UNIVERSITY OF SOUTHAMPTON

FACULTY OF BUSINESS and LAW

School of Management

Indices of Innovation: Application of Data Envelopment Analysis and Malmquist Index Analysis in the Assessment of R&D efficiency in R&D-Critical Sectors

by

Chunjia Han

Thesis for the degree of Doctor of Philosophy

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ABSTRACT

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Maintaining or increasing R&D efficiency and productivity is a constant challenge for R&D-driven businesses, and companies in these sectors often explore strategies seen be effective in related sectors, for example the adoption of 'open' innovation by the pharmaceutical sector, based on its observed success in the information technology sector as reported by Chesbrough. The papers in this thesis address two gaps in the research literature: (1) the relative lack of established quantitative measures of the performance of open or other innovation strategies, and (2) the continuing challenge of assessing the effectiveness or otherwise of the OI paradigm outside its original high-tech industry focus. The pharmaceutical industry has been claimed as one of the pioneering industries where the principle of OI has been applied. In view of the limitations of prior research on R&D efficiency and OI in this industry, the question of whether OI is the best or only prescription for innovation in the pharmaceutical industry remains a strategic one. The first paper in the sequence identifies and explores systematic measures of innovation by investigating the adaptation and application of DEA as a candidate technique for analysing the R&D efficiency performance, using data on China's high-tech industry sectors. The second paper explores how such 'indices of innovation' could be used to measure performance in terms of changes in R&D efficiency over time, in a case study of Procter and Gamble, a company widely recognised as an early adopter of OI. The third paper builds on the first two, using DEA and MI as 'indices of innovation' to measure whether adopting OI is leading to increased R&D efficiency in the pharmaceutical sector. Taken together, these papers explore (a) the feasibility if DEA and MI as new quantitative econometric 'indices of innovation', (b) their correlation with a known case of open innovation, and (c) to test the hypothesis that open innovation is increasing R&D efficiency in the pharmaceutical industry.

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DECLARATION OF AUTHORSHIP

I, Chunjia Han

declare that the thesis entitled

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and the work presented in the thesis are both my own, and have been generated by me as the result of my own original research. I confirm that:

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1. Chapter 1: Introduction

1.1 Literature Review

1.1.1 Critical Trends in Innovation

Innovation has been long viewed as a path to success, not only for corporations but also at the institutional, national and industry levels. For the corporates, innovation allows them to establish competitively dominant positions, and afford new entrants an opportunity to gain a foothold in the market (Danneels and Kleinschmidt, 2001). However, with the high failure rate of innovation varying from 40% to 90% (Gourville, 2005), innovation is also associated with the high risk. Therefore, study of innovation plays an important way for the future success.

Innovation has been studied in a variety of contexts, including economics, management and sociology. The relevance of innovation was first brought to public perception by Schumpeter (1934), who identified the importance of innovation as the main driving power of economic development. The following works by other economists continued to contribute our understanding of innovation. Through the empirical study, Solow (1957) demonstrated that innovation and technical progress play a key role for economic growth. Arrow (1962) studied the seller's dilemma about revealing and hiding technology information to the potential customers.

With the development of innovation studies, it became well known and accepted that innovation is also crucial for the company's growth and success. Therefore, establishing an efficient innovation strategy could affect the future destiny of the company (Li and Atuahene-Gima, 2001; Adner, 2006). Subsequently, a number of innovation strategies have been developed. These often reflected opposing demands, such as incremental versus radical innovation (Dewar and Dutton, 1986), continuous versus discontinuous innovation (Veryzer, 1998), sustaining versus disruptive innovation (Christensen, 1997) or closed innovation versus open innovation (OI). Incremental innovation is progress in small steps to

maintain and improve the competitive position for the existing products (Schwery et al., 2004; Song and Montoya-Weiss, 1998), while radical innovation is a breakthrough through providing completely new or revolutionary products (Ettlie et al., 1984; Henderson, 1993). Continuous innovation upgrades or enhances the existing technologies or products without fundamentally changing the dynamics of the industry (Soosay et al., 2008), while discontinuous innovation brings either a factor of 5-10 times in product performance or a significant (>30%) reduction in cost (Leifer, 1997; Leifer and Rice, 2000). Sustaining innovation, like incremental and continuous, obtains the competitive position through evolving existing technologies or products with better value (Audretsch, 2004), while disruptive innovation create a new value or market through disrupting an existing market or seemingly superior technologies (Danneels, 2004; Govindarajan and Kopalle, 2006; Henderson, 2006).

Closed innovation is "a view that says successful innovation requires control. Companies must generate their own ideas, and then develop them, build them, market them, distribute them, service them, finance them, and support them on their own" (Chesbrough, 2003b). Since large firms have greater resources for conducting R&D and using it to create barriers to new and small firms (Schumpeter, 1942), controlling in-house R&D by closed innovation has helped the companies keep successful in the past. This kind of closed innovation has played an important role of technical know-how for firms (Mowery, 1983), especially in sectors like pharmaceuticals where in-house, proprietary knowledge has driven companies for almost a century.

However, it is not the only possible source of innovation. In particular, in the networked world of innovation (e.g. Prahalad and Krsihnan, 2008) there are major opportunities for sourcing knowledge externally (Nelson and Winter, 1982). Cohen and Levinthal (1990) emphasized the ability of recognizing and commercializing the external information is critical to the firm's innovative capability. von Hippel (1986) proposed how the integration of customers such as lead users can stimulate emerging needs for new products, processes and services. Pisano (1990, 1991) states that

established firms need to balance between in-house R&D and external sources from new entrants since the moving of R&D expertise. Powell (1990) identified that both formal relationships such as licensing agreements, alliances and joint-ventures and the informal relationships have been adopted by firms to source expertise outside their boundaries. With some 'erosion factors' have developed (i.e. the growing mobility of highly experienced and skilled people, the increasing presence of private venture capital, the existence of a market for technology), the closed innovation is no longer sustainable in many competitive situations (Chiaroni et al., 2009). In these cases, a new strategy which assumes that firms "can and should use external ideas as well as internal ones, and internal and external paths to market" (Chesbrough, 2003a) is emerging.

1.1.2 Open Innovation

One of the most influential recent theories in innovation study has been open innovation. Open innovation was originally defined by its originator as "…the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation respectively" (Chesbrough, 2003b; 2006b). Chesbrough's work plays an instrumental role in providing an umbrella for various subsequent research streams (Ili et al., 2010).

Gassmann and Enkel (2004) identified three core OI processes: outside-in, inside-out and coupled, based on their empirical analysis of a database of 124 companies. Chesbrough and Crowther (2006) studied OI beyond 'high technology' industries and observed the existence of OI initiatives in lower technological and more mature industries. West and Gallagher (2006) summarized the fundamental challenges for firms in applying OI through examining the activity of firms in open source software. Dodgson et al. (2006) identified the importance of technological changes for facilitating OI strategies based on the case study of Procter and Gamble. van de Vrande et al. (2009) investigated OI practices which applied by small- and medium-sized enterprises (SMEs) with the analysis of 605 innovative SMEs

in the Netherlands. Spithoven et al. (2011) studied the absorptive capacity building in firms from traditional industries to embrace OI.

Although a significant body of knowledge has now been developed on OI (for example see Dahlander and Gann, 2010), the field of open innovation is still at an early stage, offering a wide field in which academics, practitioners and policy makers can be active (Gassmann et al., 2010). Two relevant gaps can be identified that are relevant in light of the purpose of this thesis:

(1) The scarcity of attention dedicated to measure the performance of OI, as recently highlighted by several authors (e.g. Huizingh, 2011).

(2) The lack of contributions that systematically and longitudinally assess the extent and the determinants of diffusion of the OI paradigm in a specific industry (Chiaroni et al., 2009).

The first gap - the lack of attention to measures - has been highlighted from a number of perspectives in the recent literature. Although former studies seem to indicate that companies could be benefit from OI adoption (Dodgson et al., 2006; Laursen and Salter, 2006), innovation measurement still lacks an appropriate metrics system that monitors the investments and impact of open versus closed innovation approaches in order to help companies to find their optimal strategic balance (Enkel and Lenz, 2009). Some research investigates the performance of the pioneering OI adopters such as Procter and Gamble (Chesbrough, 2006a; Chesbrough, 2006b; Gassmann, 2006; Huizingh, 2011; Lichtenthaler, 2011). However, only simple approaches to measurement systems and key performance indicators are in use, which makes it hard to evaluate open versus closed innovation approaches (Enkel et al., 2009). Initial studies in OI tend to be descriptive, which helps in understanding the concept. Next stage studies should include performance measures (Huizingh, 2011). Since 'you can't manage right what you can't measure well' (Cruz-Cázares et al., 2013), measuring the performance of OI should be one of the most important research targets in OI research.

