturing industry as well as medical equipment and instrument manufacturing industry. The Malmquist index measurement is conducted for the 5 industrial groups. The results are presented in table 5-13.

Table 5-13: Comparison of Malmquist Index in Each Industry from 2005-2011

Category	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011
Pharmaceutical industry	0.675	1.108	1.002	1.005	1.078	0.932
Number of improved units	0	2	1	1	3	2
Number of declining units	3	1	2	2	0	1
Aerospace vehicle manufacturing	1.459	1.274	1.110	1.053	1.189	0.936
Number of improved units	1	2	2	1	2	1
Number of declining units	1	0	0	1	0	1
Electronic and communication device manufacturing	1.134	1.310	0.884	1.192	1.217	1.032
Number of improved units	5	5	2	6	5	3
Number of declining units	2	2	5	1	2	4
Electronic computer and office equipment manufacturing industry	1.286	0.704	1.197	0.672	1.638	1.012
Number of improved units	3	2	2	0	3	2
Number of declining units	0	1	1	3	0	1
Medical equipment and instrument manufacturing industry	1.126	1.216	1.200	0.759	0.887	1.183
Number of improved units	1	2	2	0	0	2
Number of declining units	1	0	0	2	2	0

The Mean Malmquist index of each industry from 2005-2011 and the analysis results of decomposition index changes are shown in Table 5-14.

Table 5-14: Mean Malmquist index and the decomposition index of each industry from 2005-2011

Industry	Malmquist	effch	tech	pech	sech
Pharmaceutical industry	0.966	0.949	1.054	0.968	1.004
Number of improved units	0	1	3	1	1
Number of unchanged units	0	0	0	0	0
Number of declining units	3	2	0	2	2
Aerospace vehicle manufacturing	1.170	1.078	1.098	0.982	1.101
Number of improved units	2	2	1	1	2
Number of unchanged units	0	0	0	0	0
Number of declining units	0	0	1	1	0
Electronic and communication device manufacturing	1.128	1.065	1.086	1.046	1.024
Number of improved units	6	7	5	5	4
Number of unchanged units	0	0	0	1	1
Number of declining units	1	0	2	1	2
Electronic computer and office equipment manufacturing industry	1.085	1.037	1.026	1.025	1.012
Number of improved units	3	2	2	1	2
Number of unchanged units	0	1	0	2	1
Number of declining units	0	0	1	0	0
Medical equipment and instrument manufacturing industry	1.062	1.010	1.175	1.096	0.931
Number of improved units	1	1	2	1	0
Number of unchanged units	0	0	0	0	0
Number of declining units	1	1	0	1	2

The average annual growth rate of aerospace vehicle manufacturing was the highest, reaching 7.8%, while the average annual growth rate of the pharmaceutical industry was the lowest (-5.1%). 13 industries showed a rising trend. 1 industries remained unchanged. 3 industries presented the downturn. The technical progress index tech of each industry rose, with the medical equipment and instrument manufacturing industry experiencing the fastest rise, reaching 17.5%. The growth of electronic computer and office equipment manufacturing industry was the slowest (2.6%). Most industries are in the growing stage. Out of the 17 industries, only 4 industries experienced a decline in the technical progress index (Cruz-Cázares, 2013).

Regarding PTE, pharmaceutical industry and aerospace vehicle manufacturing experienced a drop, while other industries rose. In the aspect of SE, other industries experienced growth except medical equipment and instrument manufacturing industry. However, the growth speed was relatively slow. For example, the growth rates of the pharmaceutical industry, electronic computer and office equipment manufacturing industry as well as electronic and communication device manufacturing were 0.4%, 1.2% and 2.4% respectively (Bao-Feng, 2011).

The Mean variation trend of the Malmquist index and the decomposition index of technical innovation efficiency of each DMU from 2005-2011.

According to table 5-15, among the 17 industries, the mean of Malmquist index change of technical innovation efficiency in 11 industries was greater than 1. To be more specific, radio and television equipment manufacturing industry had the largest Malmquist index change (1.310), followed by spacecraft manufacturing (1.282). Biological product manufacturing (0.911) and office equipment manufacturing (0.911) had the smallest mean of Malmquist index change (Xiao-Di, 2008).

The average annual growth rate of the M index in radio and television equipment manufacturing, spacecraft manufacturing, electronic device manufacturing and instrument manufacturing etc. was more than 10%, and average annual growth rate in radio and television equipment manufacturing and spacecraft manufacturing even exceeded 28%. The M growth of aircraft manufacturing and repair, communication equipment manufacturing and complete electronic computer manufacturing was relatively slow, and the average annual growth rate was within 5%. The Malmquist index changes can be divided into EC and TC. The Malmquist indexes of chemicals manufacturing, Chinese patent medicine manufacturing, biological product manufacturing, domestic audio-visual equipment manufacturing, office equipment manufacturing as well as medical equipment and apparatus manufacturing etc. were below 1 (Xiao-Di, 2008).

The reasons behind this negative growth differ. The negative growth of chemicals manufacturing, Chinese patent medicine manufacturing, biological product manufacturing and medical equipment and apparatus manufacturing was mainly caused by an EC decline, while the negative growth of domestic audio-visual equipment manufacturing was mainly caused by a TC decline. The negative growth of office equipment manufacturing was caused by declines in both EC and TC (Xia et al., 2009).

Table 5-15: The Mean Change Trend of Malmquist Index and the Decomposition Index of Technical Innovation Efficiency of Each DMU from 2005-2011

Industry	M	EC	TC	PTE	SE
Chemicals manufacturing	0.974	0.977	0.997	0.979	0.999
Chinese patent medicine manufacturing,	0.945	0.913	1.035	0.928	0.984
Biological product manufacturing	0.911	0.883	1.032	0.915	0.964
Aircraft manufacturing and repair	1.003	1.011	0.992	1.006	1.005
Spacecraft manufacturing	1.282	1.099	1.166	0.940	1.169
Communication equipment manufacturing	1.020	1.000	1.020	1.000	1.000
Radar and corollary equipment manufacturing	1.077	1.109	0.972	1.000	1.109
Radio and television equipment manufacturing	1.310	1.065	1.231	1.000	1.065
Electronic device manufacturing,	1.124	1.040	1.081	1.162	0.894
Electronic component manufacturing	1.068	1.047	1.020	1.139	0.920
Domestic audio-visual equipment manufacturing	0.981	1.000	0.981	1.000	1.000
Other electronic equipment manufacturing	1.047	0.977	1.071	0.916	1.066
Complete electronic computer manufacturing	1.006	1.000	1.006	1.000	1.000
Computer peripheral equipment manufacturing	1.095	1.063	1.030	1.062	1.001
Office equipment manufacturing	0.911	0.956	0.953	1.000	0.956
Medical equipment and apparatus manufacturing	0.919	0.837	1.098	0.888	0.943
Instrument manufacturing	1.145	1.045	1.095	1.158	0.903
Mean	1.042	0.999	1.044	1.002	0.996
Number greater than or equal to 1	11	11	12	11	9

Table Note: All Malmquist index averages are geometric means

Technical efficiency change can be decomposed into PTE change and SE change under VRS (Lu et al., 2010). The data shows that the change mean of PTE of the 17 industries is 1.002, while the change mean of PTE of 11 industries is equal to or greater than 1. In accordance with input indexes selected in this dissertation, the mean of the PTE is greater than 1. This indicates that each industry in China pays attention to the input in scientific research so that PTE rises. However, looked at from the aspect of absolute value, the change mean of PTE just exceeds 1. This drags technical efficiency change to some extent. The change mean of SE for the 17 industries was only 0.996. The change mean of SE in 8 industries was less than 1. This reflects an ineffective technical innovation input scale. As such, it is necessary to attach importance to these industries, increase the input in scientific research innovation in the high-tech industry and increase SE.

5.5. Conclusion

On the basis of the previous chapter, this chapter focused on a macroscopic and dynamic research of the Malmquist index of technical innovation efficiency from DEA-based microcosmic and static technical efficiency research. This chapter studied the technical innovation efficiency measurement and change problems from the perspective of empirical analysis. It is clear that there was an increase in the M index of technical innovation efficiency in China’s high-tech industry; The EC improved, and TC also improved greatly. The mean of the Malmquist index was 1.065, and this was mainly caused by TC progress effectiveness. Several instances are seen where there was an increase in some of the industries, while other industries showed a decrease. Overall, the M index shows some level of instability. These can be attributed to the large cross section of industries in China, the large number of specific industries, the nature of their work, products, and the market conditions.

Chapter 6 AN INTERNATIONAL COMPARISON OF SCIENCE AND TECHNOLOGY POLICY AND EFFICIENCY OF TECHNOLOGICAL INNOVATION

6.1. Introduction

This chapter provides support for science and technology management departments, research institutions, institutions of higher learning and enterprises in China to develop technological innovation and formulate STP by comparing differences in STP and its orientation in China, major developed countries and other developing countries such as the BRIC Countries.

The main difference between developed and developing countries lies in the difference in their scientific and technological levels. International competition in modern times is based on scientific and technological competition. Science and technology policy (STP) is the policy formed by a country to organise, intervene, direct, and control scientific and technological activities. This policy reflects the main content of scientific and technological management and acts as an important component of scientific and technological management activities. STP has a significant acting force on the development of scientific and technological activities. A suitable STP can drive the development of science, and improve social productive forces and comprehensive national strength, while an unsuitable STP can hinder the development and progress of science and technology and cause irreparable losses for development (Pavitt, 1991).

STP is an important method by which a country directs scientific and technological activities and allocates scientific and technological resources.

Under the background of economic globalisation, the STP and economic policies of each country have shown such countries' will related to competitive strategies increasingly. Economic leaders such as America, Japan, etc., have considered scientific and technological development as leading strategies of their development in the 21st century. Policies of science and technologies have become basic public policies used to build powerful countries of science and technology fully and internal requirements for establishment and realisation of national competitive strategies (Grupp & Mogee, 2004). However, there has been no clear definition of STP in theoretical circles.

This chapter discusses important concepts and requirements of STP. An analysis of the STP of developed countries a comparison of science and technology input and orientation with Chinese STP will be drawn. The chapter will discuss implementation systems of STP, and various plans, systems, policies and policy orientation, that provide a continuous, healthy, and rapid development of science and technology; and provides support for science and technology management departments, research institutions, institutions of higher learning and enterprises in China to develop technological innovation and formulate STP.

6.2. The Concept of STP

STP was not formally used in academic spheres as a standard expression or jointly used by countries with developed economies and science and technology until the United Nations Conference of the Applications of Science and Technology (UNCAST) held by the United Nations in Geneva in 1963 (Lengwiler, 2008). Lengwiler points out that STP aims to use the resources of people and articles to promote various scientific and technological activities in all government departments and the folk and to perfect basic research on science and technology constantly.

Therefore, it is essential to pay attention to the coordination between science and technology and the environment and establish action policies, which are carried out by countries in a planned and organised way, and the system through which actions are taken to realise this policy. Thus, it is obvious that STP contains the policy and measures that a country's government makes and takes in a special historical stage to realise specific scientific and technological goals, it includes laws, regulations and rules made by organs of state power, and drives the development of science and technology.

STP reflects main the content of scientific and technological management and is an important component of scientific and technological management activities. It has become an important method by which a country allocates scientific and technological resources and basic environment of countries or regions' technological innovation efficiency. This article uses some research by and opinions of experts as a basis for defining STP (Joss, 1999).

Jean-Jacques Saloman, a French professor, defines STP as "concentrative measures taken by the government to encourage the development of scientific and technological research on the one hand; and to use the results of this research for general political goals on the other hand" (Salomon, 1984). Hui-yue (2006) thinks that STP is a system established by countries to control links of scientific and technological activities, such as input, operation, output and conversion, where scientific and technological policies of knowledge products are advanced and realised in a planned and organised way. Yuan and Xue (2007) conclude that STP is a political measure used to spread, produce, and apply science and technology purposefully. The United Nations Educational Scientific and Cultural Organization (UNESCO) gives the following definition: STP is sum of organisations, systems and implementation directions that a country or a region establishes to strengthen its scientific and technological potential, realise its goals of comprehensive development and improve its position.

Fang and Yang (2000) consider STP as a series of policies that intervene in, control and guide scientific and technological studies and technological development, and promote the industrialisation of scientific and technological achievements, in order to make up market failure and drive technical innovation of public sectors and private departments. On the basis that related literatures are settled, this article defines STP as the various plans, systems, policies and policy orientations carried out by the government to promote the continuous, healthy and rapid development of science and technology. STP is related to the current status of scientific and technological progress and policy orientation. Thus, this article mainly starts with the current status of scientific and technological progress and aims to establish the background of STP, and compare the science and technology input and orientation and implementation systems of STP in major developed countries and 'BRIC Countries'.

The National Outline on Medium and Long-term Program for Scientific and Technological Development (2006-2020) issued and implemented by China in 2006 specifically treats the long-term development of national science and technology as a basic strategy that is used to build a well-off society in an all-around way, and accelerate the construction of socialist modernisation (Serger & Breidne, 2007). It regards scientific and technological progress as the primary driving force of economic and social development, considers improvement in capability of independent innovation as a key link for adjusting economic structure, changing the growth mode and improving national competitiveness and highlights the construction of an innovative country as an important strategic choice facing the future. Science and technology input is added constantly, an increase in national finance and scientific and technological appropriation is obvious and the number of patents and papers also experience obvious growth (Rongping & Wan, 2008).

6.2.1. *Status of International STP and Establishment Background*

6.2.1.1 America

The American government sufficiently recognises the importance and necessity of timely establishment of corresponding national strategic plans. Since the 1990s, America has carried out STP in a more active manner to drive its science and technology to develop rapidly. Different sectors have issued strategic reports to intervene with high-tech development, such as the Human Genome Project (HGP), the information superhighway plan and the national nanometer plan. Such strategic plans have significant impacts on the American economy and have become one of the strategic methods through which America's industrial competitiveness and comprehensive national strength are enhanced (Alfredo Soeiro, 2006).

The formation and improvement one of a country's technological innovation are closely related to its science and technology input. From 1995 to 2001, if the research and development input of America is computed using the 1995 U.S. dollar of purchasing power parity (PPP), it would reach up to USD 1523017.7 billion. That of Japan, Germany, France and Britain would be USD 620217.5 billion, USD 302914.2 billion, USD 200110.8 billion and USD 156416.0 billion respectively. During the period from 1995 to 2001, the growth rate of America's development input was the highest among 5 industrial developed countries, its average growth rate was 5.4%, the average growth rates of Germany and Japan, were 3.3% and 2.8%, respectively, and that of France and Britain was lower than 3% (OECD, 2003). This material input basis is generated by continuous technological innovation achievements in America (Alegre et al., 2006).

America pays special attention to cultivating senior talent. Since the Second World War, it has formed an advanced scientific research system whose subjects include colleges, enterprises and national scientific institutions. This system has gradually set the trend of global basic science and technological innovation. With respect to talent introduction, America recruits technical talent all over the world by channels such as skilled migration, work visa and students and exchange visa etc. Although America reduced the approval of various kinds of visa once after occurrence of '911 Event', visa conditions have broadened during the Obama administration to introduce technical talent (Horii, 2011).

The American government knows that basic research has a profound effect on the long-term development of science and technology and the revolutionary progress of science and technology. When presidents like Bill Clinton and George Walker Bush formulated and carried out STP, they paid special attention to basic research. When George Walker Bush was in power, he increased capital input for basic science research on the investment basis of basic research whose subjects were colleges so as to ensure America's leading position in the field of global science. At the same time, developed countries including America increasingly enhanced scientisation and standardisation of STP research. In 2007, the National Science Foundation (NSF) established Science of Science and Innovation Policy (SciSIP) to provide assistance in the aspects of method foundations and platforms for research on STP. Facilities provided included exploring how to analyse management data of science and technology institutions effectively (STAR METRICS) and how to develop data mining and data demonstration tools (dashboard) etc. (Elzen et al., 2004).

By 2011, the project had funded 132 research and academic meetings and the amount of total patronage was USD 74.49 million; the amount of each subsidy ranged from USD 0.01 million to 22 million and the average amount of each subsidy was about USD 0.56 million (NSF, 2011). In 2008, America issued a route map of Science of Science Policy (SoSP), which defined SoSP as an emerging inter-discipline that devoted itself to providing quantified data foundation, methods and tools for the government's STP. The map helped decision-makers understand the law of technological innovation activities better and developing evaluations on science and technology causes (Schindler & Hilborn, 2015). In 2010, the European Union (EU) and America jointly held the EU/US Science of Science Policy workshop, advancing standardisation of research on STP methods, tools, and data in the whole of Europe (Huang et al., 2015). The overall assessment is that the US government has taken continuous steps to enhance and diffuse science and technology through universities and the industry.

6.2.1.2 Japan

Japan is a developed Asian country and the speed of its economic and technological development is apparent to all. Japan faced the problem of a shortage of resources and so in order to survive, its government paid much attention to science and technology in order to form a pattern of 'developing the country via science and technology'. Its development can be considered a miracle: from its failure in the Second World War to a powerful country of science and technology in the world today (Motohashi, 2015).

After entering the 1990s, Japan's economic bubble began to burst. During this period, the consensus of all Japanese sectors was to develop original technology, create emerging industries and use independent innovation to guide Japan out of the economic dilemma. In 1995, the Diet of Japan approved a *Basic Law on Science and Technology* at an unprecedented speed, which indicated that the STP of Japan entered a new stage where basic research was valued and innovation was emphasised. It began to transit to a situation of 'developing the nation via technological innovation'. Its main content involved the following three aspects: paying attention to exerting innovation of researchers, developing basic research, applying research harmoniously and realising the harmonious development of science and technology, human society and nature (Shibayama & Baba, 2015).

At the same time, in order to create more higher-end new technologies and new knowledge and realise great-leap-forward development in the field of invention and creation, Japan began to formulate and carry out ‘basic plans in science and technology’ and make decisions. In the years, the government invested JPY 17,000 billion to complement the budget related to science and technology. It was predicted that the first and the second-stage plans would input JPY 17,000 billion and JPY 24,000 billion respectively. The actual amounts inputted were JPY 17,600 billion and JPY 21,100 billion respectively. Specifically, the input of the first-stage plan increased by 36% compared with the fiscal years from 1991 to 1995 and the input of the second stage grew by 20% compared to the first one. However, this did not reach planned goals. Thus, the budget input of the third stage was about JPY 25,000 billion. Increased funds were mainly applied to competitive funds and preferentially developed fields to promote the scientific research development of private departments, cultivate and ensure research, promote talent communication, and perfect research and development infrastructure (Iwasa & Odagiri, 2004).

Japan comprehensively reformed its science and technology system and implemented related laws and plans simultaneously. In 2001, Japan decided to set up a ‘comprehensive conference on science and technology’, which enabled the government to coordinate the relationship among all administrative departments of science and technology in a more effective manner, and enhanced the country’s macro coordination and control of scientific and technological activities. In the same year, the Japanese government integrated the 'Ministry of Education' and 'Ministry of Science and Technology' into the 'Ministry of Education, Culture, Sports, Science and Technology (MEXT)'. This development, helped to realise complementary advantages of functions and resources, overcome shortages of the two co-existing as two independent agencies, and converted the original competitive relationship into one of close cooperation. The combination and flow of the two institutions' science and technology talent not only strengthened the communication of scientific and technological talent but also enhanced the metabolism of scientific research institutions, create favourable conditions for the development of Japan's 'industry, study and office' innovative mode and realised maximum utilisation and optimal configuration of scientific and technological resources (Lynskey, 2004).

Japanese enterprise innovation is the power source of the country's technological innovation. As a country with limited resources, Japan relies largely on the outside. To ensure that enterprises do not fall sick, they must form research and development mechanisms based on their own characteristics and adapt to market demands. The Japanese government, with the aim of enhancing private enterprises' capability of independent research and development, aroused enterprises' enthusiasm to the largest extent by using several kinds of policies to offer enterprises subsidies and favourable measures, and this had a positive effect on improving enterprises' input into research and development. According to results of Nikon Keizai Shimbun's survey on Japanese enterprises' input research and development in 2012, it was observed that Japan's input into research and development was JPY 11,760 billion, with a year-on-year growth of 4.3%, and that the country realised growth for three consecutive years (Yan, 2007). The Japanese focus on investing and proving support to science and technology has helped the country to become a highly innovative nation.

6.2.1.3 Germany

Germany is a country that attaches much importance to science and technology. It has witnessed a number of achievements in both natural science and social science. Grundgesetz für die Bundesrepublik Deutschland specifies that the basic principle of the country's technological development policies lies in free science, autonomous scientific research, auxiliary state intervention and decentralised control of the federation. The German government has been insisting on the basic principle of STP to promote development of science and technology for a long time (Peters, 2008).

The German federal government gives importance to scientific research and development. By comparing and analysing the science and technology input of major developed countries, it can be found that Germany ranks third in the aspects of total science and technology input as a proportion to GDP, and input amount per capita and capital ratio, only behind America and Japan. The order of science and technology is completely consistent with the ranking of its economic position. This also sufficiently highlights a causal relationship between input and output. In order to improve the innovative ability of national comprehensive technology, the German government proposed a slogan that states that it will construct ‘a resourcefulness workshop’ in the world and encourage innovation and the development of higher education, basic research and industrial research via a series of measures. Basic research is a basis of knowledge production. The German government has always attached importance to basic research. Colleges and Max Planck Institute are important forces of basic research in Germany and constitute the country’s main force in this field (Eickelpasch & Fritsch, 2005).