With respect to the second gap – applicable OI across and within sectors - the initial studies of OI were concentrated on high-tech industries (for example see Chesbrough, 2003b). Actually, OI was developed by Chesbrough (2003b) based on the analysis of a series of high-tech companies. The subsequent work about OI has switched their attention from the high-tech sector to the more traditional and mature sectors, aiming to understand OI in other industries (Chesbrough and Crowther, 2006). More and more industry-specific OI studies have been conducted: Sarkar and Costa (2008) reviewed extant literature on open innovation practices in the food industry and analysed their effects on the sector's innovation capabilities, and found that OI does take place within the food sector. Sieg et al. (2010) investigated managerial challenges faced by companies working with an innovation intermediary to solve R&D problems, based on the case study with seven chemical companies working with the same innovation intermediary. Ili et al. (2010) provided a comprehensive overview from the theoretical and practical perspective to highlight interesting preliminary findings about OI perceptions in the automobile industry through the analysis of 42 companies. Even OI practices in the service sector have been studied recently (Mention, 2011). Although these studies have contributed our understanding about OI in the special industries, more research focusing on the industry is still needed to broaden our knowledge on the applicability of OI. Furthermore, it remains an open question whether the OI proves to be more adequate in the attempt to achieve a better R&D productivity than a closed model for some industries (Ili et al., 2010). Industries such as the pharmaceutical sector, which have claimed to have adopted OI strategies, should provide relevant test cases for broadening our knowledge about OI beyond traditional OI research samples.

1.1.3 Open Innovation in the Pharmaceutical Sector

The pharmaceutical industry has been recognised as one of the major industries outside of high-tech which appears to have pioneered the principle of open innovation (Chesbrough, 2003b). More strategic modes of OI have already become a standard in the pharmaceutical industry, and

the trend toward OI is still growing (Gassmann, 2010). It makes the pharmaceutical industry become a potential interesting testing ground for OI research. The initial studies, such as the textbook case of Millennium Pharmaceuticals (Chesbrough, 2003b), have contributed our knowledge about OI in the pharmaceutical industry. However, in relation to the increasing demands of business conditions and management practice in this industry, the prior studies about OI in pharmaceutical industry are still limited.

A systematic review of the literature (using ISI, ScienceDirect, and Google Scholar) revealed that a relatively small number of papers have specifically focused on open innovation in the pharmaceutical industry. These studies have generally explored strategic, structural or operational aspects of OI. Fetterhoff and Voelkel (2006) advanced a model of the external innovation value chain to help biotechnology firms capture the full value of partnerships with external technology providers through the case study of Roche Diagnostics. Melese et al. (2009) studied the OI networks between academia and industry and summarised the principal models for industry-academic partnerships based on interviews with both companies and academic researchers. Talaga (2009, 2010) discussed the innovative partnership stages model which is adapted from the study in food industry and analysed the possibility of open and reverse innovation for the future of pharmaceutical R&D. Chiaroni et al. (2009) developed a framework of analysis establishing the relations between OI modes and the phases of the drug discovery and development process through a two-step research focusing the first 20 pharmaceutical biotech firms. Bianchi et al. (2011) did a similar study about the OI organisational modes in the bio-pharmaceutical industry and how these modes are interwoven with the phases of drug discovery and development process based on the similar research strategy and sample. Hunter and Stephens (2010) introduced the OI activities and possibilities in the pharmaceutical industry, and pointed out that OI is a valuable model for large pharmaceutical firms. Hughes and Wareham (2010) identified two OI concepts are not present in the innovation portfolio while three concepts get a focus, and discussed these capabilities in relation to absorptive capacity through the case study. Judd

(2013) discussed the suitability of adopting OI in the pharmaceutical industry, especially in the UK. Nigro et al. (2013) developed the use of Real Options Analysis (ROA) in the OI field for the R&D project evaluation and R&D portfolio selection in the biopharmaceutical firms. Most recently, Schuhmacher et al. (2013) found the evidence that pharmaceutical companies with more than 50% of their R&D project portfolio from external sources have better financial performance, and characterized four new types of open innovator which describe current open R&D models in the pharmaceutical industry.

These previous studies have contributed to the understanding of OI in the pharmaceuticals on the project evaluation (Nigro et al., 2013), organizational mode (Bianchi et al., 2011; Chiaroni et al., 2009), absorptive capability (Talaga, 2009; Hughes and Wareham, 2010), partnership management (Fetterhoff and Voelke, 2006; Melese et al., 2009). All the studies provide quite positive support and evaluation for the OI adoption in the pharmaceutical industry by qualitative analysis. To the best knowledge of the author, only one study (Schuhmacher et al., 2013) mentioned evaluating the performance of OI adopters in the pharmaceuticals based on data analysis, while this descriptive analysis only focus on firms' financial performance which makes it still far away from the final answer. Therefore, the most important question and the top level question for this research– whether OI is the best strategic prescription for the pharmaceutical industry – is still waiting to be answered.

1.2 Research Design

Open innovation seems to provide a broad range of benefits, while the most important one is the chance to increase the productivity of own R&D (Ili et al, 2010). Therefore, the R&D efficiency should improve after adoption of OI if it works. Based on this idea, the research is designed to develop the indices of innovation and measure the performance of OI through comparing the performance of the R&D efficiency before and after

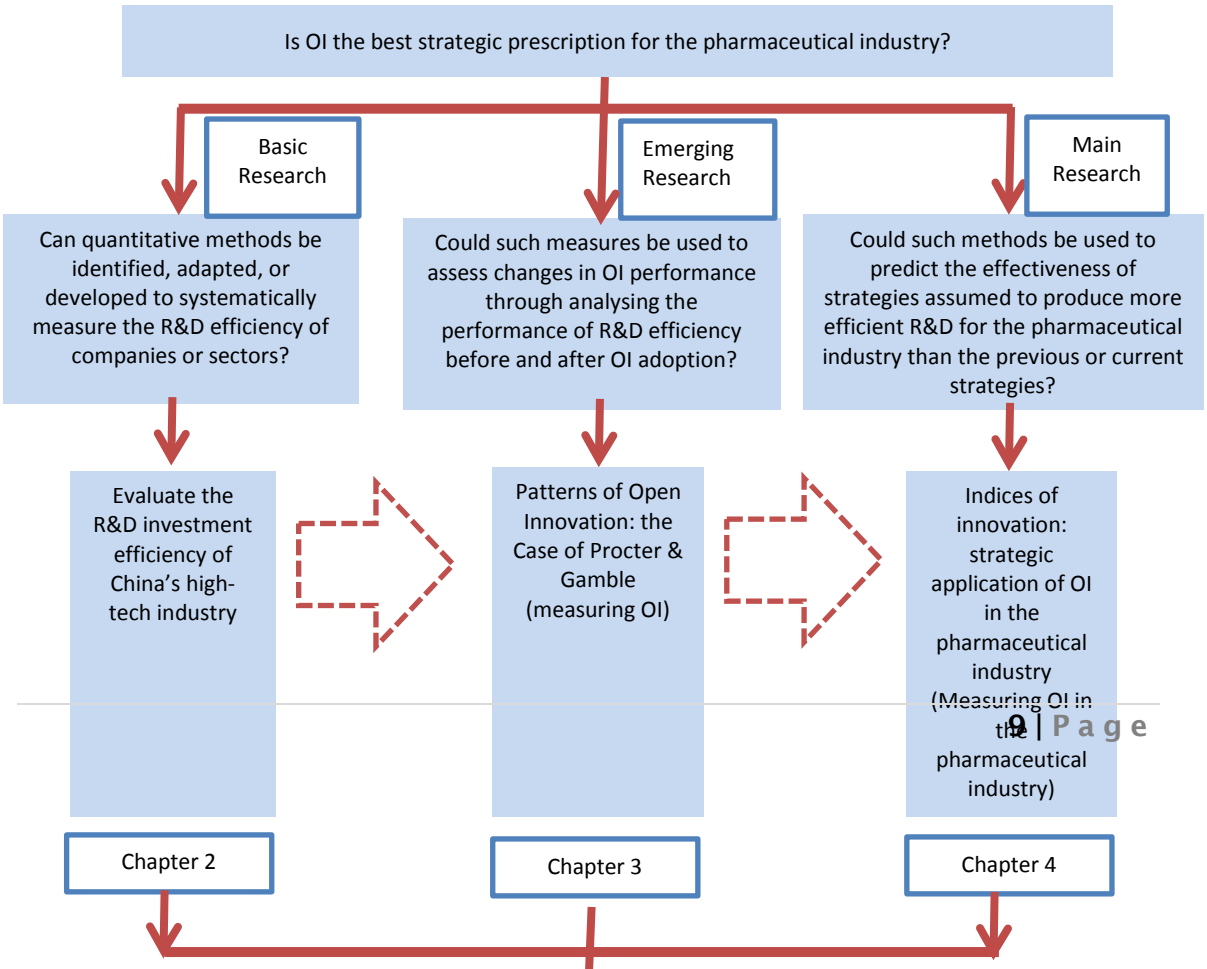
OI adoption. This research has been divided into three steps corresponding to three important questions:

(1) Can quantitative methods be identified, adapted, or developed to systematically measure the R&D efficiency of companies or sectors?

(2) Could such measures be used to assess changes in OI performance through analysing the performance of R&D efficiency before and after OI adoption?

(3) Could such methods be used to test or predict the effectiveness of strategies proposed or assumed to produce more efficient R&D for the pharmaceutical industry than the previous or current strategies?

This chapter addressed the preceding literature and historical innovation context of the research. The three main research questions defined above are then addressed respectively in the following chapters (papers). Chapter 2 discusses and explores the techniques as adopted and adapted in this research for the R&D efficiency measurement through analysing the R&D efficiency performance in China's high-tech industry. Chapter 3 explores the way for measuring the OI performance through analysing the R&D efficiency, the case study of Procter and Gamble which is widely recognised as the early OI adopter has been developed, and also the 'indices of innovation'. Chapter 4 describes 'indices of innovation' as developed based on the first two papers, to measure whether adopting OI has led to better R&D efficiency in the pharmaceutical industry. The final conclusion, along with policy implications and future research questions are summarised in Chapter 5. The overall research logic is summarized


Is OI the best strategic prescription for the pharmaceutical industry?
Basic Research
Emerging Research
Main Research
Can quantitative methods be identified, adapted, or developed to systematically measure the R&D efficiency of companies or sectors?
Could such measures be used to assess changes in OI performance through analysing the performance of R&D efficiency before and after OI adoption?
Could such methods be used to predict the effectiveness of strategies assumed to produce more efficient R&D for the pharmaceutical industry than the previous or current strategies?
Evaluate the R&D investment efficiency of China's high-tech industry
Patterns of Open Innovation: the Case of Procter & Gamble (measuring OI)
Indices of innovation: strategic application of OI in the pharmaceutical industry (Measuring OI in the pharmaceutical industry)
Chapter 2
Chapter 3
Chapter 4

2. Chapter 2: Evaluating R&D Investment Efficiency in China's High-tech Industry

Abstract

Research and development (R&D) investment activity plays a crucial role in developing high-tech industries, especially in large developing countries. In recent decades, China has made sustained investments in its domestic high-tech industries, with the goal of increasing their productivity. This paper investigates the effect of this investment on relative R&D efficiency across China's high-tech sectors. Data Envelopment Analysis (DEA) was used to generate quantitative indices for sector comparisons; this technique which has been applied widely to evaluate the efficiency and productivity of industries and sectors. It generates TE, PTE and SE, which respectively measure the overall R&D investment efficiency, the pure R&D investment efficiency excluding scale effects, and various classes of the returns to scale of R&D investment. The analysis of this study indicates that overall R&D investment efficiency did not increase from 1998 to 2009, despite R&D expenditure increasing by 2188%. Over the same period, most sectors suffered from decreasing returns to scale (DRS), presumably also reflecting the inefficient R&D investment. Most of the sectors showed significant fluctuation on R&D investment efficiency over the period. This research result indicates that the problem of China's high-tech industry may be from the inefficiency of its technology commercialization processes, and therefore represents a critical parameter for policy makers and managers seeking to improve the performance of China's high-tech industry.

Keywords

Data Envelopment Analysis (DEA); R&D investment efficiency; China's high-tech industry; Technical efficiency (TE); Pure technical efficiency (PTE); Scale efficiency (SE).

2.1 Introduction

The importance of innovation has been widely acknowledged and the growth of high-tech industry has frequently been regarded as the one of most important indices for economic development (Rosegger, 1996; Grossman and Helpman, 1991; Cainelli et al., 2006). This phenomenon is no longer confined to the developed countries; countries from emerging markets have been investing increasingly into the high-tech industry to enhance their capacity for innovation. Although the increasing level of investments would seem likely to promote innovation, it is not clear that this is occurring (see Zabala-Iturriagagoitia et al., 2007). In addition, because of the limitation of resources, investment should be prioritized strategically across the various high-tech industries in order to realize optimal levels of innovation and productivity.

Research and development (R&D) activities provide the basis for many corporate science and technology activities, and play a crucial role in enhancing the competitiveness of companies in achieving sustained and rapid growth (Zhong et al., 2011). In order to improve R&D efficiency, it is first necessary to measure it, and so quantitative methods have been adapted to analyze the efficiency of R&D investment as an index of innovation. R&D investment efficiency is improved when for the same amount of R&D input more innovation output is generated, or when less R&D input is needed for generating the same amount of innovation output. Simply, innovation efficiency can be defined as the ratio of outputs over inputs (Hollanders and Celikel-Esser, 2007). Inputs include R&D expenditure, R&D personnel and knowledge capital stock, and outputs indicate the technical improvement and economic benefit from the R&D activities.

Measuring the R&D investment efficiency from the quantitative perspective is needed to provide practical indices for measuring and managing it, especially in the developing countries. Most of the relevant

research is based on advanced markets in which the innovation production systems are more mature (for example, Mansfield, 1998; Timmer, 2003). Although the experiences from these countries are very useful, the particular characteristics of emerging markets decide the necessity and importance of measuring and understanding the R&D investment efficiency in developing countries.

As one of the main developing countries in the world, China has been making great efforts to develop its R&D capacity for high-tech industry. Firstly, China's government figures indicate that spending on R&D has increased dramatically in recent years. R&D spending has increased by 2794.044% from 1991 to 2008. Its R&D intensity, namely the R&D spending as a percentage of GDP, climbed from 0.76% in 1999 to 1.54% in 2008. On the global landscape, although China's global share in terms of gross R&D expenditure remains lower, it is currently the second to third highest investor in R&D, following the US and Japan. Secondly, from 1995 to 2004, the number of researchers in China increased by 77%. In 2006, China ranked second worldwide with 926,000 researchers, just behind the U.S. and ahead of Japan. Thirdly, China's patent applications and authorizations showed a double-digit increase, with an average increase of 16.7% and 25%, respectively, from 1986 to 2007. China's world-ranking in terms of patent application rose from the 22nd place in 1997 to the 7th place in 2007 (China Science and Technology Indicators, 2009; The Royal Society, 2011).

With these growing investments aimed at increasing innovation and productivity, China has emerged as the largest high-tech exporting country with 16.9% of global market share in high-tech products in 2006 (Eurostat's high-tech statistics, 2009). However, China is still far away from the developed countries in independent innovation capability and commercialization capability. For example, In terms of trade forms, 82% of high-tech exports belong to processing trade in 2009, i.e., "processed high-tech" exports. Under the category of high-tech products, what China actually exported is low skilled labour rather than technology (Xing, 2011).

A significant literature about the study of China's R&D capability has developed over the last decade. Zhang et al. (2003) made a contribution about the relationship between ownership and R&D efficiency based on a sample of 8341 Chinese firms. Guan et al. (2006) studied the relationship between competiveness and technological innovation capability based on the analysis of 182 industrial innovative firms in China. Liu and Buck (2007) investigated the impact of different channels for international technology spillover on the innovation performance of Chinese high-tech industries. Guan and Chen (2010) developed the measurement of the innovation production process and applied it to a cross-region study of China's high-tech innovation. Zhong et al. (2011) evaluated the relative efficiencies of 30 regional R&D investments in 2004.

Research on the R&D productivity in China began with the studies of elements affecting the performance of China's innovation capability. Later on, researchers switched their attention to the measurement of performance on China's R&D productivity. However, the relative studies in the literature only focused on the cross-region comparison on R&D investment efficiency. So the research to systematically measure the performance of R&D efficiency performance in China's high-tech industry based on industry level and the comparison across sectors and sub-sectors is still needed to help understand the innovation capability of China's high-tech industry.

The main econometric methodologies for efficiency and productivity analysis are Data Envelopment Analysis (DEA) and stochastic frontier analysis (SFA). SFA has been adapted to develop the studies about the R&D productivity. For example, Zhang et al. (2003) applied SFA approach to examine the effects of various types of ownership on R&D efficiency of Chinese firms. Wang (2007) applied SFA approach to evaluate the relative efficiency of aggregate R&D activities cross 30 countries and observed a positive correlation between R&D performance and income level. However, there are two disadvantages for SFA technique which make it unsuitable for this research: it only can be used when the production function model

is known, and more importantly it cannot accommodate many inputs and many outputs (Avkiran and Rowlands, 2008; Iglesias et al., 2010; Reinhard et al., 2000). DEA, in contrast, has several advantages in terms of evaluating the relative efficiency of R&D activities: firstly, DEA is especially valuable where the relative importance of the various inputs employed and outputs produced by a DMU (decision making units) cannot be defined; secondly, DEA allows for efficiency evaluation without necessitating the specification of a functional representation of the R&D/knowledge production technology; thirdly, R&D activities typically involves multiple inputs and multiple outputs (Wang and Huang, 2007).

Therefore, Data Envelopment Analysis (DEA) was employed to evaluate the R&D investment efficiency in this research. DEA has been widely used to evaluate the efficiency and productivity of many different kinds of entities ranging from manufacturing industry to service industry, and activities including cost efficiency measurement and operating efficiency measurement, as well as in contexts from emerging market to advanced market (Cooper et al., 2004).

Specifically, in this study the following three questions were addressed: Firstly, What change did the entire R&D investment efficiency of China's high-tech industry undergo during 1998 to 2009? Secondly, what was the relative performance of China's five major high-tech sectors in terms of R&D investment efficiency? Finally, what factors triggered this performance and what are their implications for the future performance landscape?

The remainder of this paper is organized as follows. Section 2.2 explains the research design including DEA model, research procedure, variable measurement and sample selection. Section 2.3 provides the empirical results of DEA and individual output/input ratio analysis applied to the whole industry, the five high-tech sectors and sixteen sub-sectors. Finally, section 2.4 discusses the results and makes the conclusion.