In August 2006, the German federal government unprecedentedly launched the first *High-tech Strategy for Germany* covering all policy ranges. It was aimed at exploiting leading markets, promoting the union of economic circles and the scientific community and creating free space for researchers, innovators and entrepreneurs. Its final purpose is to make Germany become one of the friendliest countries in the aspects of research and innovation all over the world and enable innovation to be converted into new products, technologies and service owing market shares (Baier et al., 2013).

In May 2012, the Federal Ministry of Economics and Technology of Germany issued a new innovative outline called *Technical Passion —— Having the Courage to Bring Forth New Ideas, Enhancing Growth and Building the Future*. The outline has three goals: to make Germany become the country that is the friendliest to technology and innovation in the world by 2020. The other strategy was to increase the number of research and development enterprises and innovation enterprises from its current numbers at 30,000 and 110,000 respectively to 40,000 and 140,000 respectively in 2020; and to keep and expand Germany's position as the number one technical export in the world. For this, Germany will take measures in three aspects: improving acceptance for new technologies, building an environment that is more favourable for innovation and enhancing technological innovation of middle and small-sized enterprises (Baier, 2013). It is clear that Germany provides a state funded initiative to promote the widespread progress of science and technology.

6.2.1.4 France

France is the fourth most powerful country in the aspects of economy and science and technology at present, and holds a leading level in fields like space science, nuclear power, aviation technology and electrons. The French government increases the degree of technological innovation continuously and proposes the total input goal that R&D will be increased year by year, which is key for science and technology development in France to reach new levels and remain at an internationally leading position all the time (Aghion et al., 2012). The demands of French enterprises' development and the continuous enhancement of competitiveness when participating in international trade bring constant growth in the demand for science and technology and makes enterprises increase input into scientific research funds (Cazavan-Jeny et al., 2011).

France sufficiently exerts roles of industrial associations in technological innovation. Each professional association in France plays a positive and important role in reflecting government functions and management, organising enterprise technological innovation and technical progress activities and organising scientific research institutions and colleges to develop research on science and technology projects (Ballot et al., 2015).

Regarding the arrangement of scientific research projects, France combines economic construction with industrial development, and increases input according to the demands for enterprise technological innovation and progress in production technology, on the basis that applied research and development research projects are considered. The country places applied scientific research projects at quite an important position, and this has a major effect on the development of French enterprises and keeps them highly competitive in the global sphere. With respect to free exploration, the government provides more finance and more space, drives openness of scientific research, strengthens subject cooperation, promotes cooperation between research institutions and enterprises and creates conditions for personnel flow (Dosi et al., 2006).

In order to cope with social challenges presently and in the future and make research enhance economic growth and develop national competitiveness, the Teaching and Research Department of France issued new policies on transfer and conversion on November 7, 2012. These policies are aimed at establishing new evaluation index systems of transfer and conversion tracking; creating a strategic steering committee for transfer and conversion at the gathering place of scientific research institutions; simplifying intellectual property management procedures of public scientific research institutions; and supporting public scientific research institutions to transfer and convert their achievements at innovative medium and small enterprises. Agence Nationale de Recherche supports joint laboratory projects of research institutions and middle and small-sized enterprises; and the building of innovative economic research centres (Bertrand, 2014).

On February 21, 2012, Strategic Investment Funds of France issued a 2020 plan in which EUR 5 billion would be directly invested in medium and small enterprises in order to enhance the innovative ability and competiveness of French enterprises. The Trust Investment Bank of France is in charge of this plan, and will sign an 8 year long-term agreement with enterprises to realise a long-acting investment mechanism. The last plan of the funds was finished successfully in 2012, when EUR 3.3 billion was invested to support 1,130 enterprises over 6 years, and a trading volume of over EUR 17 billion was realised (Bertrand, 2014).

6.2.1.5 Britain

Britain is associated with a number of innovations and the source for the Industrial Revolution. Economic development, STP regulation, and technological innovation of Britain were accompanied. Continuous diffusion and an extension of crises have made the British government pay more and more attention to science and technology. On the one hand, it hopes that science and technology will play an important role in coping with crises. On the other hand, economic crises bring about new opportunities for the great-leap-forward development of science and technology. At the same time, the government hopes that innovation and skills can be the main driving force that arouses social productive forces and drives economic recovery and prosperity. By taking certain measures and making industrial development policies such as science and technology awards and university-industry cooperation, the strength of science and technology institutions is integrated and enhanced further (CST, 2015).

Britain has a tradition of attaching importance to basic research all the time. All previous governments have invested high amounts into basic research and have also paid attention to applied research. At the end of the 1970s, the key point of British scientific research was changed from high-energy physics to biology, especially research on the application of molecular biology and medical science. The scientific foundation of British biotechnology is superior to other European countries. Britain has won over 20 Nobel prizes in this field. However, investment of Britain into systematic science and technology is less than that of competing countries. In the 1960s, Britain’s science and technology expense ranked second only to America. In the 1970s, the ranking fell to fourth. In 1978, its input was USD 7.961 billion in face, which was approximate to that of France. From 1981 to 1990, Britain’s research expenditure reduced by 10%. There is significant difference between Britain’s R&D investment and that of its main industrial competitors (ONS, 2015).

In May 2012, the UK Department for Business Innovation and Skills (BIS) announced the start of a UK Research Partner Investment Funds (UKRPIF) subsidy plan, with the aim of driving enterprises to increase investment in the R&D activities of colleges and strengthen research infrastructure construction in colleges. According to specifications, UKRPIF projects require colleges to be able to obtain more than double the funds obtained from enterprises or charity organisations taking part in the cooperation. Currently, UKRPIF has granted 0.2 billion pounds to 14 cooperative projects in 2 rounds. These have received preliminary approval, and it is predicted that the whole plan will drive 1 billion pounds of R&D input in total (BIS, 2015).

6.2.2. Current Situation and Establishment Background of BRIC Countries' STP

The 'BRIC Countries' refer to four emerging economic entities, including Brazil, Russia, India and China. As emerging economic entities, the growth of BRIC Countries in the 21st century has been quite powerful. Their proportion to world economy was increased from 8.3% in 2000 to 16.4% in 2009. Besides factors like energy and raw materials, technological innovation also plays a role in rapid growth of each country's economy to some extent, but this role is also closely related to the STP of BRIC Countries (Chan & Daim, 2012).

With respect to STP, BRIC Countries have many common features. For instance, their STP system contains policies of preferential development direction, protection of intellectual property rights, and the development of science potential, technological organisations and science and technology motivation. However, there are significant differences in each country's history, culture, political and economic systems, and economic development levels. Besides, the four countries' governments lay different emphases on the strength, direction, path and goal of science and technology policies. In the aspects of specific STPs, each country innovates according to their national conditions.

The scientific and technological system of the 'BRIC Countries' belongs to the type with concentrated coordination. This is related to the four countries being at the stage when they pursue technological innovation. According to strategic planning on science and technology in 'BRIC Countries', Brazil launched the A*ction Plans about Brazil's Science and Technology Innovation from 2007 to 2010* and China formulated *Layout Plans about China's Medium and Long-term Science and Technology Development (2006-2020)*. Both indicate that it is essential to expand and consolidate the national innovation system by relying on national and regional interaction and to decide the direction of technical development at the level of national strategies. Macro strategies and plans of Indian science and technology development are contained in the country's strategies related to the comprehensive development of economy. Since the fourth Five-year Plan, India has specially added detailed plans regarding science and technology to its five-year plan of national economic development. Other departments of social and economic development have also made science and technology plans based on this. Russia has successively issued strategies and plans regarding science and technology development for the next 10-15 years. This reflects the idea that the Russian government is making every effort to build a developed, prosperous and powerful country and further specify the position of science and technology in national security strategies (Gokhberg & Kuznetsova, 2012).

While ‘BRIC Countries’ continuously increase their total input into science and technology, they also gradually carry out innovation for scientific and technological systems, target integration of science and technology and economy and improve the utilisation ratio of science and technology funds. Specific policy measures include: a re-layout of research input and encouraging non-governmental institutions to implement independent research and development; paying attention to the mode of science and technology input, i.e., focusing on enterprises. Other measures to increase performance evaluation of R&D expenditure, and evaluate the performance of research units; and attaching importance to the conversion of scientific and technological achievements and guiding the application of generic technology to enterprises (IRDC, 2015).

The number of authorised patents from ‘BRIC Countries’ is low. Compared with developed countries like America and Britain, there is a significant difference in the protection of copyright, patent and other intellectual properties among 'BRIC Countries'. However, as internationalised process accelerates and position of technological innovation importance is improved constantly, each country's consciousness regarding the protection of intellectual property is gradually being enhanced (Tseng, 2009).

Concerning scientific and technological infrastructure, 'BRIC Countries' establish and develop innovative institution networks and scientific and technological intermediary service systems by taking measures used for construction of innovation platforms, for instance, supporting technique centres, industrial technology research institutes, science parks and incubators. Besides, their national governments coordinate the spatial distribution of scientific and technological resources, drive the development of regional innovation and promote the conversion of scientific and technological achievement transfer (Cassiolato & Lastres, 2011).

6.2.2.1. An Analysis of Common Areas in STPS in Both Developed Countries and Developing Ones.

The discussion and analysis from the previous sections help us in a cross analysis of STP across the countries. It is clear that both developed countries and developing states pay much attention to the roles of STP in scientific and technological activities and establish perfect STP systems.

STP establishment relies mainly on the national government. There is a direct relationship between the extent, to which policy goals are correct and reasonable, and a country's scientific and technological development, its level of science and technology and even its economic strength. By formulating general principles and policies, the government decides on scientific and technological fields that should be developed preferentially and organises, manages and uses scientific and technological resources of the country effectively. It also drives scientific and technological progress of the whole society by legislation, guidance of administrative and economic approaches and coordination via non-governmental scientific research forces.

All countries generally pay attention to science and technology input. Especially in modern society where the precision of science and technology is high, scientific and technological strength is a symbol of a country's comprehensive national strength.

Scientific and technological cooperation is valued by each country. As the large scientific age comes, scientific and technological cooperation seems to be quite important, including industry-university-research cooperation in China and scientific and technological cooperation and communication in the world.

6.2.2.2. An Analysis of Dissimilarities in STP of Developed Countries and Developing States

A further analysis from the previous sections, help in bringing out the differences between the STP policies across different nations. With respect to scientific and technological management modes, developed countries take diversified and dispersing modes, while developing countries adopt intensive management modes.

The degree to which each country's government intervenes with STP is different. China, a country with a centralised management for science and technology system, develops scientific and technological activities and formulates STP that is appropriate for the country's developmental goals under guidance of Chinese Academy of Science (CAS). It can be said that America does work under the direct guidance of its president and Japan carries out the activity under the leadership of the Conference on Science and Technology.

Enterprises of each country give different inputs to science and technology. In the case of China's current economic growth, the rate of capital contribution is 68.7% while the rate of science and technology contribution is only 30%. However, the two rates in Japan are 23.8% and 55%, respectively. As subjects of technological innovation, enterprises develop key techniques with proprietary intellectual property rights, and an improvement in capability of independent innovation is central to enhancing a country's competiveness.

In the aspect of talent cultivation, developing countries have two disadvantages in occupation of human resources compared with developed countries. On the one hand, being limited by the developmental level and foundation of financial resources, the input into basic education is obviously insufficient and talent cultivation is limited to some extent. On the other hand, the phenomenon that some high-end scientific and technological talent flows out is serious.

6.2.3. A Comparison of STPs and research input situation

An improvement in developed countries' position in the global system of scientific and technological innovation cannot be separated from the attention to scientific and technological innovation and a policy orientation of increasing science and technology input constantly. This is reflected by the implementation of STP, as shown in the following aspects.

6.2.3.1. Research Input of Developed Countries

America, a superpower in the world, retains its lead in the global science and technology space since it invests into R&D. However, the financial crisis led to a sharp reduction of R&D funds in business circles. After taking office, American President Obama improved science and technology input and signed the ‘Comprehensive Appropriation Act’ and ‘Recovery and Reinvestment Act of America’. In accordance with *Science and Engineering Indicators* issued by National Science Board every two years, the amount used by America for R&D was USD 400.5 billion in 2009. Although the amount was a little lower than that in 2008 when financial crisis came (USD 403 billion), it was still higher than the 2007 figure of USD 377 billion (CBO, 2014).

Even as the economic crisis eased in 2013, the input federal government’s input into scientific and technological R&D still declined. In order to avoid the negative impacts of input reduction on scientific and technological innovation, Obama submitted the 2014 budget to the parliament in advance on April 10, 2013. The budget shows an increase in the overall R&D budget (increased by 1.3% compared with the 2012 fiscal year), emphasises strategic investment for scientific and technological innovation and proposes that it is necessary to drive research, stimulate innovation and promote economic growth. For Britain, constant appearance of high-tech brings huge challenges and chances to Britain, and innovation funding is considered the most effective way to stimulate economy by innovation (CBO, 2014).

In May 2013, the Technological Strategic Committee of Britain issued Implementation Plans from 2013 to 2014 and announced that the amount of funding for innovation enterprises in Britain would be improved to GBP 0.44 billion , an unprecedented move. The main technological fields supported are renewable energy sources, future city, new materials, satellite technology, digital technology, medical treatment and public health, and medium and small enterprises. In supporting innovation enterprises, the British government also increased input into the construction of technological innovation. Up till now, it has built several technological innovation centres involving several key fields, such as advanced manufacturing, satellite application, cell therapy, offshore renewable energy sources, future city, traffic systems and unicom digital economy. By the end of 2013, public and private investment in each technological innovation centre had gone up to GBP 1.4 billion. It is expected to increase constantly in the future (ONS, 2015).

In accordance with the surveys by Ma (2014), Science, and Engineering Indicators of NSB, it can be observed that in America, the main sources and channels of R&D funds are the federal government, enterprises, colleges, and non-profit organisations. Hence, its input is diversified. In 1978, the input from non-federal government sources was more than that of the federal government. Such a trend expanded until the end of last century. Until now, the scale of the former is still above once larger than that of the latter.

Enterprises depend on R&D input and the ratio of their input to total input rises year after year. The R&D input in American business circles is so high that two thirds of R&D funds are derived from business circles. For instance, R&D

funds of Microsoft Corporation are USD 5 billion each year, approaching 50% of the total R&D funds of China all year round. Additionally, strategic emphasis of national science R&D input focuses on input into research on basic science. Input of national R&D into experimental development is also gradually expanding and attention is being paid to perfecting incentive mechanisms about the commercialisation of research findings (Xin-yuan, 2014).

6.2.3.2. Situations about R&D input of 'BRIC Countries'

'BRIC Countries' can be classified as developing countries. Although they show a rising trend in the aspect of R&D input, there is difference in the R&D subjects from which funds are obtained. Benefiting from a good international commodity market environment, Brazil, a country with abundant natural resources, leading industrial technology and scientific levels and a developed financial market had obtained rapid economic growth. However, the growth rate of its scientific and technological input had been low prior to 2008. Before the financial crisis in 2008, the science and technology input of Brazil had not grown by the same proportion as its GDP (Hanley, 2012).

From 2002 to 2008, the GDP of Brazil improved by 27% while Brazil's R&D expenditure only increased by 10% and its ratio to GDP increased from 0.98% to 1.09%. In order to keep the driving force of sustainable growth, the Brazilian government realised importance of increase in R&D expenditure, issued 'an action plan on technological innovation' in 2007 (2007-2010) and proposed that it would increase the ratio of R&D to GDP from 1.07% in 2007 to 1.5% in 2010. After the global economic recession in 2008, many countries reduced governmental input into R&D, while Brazilian government's input into R&D did not decrease significantly. As the financial revenue of Brazilian government increased, its R&D expenditure also grew and its ratio to GDP reached 1.3% in 2010. Public sectors were subjects of R&D expenditure and output in Brazil. In 2008, 55% of R&D expenditure in Brazil was provided by public sectors, the government or higher education, and the other 45% derived from private sectors. This structure of fund sources has been stable for the last 10 years (Zhong & Zheng, 2011).

Brazil follows the national scientific and technological system of Russia, which adopts patterns of the Soviet Union. Firstly, compared with capacity of science and technology departments, scale and ratio of state-owned R&D departments are larger. Secondly, the input of the country into R&D is increased. In 2013, Russia still insisted on giving powerful input into science and technology even though it was still experiencing an economic crisis. In December 2013, Medvedev prime minister of Russia presented Russian government's standpoint in the aspect of science and technology. At an award ceremony for young scientists in the aspect of science and innovation, which was held in February 2013, President Putin emphasised that the fund supply of National Science Foundation would reach RUB 25 billion. Russia will finish the modernisation and restructuring of its national defence industry complex and related industries by the newly established Advanced Research Foundation (Dahlman, 2014).

Russia's basic scientific research mainly centres on the National Academy of Sciences' system and is separated from the education system and enterprises. Much of applied scientific research is carried out by the large national scientific centre and large state-owned scientific research. The R&D network is mainly composed of research institutions and industries controlled by governmental bureaucrats. Around 77% of research belongs to state-owned research institutions. Colleges only play a minor role in the R&D of Russia. The country into R&D still increases continuously, while formed public scientific and technological resources drift away from colleges and industries. Only 3-4% of enterprises in Russian economy are state-owned, while the proportion of state-owned research institutions and their research staff has exceeded 70% (Cervantes & Malkin, 2001).

Since the liberalisation of the Indian economy in 1991, its amazing performance especially after 2005 has drawn much attention and aroused wide discussion in all countries. India has become one of the economic entities experience a high speed of growth worldwide. From 2004 to 2007, its GDP growth rate was 9% and was 6.4% in the 4^{th} quarter of 2011. Technical progress is one of the engines that drive the Indian economy to obtain powerful growth. Its science and high-tech input policy is featured by the following:

R&D input is dominated by the government, but private input increases rapidly. The total R&D expenditure of India shows an ever-increasing trend, and its R&D strength was increased from the ratio of 0.8% of GDP in 2003 to 0.88% of GDP in 2007 (IBEF, 2015).

In accordance with structure, the R&D input of Indian government holds a leading position, accounting for about two thirds of total R&D investment in the country. In recent years, this ratio has experienced a continuous reduction. However, the R&D investment of enterprises shows an ever-increasing trend. The R&D expenditure of enterprises accounted for 28% of the total expenditure in India in 2008, while the ratio was only 14% in 1991. The R&D expenditure of private enterprises was about 4 times and 3 times higher than that of state-owned enterprises and governmental research institutions, respectively. In another word, private enterprises are becoming the core of India's innovation system (IBEF, 2015).

According to research of Pei (2013), the science and technology input of the Chinese government grew rapidly in the 21st century and the strength of the country's R&D input ranks No. 1 among 'BRIC Countries'. However, China's R&D expenditure mainly focuses on experimental development and the ratio of basic research is obviously low. In 2011, China's basic research only accounted for 4.7%, while the ratio of basic research in most developed countries exceeded 10%. In accordance with science reports of UNESCO, the ratio of basic research in America and Japan was 19% and 12.5% in 2009, respectively.

6.2.4. Total science & technology input, structure and fund sources

6.2.4.1. Total science and technology input

Under the backdrop of economic globalisation, science and technology, competitiveness is reflected by science and technology input first (Schniederjans & Hamaker 2003). Both developed and developing countries treat a substantial increase in science and technology input as a national strategy through which competiveness can be improved. According to international practices, the expenditure level of R&D funds is used to express the level of a country's science and technology input, and developed countries except Japan target a situation where R&D funds account for 3% of GDP (Wang, 2007). As competition intensifies, products, which are simply labour intensive, do not have any more advantages. The competiveness of products can be improved only science and technology input is improved constantly and countries have technical R&D capacities. Thus, all countries have attached much importance to science and technology input recently and total R&D funds have grown year after year, as shown in Table 6-1.

Table 6-1: Situations around R&D fund input (One billion of national/regional currency)

Nation	2006	2007	2008	2009	2010	2011
China	300.3	371.0	461.6	580.2	706.3	868.7
USA	343.8	377.6	403.7	401.6	408.7	415.2
Japan	17273.5	17756.2	17377.2	15817.7	15696.5	15945.1
Germany	58.9	61.5	66.5	67.0	69.9	74.8

France	37.8	39.3	41.1	42.7	43.6	44.9
UK	23.2	25.0	25.6	25.9	25.8	26.9
Russian	288.8	371.1	431.1	485.8	523.4	610.4
Brazil	23.6	28.6	32.8	37.8		
India	287.8	315.8				

Although China's R&D funds have grown rapidly, there are obvious problems and differences compared with western developed countries. The absolute level of China's science and technology input is still lower than that of western developed countries. For example, America's total R&D funds were 9 times higher than that of China in 2006. Especially for R&D funds per capita, America's total R&D funds were 60 times that of China. Secondly, since the GDP of China is growing rapidly, the rapid growth of the base number makes the growth of relative quantities (ratio of R&D funds to GDP) less obvious (Table 6-2). For example, the ratio was 1.42% in China in 2006, and there was a significant difference between the ratio and the average level of developed countries, which was 2.5%. Its distance to the 3% goal commonly affirmed in the world was also longer. The National Outline on Medium and Long-term Program for Scientific and Technological Development (2006-2020) proposed that the 'total R&D input of China to GDP will improve year after year. It reached 2% in 2010 and will exceed 2.5% in 2020'. Thus, increasing R&D funds is still one of the goals of China's STP.

Table 6-2: Ratio of R&D funds to GDP (%)

Nation	2006	2007	2008	2009	2010	2011
China	1.39	1.40	1.47	1.70	1.76	1.84
USA	2.64	2.70	2.84	2.90	2.83	2.77
Japan	3.41	3.46	3.47	3.36	3.26	3.39
Germany	2.54	2.53	2.69	2.82	2.82	2.88

France	2.11	2.08	2.12	2.26	2.25	2.25
UK	1.75	1.78	1.79	1.86	1.76	1.78
Russian	1.07	1.12	1.04	1.25	1.16	1.09
Brazil	1.02	1.09	1.18	1.02		
India	0.88	0.76				

6.2.4.2. Structure of science and technology input

Input can be divided into basic research, applied research and experimental development. Specifically, basic research provides the support and guarantee for following applied research and experimental development. Therefore, the ratio of input into basic research decides a country's long-term competitiveness (Schniederjans & Hamaker, 2003). The ratio of input into basic research in developed countries went up to 18% in 2010, while that of China was only 4.8%. It is obvious that China's input into basic research is insufficient, which is related to pursuit of China for short-term goals in the process of science and technology input. Most countries spend about 60% of funds on experimental development, which accounts for the highest ratio in science and technology input. The ratio of experimental development funds in China was too high, i.e., 83.9%, and was different from developed countries, as can be seen from the comparison Table 6-3. The input into this aspect is too high, but efficiency is not high. Besides, repeatability of project approval for scientific research is high. Similar type of research is repeated, science and technology funds are scattered in several provinces and several projects, and different units and various research use a small amount of funds to carry out low-level research. Besides, the same project may obtain support from different plans, and even the total funds obtained by some projects via various plans exceed the needed funds. Some projects are studied by different units during different years and several research stages of one project can obtain support simultaneously (NBS, 2014).

Table 6-3: Structure of science and technology input (%)

Item	**China**	**USA**	**Japan**	**UK**	**France**	**Russian**	**Korea**
Year	2012	2009	2010	2010	2010	2010	2010
Basic research	4.8	19.0	12.7	8.9	26.3	19.6	18.2
Applied research	11.3	17.8	22.3	40.7	39.5	18.8	19.9
Experimental development	83.9	63.2	65	50.4	34.2	61.6	61.8

Due to lack of data, Germany, Brazil, and India are not compared but Korea is added to the comparison of science and technology input. The latest data is used for comparison. Thus, data of all countries come from different years, but they still have strong comparability.

Since the GDP of China is growing rapidly, science and technology input increases constantly; however, changes in input structure are not significant. As shown in Table 6-4, science and technology input from 2006 to 2012 grew year after year. Specifically, input into basic research in 2012 was three times higher than that in 2006 and input into experimental development was 10 times higher than that in 2006. However, there was no significant change in input structure, i.e., the ratio of basic research was not high but proportion of applied research showed a declining trend (NBS, 2014).

Table 6-4: Input structure of R&D funds in China

Index	Basic research		Applied research		Experimental development	
	R&D funds (RMB one billion)	%	R&D funds (RMB one billion)	%	R&D funds (RMB one billion)	%
2006	15.6156	5.2	50.4504	16.8	46.8936	78.0
2007	17.4370	4.7	49.2688	13.28	64.6913	82.0
2009	26.6892	4.7	73.6854	12.6	154.8507	82.7
2010	33.1961	4.6	83.3434	12.7	234.4641	82.8
2011	41.6976	4.7	98.1631	11.8	362.2271	83.5
2012	49.4304	4.8	116.3674	11.3	509.0343	83.9

6.2.4.3. Source of science and technology funds

Science and technology funds are mainly derived from three sets of institutions: enterprise funds, governmental input, and financing from financial institutions, as shown in Table 6-5 (NBS, 2014).

Table 6-5: Source of Science and Technology Funds (%)

Country	**China**	**USA**	**Japan**	**UK**	**France**	**Russian**	**Korea**
Year	**2012**	**2009**	**2010**	**2010**	**2010**	**2010**	**2010**
From enterprises	74.0	60.0	77.0	44.6	53.5	27.7	74.0
From the government	21.6	33.4	16.0	32.2	37.0	67.1	25.0
From others	4.4	6.6	7.0	23.2	9.4	5.3	1.0

At the initial stage of technological development, government funding is the main driving force for technological development. At the medium and later stages of technological development, funding of enterprises will be more important and positive. The degree of technological development in developed countries is much stronger than that of China, but funding from the Chinese government is relatively low, which indicates that the time when governmental funds are launched is brought forward in many fields of technological development (Eisenberg, 1996). Technological innovation in Russia is still at the stage where it is driven by governmental funds because of its economic structure, while western developed countries generally set governmental input goals at about 33%. Obviously, China still needs to use national finance to increase input in order to encourage technological innovation and development. Financial input into industrial and technological innovation in the aspects of space flight and aviation, computer and related fields, biology and biochemistry in particular need be increased (Dynkin & Ivanova, 1998).

Subjects of science and technology input in developed countries are enterprises and science and technology. The funding input of Global 500 enterprises usually accounts for 5-10% of sales volume. However, science and technology funding input of large and medium enterprises in China was only 0.75%. Due to insufficient funds and a low consciousness of innovation, the total science and technology input of middle and small-sized enterprises is lower. Thus, it can be observed that the input of Chinese enterprises into R&D is still insufficient. Financing of financial institutions is closely related to a countries' currency policy. During inflation, financial institutions limit science and technology loans for enterprises by measures such as curtailment of bank facility and an increase in interest. Most financial institutions are more willing to invest in science and technology projects, which are safer. However, this reduces financial institutions' financing of basic research and some applied research (Pei, 2013).

6.2.4.4. Strategic Planning

Generally, the scientific and technological systems of countries are divided into diversified dispersing types and intensive coordination types. National governments adopting the latter type will formulate plans on technological development at a national level and according to their national conditions and development stages, and try to master and control goals and the general directions of their scientific and technological development using the government's uniform guidance. Countries using the diversified and dispersing type generally only formulate professional plans and scientific and technological plans for key fields. America, Germany, and Japan utilise the diversified and dispersing overall strategies for technological development (Alegre et al., 2006).

According to Bai & Li (2011), developed countries like America, Japan and Europe, have shown a supernormal development trend in high-tech and industrial fields since the 1980s. They appropriately make strategic plans for national science and technology and enable the high-tech industry to be a growth point with the most vitality in world economy and a leading force of social wealth growth. As the most developed country of science and technology in the world, America is the first one realising the importance of appropriate establishment of corresponding national strategic planning. Since the Second World War, America has issued many strategic plans successively in each field. Such plans make great contributions to promoting the development of American science and technology and even its economy and society.

Japan knows the disadvantages brought about by insufficient strategic emphasis and following prospect of science and technology and makes every effort to learn how to make technological development strategies from America. In order to drive the development of industry in the whole of Europe, the European Community (EC) makes overall strategic plans on the technological development of the EC and Eureka Program. Many plans in the overall plan are aimed at relying on key techniques to improve competiveness. The EU established the strategic principle so that science and technology is used as guidance to drive economic development and formally started 'The Seventh Framework Program for Research' (CORDIS, 2014).

6.2.4.5. BRIC Countries

The governments of ‘BRIC Countries’ have drawn plans for the technological development at a national level and according to their national conditions and development stages, especially for the technological innovation of high-tech industry. They will master and control the goals and general directions of their scientific and technological development using the government’s uniform guidance. Thus, they belong to the intensive coordination type. One of the reasons for this is that the four countries are still at a stage where they are pursuing technological innovation. According to strategic plans of ‘BRIC Countries’ for science and technology, China has formulated a *National Outline on Medium and Long-term Program for Scientific and Technological Development (2006-2020)*, proposed that it is essential to expand and consolidate the national innovation system by promoting interaction among countries and regions, and confirming the technical development direction at the level of national strategies. India’s macro strategies and plans for technological development are contained in its national strategies on the comprehensive development of the social economy (Dahlman, 2014).

Russia approved a series of new scientific and technological projects in 2013, including the national plan *Technological Development of Russia before 2020*. On August 16, 2013, the Russian government issued the national plan *Economic Development and Innovative Economy* and decided that the government would accelerate a RUB 125.2 billion (USD 3.79 billion) construction appropriation for the Skolkovo Innovation Centre (Skoltech, 2015). The centre is considered to be an important foundation and huge driving force that ensures the implementation of ‘national plans’ and guides the development of innovative economy in Russia. Since 2013, the ‘innovation centre’ has entered a stage of rapid development. Before 2020, Skolkovo University of Science and Technology, which is matched with the innovation centre, will have attracted a large batch of internationally famous scholars and young talent to study and work here. In the process of implementing strategies of scientific planning, all countries emphasise that they will drive the overall progress of science and technology by preferentially developed projects. The science and technology plans of ‘BRIC Countries’ contains policies on preferential development directions, and stamps foundation of self-innovation by strengthening science and technology input in key fields. It uses the application of major plans of science and technology to specific fields as a breakthrough through which improvements in self-innovation capacity occur, in order to maintain pioneering advantages in strategic industrial fields (Skoltech, 2015).

To promote the rapid development of the high-tech industry, reform and innovation of scientific and technological systems are quite important. As developing countries, ‘BRIC Countries’ shoulder heavy development tasks and the total level of their financial resources are relatively insufficient. With respect to science and technology input, while overall development goals for science and technology may be in place, there can be difficulties in implementing such goals in reality. From an overall perspective, such countries also carry out innovation of their scientific and technological systems, direct efforts towards the integration of science and technology and the economy, and improve the availability and efficiency of science and technology funds constantly, when they increase the total science and technology input (BRICS Summit, 2015). The policy measures are outlined below:

R&D input should be re-allocated, and non-governmental institutions should be encouraged to carry out independent R&D. In order to arouse the enthusiasm of all social sectors for R&D, Russia adjusted the layout of R&D departments and encouraged non-governmental organisations and institutions to implement independent R&D. To promote the development of non-state-owned scientific research institutions, the Russian Congress passed an amendment of the national STP law. The amendment specifies that any organisation can obtain the position granted by the government, i.e., a centre of national science and technology, as long as it has a certain number of scientific research devices, scientific and technical people and experts and its scientific and technological work and research achievements are recognised by the world and society. This behaviour not only encourages private enterprises to expand independent R&D but also shows fairness of national policies for such enterprises (BRICS Summit, 2015).

Focus should be to the science and technology methods of enterprises. In the 21st century, innovative enterprises obtained considerable progress and gradually became subjects that carried out funding of social R&D and R&D activities. In 2012, the percentage of funds provided by enterprises out of the total R&D funds of the society was 74%, and that offered by the government was 21.6%. In total, the R&D funding expenditure of the whole country, ratio of enterprises' R&D appropriation increased from 50% in 2000 to 76.1% in 2012. Chinese enterprises are becoming more prominent in global scientific and technological innovation activities, and their R&D expenditure has occupied 13% of global enterprises' total R&D funds, and increased by 11.5% compared with that in 2000. The Brazilian government also attaches input into this aspect and specially sets up a 'green-yellow' special fund to encourage colleges and large and medium enterprises to carry out joint R&D and accelerate large and medium enterprises' participation in technical innovation (BRICS Summit, 2015).

The performance assessment of R&D expenditure should be enhanced and the performance of R&D units enhanced. In order to change the trend of state-owned R&D institutions' expenditure rising sharply while R&D output falls rapidly, the Russian government issued a government act, i.e., an evaluation system for national R&D. The main purpose of the act is to evaluate the R&D of governmental institutions in order to optimise their network. China also introduced a performance evaluation system for scientific and technological funds, for instance, it developed an international comprehensive performance evaluation of the Natural Science Foundation of China (NSFC), and this has had positive effects (BRICS Summit, 2015).

Focus must be on the commercialisation of research findings and guiding the application of generic technology to enterprises. Since the period of the '11th Five-year Plan', national science and technology plans have shown increased support for enterprises, especially support for small and medium enterprises and industry-university-research cooperation. On the one hand, the ratio of enterprises to the number of units organising science and technology planning projects has risen considerably, and many projects in 863 and support plans require that enterprises should carry out joint applications with higher institutions or R&D institutions. On the other hand, a number of plans in policy guidance ones are specially used to support enterprise innovation and commercialisation of research findings. To accelerate the degree of standardisation in the intellectual property market, the government will use R&D projects funded by public funds to provide a national registration system that offers a legal and organisational tool of intellectual properties, which is supported by governmental budget, in order for these intellectual properties to be widely applied in the economy (BRICS Summit, 2015).

At the same time, the government intensively formulates and implements laws and related right protective laws that standardise the commercialisation of science and technology. In 2008, Russia issued *The Law on Transfer of Shared Technology* allowing public R&D institutions and colleges to sell knowledge achievements to companies under contracts of governmental funds and enable the commercialisation of these technologies. The law not only specifically states rights and obligations of transferors of technology, uses of technology and entrusting parties, it also specifies detailed problems, such as the price of technical transfers, payment mode, material delivery and product acceptance (BRICS Summit, 2015).

6.2.4.6. Scientific and Technological Management System

A sound decision-making mechanism continuously improves the scientificity of decisions and enhances scientific and technological management. After taking office, American President Obama launched a series of policies and measures for science and technology. The primary task was to recover scientific integrity and enhance the decision-making mechanism. In order to enhance scientificity and the integrity of scientific and technological decisions, Obama appointed a batch of scientists with strong backgrounds in science and technology to take key management posts at the government's related supervising science departments. For example, he appointed Holdren, a famous scholar of energy and climate change, to be the president's scientific and technological counsellor and recovered the post of the president's scientific and technological assistant at the cabinet level. Obama also appointed Zhu Diwen a Nobel Prize winner, to occupy the position of the minister of the Department of Energy (OSTO, 2015).

Obama's government also ensures that the Advisory Committee of Science and Technology is composed of independent experts without tendency of ideology, issues laws, and decrees about decision-making process. This enhances scientific integrity and decision-making transparency; and ensures that the evaluation and issuance of research projects funded by the federal government is not distorted by ideology. After Lee Myung-Bak, the new president of Korea took his office, he immediately proposed the national goal 'to be a power of science and technology and become one of the 7 powers of science and technology'. He simplified governmental institutions related to science and technology to a large extent, abolished the vice prime minister system of science and technology, repealed the Department of Technological Innovation, broke up its function into parts and integrated its functions into Science and Technology Committee, Ministry of Knowledge Economy and Department of Education and Technology (OSTO, 2015).

The president is the chairperson of the Science and Technology Committee which is the highest institution of Korean STP and which has an enhanced technological position. All the newly established 5 special committees are composed of folk experts and more social participation is introduced in its decision-making. Besides, 23 stated-owned policy research institutions were re-integrated and a comprehensive research institute that focuses on medium and long-term strategic research of the country was established. In Britain, Paul Drayson, the minister of Ministry of Science and Technology, who took his office in 2008, became the first scientific and technological minister to enter the British Cabinet (OSTO, 2015). This indicates that science and technology obtains its deserved political position in Britain and also highlights that Britain wants to show its determination to cope with the financial crisis by virtue of scientific development.

6.2.4.7. Talent Cultivation

The development of the high-tech industry cannot be separated from talent cultivation and competition in technical strength eventually lies in talent competition. America treats education as the foundation of national development and a key to talent cultivation, as talent cultivation is the basic source that promotes the national economy and social development. America has continuously paid attention to STP on innovative talent cultivation. From 1901 to now, 42% of Nobel Prize winners were Americans (Capgemini, 2015).

According to America's Science and Engineering Indicators 2008, the number of the scientific engineering labour population with college degrees was 17 million in 2006. In 2005, America had 1.3879 million researchers, ranking No. 2 in the world. Among every 10,000 in the labour population, there are 93 researchers. America emphasises the cultivation of personal value and reflects a 'people-oriented' cultivation spirit everywhere, so that initiative, enthusiasm and creation of talent obtain much exertion space. This is the basic source of

America's innovation. America particularly attaches importance to advanced talent cultivation. In order to attract excellent scientific and technological talents from foreign countries, America has altered migration policies or rules several times to provide convenience for technical migrants. In addition, the American government takes measures to promote scientific and technological talent flow to establish a talent pattern that is appropriate for high-tech development (CompTIA, 2015).

On the one hand, America enriches R&D on science and technology for civil use. On the other hand, atrophy and decline in the traditional industries make scientific and technological personnel of industrial departments exceed demands. The federal government drives these scientific and technological personnel in high-tech industries and fields by policy guidance, driving interest and educational training (OSTO, 2015).

The Ministry of Economy, Trade, and Industry in Japan cooperates with large enterprises and establishes laboratories for young scientific and technological personnel, in order to discover young scientific and technological talent. To attract foreign technical personnel, the new amendment of entry and exit control issued in 1999 provides employment chances for foreign talent with special knowledge and techniques in Japan, and prohibits Japanese enterprises from employing common foreign labour force. The Ministry of International Trade and Industry set up a centre for international high-tech cooperative research and cultivation of high-tech talent at Tsukuba Scientific Town, i.e., The Graduate School of International High-tech. Local high and new technology industrial development zones of Japan also attract talent through cheap housing and favourable treatment (METI, 2015).

The EU specially values the flow and effective use of scientific research talent and allows researchers to flow in the range of EU freely to develop and apply research achievements better. The EU also proposes that it will focus on providing financial support for some key European-wide technological innovation projects, help researchers use the support in the network of scientific research more, and change Europe into a place that attracts high-level researchers to work (Gusmao, 2014).

Since 2006, the Canadian government has invested over CAD 9 billion funds into its knowledge economy. Canada’s total investment in science and technology ranks number 4 in the world. Canada’s employment subsidy plan aims to change the ways in which its citizens obtain training. The plan may provide more than CAD 15,000 in subsidies and ensure that citizens can obtain skills needed by employers. The federal government can provide up to CAD 5,000 and provisional government and employers will provide the same amount as that of the federal government. The plan hands the option of skill trainings from the government to employers and first-time job hunters (PM, 2014).

To adapt to the demands of new situations and promote competiveness, France passed the New Law of Higher Education and Research in 2013 and established a new institution named ‘Advanced Committee of Research and Higher Education Evaluation’. The institute would be responsible for evaluating and verifying higher education and research institutions. It also built a Committee of Research Strategies that would be led by the prime minister directly and be responsible for formulating national research development strategies and taking part in implementation and evaluation of strategies. At the same time, France enhanced the transformation function of higher education and research institutions. In addition, the Ministry of Future Creation Science of Korea developed its ‘international science business zone’ into a hub of global basic scientific research. This attracts 300 famous scientists from other countries to Korea and cultivates 3,000 researchers. This can serve as a good reference point for China (Arvanitis, 2014).

STP drives scientific, technological, and social progress and development from the perspective of science and technology and its effect objects are scientific and technical personnel and organisations of scientific research, for instance, R&D departments of enterprises. Based on a comparison of researchers in main developed countries, developing countries and China, it was discovered that the total number of researchers of China is not small. However, the index reflecting a country’s or a region’s scientific and technological innovation capacity is the ratio of researchers to the population or labour force rather than the absolute number of researchers (Serger & Breidne, 2007).

There is a significant difference in the number of researchers per 10,000 people when comparing China with developed countries. The number of researchers per 10,000 people in developed countries reaches 86.75 people on average, while that of China is only 27, which is less than one third that of developed countries, as shown in Table 6-6 (NBS, 2014).

Table 6-6: Comparison of the Number of People Being Engaged in R&D Activities and Research

Country	**China**	**Japan**	**UK**	**France**	**Germany**	**Russian**	**Korea**
Year	**2012**	**2010**	**2011**	**2010**	**2010**	**2011**	**2010**
People being engaged in R&D activities (1,000 people)	4617.1	878	358.6	392.9	549	839.2	335.2
R&D researchers (1,000 researchers)	2069.7	656	262.3	239.6	327.2	447.6	264.1
R&D researchers per 10,000 people	60	136	114	147	134	119	149
Researchers per 10,000 people	27	100	83	85	79	59	107

Table 6-7: Comparison of the Number of R&D Researchers (2006-2011) (every one million people)

Nation	2006	2007	2008	2009	2010	2011
China	922.79	1066.73	1185.95	852.78	890.44	963.20
Japan	5387.02	5377.74	5157.70	5147.35	5151.29	
Germany	3341.55	3479.99	3627.60	3813.60	3950.41	
France	3405.13	3566.11	3639.79	3726.70	3789.49	
UK	4190.12	4143.83	4107.59	4151.07	4134.04	4201.75
Russian	3231.10	3265.35	3140.47	3077.90	3078.10	3120.36
Brazil	597.01	611.96	628.52	667.23	710.28	

The intensity of both R&D and researchers in developed countries shows an increasingly trend. The increase in the number of researchers is closely related to the input growth of scientific research funds, and they are inseparable elements of technological elements (NBS, 2014). As shown in Table 6-7, Germany's input into scientific research funds is over 9 times higher than that of China and its input into scientific research funds per capita is 60 times higher than that of China. Undoubtedly, high-intensity input into scientific research funds will attract a number of people to enter scientific research training systems and take up scientific research activities and implementation of its scientific research talent strategy has obvious orientation.

6.2.4.8. Finance and Taxation Privileges

Finance and taxation is a major measure by which related policies encourage enterprises to carry out scientific and technological input in order to promote development of high-tech industry. All countries have recently taken corresponding incentives in the aspect of taxation in order to drive enterprises to increase technological innovation and increase science and technology input. Tax relief, expense deduction, accelerated depreciation and investment tax credit are common preferential measures (Engen & Skinner, 2007).