2.2 Research Design

2.2.1 The DEA Model

DEA is a mathematical programming methodology, which is applied to assess production efficiency by using multiple inputs and outputs (see, e.g., Kozmetsky and Yue, 1998; Yeh, 1996). The ground breaking work done by Rousseau and Rousseau (1997, 1998) proved the potential of DEA-analysis to assess R&D activities. Subsequent studies (see, e.g., Guan and Chen, 2010; Chen et al., 2006; Zabala-Iturriagagoitia et al., 2007; Zhong et al., 2011) have provided supporting evidence for its use in evaluating the innovation efficiency, especially for the high-tech industries. Two DEA models are used in this thesis: CCR model (Charnes et al., 1978) and the BCC model (Banker et al., 1984). The CCR model is designed under the assumption that production exhibits constant returns to scale. The BCC model, on the other hand, assumes that there are variable returns to scale (Wang and Huang, 2007). Therefore, in the CCR model there is a linear relation between inputs and outputs; while in the BCC model, outputs can increase by a variable percentage, depending on its position on the efficiency frontier (Hollanders and Celikel-Esser, 2007). The following section describes the two models in more detail.

Assume that there are *n* DMUs (decision making units) ($\mathrm{DMU}_j, j = 1,2,\dots,n$**). Each** DMU_j **contains *m* inputs** x_{ij} $(i = 1,2,\dots m)$ **and *s* outputs** y_{rj} $(r = 1,2,\dots s)$**. So the m*n input matrix, *X*, and s*n output matrix, *Y*, represent the data of all *n* DMUs. The efficiency rate of a unit** DMU_j **can be generally expressed as:**

$$\frac{\text{weighted sum of outputs}}{\text{weighted sum of inputs}} = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}},$$

where $u_r (r = 1,2,\dots s)$ **and** v_i $(i = 1,2,\dots m)$ **are separately output weights and input weights. The essence of DEA models in measuring the efficiency of productive unit** DMU_j **lies in maximising its efficiency rate but subject to two conditions as follows.**

- **The efficiency rate of any other units must not be greater than one.**
- **The model must include all characteristics considered, that is the weights of all inputs and outputs must not be smaller than zero.**

Let DMU_o **be the one to be evaluated. Define** ***u*** **as an** ***s*1*** **vector of output weights (i.e.,** $u=(u_1,\cdots,u_s)$**), and** ***v*** **as an** ***m*1*** **vector of input weights (i.e.,** $v=(v_1,\cdots,v_m)$**). The input-output vector of** DMU_o **is** (x_o, y_o)**. To satisfy the two conditions, the general DEA model is defined as a linear divisive programming model:**

$$max_{u,v} \quad (uy_o/vx_o)$$

$$subject\ to \quad uY/vX \leq 1$$

$$u, v \geq 0 \qquad (1)$$

To make sure the above model has an infinite number of solutions (u, v)**, we impose** $vx_o = 1$**. Then we have**

$$max_{u,v} \quad (u'y_o)$$

$$subject\ to \quad v'x_o = 1$$

$$u'Y - v'X \leq 0$$

$$u', v' \geq 0 \qquad (2)$$

where u', v' **are the notions changed from** u, v **reflecting the transformation.**

By using the duality in linear programming, the model (2) can be converted into a linear programming model which is called CCR model or BCC model by adding a constraint. In particular, let θ **be the efficiency score and** λ **be a n*1 vector of constants. The CCR model is defined as:**

$$\min_{\theta,\lambda} \ \theta$$

$s.t. \quad \theta x_o \geq X\lambda$

$Y\lambda \geq y_o$

$\lambda \geq 0$ (3)

Here θ is a scalar and its value is not greater than one. With a value equals to one, it indicates such DMU is technically efficient.

The BCC model adds the convexity constraint. It is shown as follows:

$\min_{\theta,\lambda} \ \theta$

$s.t. \quad \theta x_o \geq X\lambda$

$Y\lambda \geq y_o$

$\mathbf{\Sigma}\lambda = 1$

$\lambda \geq 0$

(4)

Again, DMU_o is technically efficient if θ is equal to one.

2.2.2 Research Procedure

The study looks at three levels. Firstly, at the industry level it examines the R&D investment efficiency of the whole China's high-tech industry between 1998 and 2009. Secondly, at the sector level, the performance of five China's high-tech sectors on the R&D investment efficiency from 1998 to 2008 is evaluated. The evaluation is based on the DEA test and individual output/input ratio analysis. Finally, in order to explore more deeply any efficiency changes associated with the R&D investment, the performance of 16 sub-sectors over time is examined by comparison of the years 2001 and 2008.

Both the CCR and BCC variants of the DEA model are employed in this research. This permits the calculation of the technical efficiency (TE) score, pure technical efficiency (PTE) score and scale efficiency (SE) score. The TE

score is calculated as the ratio of the actual productivity to the maximum attainable productivity (Sharma and Thomas, 2008). It is calculated in the CCR DEA model under the assumption of constant returns to scale: in this case, the maximum attainable productivity is presented as the distance from the constant returns to scale frontier. The PTE score is calculated in the BCC DEA model as the ratio of the actual productivity to the maximum attainable productivity: in this case, the maximum attainable productivity represents the distance from the variable returns to scale frontier, which means, in contrast to the TE score, the PTE score excludes scale effects (Gulati, 2011). The SE score can be derived from the BCC model if the technology exhibits variable returns to scale. If there is a difference between the TE score and PTE score for a particular sector DMU, then this unit is characterized by scale inefficiency (Wang and Huang, 2007). The SE score is then defined as the ratio of constant returns to scale Technical Efficiency to the Variable Returns to Scale Technical Efficiency (Sharma and Thomas, 2008). Once the BCC is established, the analysis can be used to determine whether a particular DMU is experiencing increasing, constant, or decreasing returns to scale (Chen et al., 2006). Thus the DEA analysis process generated three key indices: the SE scores, PTE scores and TE scores. These scores can then be used to evaluate the R&D investment efficiency by industry, sector, or company over time.

2.2.3 Variable Measurement and Sample Selection

2.2.3.1 Input Parameters

Industrial R&D investment is often a complex process, with multiple inputs and outputs. One of the advantages of adopting the DEA analysis is that multiple inputs and outputs can be measured more than can be accommodated using conventional econometric techniques (Cooper et al., 2004). This multiple DEA analysis study was begun by selecting the appropriate inputs and outputs based on the previous literature. The inputs to innovation production activities are physical resources and

mainly manpower, which are usually measured in annual total R&D expenditures and R&D personnel (Wang and Huang, 2007).

The R&D expenditure refers to the total internal expense, covering all projects involving fundamental research, applied research or experimental development, as well as the 'overhead' expenses related to the management and services for these projects (Zhong et al., 2011). In this case, the internal expenditure of R&D funding is employed to represent the R&D expenditure index. Since the study focuses on industrial R&D investment efficiency, only internal expense is included (exclusive of external). This R&D expense input index has been widely used, and found to be suitable in previous studies (Guan and Chen, 2010; Zhong et al., 2011; Chen et al., 2006).

The R&D personnel input figure includes all staff are engaged in either fundamental research, application research or experimental development (Zhong et al., 2011). The number of research staff on R&D activities can be taken as the R&D personnel input index. However, based on the previous studies, the full-time equivalence (FTE) cost of scientists and technologists on R&D activities was adopted as the R&D personnel input index, since the R&D personnel input index is considered to be more accurate than the research staff number.

However, for the macro-level analysis such as the industry study on country level, the effect of knowledge capital stock should also be considered, especially for the developing country due to their knowledge capital stock is changing dramatically and has strong potential impact to the country's future innovation performance. The support evidence comes from the basic hypothesis behind Romer's knowledge production function (Romer, 1990), which is the idea generation does not "fall from heaven", but derives from prior knowledge stock available and human capital (Guan and Chen, 2010). Therefore, knowledge capital stock is employed as the third input in this research. The accumulated patents stock is used as a proxy measure of knowledge capital stock, which is consistent with prior studies (see Furman et al., 2002; Hu and Mathews, 2008).

2.2.3.2 Output Parameters

The process of innovation production is complex. If we consider all the details in this process, it will be impossible to measure its performance. Therefore, the former studies tried to simplify the whole process to make it possible to be measured, without affecting the final result (see Guan and Chen, 2010). The acceptable process could be a system that first obtains technology, then transforms the technology into specific product development achievements, and finally to output by extending R&D activities to productive development and commercial activities (Zhong et al., 2011). So the main outputs of industrial R&D activities are not only technical improvement, but also include economic benefit.

The initial, direct outcome of R&D investment is technical improvement. The patents may be the most appropriate proxy of this technical improvement (see Guan and Chen, 2010; Wang and Huang, 2007). Although not all inventions are patentable or patented and the inventions which are patented have different quality (Griliches, 1990), former studies including empirical evidence indicate that patents provide a fairly reliable measure of innovation production activities (see Acs et al., 2002; Pakes and Griliches, 1984). Therefore, this study employed the number of patent applications to measure the technical improvement. Here the number of patent applications refers to the quantity of accepted patent applications given to the sector/sub-sector by the patent office in the given year.

Economic benefit is the key purpose of company's R&D investment behaviour. The success or failure of innovation activities on economic benefit could be observed from the performance of sales and revenues, particularly on new products. As Freeman and Soete (1997) discussed, an innovation in the economic sense is accomplished only with the first commercial transaction. Therefore, two indices – value-added from new products and the sale revenue for new products - which record the economic performance of new products, are adapted in this research. Here value-added from new products refers to the value-added achieved from the development of new products in the given year. The sale revenue for

new products refers to the sale revenue achieved from sales of new products in the given year.

2.2.3.3 Time Lag Effects

Previous studies indicated that time lags between the inputs and the outputs could be important factors. However, there is no generally accepted time lag for R&D inputs and outputs. Goto and Suzuki (1989) studied the average time before the sale of a product resulting from R&D technology based on survey data for Japanese firms and found that the time lag varied among major industries. Adams and Griliches (2000) studied the relationship between research output and R&D in eight fields of university research, and considered the time lag to be 5 years. Guellec and van Pottelsberghe de la Potterie (2004) considered the lag effects of business and public R&D capital stocks on multi-factor productivity growth of 16 countries to be 1 and 2 years, respectively. Wang and Hua (2007) conducted a preliminary test, which showed that a 3-year lag is most appropriate in the study of relative efficiency of R&D activities across countries when using aggregate data. Guan and Chen (2010) conducted a preliminary test of time lags, using a series of correlation and regression analyses, and concluded that the most appropriate time lags for the efficiency study of China's R&D activity would be 2-year lag for the R&D process and 1-year lag for the commercialization process. Following these studies, the preliminary test was given in this study aimed to find the suitable time lag between inputs and outputs, which shows that 2-year lag for the applied patent number and 1-year lag for the value-added from new products and the sale revenue for new products are appropriate (For example, if the dataset of the inputs is from the statistical data in 2003, the output data of the applied patent number should come from the statistical data in 2005 with 2-year lag, and the outputs data of the value-added from new products and the sale revenue for new products should come from the statistical data in 2006 with 1-year lag).

The robustness of this selection was tested in two ways. There are normally two ways to test the robustness of DEA analysis results: firstly,

by choosing two consecutive cross-sectional datasets to provide an approach for a robustness test by longitudinal comparisons (see Guan and Chen, 2010; Zabala-Iturriagagoitia et al., 2007); secondly, by varying the length of time lags to provide a robustness test (e.g., Hollanders and Celikel-Esser, 2007). Due to this study utilising panel data, the cross-sectional dataset already included into the data analysis. For the other robustness test, two different time lags were selected and adapted, in order to see whether current introduction of time lag has an effect of the final results. These two time lags are 2 years' lag which shows that 1-year lag for the applied patent number and 1-year lag for the commercial revenue, and 4 years' lag which shows 3-year lag for the applied patent number and 1-year lag for the commercial revenue. The analysis results show that, although the exact score per sector per year has changed, the general performance of each sector looks similar which indicates that current introduction of time lag has limited effect on the general analysis results. And because this 3 years' time lag was selected based on preliminary test, it is more suitable to be adapted in this study. The analysis of results from the other two time lags (2 years' lag and 4 years' lag) can been seen in the appendix (Table A.1-6).

Another potential issue is the time lag difference among sectors. The product development lead time in different sectors is different (see Arundel et al., 1995). To avoid this difference affecting the research result, a test of time lag was needed. Based on the above tests which adapted two other time lag choices (2-year time lag and 4-year time lag), we can see that for most of sectors the performance and ranking are stable in the test results. This indicates that the time lag adopted in this study is broadly suitable. However, from the experience in mature market, the Medicine sector - as defined in this database - normally has much longer product lead time since its characteristics and regulation (see Munos, 2009). Therefore, one test was developed through adoption of longer time lag for the Medicine sector to observe whether the time lag difference has an effect for the result. 8-year time lag was employed in this test, in line with

previous studies (Hashimoto and Haneda, 2008; Odagiri and Murakami; 1992).

The test result is documented in the Appendix (Table A.7-9). Due to the limitations of the time lag effect, only a short period performance of Medicine sector (2003-2008) could be observed. Comparing the research results from four tests of time lag, the general performance of Medicine sector with 8-year time lag is consistent with the ones from other tests which showed the trend of improvement on R&D efficiency. However, with an 8-year time lag, the R&D efficiency of Medicine sector ranked at second among all sectors, even higher than the Electronics sector (EEACE) and the Instrument sector (MEAMI), which was not observed at other time lags. With the comparison of expenditure for new product development, labour productivity and gross industrial output value, Medicine sector shows lower performance than Electronics sector (see Ministry of Science and Technology of the People's Republic of China, 2011). The differing test results indicate that the 8-year time lag is not suitable for China's medicine sector. The 8-year time lag is broadly accepted in pharmaceutical industry studies of mature markets such as Japan, America and Europe (for example Hashimoto and Haneda, 2008). However, comparing with mature markets, the China's medicine sector has a different situation. China was still staying at the imitative innovation stage in pharmaceutical industry during the test period of 1993-2008 (Ding et al., 2011). One of the potential explanations is that the time required for clinical trials and drug approvals in China is shorter than time in mature markets (Wang and Kang, 2005). Therefore, based on the analysis, the time lag of Medicine sector adapted in this research is consistent with the one for other sectors.

2.2.3.4 Data Sources

As the subject of this first study is China's high-tech industry, both data of inputs and outputs from 1995-2009 were taken from China Statistics Yearbook on High-tech industries, as compiled by the Chinese State Statistical Bureau. China's high-tech industry is divided into 5 sectors and 21 sub-sectors according to the categorization in the yearbook. The

dataset includes sectors of Manufacture of Medicines (with 3 sub-sectors), Manufacture of Aircraft and Spacecraft (with 2 sub-sectors), Manufacture of Electronic Equipment and Communication Equipment (11 sub-sectors), Manufacture of Computers and Office Equipment (with 3 sub-sectors), and Manufacture of Medical Equipment and Measuring Instrument (with 2 sub-sectors). Their categorization of China's high-tech industry in that yearbook is shown in Table 2.1. Based on that categorization, the R&D investment efficiency could be analysed at three distinct levels: the whole high-tech industry, the five big high-tech sectors and the 16 high-tech sub-sectors. The primary results are summarized below. This is the most up-to-date and detailed data on China's high-tech industry currently available. China Statistics Yearbook on High-tech industries is published every year, and is free to download for both Chinese and English versions from the official website of Chinese State Statistical Bureau.

All financial inputs and outputs were expressed in Chinese currency, as 10,000s RMB$ Since the duration of the sample period was more than ten years, the expenditure indicators were adjusted by comparable price index in 1995, to remove the inflation impact over period. The basic statistics for the main variables used to study the R&D performance of China's high-tech industry from three levels (whole industry, sectors and sub-sectors) are reported respectively in Table 2.2, Table 2.3 and Table 2.4.

Table 2.1: Categories of China's high-tech industry

NO.	Sectors	Abbr.	NO.	Sub-sectors*
1	Manufacture of Medicines	Medicines	1	Manufacture of Chemical Medicine
			2	Manufacture of Finished Traditional Chinese Herbal Medicine
			3	Manufacture of Biological and Biochemical Chemical Products
2	Manufacture of Aircrafts and	AAS	4	Manufacture and Repairing of Airplanes

	Spacecraft		5	Manufacture of Spacecraft
3	Manufacture of Electronic Equipment and Communication Equipment	EEACE	6	Manufacture of Communication Transmitting Equipment
			7	Manufacture of Communication Exchanging Equipment
			8	Manufacture of Communication Terminal Equipment
			9	Manufacture of Radar and Its Fittings
			10	Manufacture of Broadcasting and TV Equipment
			11	Manufacture of Electronic Vacuum Appliances
			12	Manufacture of Semiconductor Appliances
			13	Manufacture of Integrate Circuit
			14	Manufacture of Electronic Components
			15	Manufacture of Domestic TV Set and Radio Receiver
			16	Manufacture of Other Electronic Equipment
4	Manufacture of Computers and Office Equipment	CAOE	17	Manufacture of Entire Computer
			18	Manufacture of Computer Peripheral Equipment
			19	Manufacture of Office Equipment
5	Manufacture of Medical Equipment and Measuring Instrument	MEAMI	20	Manufacture of Medical Equipment and Appliances
			21	Manufacture of Measuring Instrument

*There are 21 sub-sectors in categories of China's high-tech industry. Due to the lack of data in some sub-sectors, only 16 sub-sectors met the completeness criteria for this research. (Sub-sectors NO. 5, 7, 9, 10, 19 were excluded).

Table 2.2: Descriptive statistics for main variables in the whole industry study

Variables	Mean	Standard deviation	Maximum	Minimum
R&D expenditure	1616497	1296985.664	4084257.48	178474.1
Full-time equivalent of R&D personnel	111700.7	38337.46342	188986.54	57838
Accumulated patents stock	2518	2627.829523	8141	312
Patent applications	12417.25	13564.50523	39656	713
Value-added from new	56663054	33088083.42	107298051	14243655

products				
Sale revenue for new products	55305287	33364143.32	108102978.8	12272350
Sample size of DMU	12			

Data sources: Data comes from China Statistics Yearbook on High-tech industries, as compiled by the Chinese State Statistical Bureau. China's high-tech industry is divided into 5 sectors and 21 sub-sectors according to the categorization in the yearbook. This is the descriptive statistics of data in the first level study about the whole China's high-tech industry. Here the unit of R&D expenditure, value-added from new products and sale revenue for new products is 10,000 RMB$; the unit of patent applications and accumulated patent stock is item.