A core method the United States Federal Government uses to support the development of its high-tech industry is 'market selection and government promotion', and the main fiscal taxation policies the country takes involve preferential tax policies, R&D support and government procurement. Such preferential policies involve the following aspects: deducting R&D expenditure by capitalisation and expensing before taxation; investment tax credit of risk investment volume and tax preferences aiming at reducing business risks and increasing financial subsidy. In addition, the American government directly drives the development of enterprises by implementing a protective purchasing polity for enterprise products that are in accordance with its policies on the scientific and technological industry. The government's purchasing policy tools play an important role in innovation activities of high-tech enterprises in America and significantly drive the development of local high-tech industry (Engen & Skinner, 2007).

6.2.4.9. Industry-university-research Cooperation and International Cooperation

The huge role that industry-university-research cooperation, a worldwide trend, plays in economy, science and technology, educational and social progress has become increasingly obvious. Its effect on development of high-tech industry in particular is self-evident and draws much attention from each country's government. Established science parks have been important bases where many countries develop industry-university-research cooperation. As early as the 1960s, the great mass fervour that combos of teaching, scientific research and production were built appeared and science parks, industrial parks of science and technological islands rose in response to the proper time and conditions. Up till now, Europe has established several hundred high-tech parks, Japan has built over 40, Italy has constructed 30 and Silicon Valley has over 8,000 enterprises. At science parks, enterprises achieve a number of successful examples of industry-university-research combination by establishing cooperative research centres and developing cooperative research, contractual cooperation and technology investment (Santoro & Chakrabarti, 2002).

Industry-university-research cooperation in America is multilevel, multiform and large-scale. It mainly involves the following aspects: enterprises subsidising colleges to carry out scientific research; the establishment of cooperative laboratories; entrusted research; special united research and building colleges, industrial research centres etc. Currently, there are three kinds of American universities-industrial research centres: University-Industry Cooperation Research Centre (UICRC), Engineer Research Centre (ERC) and Science and Technology Centre (STC). From the 1980s until the beginning of the 1990s, the congress formulated a series of acts to encourage federal scientific research institutions, universities, and enterprises to cooperate and accelerate technological transfer (NSF, 2014).

For instance, the Stevenson-Wydler Technology Innovation Act, Federal Technology Transfer Act of 1986, and National Competitiveness Technology Transfer Act were developed and perfected gradually. These acts detail rules and strengthen effectiveness. It plays an important role in driving industry-university-research integration and transformation of new knowledge to technology, promoting development of enterprises and industry and accelerating technological innovation. The industry-university-research cooperation of Japan has its characteristic ways of cooperation, having developed over a long term period. Entrusted research systems, joint research systems, scholarship, donation fund systems, and joint research centres are mainly involved, and have played an important role in driving the development of the Japanese economy after the war (NSF, 2014).

6.2.4.10. International Cooperation of BRIC Countries

BRIC Countries' enhance comprehensive technological cooperation with transnational corporations, international multilateral agencies and foreign colleges to drive the chronological innovation in their own countries. On the one hand, they build platforms, emphasise industry-university-research cooperative policies, drive close relationships among participants of the innovation process, reach a consensus in the aspects of risk sharing, and gain sharing of industry-university-research cooperation. On the other hand, they develop international scientific and technological cooperation and enhance scientific and technological levels. They cooperate with transnational corporations to make their country's scientific research departments and enterprises gradually improve their R&D ability and innovation levels (Noskova & Gazeta, 2014).

They establish contact with international multilateral institutions (such as the World Bank and United Nations Development Program (UNDP), and obtain funds and influence from these institutions; enhance subsidies for technological innovation projects of their countries; and strengthen cultivation for innovative talent. Brazil is actively involved in international scientific and technological cooperation and communication, and cooperates mainly with American scientists. Russia actively takes part in high level international projects and research involving space unions such as the International Space Station. Such cooperation is supported by the Space Agency of Russia and is an important element for the implementation of a national space program. Russia is a positive participant in both the Committee for Space Research (CSR) and United Nations Committee on the Peaceful Uses of Outer Space (COPUOS). Russia has formed a lot of united laboratories, research, education and innovation unions and partnership. Besides cooperative research and development, developing countries may directly introduce foreign techniques in many forms. India's international technological cooperation has grown rapidly and the number of its foreign R&D centres has increased considerably. For instance, the number increased from less than 100 in 2003 to 750 at the end of 2009 (WTO, 2014).

Most of these research centres are related to information and communication technology, the automobile industry and the pharmaceutical industry. Meanwhile, India's foreign direct investment (FDI) has grown gradually since 2005 and most of it flows into technology-based risk projects in developed countries' manufacturing fields. India attaches importance to overseas technology-based mergers and the increase overseas mergers brings considerable technological skills to Indian enterprises. By merely relying on techniques and ability that are competitive in global market, Indian enterprises are moving step by step towards internationalisation (WTO, 2014).

6.2.4.11. Technological Innovation Orientation of Military and Civilian Integration

Hongzhong (2007) emphasised that China's preferentially developed fields should reflect the requirements of national strategies and industries supported by the country's direct investment, such as the military industry and aerospace industry. STP on the development of these industries in foreign countries is not consistent. However, it can be observed that there is an increasingly close relationship between preferentially developed industries in the country and the private economy, i.e., the orientation of military and civilian integration. During military and civilian integration, each country's STP is not completely the same. Countries not only guide the technological development of military and civilian integration in STP but also establish decision-making and regulation institutions for military and civilian integration.

At the end of the Cold War, America enhanced economic construction and reduced input into national defence. As such, the original military and civilian separation system could not adapt to the changing global science and technology and security situation. Under the requirement that input should be reduced and military advantages ought to be kept, the American government proposed development strategies for military and civilian integration (Held, 1999). The *Potential Estimation on Military and Civilian Integration* issued by America in 1994 viewed military and civilian integration as a long-term development plan and formulated an overall design for national strategies. The Ministry of National Defence also formulated related policies to promote military and civilian integration extensively.

Japan mainly adopts civil-military integration development strategies, formulates related STP, develops dual-use technology energetically, establishes state innovation system, attaches importance to basic research on military and civilian integration, insists on military and civilian integration development, and has dual-use advantages in the aspects of information technology, robots and automobile shipping industry (Held, 1999).

Britain also formulated a series of policies to promote the integration of military and civilian techniques, established an innovation system of national foundation, and emphasises that one of the important contents of its technological innovation strategy is to ensure that scientific achievements in national defence and military industrial technology can be more widely applied for civilian use. The *Defence-related Science and Technology and Innovation Strategies Facing the 21st Century* issued by the Ministry of Defence of Britain outlined new plans for dual-use technology involved in basic research and scientific research on civil use. The construction of an innovation system of defence-related science and technology with military and civilian integration is also viewed as an important way to improve Britain's scientific and technological levels and international competiveness (Schnaublet, 2011).

In 1994, the French government specifically proposed that some national defence industries should consider working towards the direction of dual-use. In its military plans from 2003 to 2008, France proposed that it is essential to give priority to the development of dual-use technology in order to enhance research and technical development (Schnaublet, 2011).

6.2.4.12. An international comparison of the allocation of scientific and technological resources and technological innovation orientation.

The discussions from the previous section help us to compare the resources and their allocation across different countries. Industrial developed countries' policies on the allocation of scientific and technological resources concentrate national technological sources on strategic industries and adapt to national industrial policies. Thus, policy orientations on the allocation of scientific and technological resources will affect industrial policy and development tendency of these industries. The establishment of national industrial policies is a summary of the experience in industrial development and a process in which guidance is given to the future. Policy implementation may mobilise existing resources sufficiently, coordinate each party's benefits and ensure a healthy development of industries. The STP is a summary of the experience of high-tech industry operations, scientific research innovation, orientation for future technological development, and guidance for allocation of scientific and technological resources.

From the previous section, it is seen that as the largest economic entity in the world, America's high-tech development contributes significantly to global science and technology, and this is closely related to constant transfer of scientific and technological resources to the high-tech industry. In the process of changing the economic structure of America, STP was used to guide its technological resources to concentrate on the high-tech industry, focus on providing a good external environment and an operating mechanism for resource allocation, and for ensuring the smoothness of allocation of scientific and technological resources. In the 1980s, America actively supported the development of information technology and used finance and taxation and pricing policies to guide and help private enterprises invest in the application and development of information infrastructure and information technology. This in turn greatly promoted the construction and popularisation of information technology of national information infrastructure.

The discussion about Japan indicates that the key to the technological development of Japan, especially rapid development of the high-tech industry represented by the electronic information industry lies in a set of long-acting STP systems. This is reflected in the following three aspects. STP should be actively adjusted, and there should be a guide for the optimal allocation of scientific and technological resources. The market mechanism should be sufficiently utilised, technological development laws should be followed, the direction of technological development should be confirmed, and scientific and technological force should be deployed and concentrated in order to develop key fields and advance the development of the high-tech industry (Hongzhong, 2007).

Complete authority should be given to the dominant role of primate enterprises' in R&D. The number of non-governmental researchers of Japan accounts for 61% of the total number of researchers and their expenditure is about 80%. These enterprises rely on their own R&D forces to track global high-end industries and rapidly develop new products (CompTIA, 2015).

EU members also guide scientific and technological resources to competitive industries through various kinds of STP and enhance the competiveness of their own countries and regions. For instance, Biotechnology Opportunities of Germany states that the most important innovation field is biotechnology and bioscience and consequently formulates supportive policy measures. Research departments in France try to carry out network communication and cooperative channels, explore technology transfer networks and establish basic technical transfer centres. They also provide technical innovation centres and technical resource centres, in order to provide services for enterprises and help with scientific and technological resource optimisation and allocation emphasised that China's preferentially developed fields should reflect requirements of national strategies and industries supported by the country's direct investment, such as the military industry and aerospace industry (Arvanitis, 2014).

6.2.5. International Comparison of Implementation of STP and the Efficiency of Technological Innovation

6.2.5.1. A Comparison of the Number of People Carrying Out STP

The department of higher education has a lower ratio when the number of personnel at each executive department of China is compared with that of the other countries. It equates to about 50% of that of developed countries and two thirds the number of R&D personnel at departments of higher education in Japan, France and Germany, as shown in Table 6-8 (NBS, 2014).

Table 6-8: A Comparison of the Quantitative Proportion of R&D Personnel at Executive Departments（%）

Country	**China**	**Japan**	**UK**	**France**	**Germany**	**Russian**	**Korea**
Year	**2012**	**2010**	**2011**	**2010**	**2010**	**2011**	**2010**
Business enterprise sector	72.9	70	44.1	58.7	61.4	52.4	68.7
Governmental department	8.4	7	5.4	12.8	16.5	32.9	8
Department of higher education	14.7	21.4	48.6	27.1	22.1	14.4	21.9

6.2.5.2. Comparison of Science and Technology Funds According to Executive Departments

The executive departments of science and technology funds mainly include enterprises, the government and departments of higher education. According to Table 6-9, it can be observed that the proportion of science and technology funds held by department of higher education in China is relatively low compared with the average standard of the four developed countries in the table at 19%. As such, science and technology expenditure made by departments of higher education in China can be improved significantly. In the same vein, science and technology funds of governmental sectors need be reduced appropriately (NBS, 2014).

Table 6-9: A Comparison of Science and Technology Funds According to Executive Departments（%）

Country	**China**	**USA**	**Japan**	**UK**	**France**	**Russian**	**Korea**
Year	**2012**	**2011**	**2011**	**2011**	**2011**	**2011**	**2011**
Business enterprise sector	76.2	68.3	77.0	61.5	63.4	61.0	77.0
Governmental department	15.0	12.1	8.0	9.3	14.1	29.8	12.0
Department of higher education	7.6	15.2	13.0	26.9	21.2	9.0	10.0
Private non-profit department	1.2	4.3	1.0	2.4	1.2	0.2	2.0

6.2.5.3. Comparison about Implementation and Control of STP

Currently, there is little research on the implementation of STP in China and foreign countries. However, there have been some important studies in this area. For instance, Lou and Gu (2005) deem that clearness o STP executive bodies may have an impact on whether STP can be implemented successfully. They also note that performers of STP are subjects carrying out STP and act as a key to the implementation of STP. Countries with developed science and technology pay significant attention to the implementation, supervision and control of STP (NBS, 2014).

With the exception of America, other developed countries such as Japan, Germany, Russia and France, adopt a uniform management mode, i.e., these countries establish special institutions that will be responsible for all the planning and affairs related to science and technology (CORDIS, 2014), including construction of laws and regulation, supervision over execution, policy evaluation and control etc. Since special uniform institutions are in charge of uniform management and appropriation related to financial science and technology funds, funds can be effectively distributed to carry out key R&D and give enough fund support for large-scale national projects.

In America, the White House set up an STP office as the main management department. The President's Consultative Committee of Science and Technology and the United States Science and Technology Committee are also responsible for matters related to science and technology. In recent years, America has considered the integration of science and technology departments.

America, Japan and major developed countries in the EU have established sound science and technology information systems and of their developed database and management information systems provide good information service for the implementation, management, supervision, evaluation and control of STP (OSTO, 2015).

6.2.6. Lessons for China

6.2.6.1. Improving Science and Technology Input Further and Optimising Structure of Science and Technology Input

Discussions from the previous sections provide a number of learning points for China. China should focus on human resources in the field of science and technology as they are the sources of technological innovation. In the final analysis, international competition lies in talent competition in the contemporary era. All countries attach much importance to the cultivation of human resources in the field of science and technology. The Chinese government need to build an external environment that is better and more favourable for talent development. The government should also formulate policies related to human resources, which enhance technological innovation and guarantee policies for the material resources of science and technology (Schniederjans & Hamaker, 2003).

Although China's overall science and technology input has grown rapidly, the R&D/GDP ratio was only 1.54% in 2008. There was a considerable difference between this and that of developed countries. The government should not only accelerate public financial expenditure of science and technology but also make incentive policies such as tax credit for R&D equipment in order to drive enterprises' R&D input and provide critical fund support for scientific and technological development and for building an innovative country during 'the 12th Five-year Plan'. Optimising the structure of science and technology is an urgent affair (Shujing, 2009)

It is necessary to strengthen basic research since it is the foundation of scientific and technological development and represents the capability of a country's original innovation. It also plays a decisive role in the sustainable development of the entire social economy. There is a large gap between China's basic research and the advanced level globally. Furthermore, the share occupied by basic research in China's science and technology input was continuously reduced, and fell from 5.96% in 2004 to 4.7% in 2007 (Tseng, 2009).

Focus is needed to be placed on basic research to build an innovative country. This step will increase support for basic research on leading-edge science and technology problems such as core mathematics, condensed-state matters and new effect, deep structure of matters and law of universal large-scale physics, life process, and cognitive science etc. It also provides significant strategic demands of the country, such as the mechanism of human activities on global system, scientific basis made under extreme environmental conditions and major mechanical problems about aerospace etc.). China also needs to realise double-force driving, i.e., free and exploratory basic research driven by cognition of the world, and oriented basic research driven by demands for security strategies. In addition, China needs to work hard churn out innovative achievements with much influence in the main direction of global scientific and technological development, solve bottleneck problems of science and technology in several fields of significant strategic demands, and improve China's ability to use basic research to solve major problems (Utsch et al., 1999).

China should include science and technology input and matched resources to new industries and new techniques with strategic significance. It should adjust and optimise industrial structures, actively develop strategic and emerging industries and realise breakthroughs in the field with the most conditions. This is an important way to occupy a commanding height of economic growth. It should give major support to the development of science and technology and industries in the fields of new energy, new materials, biological medicine and aerospace. China should form complete policy systems for technological R&D, industrial organisation and industrial policies; sufficiently encourage enterprises to play a dominant role; and shape technological breakthroughs and a batch of forerunner industrial groups with strong capabilities for independent innovation (Wang, 2007).

6.2.6.2. Enhancing the Innovation Mechanism of the Scientific and Technological System

The innovation mechanism of the scientific and technological system is a key factor for improving the efficiency of science and technology input. Under conditions at this stage, China’s performance in the aspect of innovation system construction mainly benefits from the sustainable growth of its R&D input. From medium and long-term perspectives, the innovation mechanism of scientific and technological systems is a more fundamental task and more important compared with a simple increase in science and technology input. Science and technology input serves as a flow, while huge reserves of scientific and technological resources and relatively solidified management systems of science and technology have a more significant impact on innovative performance (WTO, 2014).

For China, the largest constraint the scientific and technical system reform faces is not capital or technology but the original organisation structure of science and technology. For example, although some industrial technology research institutes established at some regions now put forward new strategies and policy thoughts, the result will be that ‘they wear new shoes but stick to the old path’ if they still use the traditional operation mechanism system and traditional appraisal mechanism. As a result, it is difficult to change the problem of innovation efficiency (Wang, 2007).

Realising this, China’s difficulty in crossing the sea of Darwin and realising commercialisation of research findings may be more profoundly understood. Reforms and the innovation of the scientific and technological system should break traditional modes of science and technology input, i.e., the input pattern where state-owned scientific research institutions and state-owned enterprises benefit the most. With respect to the next step, it is essential to encourage all social subjects to be engaged in innovative activities. Objects of science and technology input are all enterprises, units, and individuals that aspire for innovation (Tseng, 2009).

Specifically, reforms and innovation of the scientific and technological system should play the dominant role of technological innovation of enterprises, rather than only use administrative or economic approaches to arouse enterprises’ enthusiasm for input. According to available data, enterprises' R&D input has occupied over 70% of overall R&D input up to now. However, the dominant role of enterprises in technological innovation has not been effectively established. The reasons for this vary. In order to put the technological innovation system whose subjects are enterprises into practice, it is important to pay attention to the development of small and medium technology-based enterprises, create a system environment that enhances enterprises' innovation, and formulate a good system mechanism of sharing enterprises' innovation risks (Shujing, 2009).

In addition, reforms, and innovation of the scientific and technological system mechanism should reform and perfect exist assessment mechanisms of science and technology. Currently, R&D output is mainly judged by indexes like paper and application for patent. In fact, achievements like paper and patent, industrialisation has a long way to go. Technological innovation is more important than knowledge innovation for a developing country than for western developed countries. Thus, it is essential to emphasise the integration of science and technology and the economy, and the industrialisation and mercerisation of technological achievements (Shujing, 2009).

6.2.6.3. Valuing Human Resources of Science and Technology and Enhancing Cultivation and Introduction of Innovation Talent

Human resources of science and technology are sources of technological innovation. In the final analysis, international competition lies in talent competition in the contemporary era. With respect to the number of researchers per 1,000 labour populations, China ranks low among several major developed and has had no Nobel Prize winner until now. Additionally, the number of scientists with much influence in each subject area is much lower than that of developed countries like America, Britain, and Japan (Schniederjans & Hamaker, 2003).

The shortage of innovative talent has become a bottleneck restraining China's scientific and technological development. Education is as a major channel and talent is vital to building an innovative country. An inevitable choice for China to improve its capability for independent innovation and build a nation where innovation originates is to insist on the policy that attach equal importance to cultivation and introduction, and actively enhance the development of innovative talent (Tseng, 2009).

It is essential to form an environment where knowledge, talent and innovation are respected, basic laws of technological innovation are used as criterion to establish standards of talent selection and use; opinions, practices and mechanism that constrain talent growth and prevent talent from playing their roles sufficiently are eliminated, and the implementation of incentive measures and talent policies is ensured. Subjects like colleges, research institutions and enterprises should undertake different duties in the construction of innovative talent systems according to their respective features and advantages. In particular, colleges should play a dominant role in cultivating innovative talent for the country (Fang & Yang, 2000).

Faced with the challenge of Western countries using crises to net talents energetically, China should not only take measures to prevent excellent talent from flowing out but also create good conditions in the aspects of environment and policy, actively fight for the return of excellent talent and make fuse of human resources of global science and technology. In addition, it is necessary to realise existing plans on innovative talent, consult experience of India, makes innovative plans for technological talent, carry out scholarship plans in higher education institutions, specially support innovation-based young talent with much performance, and attract, cultivate and encourage more young people to take up scientific research (WTO, 2014).

6.2.6.4. Paying Attention to Environmental Construction of Technological Innovation

Based on the technological innovation practice of developed countries, the construction of a national innovation system has a profound economic, historical and socio-cultural background to it, and the soft environment of technological innovation enhances the aggregation of innovative talent and development of innovative activities. More fundamentally, a soft environment is an atmosphere, which is advantageous for innovation, and its essential function is to foster the cultural environment of innovation, i.e., the whole society's consciousness of innovation and driving force of innovation (Elzen et al., 2004).

This is the reason why financial input into science and technology has been constantly increased in recent years but the effect of scientific and technological innovation activities is not ideal. This phenomenon is appropriate for developing countries as well. Currently, the interaction between industrial circles and academic institutions in 'BRIC Countries' is ineffectively, relations among colleges, industries and governmental research institutions are weak, and the synergistic effect of development is insufficient. One of the main bottlenecks preventing BRIC Countries from realising the overtaking strategies of science and technology is that they lack a soft environment for technological innovation. It is difficult for a soft environment of innovation to form by itself (Dahlman, 2014).

Thus, the government needs to guide it to an extent, promote the formation and development of innovation culture, and create a legal and institutional environment and policy environment that encourages innovation. An innovative environment is the result of a comprehensive effect of each policy and system. On the one hand, the government needs to work hard to eliminate institutional and systematic obstacles that affect and restrain innovation. On the other hand, the government should formulate new strategies and policies that promote innovation and integrate several kinds of national innovation resources comprehensively. For instance, it should integrate innovation policy with STP, as well as industrial policies, finance and taxation policies and trade policies, form resultant force of policies, promote policy coordination at each link of the innovation chain, arouse enthusiasm in every aspect and enhance harmony and continuity of inputs at each link. At the same time, laws should protect the construction of a technological innovation environment (Dosi et al., 2006).