Table 2.3: Descriptive statistics for main variables in 16 sub-sectors study

Variables	Mean	Standard deviation	Maximum	Minimum
R&D expenditure (2001)	23305	24029.9	88187.82	2944.948
R&D personnel (2001)	3343.875	3520.659	14425	844
Accumulated patents stock (2001)	44.625	56.74725	175	4
Patent applications (2001)	106.4375	98.98079	331	6
Value-added from new products (2001)	1696668	2145986	7447041	132983.9
Sale revenue for new products (2001)	1648856	2039920	6811947	106166.1
R&D expenditure (2008)	137491.6	119556.2	461649.2	18802.78
R&D personnel (2008)	7373.378	6841.567	27720.36	1262.46
Accumulated patents stock (2008)	229.5	181.1706	501	11
Patent applications (2008)	1074.938	920.0535	3614	47
Value-added from new products (2008)	4732791	5812012	20841837	629713.7
Sale revenue for new products (2008)	4650793	5812697	20279665	584431.5
Sample size of DMU	55			

Data sources: Data comes from China Statistics Yearbook on High-tech industries, as compiled by the Chinese State Statistical Bureau. China's high-tech industry is divided into 5 sectors and 21 sub-sectors according to the categorization in the yearbook. This is the descriptive statistics of data in the third level study about the comparison research of 16 sub-sectors from China's high-tech industry in 2001 and 2008. Here the unit of R&D expenditure, value-added from new products and sale revenue for new products is 10,000 RMB$; the unit of patent applications and accumulated patent stock is item.

Table 2.4: Descriptive statistics for main variables in five sectors study

Variables	Mean	Standard deviation	Maximum	Minimum
R&D expenditure (Medicines)	165645.2	110542.9	368216	42785
R&D personnel (Medicines)	13841.83	3370.09	19584.38	9528
Accumulated patents stock (Medicines)	417	326.526	1134	113
Patent applications (Medicines)	1294.909	1026.891	3056	257
Value-added from new products (Medicines)	3866045	2261652	8279468	1273707

Sale revenue for new products (Medicines)	3536810	2130015	7705194	1056384
R&D expenditure (AAS)	152167.6	76563.53	256195.5	65067
R&D personnel (AAS)	30680.5	6758.321	40748	18145
Accumulated patents stock (AAS)	108.7273	51.74957	192	38
Patent applications (AAS)	247.2727	229.9	810	79
Value-added from new products (AAS)	2095044	1227502	3822463	428448.7
Sale revenue for new products (AAS)	1952164	1193183	3840623	352557.1
R&D expenditure (EEACE)	859331.6	725592.8	2163308	51289
R&D personnel (EEACE)	44156.15	22345.48	95091.24	15398
Accumulated patents stock (EEACE)	1104	1326.545	4268	84
Patent applications (EEACE)	6499.091	7946.413	24680	243
Value-added from new products (EEACE)	30395572	15549722	54364062	9887901
Sale revenue for new products (EEACE)	29618161	15819338	54883987	8173422
R&D expenditure (CAOE)	159545.3	142948.5	400446.3	5473
R&D personnel (CAOE)	7647.945	4863.667	17483.75	1355
Accumulated patents stock (CAOE)	171.1818	227.9126	711	6
Patent applications (CAOE)	1177.727	1178.783	3266	34
Value-added from new products (CAOE)	14116942	10742944	35056725	2228038
Sale revenue for new products (CAOE)	13903414	10645668	34329416	2293097
R&D expenditure (MEAMI)	55466.04	42979.41	152869.9	13860
R&D personnel (MEAMI)	8348.066	1094.947	11132.08	6788
Accumulated patents stock (MEAMI)	205.9091	177.1798	591	41
Patent applications (MEAMI)	722	756.983	2634	100
Value-added from new products (MEAMI)	1586269	1242651	4186301	425559.7
Sale revenue for new products (MEAMI)	1494948	1158180	3822655	396889.9
Sample size of DMU	32			

Data sources: Data comes from China Statistics Yearbook on High-tech industries, as compiled by the Chinese State Statistical Bureau. China's high-tech industry is divided into 5 sectors and 21 sub-sectors according to the categorization in the yearbook. This is the descriptive statistics of data in the second level study about the five sectors in China's high-tech industry. Here the unit of R&D expenditure, value-added from new products and sale revenue for new products is 10,000 RMB$; the unit of patent applications and accumulated patent stock is item.

2.3 Empirical Results

2.3.1 Overall Efficiency of China's High-tech Industry

The R&D investment efficiency across the high-tech industry sectors was examined for the period 1998 to 2009, and the final results, including TE score, PTE score and SE score are summarized in Table 2.5. Examination at

the whole high-tech industry level indicates that the R&D investment efficiency in China's high-tech industry was mostly unchanged over the period 1998 to 2009 (see Table 2.5). This was despite rising R&D expenditure over the period.

Table 2.5: Efficiency scores and returns to scale of the whole high-tech industry in years 1998-2009

Year	Technical Efficiency	Pure Technical Efficiency	Scale Efficiency	Returns To Scale
1998	1	1	1	-
1999	0.904	1	0.904	irs
2000	1	1	1	-
2001	1	1	1	-
2002	1	1	1	-
2003	1	1	1	-
2004	1	1	1	-
2005	1	1	1	-
2006	0.948	0.975	0.973	drs
2007	1	1	1	-
2008	1	1	1	-
2009	1	1	1	-
Average	0.988	0.998	0.99	

irs and drs stand for increasing and decreasing returns to scale, respectively.

The only two obvious changes were the downturns in years 1999 and 2006. Both of these appear to result from reductions in Scale Efficiency (SE); however, the first downturn was associated with increasing returns to scale (IRS) and the second with decreasing returns to scale (DRS). Except for these two years, all the other R&D investment efficiencies from 1998 to 2009 were unchanged. The potential conclusion is that, even with more than ten years development, the R&D investment efficiency in China's high-tech industry has not exhibited any dramatic improvement.

2.3.2 Patents Performance

This result suggests a disappointing prospect for the development of China's high-tech industry investment. To investigate further the factors

which may underlie the unchanged efficiency, the growth ratios of the inputs and outputs were analysed further (Figure 2.1). This analysis showed that although increasing R&D expenditure appeared to be correlated with a dramatic increase in the number of patent applications, there only appeared to be a limited economic benefit in terms of new high-tech product revenues. This finding in turn may suggest that although increasing R&D investment (inputs) does appear to have improved the efficiency of technology production in terms of patents, this improvement did not result in a complementary increase in new product revenue, suggesting that the commercialization process for technology was still inefficient. This would explain, at least in part, the flat R&D performance of the whole high-tech industry over the period of observation. However, this does not rule out a positive longer-term effect; this point should be returned to in the discussion.

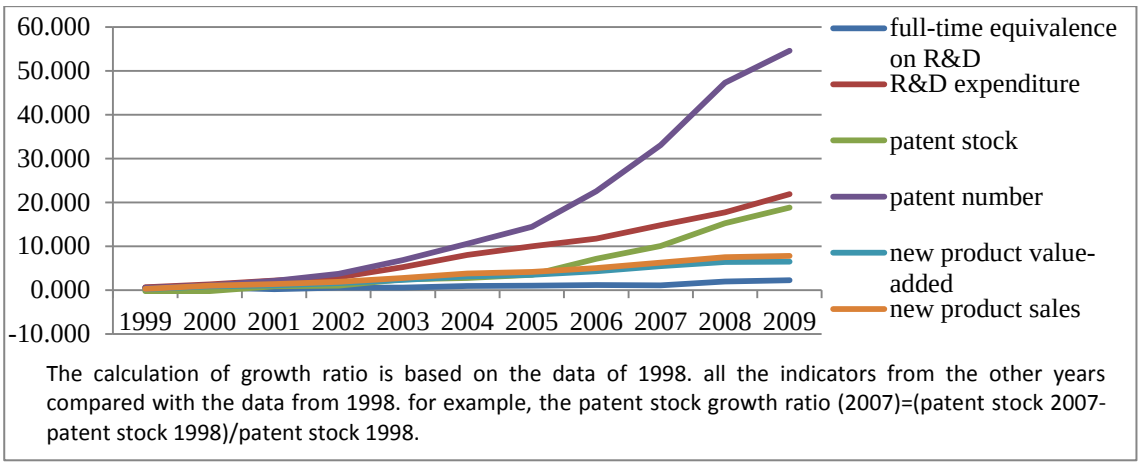


Figure 2.1: The growth ratio of R&D investment inputs and outputs

2.3.3 Further Analysis

2.3.3.1 Technical Efficiency

The TE scores reflect the overall R&D investment efficiency. Most of the sectors showed significant fluctuation over the period (see Table 2.6 and Figure 2.2). The R&D investment efficiency of the Computer sector (CAOE) was consistently the highest until 2006. The Electronics sector (EEACE)

and the Instrument sector (MEAMI) followed the Computer sector until 2006, but then overtook it in 2007 and 2008. Aerospace (AAS) was the lowest-performing sector of the five high-tech sectors.