One of the basic functions of the government when it drives the construction of a national innovation system is to make laws, regulations and management methods that protect the legal interests of each participant in technological cooperation. The government also solves problems that may appear in cooperation such as delimitation of property rights, risk sharing, participation of interests, and belonging of achievements; attach importance to intellectual property protection, arouse the enthusiasm of each participant effectively and promote the effective transfer and diffusion of technological achievements (CORDIS, 2014).

6.2.6.5. Attaching Importance to International Communication and Cooperation

International scientific and technological cooperation has an important driving effect on the accumulation of human resources in the field of science and technology. In accordance with the experience of India and Russia, it can be observed that international scientific and technological cooperation including further study, communication among peers and cooperative research has become an important form for the global flow of human resources in the field of science and technology (Chan & Daim, 2012).

China needs to implement a plan for the cultivation and introduction of high-end innovation talent through international scientific and technological cooperation. It must develop cooperation plans for human resources in the field of science and technology through ways such as technological investigation, talent introduction, international meetings, information exchange, technological exhibitions and experts' exchange visits; and encourage innovation-based technological talent to take part in international technological cooperation and communication at all levels, fields and dimensions. The government can guide and organise colleges and scientific research institutions in a planned way to develop cooperative research on scientific problems with international competiveness, which they encounter jointly and in various forms (Camisón-Zornoza et al., 2004).

At the same time, it is essential to make full use of domestic and foreign talent resources and actively introduce high-level foreign talent according to the demands of technological introduction and industrial development. Besides, considering that 'BRIC Countries' have common interests and visions, China may advance the construction of a mechanism of technological cooperation with other 'BRIC Countries', take part in important field and project associations and promote deep cooperation in the aspects of information sharing, service systems, talent communication and cooperative mechanisms (BRICS Summit, 2015).

6.2.6.6. Perfecting an Assessment and Innovation System

An important expression of a country's scientific and technological strength and potential is to enhance its basic research innovation system. Original achievements in scientific research can not only lead and guide a series of future research in the right direction but also explore new fields of new subjects in order to enable the country maintain a leading position in the field in the long term (BRICS Summit, 2015).

Thus, developing countries should keep increasing input in basic research and further improve their management of basic research. In particular, they need to study and formulate a scientific, standard, and feasible performance appraisal system for basic research, use the lever performance assessment appropriately, create a good environment for scientific research. They should sufficiently arouse the enthusiasm of researchers, provide researchers with the most original thoughts with sufficient scientific research resources, and guide and encourage researchers to insist on constant innovation when they take up basic research (Ballot et al., 2015).

It is essential to attach importance to the cultivation of enterprises' independent innovation ability; strengthen enterprises' dominant role in independent innovation. There is a need to integrate scientific and technological resources; advance the opening and sharing of scientific and technological resources. A perfect allocation mechanism for scientific and technological resources is needed to carry out intellectual property, standard and brand strategies. Enterprises must be encouraged to build their technological innovation centres; encourage applied technology research institutions to partner with and support enterprises to promote long-term and stable cooperation with higher institutions and research institutes; build uniform scientific and technological management institutions and information systems; and drive independent innovation and commercialisation of technological achievements effectively (Tseng, 2009).

6.3. Conclusion

This chapter has presented a detailed comparative study of the manner in which STPs are arranged in BRIC countries, and in the developed countries such as Germany, the USA, France, the UK, and other nations. It is clear that the STPs in the advanced countries have provided a huge incentive to the high-tech industries. There is active involvement of the industry, and the academia, and this has helped innovation to flourish. The STPs are given sufficient funds, along with incentives such as tax breaks, which help the innovative ideas to grow. In BRIC countries, STPs are given sufficient funds and infrastructure, but they lack the research capability, and the ability to become innovative. The growth of innovative ideas, products, and processes, are slow. In advanced countries, there is a high capital intellect from the universities that support research. As a result, there is faster development of innovation, and innovative ideas. The west sees large participation from private enterprises, and thus innovation, incubation of new ideas, and growth is faster. China has taken a lead in developing a large number of STPs in many areas, and these were studied in chapters 4 and 5. However, the true spirit of innovation is lacking, due to less research in universities, and in private organisations. While it is true that China spends large amounts for the development of STPs, other than a few high-tech products, the majority of products are borrowed from the west. This attitude has to change if China wants to become a serious contender of high-tech products.

Chapter 7 DISCUSSION, CONCLUSION & RECOMMENDATIONS

7.1. Discussion of Main Findings

The previous chapters presented the research findings from analysis of data concerning the innovation efficiency of DMUs, 5 industry sectors, and 28 industries in the high-tech sector of China. Chapter 6 discussed the development of STPs and compared the set up of China with other BRIC and advanced nations.

Chapters 4 and 5 show clearly that the Malmquist index is unstable and there are variations in the M value for different DMUs and different industries. It is clear that a stable and high M index will help the Chinese high-tech firms to increase their innovation efficiency. Over the years, China's high-tech industries and enterprises have enhanced R&D expenditure and investment, and imported advanced technology, under the belief that such implants and measures will increase the innovation efficiency. It appears that the government is investing without any strategy and thought. There appears to be a gross ignorance of efficiency that do not comply with the development requirement of independent innovation nor meet the requirements of independent innovation and economic growth in the Chinese society. Since the purpose of innovation is to improve efficiency, if the innovation process lacks efficiency, then the innovation significance will be weakened.

With these observations in mind, this chapter proposes certain measures to improve innovation efficiency in China's high-tech industry based on the cognition and evaluation of innovation efficiency of China's high-tech industry. Some of the methods suggested include scale expansion of some high-tech industries, rational allocation of R&D funds, reduction of the proportion of investment in fixed assets and an improvement of the innovation ability of personnel in high-tech industries.

Chapter 5 provides evidence which shows that the innovation efficiency of China's high-tech industries is erratic. Based on a static analysis of the innovation efficiency of China's high-tech industries in 2011, the results show that out of the 17 industries, five industries are on the production frontier; three industries are in the decreasing state; nine industries are in the state of decreasing scale. As such, it is necessary to increase the input in technical innovation elements. From the perspective of input slacks, relative to the industries on the production frontier, some elements can be reduced under the condition of keeping the existing output scale.

Some observations are as follows. The number of full-time scientific research personnel needs to decrease. This indicates that the innovation ability of scientific research personnel still has a large potential and needs further improvement. The expenditure on R&D and expenditure on new products development can decrease, and this could lead to an improvement in the allocation efficiency of R&D funds. It is also necessary to allocate funds rationally in the technical innovation process. Similarly, the proportion of investment in fixed assets also needs to be reduced in order to boost technical innovation efficiency in China’s high-tech industries.

It can also be seen from the perspective of insufficient output that R&D output of nine industries is insufficient under the condition of keeping the existing input level. This indicates input suffer due to lack of innovation efficiency. This is related to the innovation ability of personnel, fund allocation rationality, the proportion of investment in fixed assets and input scales. Based on the projection analysis results, an unreasonable proportion of each input element in technical innovation is not small; especially for the investment in fixed assets, which can be reduced by up to 90% in some industries. The decreased proportion of 7 industries reached 60%. As per the innovation efficiency changes of China’s high-tech industries from 2005-2011, the fluctuation range of Malmquist index is high.

The relationship between technical innovation input and output is not clear. The Malmquist index is greatly influenced by the TC index, and indicates the change consistency. Thus, it is necessary to enhance the force of technical innovation and boost technical innovation ability. This observation holds for electronic device manufacturing and electronic component manufacturing, where it is necessary to continuously absorb and introduce knowledge of science and technology and methods. In spacecraft manufacturing, aircraft manufacturing, and repair as well as radar and corollary equipment manufacturing sectors, it is necessary to expand the industry scale and improve the technical innovation ability of the personnel.

7.1.1. Increase of Technical Innovation Input Scale

Bai and Li (2011) researched the scale and innovation efficiency from an industry and enterprise perspective and observed that enterprise or industry scale has a positive influence on innovation efficiency. This is consistent with the observation that insufficient innovation efficiency in most industries is caused by low scale efficiency.

Results in Chapter 5 and 6 indicate from the 2011 measurement of industrial technical efficiency, that the scale efficiency of complete electronic computer manufacturing, computer peripheral equipment manufacturing, domestic audio-visual equipment manufacturing, communication equipment manufacturing and radio & television equipment manufacturing are in an efficient state due to sufficient market competition. The observations are that nine industries need to improve the efficiency scale. The SE of spacecraft manufacturing is only 0.208; the SE of radar and corollary equipment manufacturing is only 0.386. Biological product manufacturing, chemicals manufacturing, Chinese patent medicine manufacturing, aircraft manufacturing and repair, other electronic equipment manufacturing and office equipment manufacturing need to expand industry scale and boost SE.

Technical innovation input mainly covers the fundamental core inputs of work force, financial resources, and material resources. Each fundamental core resource element input may differ according to the differences in industrial characteristics and regional differences, but all have representative resource elements. In the process of increasing input scale, it is necessary to rationally allocate resources and give play to overall resource advantage, and focus on the allocation of core resource elements in high-tech industries (Alegre et al., 2006).

The work force element is mainly measured by R&D personnel input, and in this dissertation, this is expressed by the number of conversed full-time R&D activity personnel. Financial resource element mainly selects R&D fund input, which can measure how an industry or an enterprise values technical innovation activities. There are many material resource input indexes such as fixed asset and advanced equipment asset. This dissertation selected investment in fixed assets, and the measurement results are comprehensive and more representative (Zhou et al., 2005).

From the findings of chapters 4 and 5, the mean of comprehensive technical efficiency of China's high-tech industry in 2011 was not high (only 0.590). Among the main decomposition factors, SE of spacecraft manufacturing was the lowest (only 0.208). The SE of radar and corollary equipment manufacturing is 0.386. It is therefore necessary to enhance input force in order to develop spacecraft, radar, and corollary equipment manufacturing.

7.1.2. Countermeasures Based on Static Analysis to Increase Core Element Input in High-Tech Industry

The input scale of China's high-tech industry can be worked out by combining the basic features of input elements and relevant data features in the DEA mode (Guan & Chen, 2010). Based on the features of the DEA- C^2R effective data in Table 6-5, the CRSTE of industrial innovation in 2011 is divided into the following intervals: CRSTE=1; 0.500≤CRSTE<1; 0.350≤CRSTE<0.500; 0<CRSTE<0.350. In this way, the number of DMUs in each interval and the percentage of this number to total DMUs can be obtained, as shown in Table 7-1.

Table 7-1: DMU Interval Distribution

Interval distribution of CRSTE	Number of DMU	%
Crste=1	5	29.41
0.500<=Crste<1	3	17.65
0.350<=Crste<0.500	6	35.29
0<Crste<0.350	3	17.65

Twelve non-DEA effective units are between 0.100 and 0.600, forming two pole differences. The Non-DEA effective technical innovation efficiency is shown in Table 7-2.

Table 7-2: Non-DEA Effective Technical Innovation Efficiency

Industry	**crste**	**vrste**	**SE**	**Scale state**
Chemicals manufacturing	0.379	0.384	0.989	irs
Chinese patent medicine manufacturing,	0.580	0.637	0.910	irs
Biological product manufacturing	0.354	0.588	0.602	irs
Aircraft manufacturing and repair	0.323	0.372	0.869	irs
Spacecraft manufacturing	0.144	0.691	0.208	irs
Radar and corollary equipment manufacturing	0.386	1.000	0.386	irs
Electronic device manufacturing	0.488	0.963	0.507	drs
Electronic component manufacturing	0.484	0.808	0.599	drs
Other electronic equipment manufacturing	0.423	0.592	0.716	irs
Office equipment manufacturing	0.594	1.000	0.594	irs
Medical equipment and apparatus manufacturing	0.344	0.489	0.703	irs
Instrument manufacturing	0.538	1.000	0.538	drs

From the data, it is seen that with the exception of electronic device manufacturing, electronic component manufacturing and instrument manufacturing, which are in a state of decreasing scale, the other 9 industries are in a stage of increasing scale. The SE of some industries with fierce market competitions is high, while the SE of some industries such as spacecraft manufacturing and radar and corollary equipment manufacturing is not high. The SE is also a major factor that could lead to low CRSTE (Lundvall, 2009).

According to Table 7-2, apart from the 5 industries with a CRSTE of 1, only 2 industries with a VRSTE of 1 must increase their scale. These include radar and corollary equipment manufacturing and office equipment manufacturing. The VRSTE of chemicals manufacturing, Chinese patent medicine manufacturing, biological product manufacturing and spacecraft manufacturing improves greatly relative to CRSTE. The utilisation rate of scientific and technological resources of these industries (i.e. the VRSTE) is not low. However, due to industry scale limitations, the input in R&D manpower and funds are insufficient. Thus, for some industries, it is urgently necessary to increase input and expand the scale of the industry (Ze-Cong & Zhong-xiu, 2006).

After the scale increases, the frontier of the DMU will change. If VRSTE serves as the input increase basis, the SE of the DMU is shown in Table 7-3.

Table 7-3: CRSTE Changes of China's High-Tech Industry

Industry	Change	Added value
Chemicals manufacturing	0.379→0.384	0.005
Chinese patent medicine manufacturing,	0.580→0.637	0.057
Biological product manufacturing	0.354→0.588	0.234
Aircraft manufacturing and repair	0.323→0.372	0.049
Spacecraft manufacturing	0.144→0.691	0.547
Radar and corollary equipment manufacturing	0.386→1.000	0.614
Other electronic equipment manufacturing	0.423→0.592	0.169
Office equipment manufacturing	0.594→1.000	0.406
Medical equipment and apparatus manufacturing	0.344→0.489	0.145

Since these industries present increasing scale overall, this indicates some input elements have weakness, which results in the waste of other elements.

Table 7-4: Summary of Input Slacks (C^2R)

Industry	S_1^{-0}	S_2^{-0}	S_3^{-0}	S_4^{-0}
Chemicals manufacturing	4693.139	63203.859	0.000	188.855
Chinese patent medicine manufacturing,	3190.048	29116.111	0.000	210.111
Biological product manufacturing	0.000	7607.141	0.000	246.229
Aircraft manufacturing and repair	0.000	174111.734	59634.578	0.000
Spacecraft manufacturing	0.000	47247.700	0.000	9.482
Radar and corollary equipment manufacturing	0.000	0.000	0.000	0.000
Other electronic equipment manufacturing	0.000	12989.315	28623.001	237.761
Office equipment manufacturing	0.000	0.000	0.000	0.000
Medical equipment and apparatus manufacturing	0.000	22092.192	1061.300	93.201

S_1^{-0}, S_2^{-0}, S_3^{-0} and S_4^{-0} respectively correspond to core input elements of China's high-tech industries: the number of converted full-time R&D personnel, expenditure on R&D, expenditure on new products development and investment in fixed assets. Since the above industries present increasing scale, non-0 elements show slack. The elements with S_1^{-0} of 0 may be the weakness of the industry and the corresponding input should be increased. In accordance with Table 7-4, except chemicals manufacturing and Chinese patent medicine manufacturing, scientific and technical personnel input is vital, followed by the input in expenditure on new products development. Take spacecraft manufacturing for example. Except the input in R&D funds, other elements need to increase rapidly in large quantity. Moreover, VRSTE of office equipment manufacturing and radar & corollary equipment manufacturing is 1. Each element is allocated rationally. It is necessary to expand production scale according to original proportion to gain more output.

7.1.2.1. Countermeasures Based on Dynamic Analysis to Increase Core Element Input in High-Tech Industry

In Chapter 5, the Malmquist index was used to analyse the innovation efficiency of China's high-tech industry in detail. The Malmquist index is influenced by the CRSTE index and the TC index, while the CRSTE index is influenced by PTE change and scale changes. As such, the countermeasures for input scale of China's high-tech industry can be concluded from the results of the dynamic analysis of innovation efficiency of China's high-tech industry (Liu & Pan, 2007). The SE of 9 industries was greater than or equal to 1. Spacecraft manufacturing had the fastest annual average scale rise (16.9%), followed by radar and corollary equipment manufacturing (10.9%). Other electronic equipment manufacturing and radio & television equipment manufacturing experienced a rise, with growth rates of 6.6% and 6.5% respectively. Other industries had almost no growth while some even experienced a drop.

For example, biological product manufacturing and Chinese patent medicine manufacturing dropped at a speed of 3.6% and 1.6% respectively. The SE strongly reflects the management level. The SE in different industries differed though. Overall, the TC index of China's industrial innovation efficiency rose. The decline in CRSTE was mainly caused by a decline in SE. The SE of these industries in China was generally low. Chemicals manufacturing, Chinese patent medicine manufacturing, biological product manufacturing, electronic device manufacturing, electronic component manufacturing, office equipment manufacturing and medical equipment and apparatus manufacturing all have late-mover advantages (Jianhua & Peng, 2008).

7.1.2.2. Rational allocation of technical innovation funds in high-tech industry

Expenditure on R&D reflects practical R&D fund input in the technical innovation activities of high-tech industries. It is a major control element input adjusting innovation output under certain personnel and technical level. It is a low index. In fact, the influence of R&D activities on knowledge is not just reflected in current period, but is also reflected in future knowledge production. Technical innovation fund output in the high-tech industry (expenditure on R&D) has a wide range. To see the impact of fund input of high-tech industries, small-range expenditure on new products development can be used to show a more accurate innovation fund input. As such, technical innovation funds studied in this dissertation include the two expenditure input elements. Although the two elements have no linear relation, they are of some relevance. They are flow indexes and may have certain input and output value lags (Becker & Dietz, 2004).

However, in view of price change factors and data availability, current output expectation is the main decision basis of current input. Thus, expenditure input in this dissertation was calculated strictly according to the DEA model of current input and output, which reflects time-point thinking of input element decision-makers in a more accurate manner and further complies with social reality (Klaassen et al., 2005). The rational expenditure allocation put forward in the following section follows this argument.

7.1.2.3. Countermeasures for Rational Expenditure Allocation in High-tech Industry

Behaviours of expenditure input and DMU between innovation and imitation are relevant. Innovation and imitation are however two concepts without clear definition in the research and development field. Camisón-Zornoza et al, (2004), based on their samples, noted that 60% successful innovations with patents would be imitated by other factories within 4 years. During a survey of R&D in each industry, Bhattacharya and Bloch (2004) discovered that in more than one half of industries, even the great innovations with patents would be imitated within 3 years or less. In addition, the cost of imitation is much lower than the cost of R&D. Camisón-Zornoza et al, (2004) pointed out that imitation cost was only 65% of R&D cost. Hall and Mairesse (2006) point out that the imitation cost of most industries is less than 75% of the R&D cost.

In accordance with existing technical protection systems, a technology, which is successfully imitated, cannot always gain the patent and Japan is a successful example. Meanwhile, technical imitation is also introduced to study how backward countries narrow the technical gap with developed countries in development economics and international economics (Akiyama & Furukawa 2009). Even in developing countries, imitation and independent R&D also exist. The public sector tends to invest in R&D, while the R&D motivation of the private sector is much less. They find that if the control of imitation behaviour is enhanced by the regulation enterprises, competitors' innovation profit can improve and this can in turn promote industrial technical innovation. Table 7-5 presents values for the fixed investment slacks of the high-tech industry of China.

Table 7-5: Fixed-Asset Investment Slacks of China's High-Tech Industry in 2011

Industry	**R&D expenditure slacks** S_2^{-0}	S_2^{-0} **slack proportion**	**Slacks of expenditure on new products development** S_3^{-0}	S_3^{-0} **slack proportion**
Chemicals manufacturing	63203.859	6.30%	0.000	0.00%
Chinese patent medicine manufacturing,	29116.111	11.36%	0.000	0.00%
biological product manufacturing	7607.141	4.36%	0.000	0.00%
Aircraft manufacturing and repair	174111.734	13.87%	59634.578	4.75%
Spacecraft manufacturing	47247.700	26.25%	0.000	0.00%
Communication equipment manufacturing	0.000	0.00%	0.000	0.00%
Radar and corollary equipment manufacturing	0.000	0.00%	0.000	0.00%
Radio and television equipment manufacturing	0.000	0.00%	0.000	0.00%
Electronic device manufacturing,	0.000	0.00%	106407.549	8.24%
Electronic component manufacturing	30784.158	2.85%	0.000	0.00%
Domestic audio-visual equipment manufacturing	0.000	0.00%	0.000	0.00%
Other electronic equipment manufacturing	12989.315	6.93%	28623.001	15.27%
Complete electronic computer manufacturing	0.000	0.00%	0.000	0.00%
Computer peripheral equipment manufacturing	0.000	0.00%	0.000	0.00%
Office equipment manufacturing	0.000	0.00%	0.000	0.00%
Medical equipment and	22092.192	10.74%	1061.300	0.52%

Industry	R&D expenditure slacks S_2^{-0}	S_2^{-0} slack proportion	Slacks of expenditure on new products development S_3^{-0}	S_3^{-0} slack proportion
apparatus manufacturing				
Instrument manufacturing	0.000	0.00%	0.000	0.00%
Mean	22773.659		11513.319	

We can see from Table 7-5 that the irrationality of innovation expenditure in China's high-tech industry is serious. Many industries input expenditure according to innovation requirements. Since the skill of their personnel is limited and the level of advanced equipment less, they can only reach the degree of imitation (Zhou, 2006). Aircraft manufacturing and repair, electronic device manufacturing, electronic component manufacturing and medical equipment & apparatus manufacturing show unmatched expenditure and output. If such expenditure is related to technical absorption or is transferred to a technology import field, there will be a positive influence on innovation efficiency improvement (Liu & Zou, 2008).