Table 2.6: Technical efficiency scores of five sectors in years 1998-2008

Year	Medicines	AAS	EEACE	CAOE	MEAMI
1998	0.381	0.102	0.598	1	0.459
1999	0.373	0.141	0.525	1	0.507
2000	0.333	0.157	0.634	0.72	0.706
2001	0.468	0.089	0.411	0.833	0.643
2002	0.538	0.139	0.46	0.765	0.571
2003	0.473	0.123	0.43	1	0.693
2004	0.533	0.199	0.506	1	0.622
2005	0.55	0.096	0.663	1	0.993
2006	0.771	0.172	0.745	0.956	0.632
2007	0.689	0.339	1	0.951	0.859
2008	0.633	0.341	1	0.887	1
Average	0.522	0.173	0.634	0.919	0.699
Rank	4	5	3	1	2

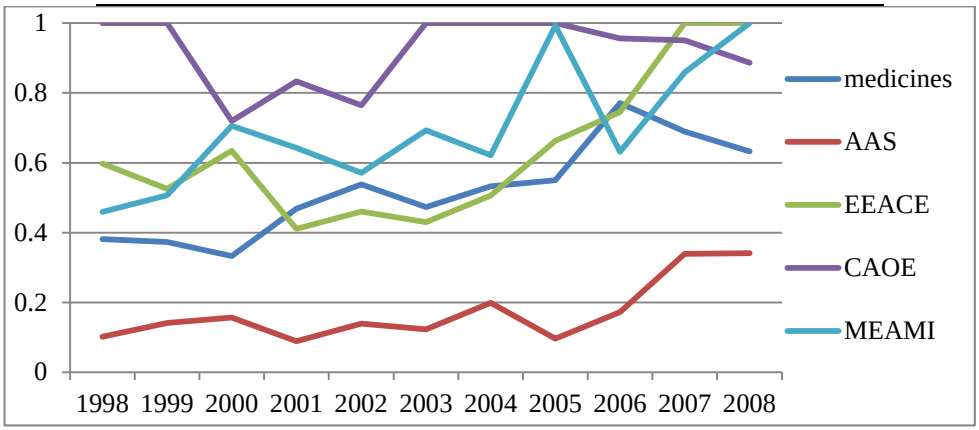


Figure 2.2: The annual variation of the R&D investment TE in five high-tech sectors from 1998 to 2008

2.3.3.2 Pure Technical Efficiency (PTE)

The PTE scores, which reflect the pure R&D investment efficiency excluding scale effects, showed a similar pattern of fluctuation and change to the TE analysis. The Computer sector achieved the highest and most consistent PTE scores from 1998 through to 2008 (see Table 2.7 and Figure 2.3). The PTE scores of the Electronics sector were the second

highest but fluctuated more over the period. All the other three sectors showed an improvement in their PTE scores over the period. Over this period, the Aerospace sector also had the lowest PET scores, echoing the pattern of TE results.

Table 2.7: Pure technical efficiency scores of five high-tech sectors in years 1998-2008

Year	Medicines	AAS	EEACE	CAOE	MEAMI
1998	0.393	0.104	1	1	0.55
1999	0.381	0.144	0.818	1	0.566
2000	0.335	0.162	1	0.792	0.782
2001	0.47	0.111	0.759	1	0.694
2002	0.539	0.163	0.794	0.874	0.605
2003	0.474	0.153	0.838	1	0.72
2004	0.572	0.206	1	1	0.634
2005	0.588	0.165	0.936	1	1
2006	0.846	0.193	0.808	1	0.637
2007	0.689	0.353	1	1	0.869
2008	0.647	0.402	1	1	1
Average	0.539	0.196	0.905	0.97	0.732
Rank	4	5	2	1	3

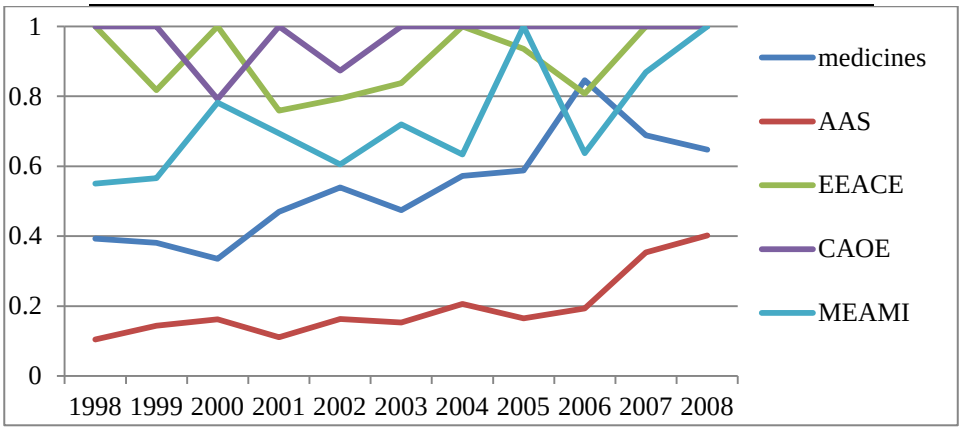


Figure 2.3: The annual variation of the R&D investment PTE in five high-tech sectors from 1998 to 2008

2.3.3.3 Scale Efficiency (SE)

Scale efficiency (SE) scores, which reflect various classes of the returns to scale of R&D investment, did not show any consistent pattern of change across the sectors during this period. SE was highest in the Medicine

sector, followed by Instrument and Computer sectors (see Table 2.8 and Figure 2.4).

Table 2.8: Scale efficiency scores and returns to scale of five high-tech sectors in years 1998-2008

	Medicines		AAS		EEACE		CAOE		MEAMI	
Year	SE	RTS	SE	RTS	SE	RTS	SE	RTS	SE	RTS
1998	0.97	drs	0.984	irs	0.598	drs	1	-	0.835	Irs
1999	0.978	irs	0.981	irs	0.642	drs	1	-	0.896	Irs
2000	0.995	drs	0.966	irs	0.634	drs	0.909	drs	0.903	Irs
2001	0.995	irs	0.796	drs	0.542	drs	0.833	drs	0.928	Irs
2002	0.998	irs	0.85	drs	0.579	drs	0.875	drs	0.944	Irs
2003	0.999	drs	0.801	drs	0.513	drs	1	-	0.963	Irs
2004	0.932	drs	0.966	drs	0.506	drs	1	-	0.981	Irs
2005	0.935	drs	0.583	drs	0.708	drs	1	-	0.993	Irs
2006	0.911	drs	0.892	drs	0.921	drs	0.956	drs	0.993	Drs
2007	1	-	0.958	drs	1	-	0.951	drs	0.988	Drs
2008	0.978	drs	0.848	drs	1	-	0.887	drs	1	-
Average	0.972		0.875		0.695		0.946		0.948	
Rank	1		4		5		3		2	

RTS is returns to scale. irs and drs for increasing and decreasing returns to scale, respectively.

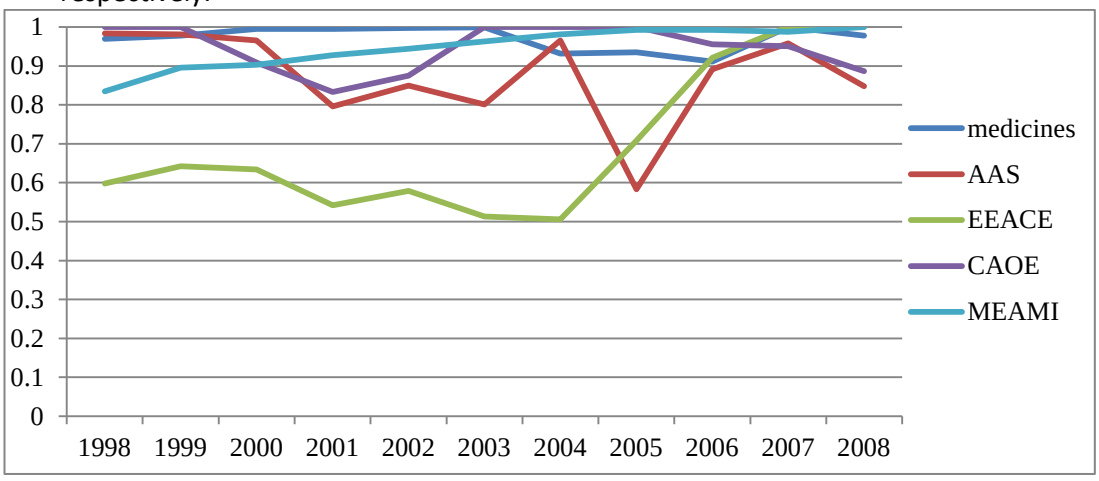


Figure 2.4: The annual variation of the scale efficiency scores in five high-tech sectors from 1998 to 2008

The average SE scores of the Electronics sector was the lowest of all the high-tech sectors although it has begun to increase since 2005. At the same time, the SE score of the Computer sector started to decline. Based

on the observation of the SE score progress, the initial conclusion is that there was no marked difference in returns to scale across the sector during this period. Further analysis of the SE data indicated that returns to scale (RS) metrics might provide useful indices for the management of R&D investment efficiency. There are three possible classes of returns to scale: decreasing (DRS), increasing (IRS) and constant (CRS). CRS is indicated by an SE score of 1; DRS, signified by a decrease in the relative output for a given incremental input, and an associated decline in the consequent revenue/profit. The policy implications for such a sector appear to be that active monitoring and management of RS metrics may provide useful indices for control and allocation of R&D investment. IRS, signified by an increase in the relative output for a given incremental input, suggests that for such a sector the incumbent R&D investment is insufficient to fully utilize the potential production capacity, therefore making the sector suffer from scale inefficiency. China's high-tech sectors suffered from DRS for most of the test period, with the exception of the Instrument sector. The Electronics and Instrument sectors both saw CRS, signifying the best scale efficiency performance in 2008; Electronics, suffered from DRS before 2007, whereas the Instrument sector suffered from IRS before 2006.