Through static analysis, expenditure input irrationality may be related to ownership nature, i.e. whether it is publicly-owned or privately-owned. In recent years, the decrease in government ownership or increase in private ownership is considered as beneficial to enterprise innovation (Avnimelech & Teubal, 2006). Onetti et al. (2012) observed that the private economy had more innovation impetus and innovation efficiency. R&D processes and results are characterised by large uncertainties. In the high-tech industry, market structure and competitive capacity also have a positive influence on research and development.

It can be seen from Table 7-5 that for the industries with intensive publicly-owned enterprises, the proportion of innovation R&D expenditure slacks is larger and the amount involved is higher, such as in aircraft manufacturing and repair and spacecraft manufacturing. Thus, improving innovation efficiency of the industries with intensive government ownership through indirectly promoting private R&D input or R&D funds provided by the government is a significant countermeasure for some industries (Guan et al., 2005).

Internal and external innovation incentive policies will influence rational allocation of R&D expenditure. In the empirical research of Smith et al. (2010), the innovation incentive of enterprises with equity separation is less than that of the enterprises with ownership concentration. This supports the proposal by Holmstrom and Tirole (1995) that high agency costs and contract costs of large enterprises caused by equity separation and supervision difficulty would be bound to reduce innovation investment incentives.

Aghio and Tirole (1994) carried out an analysis using the GHM model and noted that enterprises were regarded as a behaviour entirety in the above analysis to study the effects of external conditions in enterprises' R&D

behaviour. In fact, R&D investment as a production input behaviour of enterprises also encounters internal incentive problems. Especially for modern incorporated enterprises, enterprise owners, operators and research personnel will form principal-agent relations for R&D activities of a technology. As a branch of enterprise theory, the principal-agent theory has developed since 1970s, represented by the classical work of Holmstrom (1979). It is used to solve the problem of how to design an effective mechanism to solve the efforts of the agent under the condition of information asymmetry.

Thus, based on the countermeasures of rational allocation of expenditure, expenditure should be mainly allocated to establish rational incentive mechanisms. Policy implementation methods and implementation mechanism of government-funded enterprises or industrial technical innovation decide and influence technical innovation effectiveness largely. The government mostly adopts indirect policy implementation methods for enterprises' technical innovation activities in order to establish governmental technical innovation input policy systems with innovation input.

7.1.2.4. Countermeasures for Rational Expenditure Allocation in High-tech Industry on the Basis of Industrial Market Structure

Schumpeter theory of innovation (1934) stressed that for different market structures, the innovation impetus of the main market players was different. There are also differences in innovation expenditure input. Even so, empirical literature still regards Schumpeter's innovation tradition as the existence of a continuous and positive relationship between enterprise scale and innovation. Galbraith further expanded Schumpeter's large-manufacturer "technical structure" ideas and stressed the importance of market structure in innovation. The existence of large monopolistic enterprises in industrial markets is a complete tool leading to technical change and the most effective inventors and communicators of technical innovation (Acs & Audretsch, 1987). Spacecraft manufacturing may be an example of this. However, this still needs to be verified. Another view states that as the scale of monopolistic enterprises expands, management costs also rise. This may offset the rise in R&D efficiency brought about by scale expansion.

Another possibility is that as the scale expands, the gains obtained by special research personnel in innovation results decrease. Scherer (1965) discovered that enterprise R&D input would not rise with enterprise scale expansion. On the contrary, the R&D input of some large enterprises is less. These however differ for specific industries. The research of Mansfield (1968) shows that as enterprise scale expands, enterprise R&D input will reduce. However, in later research, Mansfield found that large enterprises often excessively invested in fundamental research, but invested less in applied research and experimental development.

Acs and Audretsch (1987), in their study of market structure and innovation input, found that in an imperfect competition market structure, innovation input, innovation activity personnel and innovation output of large enterprises will be higher than that of small-scale enterprises. For perfect competition industries, the innovation input incentive of large enterprises will be much less. Utsch et al. (1999) further discovered that enterprise scale and R&D expenditure had non-linear relationships (non-reverse "U" relationship), i.e. both small enterprises and large enterprises have strong R&D strength, while the R&D expenditure of general scales is relatively small.

From an observation of the market structure of China's high-tech industry and expenditure input rationality, it can be noted that the expenditure input of the industries with sufficient competition such as complete electronic computer manufacturing, computer peripheral equipment manufacturing, domestic audio-visual equipment manufacturing and communication equipment manufacturing is more rational. Expenditure allocation rationality of monopoly industries formed by national input, such as spacecraft manufacturing, aircraft manufacturing & repair and medical equipment & apparatus manufacturing, needs adjustment.

7.1.2.5. Reduction of fixed-asset investment proportion in the high-tech industry

In China, fixed-asset investment proportions are different in different industries. In particular, the investment requirement for scientific research funds provided by the state has a specific proportion requirement for fixed assets, so that the fixed-asset investment proportion is improved in some industrial innovation activities, in order to reach the standard (Qin & Song, 2009). Thus, input slacks form, as shown in Table 7-6.

Table 7-6: Fixed-asset Investment Slacks of China's High-tech Industry in 2011

Industry	**Fixed-asset investment slacks S_4^{-0}**	**S_4^{-0} slack proportion**
Chemicals manufacturing	188.855	18.84%
Chinese patent medicine manufacturing,	210.111	43.55%
biological product manufacturing	246.229	50.45%
Aircraft manufacturing and repair	0.000	0.00%
Spacecraft manufacturing	9.482	13.95%
Communication equipment manufacturing	0.000	0.00%
Radar and corollary equipment manufacturing	0.000	0.00%
Radio and television equipment manufacturing	0.000	0.00%
Electronic device manufacturing,	1583.053	78.52%
Electronic component manufacturing	253.829	21.48%
Domestic audio-visual equipment manufacturing	0.000	0.00%
Other electronic equipment manufacturing	237.761	45.99%
Complete electronic computer manufacturing	0.000	0.00%

Industry	Fixed-asset investment slacks S_4^{-0}	S_4^{-0} slack proportion
Computer peripheral equipment manufacturing	0.000	0.00%
Office equipment manufacturing	0.000	0.00%
Medical equipment and apparatus manufacturing	93.201	28.17%
Instrument manufacturing	0.000	0.00%
Mean	166.031	

From Table 7-6, it is seen that fixed-asset investment slacks mainly occur in fields such as chemicals manufacturing, Chinese patent medicine manufacturing, biological product manufacturing, electronic device manufacturing, electronic component manufacturing, other electronic equipment manufacturing and medical equipment and apparatus manufacturing. Relatively speaking, since the overall innovation level of China's high-tech industry is not high and fixed-asset input is characterised by one-time and long-term usability, the slack is not a very serious problem. However, it is necessary to pay attention to the rationality of fixed-asset investment.

7.1.2.6. Improvement of Innovation Ability of Scientific Research Personnel

The innovation ability of scientific research personnel in China's high-tech industry has experienced rapid improvement. From 2005-2011, both the quality and quantity improved significantly. However, the effects of the quantity of R&D scientific research personnel on technical innovation efficiency present different results in different studies.

Table 7-7: Investment Slacks of Full-time Scientific Research Personnel in 2011

Industry	S_1^{-0}	S_1^{-0} slack proportion
Chemicals manufacturing	4693.139	10.67%
Chinese patent medicine manufacturing,	3190.048	23.02%
biological product manufacturing	0.000	0.00%
Aircraft manufacturing and repair	0.000	0.00%
Spacecraft manufacturing	0.000	0.00%
Communication equipment manufacturing	0.000	0.00%
Radar and corollary equipment manufacturing	0.000	0.00%
Radio and television equipment manufacturing	0.000	0.00%
Electronic device manufacturing,	0.000	0.00%
Electronic component manufacturing	13722.125	24.20%
Domestic audio-visual equipment manufacturing	0.000	0.00%
Other electronic equipment manufacturing	0.000	0.00%
Complete electronic computer manufacturing	0.000	0.00%
Computer peripheral equipment manufacturing	0.000	0.00%
Office equipment manufacturing	0.000	0.00%
Medical equipment and apparatus manufacturing	0.000	0.00%
Instrument manufacturing	0.000	0.00%
Mean	1270.901	

The quantity and ability of scientific research personnel are major factors influencing the innovation efficiency of China's high-tech industry. There are not many industries with scientific research personnel slack. The slack proportion is within 25%. However, the quantity and ability of scientific research personnel have become major obstacles of overall innovation efficiency in non-slack industries. Under the state of ideal proportion input, affected by the quantity and ability of scientific research personnel, the innovation efficiency is also not high, thus leading to slacks of many other factors. This is consistent with the conclusions Shujing (2006).

In regional technical innovation analysis, some research results show a slack of the number of scientific research personnel. Especially in the regions with concentrated scientific and technical personnel such as Shaanxi, Hubei and Beijing, the slack of scientific research personnel is large. Thus, it is suggested that they dissolve some scientific research personnel, reserve and actively introduce high-level scientific research personnel. This needs further analysis from the perspective of human capital and structure. Further research can be carried out from two aspects:

On the one hand, industrial data of some developed countries such as America and Japan can be added. In particular, technical innovation benchmark of developed countries can be selected for analysis and the differences compared with China’s technical innovation personnel. On the other hand, relevant data of human capital structure of high-tech industry can be collected for further analysis. Through empirical analysis, the technical innovation ability of China’s scientific and technical personnel needs to improve. Enhancing policy-industry-study-research cooperation and establishing long-term mechanism for policy-industry-study-research cooperation is an effective solution to the problem of human resource input in China’s high-tech industry (Kemp, 2000).

7.1.3. Summary

Based on the analyses from previous chapters, this chapter has analysed countermeasures, which can be taken to improve technical innovation efficiency, and proposes suggestions on the combination of input elements. Some of the major observations are summarised below:

The innovation level of China's high-tech industry is not high. Thus, it is necessary to enhance the technical innovation element input scale. Attention should also be paid to inputting according to industrial features and element proportions.

R&D expenditure and expenditure on new products development should be rationally allocated, in line with the development stages of China's high-tech industry; Rational allocation of innovation and imitation expenditure, rational allocation of governments' direct and indirect input, expenditure input and incentive should all be considered. Fixed-asset input proportion of some industries in technical innovation should be suitably reduced. The construction of policy-industry-study-research technical innovation mechanisms should be enhanced and the innovation ability of scientific research personnel boosted.

7.2. Discussion of Chapter Findings

The research has presented two sets of data in chapters 4, 5, and 6. In Chapter 4, 28 DMUs were selected and the innovation of the high-tech in industry regions was presented using panel data. In Chapter 5, five industry sectors and 17 high-tech industries from these sectors were analysed for their technical innovation efficiency. In these chapters, data was presented in various tables and briefly described. This chapter discusses the data and findings in detail. References are made for each table and the sections in which they occur.

7.2.1. Discussion of findings from Chapter 4

7.2.1.1. Discussion of Technical Innovation Efficiency of DMUs

Findings from the panel data and a preliminary review were presented in section 4.2.1. Please refer to 'Table 4-3 STE of CRSTE under CRS during 2005-2011'. In the table, the number of provinces with an efficiency value reaching 1 over the period from 2005 to 2011 is counted in the last column. As a whole, the number of provinces on the production frontier in each year is small, although the number was relatively large in 2010. There are 7 provinces on the production frontier, including Beijing, Tianjin, Fujian, Hunan, Guangdong and Chongqing. The numbers were small in 2005, 2006 and 2007. There were four provinces on the production frontier.

At the provincial level, only one province is always on the production frontier from 2005 to 2011, Tianjin City. The Tianjin City maintained its technical efficiency at all times in the sample period. Guangdong province was on the production frontier for 6 years from 2005 to 2011. Yunnan was on the production frontier for 5 years. Beijing was on the production frontier for 4 years.

When STE<1, it indicates that high-tech innovation is ineffective. There is a certain distance between the production point and the production frontier, and this means that there can be further improvements in the output (Bian & Yang, 2010). In observing the entire data of the 28 provinces from 2005 to 2011, it can be observed that most provinces are in a state of DEA inefficiency. The reasons for this are as follows.

From 2005 to 2011, China's economy was on the rise. Although the subprime crisis had certain effects, the measures set in place to expand internal demand in China led to a successful resistance of the economic downturn momentum. China's high-tech industrial development also continuously advanced from 2005 to 2011. Regardless of the scale of the high-tech industry or the output value of the high-tech industry, the high-tech industry has advanced continuously and is progressing rapidly (Hong & Yue, 2013).

However, this brings about the question on why this progress trend is not obviously reflected in the STE. The main reason for this occurrence is that relative to the output of high-tech industry, the input in high-tech industry is redundant and the output is crowded. Each province provides a large quantity of fixed assets and human capital in the high-tech industry as inputs. The provinces increase investment for independent research, development, and new product development. However, the output fails to improve significantly, especially in terms of output value and net profit of new products. On the one hand, scientific research input is transformed to the patent and then as new products for production and marketing, which has a certain lag period and hysteresis effects. On the other hand, many new products are not in internally leading positions. The profit of new products is low. The output income of new products is also not high, thus, STE is low (Wang et al., 2013).

7.2.1.2. Discussion of CRSTE Efficiency Analysis

STE calculated for CRS, called CRSTE is the efficiency to be studied in this dissertation (Zhao et al., 2015). In 2011, the CRSTE of technical innovation of China's high-tech industry was low, with a mean of only 0.670. The maximum value of CRSTE is 1 and the minimum value is 0.253. It can be seen from the Table 4-3 that only the CRSTE values of Beijing, Tianjin, Fujian, Hunan, Guangdong and Chongqing were 1. Thus, only these provinces are in the state of DEA effectiveness. Other provinces are in the state of DEA inefficiency. Among the 22 provinces with non-DEA effectiveness, Hainan ranks top, reaching 0.951, while Jiangxi is the lowest, with a value of only 0.253. The efficiency value of 12 provinces was lower than the mean 0.670. In particular, non-DEA effective DMUs, which are lower than the mean, include eastern provinces (Hebei and Liaoning), middle provinces (Shanxi, Jilin, Heilongjiang, Jiangxi and Hubei) and western provinces (Inner Mongolia, Guangxi, Sichuan, Yunnan and Shaanxi). This indicates that the technical innovation efficiency of China's high-tech industry is generally in a state of inefficiency. From the static perspective, this phenomenon shows that the DEA effectiveness of the CRSTE has no direct causal relationship with the regional location.

The CRSTE is actually the product of the PTE and SE. Thus, the main reasons for the non-DEA effectiveness of CRSTE include technical efficiency value added scale efficiency value. The main cause of non-DEA effectiveness of the CRSTE is non-DEA effectiveness of SE, i.e. scale inefficiency, as the change direction of the two is basically consistent. The non-DEA effectiveness of CRSTE in Jiangsu, Henan, Hainan and Ningxia were completely caused by scale inefficiency, while the non-DEA effectiveness of CRSTE in other provinces was jointly caused by technical inefficiency and scale inefficiency (Wang et al., 2014). Table 4-3 further shows that the causes of scale inefficiency are different. Some are due to increasing returns to scale while some are due to decreasing returns to scale.

7.2.1.3. Discussion of VRSTE Efficiency Analysis

PTE calculated under VRS is also called VRSTE, and it is the gap between the inefficient unit and the unit on the production frontier, under the assumption of VRS and the largest output of DMU with a given input combination (Wang et al., 2012). The low mean of the CRSTE of China's high-tech industry is mainly because of low PTE. It can be seen from Table 4-3 that the mean is 0.736. Among the 28 provinces, the PTE of 11 provinces is 1, on the production frontier. These provinces realise the optimal resource allocation, accounting for about 39.29%. This is because these provinces increase the strength of resource integration and improve comprehensive competitive power, thereby improving, PTE. However, 17 provinces are not on the production frontier. The mean of PTE in 13 provinces is below 0.736. Among the 17 DMUs with non-DEA effectiveness of PTE, Guizhou has the highest efficiency, reaching 0.907, followed by Gansu (0.876). There are many provinces with low efficiency. The efficiencies of Hebei, Jilin, Heilongjiang, Jiangxi, Hubei, Guangxi, Sichuan and Shaanxi are all below 0.6. Jiangxi has the lowest efficiency value at 0.265.

7.2.1.4. Discussion of SE Efficiency Analysis

It can be seen from Table 4-3 that the mean of SE is 0.921. Among the 28 provinces, 7 provinces are on the production frontier, including Beijing, Tianjin, Anhui, Fujian, Hunan, Guangdong and Chongqing). These 7 provinces have large technical innovation scales of the high-tech industry, good development and leading operation management mechanisms for scientific research innovation and good human capital structures. They are the bellwethers driving the development of China's high-tech industry. In terms of the scale state, among the 28 provinces, the RS of 17 provinces is increasing, accounting for 60.72%. The RS of Beijing, Tianjin, Zhejiang, Anhui, Fujian, Hunan, Guangdong and Chongqing is constant, accounting for 28.57%. The RS of Jiangsu, Shandong and Henan is decreasing, accounting for 10.71%.

It is seen that in Table 4-4, S_1^{-0} of 5 provinces is not equal to 0; S_2^{-0} of 11 provinces and S_3^{-0} of 4 provinces are not equal to 0; and S_4^{-0} of 4 provinces is not equal to 0. The input indexes corresponding to the non-zero slack variables are the key objects of concern for improving SE. To be more specific, under the condition where the output does not reduce, Hebei, Zhejiang and Yunan need to reduce the number (X_1) of converted full-time scientific research personnel and expenditure on R&D (X_2). At the same time, Shanxi needs to reduce the number (X_1) of converted full-time scientific research personnel. The province of Liaoning needs to decrease Expenditure on R&D (X_2), Expenditure on New Products Development (X_3) and Investment in Fixed Assets (X_4) simultaneously.

Shanghai needs to decrease the number (X_1) of converted full-time scientific research personnel and Expenditure on New Products Development (X_3). Anhui and Sichuan need to reduce Expenditure on New Products Development (X_3) and Investment in Fixed Assets (X_4). Jiangxi needs to reduce Expenditure on R&D (X_2), and Shandong needs to reduce Expenditure on R&D (X_2) and Investment in Fixed Assets (X_4).

Hubei, Guangxi, Shaanxi and Gansu need to reduce Expenditure on R&D (X_2). For the index X_1, Zhejinag needs to reduce the highest amount, 6446.728. For the index X_2, Liaoning needs the highest reduction, as it reaches 90493.397. For the index X_3, Shanghai needs to reduce the most. For the index X_4, Anhui needs to reduce the most, as it reaches 117.652. In addition, 14 DMUs including Beijing and Tianjin do not need to reduce their input, as their four slack variables are 0. This fact shows the main cause for non-DEA effectiveness of SE of 8 DMUs including Hebei and Shanxi is not excessive input, but small output relative to the fixed input.

7.2.1.5. Discussion of Input and output reduction scale inefficiency

Tables 4-5 and Table 4-6 need a closer study since they illustrate the input and output reduction scale inefficiency. Consider the Guizhou Province for example; in terms of the input, the proportion of the decrease of the four indexes is the same, i.e. 9.34%. However, in terms of output, there are large differences. Obviously, the index (Scales Revenue of New Products) (Y_3) is the main factor which leads to non-DEA effectiveness of the province. In addition, 96.84% can still be increased, i.e. increasing to 2645533.86 thousand Yuan from 1344024.80 thousand Yuan. The output Value of New Products (Y_2) can still increase by 62.88%, if 1684658.40 thousand Yuan is increased to 2743934.59 thousand Yuan. The analysis for other units is also similar.

It can be seen from Table 4-5 that four input indexes of 16 non-DEA effective

DMUs need to decrease to different degrees. Among the four indexes X_1, X_2, X_3 and X_4, Jiangxi Province declines the most, reaching 64.73%, 71.57% and 64.73%, respectively. This is closely related to the result that the province has the smallest comprehensive efficiency. Among the indexes X_1, X_2, X_3 and X_4, Guizhou has the smallest reduction range, reaching 9.34%. Unlike the situation where input indexes reduce to different degrees, the increase range of the output indexes differ a lot, including slight increase, large increase and no increase (Chen & Guan, 2012).

For the index Y_1, only Liaoning needs to increase 35.23%. The remaining 27 DMUs do not need to increase. The original data of the patent application number for this province is 746, while the ideal number is 1009. For the index Y_2, 15 DMUs do not need to increase. Heilongjiang has the largest increase range, i.e. 181.48%. The numerical value of the original data Output Value of New Products of this province is 3543216.1 thousand Yuan, increasing to 9973337.40 thousand Yuan. For the index Y_3, 14 DMUs do not need to increase. Heilongjiang still has the largest increase range, i.e. 235.88%. The numerical value of the original data sales revenue of new products of this province is 2890216.1 thousand Yuan, increasing to 9707626.33 thousand Yuan.

7.2.2. Discussion of causes for unstable Malmquist Index

Please refer to the data in ‘Table 4-9 Diagram of M, EC and TC Index

Changes during 2005-2011’ The largest feature of the total factor productivity of the 28 provinces is not stable enough, and the fluctuation is large. These are seen from the DMU and the time perspectives. From the perspective of DMU, the Malmquist index of each DMU changes to different degrees during the 7 years. In addition, the changes have no pattern, they go from descending to rising and then declining again, or from rising to descending and then rising again. There are various situations. From the time perspective, the number of DMUs with Malmquist index greater than 1 reduces from 13 in 2006 to 9 in 2011. The large fluctuations in total factor productivity fully indicate that they are still in rapid development. All kinds of input and output factors often have large fluctuations (Qian-Xiao & Wen, 2012).

We suggest the following as reasons for the instability of the Malmquist index. Overall, the DMUs present large fluctuations in total factor productivity, but the causes of these fluctuations are different for each DMU. This can be seen from the EC index and TC index decomposed from the Malmquist index (Odeck, 2000).

With reference to data in Table 4-4, it is seen by synthesising the change degree of the two indexes of each DMU from 2005-2011 that the causes of total factor productivity for the high-tech industrial innovation of these provinces are very complex. These causes can be divided into 6 situations, and these are as follows.

1) Malmquist index decline caused by EC degradation, such as Hebei in 2006-2007 and Inner Mongolia in 2006-2009

2) Malmquist index decline caused by TC degradation, such as Tianjin in 2006-2007 and Shanxi in 2007-2008

3) Malmquist index rise caused by EC improvement, such as Heilongjiang and Henan in 2005-2006

4) Malmquist index rise caused by TC improvement, such as Inner Mongolia in 2008-2009 and Hunan in 2008-2009

5) Malmquist index decline caused by EC and TC degradation, such as Tianjin in 2007-2008 and Jilin in 2008-2009. Take Jilin for example. Its two indexes decrease by 19.4% and 53.9%

6) Malmquist index rise caused by EC and TC improvement, such as Zhejiang in 2005-2006 and Beijing in 2006-2007.

7.2.2.1. Discussion of PTE and SE changes

The results listed in Table 4-10 provide information about the innovation activities of the 28 provinces in high-tech industry from 2005-2011. The data is used to find the reasons for comprehensive efficiency invariability, improvement or degradation can be explained from PTE and SE perspectives, and mainly include the following situations:

EC invariability can be caused by an unchanged PTE and SE (Chen et al., 2010). Take the year 2011 for example. The four DMUs including Beijing, Tianjin, Hunan and Guangdong experienced this situation, accounting for 1/7.

An EC value decline can be caused by PTE degradation (Wang et al., 2013). Take the year 2011 for example. 10 DMUs including Hebei, Liaoning, Jilin, Zhejiang, Anhui, Hubei, Guangxi, Yunnan, Shaanxi and Gansu experienced this situation, accounting for 35.72%. Even if SE rises or remains unchanged, due to PTE decline, EC also decreases.

An EC rise can be caused by PTE improvement (Sun et al., 2012). In 2011, the SE of Shanghai was equal to 0.999, approximately equal to 1; EC=1.028 is basically caused by PTE improvement. Fujian also experienced this situation, SE=1.00. Because of a PTE improvement, the EC rose by 23.4%.

An EC decline can be caused by SE degradation (Wang et al., 2013). Take Inner Mongolia, Henan and Ningxia in 2010-2011 for example. Their PTE change value was 1, but their EC value declined. Besides, their change value was completely consistent with the SE change value.

An EC rise can be due to SE improvement (Sun et al., 2012). For example, in 2011, Hainan's EC ratio increases by 41.9% compared with 2010. This proportion was completely caused by SE rise.

An EC decline can be caused by a decline PTE and SE (Wang et al., 2013). Shanxi, Jiangxi and Sichuan experienced such a situation in 2011.

An EC rise can be caused by a decline in PTE and SE (Sun et al., 2012). Heilongjiang, Jiangsu and Chongqing in 2011 experienced such a situation. Heilongjiang is also the province with the largest EC change in 2011, with an

EC of 1.75.

7.2.2.2. Discussion of M Mean change and trend of 28 DMUs

Change in the Malmquist index for innovation efficiency and the decomposition results of China's 28 provinces from 2005-2011 are given in Table 4-11. It can be observed from the table that in recent years, the Malmquist index of innovation efficiency of the high-tech industry increased by 0.2% on average; the growth rate reached its highest (12.8%) in 2007 and reached its lowest (-7.9%) in 2008. The mean of technical efficiency was 1.081 in 2011, an increase of 8.1%. This is the main driving force for the rise in technical innovation efficiency. The mean of the PTE change is 1.050, up 5%. The mean of the SE change is 1.029, up 2.9%. The mean of technical progress index is 0.927, down 7.3%. This indicates a decline in the optimal frontier of technical innovation and a decrease in technical progress and innovation ability, which restrains the rise in technical innovation efficiency to an extent. From 2005-2011, the technical innovation efficiency rose slightly by 0.2% due to an 8.1% improvement in technical efficiency.

In 2009-2011, technical innovation efficiency showed a declining trend. In recent years, the state, scientific research institutions and enterprises have paid much attention to the innovation ability of the high-tech industry and increased capital input. There has also been a rapid emergence of scientific and technological achievements. However, despite these efforts, input-output or technical innovation efficiency has not improved. The main reason behind this could be that independent innovation of China's high-tech industry is influenced by fluctuations in policy. Besides, many scientific and technological achievements are in theoretical form and fail to be transformed into real products. Macroeconomic fluctuations, which arose during the global financial crisis in 2008, also had a significant impact on technical innovation efficiency (Fu et al., 2011).

7.2.2.3. Discussion of Regional comparison of Malmquist Index

With reference to the data given in Table 4-12, it is clear that 11 provinces Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan belong to the eastern region. The 8 provinces including Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henna, Hubei and Huanan belong to the central region. Nine provinces including Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaaxi, Gansu and Ningxia belong to the west region. According to table – comparing the Malmquist index of each region from 2005-2011, the innovation efficiency growth of high-tech industry in the east region is not stale; the growth rate in 2006-2007 was as high as 58.5%, but reduced to 6.4% in 2009-2010. In 2010-2011, out of the 11 eastern provinces, the Malmquist index in 9 of the provinces was less than 1. There has been a stable rise in innovation efficiency in the central region. With the exception of 2007-2008 when it went down by 2.1%, innovation efficiency has experienced increases annually. Among the 8 middle provinces, at least half of the provinces experienced an improvement innovation efficiency. In the west, the Malmquist indexes for 2005-2006 and 2010-2011 were less than 1. It presents the growth trend in the remaining four years. However, in 2010-2011, among the 9 western provinces, 6 provinces showed a negative growth of technical innovation efficiency.

7.2.2.4. Overall assessment of findings for DMU analysis

The empirical results of the Malmquist index model show that there was a slight rise in the Malmquist index of technical innovation efficiency in China's high-tech industry; the EC improved, but TC declined. The mean of Malmquist index was 1.002, which is offset by EC progress effectiveness and a decline in TC.

At a regional level, in the aspect of the technical innovation efficiency growth rate of high-tech industry, the central region showed a strong growth trend; SE plays an important promotion role in the rise in technical innovation efficiency in the eastern region (1.046). However, the three regions need to enhance TC. The western region in particular needs to improve SE and excavate efficiency growth brought on by a matched scale structure.

From the provincial data, it can be observed that the mean of the Malmquist index changes for more than half of the provinces was greater than 1. These provinces are mainly concentrated in the eastern region. To be more specific, Chongqing had the largest Malmquist index change (1.227), followed by Hunan (1.218); Yunnan had the smallest change (0.804).

Concerning the static and dynamic analysis, the following preliminary conclusions can be drawn.

The innovation status of the 28 provinces in high-tech industry is not ideal. From the static analysis, in 2011, only 6 provinces had an effective DEA of STE; the STE of about 78.57% DMUs were non-DEA effective. For PTE, 17 DMUs were non-DEA effective, accounting for 60.71%; for SE, 21 DMUs were non-DEA effective, reaching 75% (see Table 4). From the dynamic analysis, only 9 provinces improved M in 2010-2011. The M of 75% provinces was less than 1. Only 12 provinces showed an improvement in EC. TC was relatively ideal, with 19 provinces having a TC greater than 1, showing a rising trend.

In dynamic analysis, from 2005-2011, M index changes exhibited large variations and instability. The development of each DMU had no distinct pattern (see Table 4-13). This fully shows that in the rapid development stage of China's high-tech industry, various input-output indexes in innovation activities are changing continuously. The original data in the annex also speak volumes for this problem.

7.2.3. Discussion of findings from chapter 5

7.2.3.1. Discussion of technical innovation efficiency of high-tech industries

It can be seen from Table 5-4 that all technical efficiency values are between 0 and 1. As mentioned above, efficiency values measured by the DEA model are a group of limited values. If the efficiency value is 1, this means the industry is on the production frontier and is effective technically (Chu et al., 2010). In Table 5-4, the number of industries with an efficiency value of 1 from 2005 to 2011 is counted in the last column. Overall, there is not much variation in the number of the industries on the production frontier in each year. In 2006 and 2009, there were 7 industries on the production frontier. In other years, there were 5 industries on the production frontier.

At the industrial level, only one industry was always on the production frontier from 2005 to 2011: complete electronic computer manufacturing. Complete electronic computer manufacturing maintained its technical effectiveness during the entire sample period. Communication equipment manufacturing and domestic audio-visual equipment manufacturing were on the production frontier for 6 years, from 2005-2011. Communication equipment manufacturing was on the non-production frontier in 2010, while domestic audio-visual equipment manufacturing was on the non-production frontier in 2008. Computer peripheral equipment manufacturing, radio, and television equipment manufacturing were on the production frontier for 5 years. Medical equipment and apparatus manufacturing was on the production frontier for 6 years. Chinese patent medicine manufacturing was on the production frontier for 2 years.

According to Rouse and Chiu (2009) when the STE＜1, this indicates that high-tech innovation is ineffective, i.e. there is certain distance between the production point and the production frontier, which means that there can be further improvements in output. Based on an observation of the entire data for the 17 industries from 2005 to 2011, most industries are in a state of DEA inefficiency. The mean of STE tended to increase from 2005 to 2009 but declined afterwards. This trend is consistent with the development of Chinese economy, as it experienced rapid growth from 2005 and 2009. However, following the subprime crisis and investment redundancy in high-tech industry, there was a decline in the efficiency of the high-tech industry after 2009.

7.2.3.2. Discussion of industry based SE analysis of 2011

Please refer to the data in Table 5-6 Summary of Input Slacks. From the table, S_1^{-0} of 3 industries is not equal to 0; S_2^{-0} of 8 industries is not equal to 0; S_3^{-0} of 4 industries is not equal to 0; and S_4^{-0} of 8 industries is not equal to 0. The input indexes corresponding to the non-zero slack variables are the key objects of concern for improving SE. To be more specific, under the condition where the output does not reduce, chemicals manufacturing, Chinese patent medicine manufacturing and electronic component manufacturing need to reduce the number (X_1) of converted full-time scientific research personnel, Expenditure on R&D (X_2) and Investment in Fixed Assets (X_4)at the same time. Aircraft manufacturing and repair needs to reduce Expenditure on R&D (X_2) and Expenditure on New Products Development (X_3) simultaneously. Biological product manufacturing and spacecraft manufacturing must decrease their Expenditure on R&D (X_2) and Investment in Fixed Assets (X_4). Electronic device manufacturing must reduce Expenditure on New Products Development (X_3) and Investment in Fixed Assets (X_4) in the meantime.

Other electronic equipment manufacturing and medical equipment and apparatus manufacturing need to reduce Expenditure on R&D (X_2), Expenditure on New Products Development (X_3) and Investment in Fixed Assets (X_4) in the meantime. For the index X_1, electronic component manufacturing needs to reduce the most, as it reaches 13722.125. For the index X_2, aircraft manufacturing and repair needs to reduce most, as it reaches 174111.734. For the index X_3, electronic device manufacturing needs to reduce most, as it reaches 106407.549. For the index X_4, electronic device manufacturing needs to reduce most, as it reaches 1583.053. In addition, 8 DMUs including communication equipment manufacturing and complete electronic computer manufacturing do not need to reduce the input, as their four slack variables are 0. This fact shows the main cause of non-DEA effectiveness of SE of 3 DMUs (radar and corollary equipment manufacturing, office equipment manufacturing and instrument manufacturing) is not excessive input, but small output relative to the fixed input (Yang et al., 2011).

7.2.3.3. Discussion of input slacks

Overall, 3 output indexes Scales Revenue of New Products (Y_3), Gross value of New Products (Y_2) and Patent Applications (Y_1), influence non-DEA effectiveness. They have 8 surplus variables, 3 surplus variables and 2 surplus variables greater than 0 respectively. Horizontally, among 9 DMUs with non-DEA effectiveness, there is 1 industry with 3 surplus variables greater than 0, accounting for 11%. There are 2 industries with 2 surplus variables greater than 0, accounting for 22%. There are 6 industries with 1 surplus variable greater than 0, accounting for 67%. It can be seen from Table 5-6 that the major cause of non-DEA effectiveness of SE of 9 industries is that their output levels are low. This provides an important basis for improving the innovation efficiency of these industries (Xiaoya & Jinchuan, 2010).

7.2.3.4. Discussion of causes for an unstable Malmquist Index

Overall, while there are large fluctuations in total factor productivity, the causes of the fluctuations differ for each DMU. This can be seen from EC index and TC index decomposed from the Malmquist index. It can be found through synthesizing the change degree of the two indexes of each DMU from 2005-2011 that the causes of total factor productivity of high-tech industrial innovation of these industries are very complex. These causes can be divided into 6 situations (Balcombe et al., 2008).

The Malmquist index decline was caused by EC degradation in the case of radar and corollary equipment manufacturing in 2007-2008, medical equipment and apparatus manufacturing in 2009-2010 and office equipment manufacturing in 2010-2011. The Malmquist index decline was caused by TC degradation in the case of medical equipment and apparatus manufacturing in 2005-2006 and complete electronic computer manufacturing in 2006-2007. The Malmquist index rise was caused by EC improvement in the case of instrument manufacturing in 2005-2006 and electronic component manufacturing in 2008 and 2009.

The Malmquist index rise was caused by TC improvement, as was the case with communication equipment manufacturing in 2005-2006 and radio & television equipment manufacturing in 2009-2010. Malmquist index decline caused by EC and TC degradation, as was the case with biological product manufacturing in 2005-2006 and office equipment manufacturing in 2008-2009. Take office equipment manufacturing for example. Its two indexes decrease by 26.6% and 37.7% respectively.

The Malmquist index rise was caused by EC and TC improvement in the case of spacecraft manufacturing in 2005-2006, radio & television equipment manufacturing in 2006-2007 and office equipment manufacturing in 2009-2010.

7.2.3.5. Discussion of analysis of PTE and SE changes

Based on information in Table 5-11 on the high tech industrial innovation activities in the 17 industries from 2005-2011, the causes for comprehensive efficiency invariability, improvement, or degradation can be explained from PTE and SE perspectives, and mainly include the following:

EC invariability is due to unchanged PTE and SE. Take the year 2011 for example. Four DMUs (including radio and television equipment manufacturing, domestic audio-visual equipment manufacturing, complete electronic computer manufacturing and computer peripheral equipment manufacturing) experienced this situation, accounting for 23.5%.

A decline in the EC value can be caused by PTE degradation. Take the year 2010-2011 for example. 3 DMUs (including chemicals manufacturing, Chinese patent medicine manufacturing and spacecraft manufacturing) experienced this situation, accounting for 17.6%. Even if the SE rises or remains unchanged, due to a decline in PTE, EC also decreases.

An EC rise can be caused by PTE improvement. In 2010-2011, the SE of instrument manufacturing was equal to 0.736. Due to a significant improvement in PTE, EC improved. The EC value rose by 16.0%; medical equipment and apparatus manufacturing also experienced this. The SE was 0.75. Because of an improvement in PTE, EC rose by 7.8%.

An EC decline can be caused by SE degradation/decrease. Take office equipment manufacturing in 2010-2011 for example. Its PTE change value was 1, but its EC value declined. Besides, its change value was completely consistent with its SE change value. The PTE change value of electronic device manufacturing and other electronic equipment manufacturing in 2010-2011 was approximately 1, while the EC value declined. The change value was also completely consistent with SE change value (Hashimoto & Haneda, 2008).

An EC rise can be caused by SE improvement. Similar to the fourth situation, there was also EC rise situation caused by SE improvement. For example, in 2011, the EC ratio of communication equipment manufacturing increased by 21.6% compared with 2010. This proportion was completely caused by a 21.6% SE rise.

An EC decline can be caused by PTE and SE decline. Chinese patent medicine manufacturing and spacecraft manufacturing in 2010-2011 experienced this situation.

An EC rise can be caused by a PTE and SE rise, such as the case of radar and corollary equipment manufacturing in 2010-2011. It is also the industry with largest E change in 2010-2011, with an EC of 1.229.

7.2.3.6. Discussion M mean change and the trend of 17 DMUs

From the results given in Table 5-12, in 2009-2011, technical innovation efficiency showed a declining trend. Although in recent years, the state, scientific research institutions and enterprises have paid much attention to the innovation ability of the high-tech industry and increased capital input, and scientific and technological achievements have emerged rapidly, input-output or technical innovation efficiency has not improved. The major reason for this may be that independent innovation in China's high-tech industry is greatly influenced by fluctuations in policy. Besides, many scientific and technological achievements are in theoretical form and fail to form real products. Macroeconomic fluctuations, which arose during the global financial crisis in 2008, also had a significant impact on technical innovation efficiency (Chen et al., 2009).

7.2.3.7. Overall assessment of the findings for high-tech industries

Overall, it some variation in the M index is evident across different industries. There is variation in the growth rate of the high-tech industry, the average annual growth rate of the Malmquist index in aerospace vehicle manufacturing was the highest, reaching 17%, followed by electronic and communication device manufacturing with an average annual growth rate of the Malmquist index reaching 12.8%. The average annual growth rate of the Malmquist index in electronic computer and office equipment manufacturing industry was 8.5%, while the Malmquist index in the pharmaceutical industry experienced a rapid decline. The TC of these industries was good, however it is necessary to improve SE and excavate efficiency growth brought about by a matched scale structure.

According to the industrial change data, the mean of the Malmquist index changes for more than half of these industries was greater than 1. These industries mainly concentrate in aerospace vehicle manufacturing, electronic and communication device manufacturing and electronic computer and office equipment manufacturing industry. To be more specific, radio and television equipment manufacturing had the largest changes (1.414), followed by spacecraft manufacturing (1.326). Biological product manufacturing had the smallest changes (0.963).

Concerning the static and dynamic analysis, the following preliminary conclusions can be drawn. The innovation situation of the 17 industries is not ideal. From the static analysis, in 2011, only 5 industries had an effective DEA of STE. The STE of about 70.59% DMUs was non-DEA effective. For PTE, 9 DMUs were non-DEA effective, accounting for 52.94%; for SE, 12 DMUs were non-DEA effective, reaching 70.59% (see Table 4). In the dynamic analysis, only 9 industries experienced an improvement in M in 2010-2011. The M of 47.06% industries was less than 1. Only 9 industries experienced an improvement in EC. The TC was relatively ideal however. The TC of 13 industries was greater than 1, showing a rising trend.

In the dynamic analysis, from 2005-2011, there were large fluctuations in the M index changes. The development of each DMU had no pattern (see Table 5-7). This clearly shows that China's high-tech industry is in a rapid development stage. Various input-output indexes in innovation activities were also changing continuously. The original data in the annex also speak volumes for this problem. The next chapter discusses methods to improve the innovation efficiency of the high-tech industries in China.

7.3. CONCLUSION

7.3.1. Main Contributions of This Dissertation

Innovation efficiency reflects the competitiveness of the high-tech industry. As a result, it has been a major focus of study in the academic world. This dissertation reviewed the development conditions of China's high-tech industry, applied the DEA model and the Malmquist index model based on DEA model to comprehensively, systematically measure, and calculate the innovation efficiency of China's high-tech industry through provincial, regional, and industrial data. A number of important conclusions are drawn, and these are indicated as follows.

The DEA model was applied to compare the number of provinces on the frontier annually through a static analysis of the innovation efficiency of 28 provinces from 2005-2011. It was observed that only Tianjin has been on the production frontier for the 7 years under study.

Through an analysis of STE of provincial high-tech industry in 2011, which was further decomposed into PTE and SE, the differences and sources of innovation effeminacy for the different provinces were compared. It was noted that technical inefficiency, scale inefficiency or both cause DEA inefficiency. Through projection analysis, the main reduction factors of non-DEA effective DMU input and the main increase factors of the output were calculated.

The Malmquist index, EC index and TC index of 28 DMUs from 2005-2011 were calculated using DEAP2.1 software. The reasons behind the Malmquist index fluctuations for each DMU were analysed in detail.

The EC index was further decomposed into PTE and SE. The reasons behind comprehensive efficiency invariability and improvement or degradation of DMU were explained from the perspective of PTE and SE.

The M mean change of 20 DMUs from 2005-2011 was measured and the trend analysed. Through a comparison of the Malmquist index for each region, it is evident that the average annual growth rate of the Malmquist index was the highest in the central region and exhibited a rising trend. The dissertation also described and analysed the Malmquist index of technical innovation efficiency for each DMU from 2005-2011, as well as the variation trend of the means of the decomposition index.

Compared to previous research on this subject, this dissertation comprehensively and systematically analysed innovation efficiency of China's high-tech industry at regional, provincial and industrial levels and obtained complete, rich and revelatory results. All the results corroborate each other and have consistent logic. The research forms a comprehensive and three-dimensional cognition of innovation efficiency of China's high-tech industry and avoids the scattered property of isolated and short-term analysis results.

7.3.2. Policy Recommendations

In keeping with optimal resource configurations, industry clusters are regarded as a key strategy for developing the high-tech industry. They give full play to the gathering, leading and radiation effects of high-tech zones; accelerate industries to gather in preponderant regions and major central cities; further extend and perfect the industry chain; and allow for the formation competitive industry clusters. From 2005-2011, innovation in 28 provinces in China's high-tech industry from 2005-2011 was not at ideal levels. As such, there is significant room for improvement. The Malmquist indexes in the eastern, central, and western regions differ greatly. This indicates that China's resource allocation is unbalanced.

From the perspective of institutional economics, China's existing market economic system is imperfect; the level of market economy is not high; and right-based resource allocation still exists. Thus, resources cannot be completely allocated by the market. As such, input slack occurs in some regions while input shortage appears in other regions. The effeminacy was also greatly affected. It is therefore necessary to further expand market freedom, allow market forces to allocate resources and improve the resource utilisation ratio. It is also necessary to be based on resource optimal configuration, regard industry clusters as a key strategy for developing the high-tech industry, give full play to the gathering, leading and radiation effects of high-tech zones, accelerate industries to gather in preponderant regions and main central cities, further extend and perfect the industry chain and form competitive industry clusters.

The basic innovation ability construction of each province should be enhanced and sustainable development realised. It is also necessary to recommend development strategies of the high-tech industry at a national strategic level, further enhance independent innovation capabilities of the high-tech industry in each province and city, boost development levels of the high-tech industry, and promote optimisation and upgrade of industrial structure. Each province should actively encourage enterprises, colleges, and scientific research institutions to undertake major special projects, national scientific and technical infrastructures; and to create national high-tech industrial development plans, national scientific centres, and national laboratories; undertake other construction tasks and provide support.

The training of high-tech personnel and construction of teams should be accelerated. For the central region and western region, the personnel attraction force needs to be enhanced and the first resources for innovation gathered. The number of scientific and technical activity personnel as one of the important inputs in China's high-tech industry is obviously positively correlated with the innovation efficiency of the high-tech industry. The improvement in the quantity and quality of human resources and the rational allocation of other resources will certainly help improve technical innovation efficiency. Human resources are the most important strategic resource.

To accelerate the development of the high-tech industry, technical innovation and people should be the primary focus. Education should be implemented first in the strategy of reinvigorating China through human resource development. Personnel work should be regarded as a long-term strategic task; a good quality, rationally structured large-scale personnel team should be developed and a solid personnel guarantee provided, in order to realise leap forward significantly in the development of science and technology. Additionally, it is necessary to enhance high-level personnel training work in order to cultivate a batch of technology-based entrepreneurs who understand high technology and modern enterprise management, introduce personnel and intelligence through multiple channels and ways, pay attention to cooperation with transnational corporations and import advanced technology, management and personnel.

The dominant role of enterprises should be strengthened, enterprise innovation ability should be further improved and industry-university-research cooperation pushed further. Focus should not be on boosting the development of the high-tech industry only. Value should be placed on improving independent innovation capability. In today's world, competition in the high-tech industry is mainly reflected in the completion of independent innovation capability and intellectual property. To develop the high-tech industry, it is necessary to improve independent innovation capability. Importance is needed for developing original innovation ability and integrated innovation ability. There is a need to introduce, digest and absorb re-innovation ability, and break through significant key techniques restricting industrial transformation and upgrade. China must develop high-tech techniques, which have leading roles and strategic significance for China's economic and social development. It must achieve key breakthroughs and leaping development, developing leading strategies, realise large-scale industrialisation; and cultivate a batch of high-tech enterprises with international competitiveness.

It is necessary to accelerate the establishment of a market-oriented technical innovation system with enterprises as the main body. A combination of industry-university-research should be encouraged to make enterprises the subject of R&D input. The area of independent innovation; guide and support enterprises to increase their R&D force; strive to build world-class brands; innovate for the system and mechanisms must be given. It is important to give full play to the important functions of applied research institutes and college, and adopt feasible measures. There is a need to enhance the research and development of common technologies. In addition, it is necessary to vigorously develop all kinds of application electronic products, software and information application systems, and provide more powerful support for national economy and society construction. It is also important to implement fundamental research, technical research and science and technology support programs, enhance the support force of government procurement for independent innovation, perfect technical standards on government procurement and product catalogues, establish and perfect independent innovative product certification system, affirmation standards and evaluation systems.

Enterprise capital input has significant positive effects on technical innovation efficiency in the west region for scientific and technological activities. To promote technical innovation of enterprises in the west region, in addition to increasing science and technology input, “technology diffusion” in China’s middle region and east region should be encouraged. In the meantime, it is necessary to prevent excessive fixed-asset investment in the west region and promote coordination and rational allocation of labour, financial resources and material resources.

To boost the development of the high-tech industry and establish an operation mechanism complying with development laws of high-tech industry, it is necessary to accelerate innovation environment, speed up industrialisation of knowledge and technical results, support technology market development, expand technology and project sources, and promote industrialisation of technical results. It is necessary to fund the colleges, which establish technical transfer institutions, encourage and support the development of scientific and technological intermediaries, enhance the training, assessment, standardisation and supervision of the personnel in scientific and technological intermediaries. These institutes should promote a healthy and orderly development of scientific and technological intermediaries. Related departments in institutional innovation should actively establish simple and efficient management systems. It is necessary to vigorously drive intermediary organ development and industrial association construction and to actively develop professional service organs such as a technical patent agency, accrediting body, venture capital institutions, information and consulting companies, accounting firms and law firms. In the meantime, it is important to give full play to technical innovation advantages and the gathering function of high-tech industry bases, and to enhance the research, development, and industrialisation of great techniques.

A multi-level capital market should be established and the financing environment improved. To accelerate the cultivation and development of the high-tech industry, it is important to perfect finance and taxation policy support. Support and guidance should be given and social capital input must be encouraged. There is a need to strengthen financial support forces, perfect tax incentive policies, and combine tax reform directions and tax type features. These should aim at features of high-tech industry to study, perfect, encourage, innovate and guide tax support policy for investment and consumption on the basis of comprehensively implementing tax policies which promote science and technology input and the commercialisation of research findings, and support the development of the high-tech industry.

It is necessary to encourage financing functions of a multi-level capital market. The governments at each level, institutions, and banks should jointly set up re-guarantee funds to provide credit re-guarantees for small short-term financial needs. They should also expand the sources and channels of enterprise innovation funds, and encourage policy banks, commercial banks and guarantee institutions to carry out experimental units for the intellectual property pledge business.

7.3.3. Suggestions for Future Research

Due to limitations caused by the condition of the data, there are several challenges that have had to be addressed, or that due to workload, have not yet been addressed. Thus, it is necessary to study in greater depth in the future. Some of these areas are outlined as follows:

During the analysis of innovation efficiency of the provincial high-tech industry, the analysis was limited to the years from 2005-2011 and 28 provinces only, due to data shortage.

Due to the shortage of survey data, the analysis mainly concentrates on macroeconomic data at the provincial, regional, and industrial levels. Enterprise micro-data lack. If micro-data is added, the content of this dissertation will be enhanced.

There is a lack of international comparative analysis. Because of the workload, data collection difficulties, and analysis methods, a comparative analysis of China's high-tech industry and foreign high-tech industries is lacking. Through a comparison of both, the advantages, disadvantages and the forming reasons can be identified, and a development direction specified for China's high-tech industry.

The above problems and the topics, which are not included in this dissertation, are worth researching in the future. Additionally, the ways in which industrial concentration can be improved and high-tech industry regions rationally distribution should be examined. It is also necessary to develop new analysis methods. For example, an innovation efficiency measurement of “three kinds of wastes (waste water, waste gas and solid waste)”, energy sources and carbon emission can be proposed. All these are important topics, which can be researched in the future.

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Annex

Original Data of Industry-based Innovation Efficiency of China's High-Tech Industry

Year	Industry	Patent applications	Output value of new products (10 thousand Yuan)	Sales revenue of new products (10 thousand Yuan)	Converted full-time quantity of R&D activity personnel (number of personnel/year)	Internal expenditure of R&D funds (10 thousand Yuan)	Expenditure on new products development (10 thousand Yuan)	Investment in Fixed Assets (100 million Yuan)
2005	Chemicals manufacturing	1133	3674771	3327695	12574	273832	300482	289.3
2005	Chinese patent medicine manufacturing	1288	1125252	1045794	4976	91512	97048	140.52
2005	biological product manufacturing	242	158905	171308	1534	22955	28373	116.5
2005	Aircraft manufacturing and repair	314	3700713	3335683	27720	239156	270864	64.2
2005	Spacecraft manufacturing	14	34884	37857	2150	38813	30769	5.78
2005	Communication equipment manufacturing	6602	16873125	16431725	49679	1196585	1267879	139.89
2005	Radar and corollary equipment manufacturing	9	243074	258585	1810	24472	27487	8.86
2005	Radio and television equipment manufacturing	101	165620	161757	1740	18105	27438	9.96
2005	Electronic device manufacturing,	812	5207840	5127979	15211	328721	355849	399.08
2005	Electronic component manufacturing	947	3027015	3023700	13672	257997	315540	345.87
2005	Domestic audio-visual equipment manufacturing	2434	13061339	13313107	11573	500884	589840	70.19
2005	Other electronic equipment manufacturing	117	234351	203515	1407	20401	27294	89.14
2005	Complete electronic computer manufacturing	1020	12331549	12278252	7452	211999	271034	49.66
2005	Computer peripheral equipment manufacturing	796	7827349	7750678	8943	207560	307709	102.91
2005	Office equipment manufacturing	47	667848	671983	1089	14921	39045	15.57

Year	Industry	Patent applications	Output value of new products (10 thousand Yuan)	Sales revenue of new products (10 thousand Yuan)	Converted full-time quantity of R&D activity personnel (number of personnel/year)	Internal expenditure of R&D funds (10 thousand Yuan)	Expenditure on new products development (10 thousand Yuan)	Investment in Fixed Assets (100 million Yuan)
2005	Medical equipment and apparatus manufacturing	401	332455	319050	1262	34481	33142	38.83
2005	Instrument manufacturing	501	1521983	1539155	9870	131381	145303	108.09
2006	Chemicals manufacturing	1047	4198921	4030313	16671	354237	355785	291.01
2006	Chinese patent medicine manufacturing,	1133	1352022	1237459	5748	128358	151370	139.31
2006	biological product manufacturing	124	254650	221846	1706	30592	33345	170.59
2006	Aircraft manufacturing and repair	477	3326899	3006429	24692	285261	317913	70.37
2006	Spacecraft manufacturing	33	44364	44002	2681	48157	31610	10.02
2006	Communication equipment manufacturing	11069	18703408	17708892	48573	1313245	1375378	200.5
2006	Radar and corollary equipment manufacturing	42	497879	469829	3479	55566	35893	7.82
2006	Radio and television equipment manufacturing	212	220513	221253	1502	29932	45245	11.28
2006	Electronic device manufacturing,	1531	6103774	4896484	14318	409283	465931	615.41
2006	Electronic component manufacturing	930	3768562	3917878	16577	431186	569796	493.48
2006	Domestic audio-visual equipment manufacturing	2843	13792880	14153090	11424	506453	593326	78.72
2006	Other electronic equipment manufacturing	81	344928	367396	1944	23189	36880	115.16
2006	Complete electronic computer manufacturing	1228	18805216	18891472	13079	408545	443481	41.77
2006	Computer peripheral equipment manufacturing	1950	9974683	9949934	11171	306546	356811	121.43
2006	Office equipment manufacturing	43	804983	789682	341	14160	27773	24.82
2006	Medical equipment and apparatus manufacturing	503	394198	368768	2354	52409	50568	62.72
2006	Instrument manufacturing	976	2101473	2004348	11461	154580	191352	147.61
2007	Chemicals manufacturing	1367	5442018	5008854	19302	418799	470476	326.57

Year	Industry	Patent applications	Output value of new products (10 thousand Yuan)	Sales revenue of new products (10 thousand Yuan)	Converted full-time quantity of R&D activity personnel (number of personnel/year)	Internal expenditure of R&D funds (10 thousand Yuan)	Expenditure on new products development (10 thousand Yuan)	Investment in Fixed Assets (100 million Yuan)
2007	Chinese patent medicine manufacturing,	1340	1610159	1365520	7420	156873	176588	160.89
2007	biological product manufacturing	264	558063	476100	2769	55225	51628	153.25
2007	Aircraft manufacturing and repair	745	3972565	3722989	24264	372268	398801	112.47
2007	Spacecraft manufacturing	65	73120	68340	2918	53671	39465	14.09
2007	Communication equipment manufacturing	16342	30988971	29380905	74887	1571255	1645118	238.5
2007	Radar and corollary equipment manufacturing	98	751370	700094	3233	75403	79931	11.12
2007	Radio and television equipment manufacturing	589	475966	416645	2492	31603	39758	17.7
2007	Electronic device manufacturing,	2257	8135434	7680842	18728	451203	630300	871.62
2007	Electronic component manufacturing	1436	6595165	6245816	23168	534484	765597	526.01
2007	Domestic audio-visual equipment manufacturing	3614	14750133	15060981	17750	542685	708747	78.39
2007	Other electronic equipment manufacturing	344	652227	644881	2152	38576	59276	137.16
2007	Complete electronic computer manufacturing	999	16644030	16209232	14995	349811	421187	76.66
2007	Computer peripheral equipment manufacturing	2215	10905205	11108163	13520	446310	566989	136.68
2007	Office equipment manufacturing	52	870057	829959	1196	22049	25188	23.11
2007	Medical equipment and apparatus manufacturing	995	729256	757240	3468	73163	87086	93.97
2007	Instrument manufacturing	1639	3281783	3079244	14680	231930	313408	207.37
2008	Chemicals manufacturing	1587	6827456	6415616	24797	520940	563888	410.8
2008	Chinese patent medicine manufacturing,	1751	1939867	1773552	10524	162600	168829	198.28
2008	biological product manufacturing	254	825456	719740	2717	66422	85150	209.82
2008	Aircraft manufacturing and repair	946	4511668	4524182	16604	441850	425487	137.73

Year	Industry	Patent applications	Output value of new products (10 thousand Yuan)	Sales revenue of new products (10 thousand Yuan)	Converted full-time quantity of R&D activity personnel (number of personnel/year)	Internal expenditure of R&D funds (10 thousand Yuan)	Expenditure on new products development (10 thousand Yuan)	Investment in Fixed Assets (100 million Yuan)
2008	Spacecraft manufacturing	90	195774	205624	2742	78019	68936	21.58
2008	Communication equipment manufacturing	16159	30679184	30989691	92972	2021334	2280979	275.46
2008	Radar and corollary equipment manufacturing	70	158570	164617	2813	37973	42449	17.06
2008	Radio and television equipment manufacturing	600	586881	536663	2364	46672	59938	32.83
2008	Electronic device manufacturing	3273	11709935	11446943	20508	613113	815700	949.11
2008	Electronic component manufacturing	2057	7520956	7385399	24912	585300	755823	638.25
2008	Domestic audio-visual equipment manufacturing	3189	14600830	15763132	20256	630175	765367	115.75
2008	Other electronic equipment manufacturing	561	1694110	1304320	8405	94818	145394	169.82
2008	Complete electronic computer manufacturing	1171	25667153	24974827	14232	347172	537765	76.25
2008	Computer peripheral equipment manufacturing	3306	16615192	16454350	14994	432096	685921	187.08
2008	Office equipment manufacturing	63	890736	848209	1826	29693	28394	21.91
2008	Medical equipment and apparatus manufacturing	1326	988785	946912	3485	95907	114285	108.73
2008	Instrument manufacturing	2928	4166731	3760767	18775	306995	385655	344.49
2009	Chemicals manufacturing	2340	9018293	8468850	31457	636142	680413	543.61
2009	Chinese patent medicine manufacturing,	1827	2659895	2342221	11766	203612	210019	292.04
2009	biological product manufacturing	321	1024667	991985	5186	96793	108059	262.19
2009	Aircraft manufacturing and repair	1362	2909253	2562529	20587	517029	627015	157.85
2009	Spacecraft manufacturing	142	192147	159185	2448	140793	137616	22.8
2009	Communication equipment manufacturing	18913	39912928	41430667	85735	2388342	2793220	345.26
2009	Radar and corollary equipment manufacturing	123	533778	514724	3768	73858	75597	13.58

Year	Industry	Patent applications	Output value of new products (10 thousand Yuan)	Sales revenue of new products (10 thousand Yuan)	Converted full-time quantity of R&D activity personnel (number of personnel/year)	Internal expenditure of R&D funds (10 thousand Yuan)	Expenditure on new products development (10 thousand Yuan)	Investment in Fixed Assets (100 million Yuan)
2009	Radio and television equipment manufacturing	540	665887	588380	3073	38732	60413	37.99
2009	Electronic device manufacturing	5165	12211180	12010483	32278	684095	878320	969.05
2009	Electronic component manufacturing	3278	11003421	10918384	34900	675056	780830	611.53
2009	Domestic audio-visual equipment manufacturing	3594	16003497	15386164	14945	590999	726350	117.03
2009	Other electronic equipment manufacturing	872	1536490	1478924	8363	97405	127781	249.9
2009	Complete electronic computer manufacturing	3500	7646322	9492276	17075	422017	510656	61.36
2009	Computer peripheral equipment manufacturing	4278	12664257	12542334	16366	525557	712642	176.36
2009	Office equipment manufacturing	144	498901	496619	1986	41092	48181	31.88
2009	Medical equipment and apparatus manufacturing	1009	1241924	1126830	5523	143234	171711	147.54
2009	Instrument manufacturing	3808	4551360	4759345	21878	406071	527000	438.76
2010	Chemicals manufacturing	2792	11951655	11455030	37291	814547	878141	730.78
2010	Chinese patent medicine manufacturing,	2098	3200938	2943796	10458	207721	225868	372.99
2010	biological product manufacturing	382	1462287	1387671	5374	132828	140126	368.71
2010	Aircraft manufacturing and repair	2014	4897219	4485881	25910	853331	964989	215.98
2010	Spacecraft manufacturing	158	241373	235747	2339	75096	68418	34.87
2010	Communication equipment manufacturing	16886	41210183	42748773	98510	3047068	1994365	441.31
2010	Radar and corollary equipment manufacturing	288	488398	431244	4425	56977	80554	24.16
2010	Radio and television equipment manufacturing	1459	628644	711803	2130	40771	67349	55.02
2010	Electronic device manufacturing,	6887	15026419	14657975	31929	933299	1296953	1508.29
2010	Electronic component	4879	14915381	14970598	47274	870798	1049434	815.3

Year	Industry	Patent applications	Output value of new products (10 thousand Yuan)	Sales revenue of new products (10 thousand Yuan)	Converted full-time quantity of R&D activity personnel (number of personnel/year)	Internal expenditure of R&D funds (10 thousand Yuan)	Expenditure on new products development (10 thousand Yuan)	Investment in Fixed Assets (100 million Yuan)
	manufacturing							
2010	Domestic audio-visual equipment manufacturing	4212	14558076	15392293	21422	635762	751944	146.68
2010	Other electronic equipment manufacturing	964	1909927	1802197	5822	139420	152111	329.45
2010	Complete electronic computer manufacturing	5644	14564760	15335388	22225	447584	563301	116.59
2010	Computer peripheral equipment manufacturing	4990	30267515	27639164	44846	690884	861000	386.99
2010	Office equipment manufacturing	176	1204720	1240132	1438	37193	55358	22.04
2010	Medical equipment and apparatus manufacturing	1217	945045	880563	7303	148612	206115	209.68
2010	Instrument manufacturing	4142	6446394	6360610	28267	475244	643471	620.69
2011	Chemicals manufacturing	3229	11672479	10844461	43985	1002710	1070585	1002.22
2011	Chinese patent medicine manufacturing,	2153	3749457	3446421	13856	256329	280804	482.46
2011	biological product manufacturing	524	2154652	2048086	6284	174290	205828	488.02
2011	Aircraft manufacturing and repair	2125	4586986	4619963	25424	1255553	1156868	190.16
2011	Spacecraft manufacturing	289	356494	360362	4073	180017	183279	67.97
2011	Communication equipment manufacturing	23751	45463632	46192610	112346	3532317	4494800	540.67
2011	Radar and corollary equipment manufacturing	361	836230	752468	2809	78121	131179	38.66
2011	Radio and television equipment manufacturing	2881	1339879	1298986	4053	78966	119441	94.9
2011	Electronic device manufacturing,	9902	18429763	17858509	42442	1290626	1784389	2016.23
2011	Electronic component manufacturing	7532	16776592	16971775	56700	1080411	1380871	1181.61
2011	Domestic audio-visual equipment manufacturing	3275	18023659	19026208	16822	757855	917630	132.94

Year	Industry	Patent applications	Output value of new products (10 thousand Yuan)	Sales revenue of new products (10 thousand Yuan)	Converted full-time quantity of R&D activity personnel (number of personnel/year)	Internal expenditure of R&D funds (10 thousand Yuan)	Expenditure on new products development (10 thousand Yuan)	Investment in Fixed Assets (100 million Yuan)
2011	Other electronic equipment manufacturing	1658	2124124	2017889	6578	187410	283899	516.93
2011	Complete electronic computer manufacturing	6284	24765777	33655127	16152	697904	1077812	346.83
2011	Computer peripheral equipmentmanufacturing	4524	29768013	32831137	26690	747540	928256	390.2
2011	Office equipment manufacturing	372	1044478	902253	2855	67820	84844	26.61
2011	Medical equipment and apparatus manufacturing	1705	919398	862209	7097	205736	257477	330.8
2011	Instrument manufacturing	6653	8644229	8242654	33995	655068	788242	945.01