In summary, it appears that most of the high-tech sectors in China have been suffering from decreasing returns to scale over the decade 1998-2008. This DRS trend may be a consequence of uncontrolled expansion of enterprises in these sectors, and/or increasing intensity of market competition. Another possible explanation is the monopolistic position of the high-tech sector in China, effectively reducing/removing competition.

2.3.3.4 Individual Output/Input Ratio Analysis

As shown in Table 2.9 and Table 2.10, ratio analysis was employed to examine the differences on individual output/input items among the five sectors. Table 2.6 presents the ratios of number of patents over the three inputs respectively: R&D expenditure, R&D personnel and the accumulated patents stock. Here, sectors 1 to 5 represent the Medicines sector,

Aerospace sector, Electronics sector, Computer sector, Instrument sector, respectively.

Table 2.9: Individual output/input ratio analysis in terms of number of patents in years 1998-2008

ratio measures	sector	year											average	rank
		1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008		
patent number/full-time equivalence on R&D	sector 1	0.027	0.025	0.025	0.050	0.056	0.082	0.086	0.093	0.155	0.171	0.156	0.084	3
	sector 2	0.003	0.003	0.002	0.004	0.003	0.006	0.009	0.004	0.012	0.021	0.027	0.009	5
	sector 3	0.016	0.018	0.026	0.036	0.053	0.081	0.099	0.141	0.179	0.276	0.260	0.108	2
	sector 4	0.025	0.019	0.018	0.065	0.091	0.242	0.186	0.202	0.150	0.237	0.187	0.129	1
	sector 5	0.015	0.015	0.028	0.033	0.038	0.063	0.066	0.109	0.111	0.168	0.237	0.080	4
patent number/R&D expenditure	sector 1	0.006	0.005	0.004	0.007	0.008	0.007	0.007	0.007	0.010	0.009	0.008	0.007	4
	sector 2	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.002	0.003	0.001	5
	sector 3	0.005	0.004	0.004	0.003	0.004	0.004	0.005	0.006	0.008	0.009	0.011	0.010	2
	sector 4	0.006	0.004	0.002	0.006	0.007	0.008	0.011	0.005	0.007	0.008	0.008	0.009	3
	sector 5	0.007	0.007	0.011	0.010	0.010	0.012	0.010	0.013	0.011	0.014	0.017	0.016	1
patent number/patent stocks	sector 1	1.404	2.434	2.112	2.442	3.168	2.413	4.237	3.504	5.900	2.642	2.695	2.996	4
	sector 2	0.908	1.946	2.447	0.434	1.737	1.266	2.686	1.230	2.326	6.986	4.219	2.381	5
	sector 3	2.893	4.958	7.989	4.618	5.150	5.019	5.906	6.541	5.249	6.811	5.783	5.538	2
	sector 4	3.778	13.50	10.69	5.596	8.087	7.275	10.81	35.11	6.875	4.530	6.905	10.29	1
	sector 5	2.128	3.293	3.484	3.213	1.913	2.976	2.792	6.333	2.343	3.735	4.457	3.333	3

Table 2.10 shows that: (1) The Computer sector performed at the best level on R&D personnel ratio and patent stocks ratio. (2) The Instrument sector ranked first in R&D expenditure ratio but did not perform well in the other ratios. (3) The Electronics sector ranked second in all output/input ratios. (4) The Aerospace sector operated least efficient among the five sectors. (5) The Medicines sector performed only better than the Aerospace sector. Noticeably, it ranked third in the R&D personnel ratio due to its consecutive increase in full-time equivalence productivity on patents between 2001 and 2007.

Table 2.10 represents the ratios of new product annual sales to three outputs in each industry: R&D expenditure, R&D personnel and the accumulated patents stock. This analysis shows that the Computer sector and Electronics sector ranked first and second across every ratio. The Medicines sector and Instrument sector operated less efficiently, and again the Aerospace sector exhibited the lowest performance. This analysis supports the initial conclusion from the earlier analyses that the Computer sector is the most efficient sector within China's high-tech

industry, followed with the Electronics sector and Instrument sector; the Aerospace sector has the worst performance on R&D investment efficiency.

Table 2.10: Individual output/input ratio analysis in terms of new product annual sales in years 1998-2008

ratio measures	sector	year											average	rank
		1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008		
new product sales/full-time equivalen	sector 1	110.87	113.78	152.62	191.02	200.68	256.8	246.81	237.43	291.1	444.1	393.4	239.88	3
	sector 2	14.234	14.708	20.222	54.349	44.81	71.58	64.014	86.101	96.91	137	128.6	66.5895	5
	sector 3	530.81	361.06	579	639.8	729.48	819.8	790.52	714.71	605.8	862.5	577.2	655.514	2
	sector 4	1692.3	868.01	710.29	1603.7	1286.9	2486	1941.7	2895.6	2139	1799	1964	1762.48	1
	sector 5	58.469	62.735	83.255	93.43	83.929	146.8	150.41	218.12	261.3	379.2	343.4	171.003	4
new product sales/R&D expendit	sector 1	24.691	22.673	26.744	26.694	27.079	22.84	19.019	19.05	17.96	22.7	20.93	22.7624	4
	sector 2	5.4184	6.1262	10.224	13.765	16.617	15.79	12.116	13.29	11.95	13.48	14.99	12.161	5
	sector 3	159.36	85.849	94.808	54.541	57.206	43.61	35.993	30.159	26.28	28.63	25.37	58.3461	2
	sector 4	418.98	205.55	76.859	141.49	99.069	83.7	118.02	73.187	100.4	63.81	85.73	133.341	1
	sector 5	28.636	28.77	33.568	28.382	21.149	27.19	23.719	27.023	25.04	32.63	25.01	27.3737	3
new product sales/patent stocks	sector 1	5772.6	11012	12873	9261.2	11258	7529	12203	8937.9	11110	6858	6795	9419.18	4
	sector 2	4052.4	10292	21684	5418.5	26361	15879	19568	24677	19359	45081	20003	19306.8	3
	sector 3	97303	101978	175781	80994	71024	50975	47021	33243	17783	21277	12859	64567	2
	sector 4	254789	618894	418527	137442	114501	74797	112838	502089	97839	34363	72578	221696	1
	sector 5	8444.5	13891	10528	9012.5	4255.3	6941	6347.1	12686	5516	8409	6468	8408.89	5

2.3.3.5 Summary of Analysis: Sector-level Indices

Based on the analysis of the TE, PTE, SE and output/input ratio, the Computer sector achieved the best R&D investment efficiency among China's five biggest high-tech sectors. However, apparently suffering from decreasing returns to scale, its efficiency has been declining since 2006. On present trends, the Electronics sector and Instrument sector might be predicted to overtake the Computer sector, as the best R&D investment efficient high-tech sector in China, based on their performance in the test of DEA and output/input ratio. The other two sectors - medicines sector and Aerospace sector have been suffering from low R&D investment efficiency, which may come from the effects of monopoly, and may call into question that investment strategy.

2.3.4 Detailed Sub-sector Analysis

Following on from the sector-level ratio analysis, the R&D investment efficiency within specific sub-sectors was moved on to explore. Of the 21

high-tech sub-sectors covered in the Bureau data, only 16 could be accepted into analysis: 5 had to be excluded because of incomplete data. More detailed analysis of the 16 defined sub-sectors revealed that their individual R&D investment efficiencies changed dramatically in year 2001 and 2008.

The overall pattern which emerges from the sub-sector analysis is of gradual decline in TE and PTE, some rise in SE and a fairly dramatic rise in the number of sub-sectors undergoing DRS. Over the same sample period, average SE scores across the sub-sectors were increasing, and the number of sub-sectors which were suffering from DRS rose dramatically. In addition, fewer sub-sectors were performing with high R&D investment efficiency (see Table 2.11). In Figure 2.5(a) and 2.5(b), the distribution of PTE/TE ratios was plotted, and indicate their relationship to the average PTE and TE scores (solid lines). In Figure 2.6(a) and 2.6(b), the situation as a series of four-quadrant grids framing the potential zones of behaviour between key parameters was portrayed. The positive relationship between TE score and PTE score in Figure 2.5a could be observed. And the relationship is much stronger in Figure 2.5b, which suggests the PTE level is more important in improving the TE score.

In Figure 2.5a: (1) The lines perpendicular to the x-axis and the y-axis are, respectively, the average value of the TE score and PTE score for the 16 high-tech sectors, (2) The numbered points on the grid represent the individual sectors represented in table 2.11. Black means increasing returns to scale, red means decreasing returns to scale, and green means constant returns to scale.

In Figure 2.5b: (1) the lines which are perpendicular to the x-axis and the y-axis are, respectively, average value of TE and PTE scores of 16 sub-sectors, that is x=0.599, y=0.747. (2) The numbers represent the various sub-sectors in Table 2.11. The black colour means increasing returns to scale, the red colour means decreasing returns to scale, and the green colour means constant returns to scale. Figure 2.5b shows the equivalent data for 2008 on the same axes.

In both Figure 2.5a and 2.5b, the sectors in zone A exhibit both high PTE and TE scores. Sectors in zone B show high PTE scores, but low TE scores. Zone C sectors exhibit low score on both PTE and TE. There are few sectors in zone D, making high TE score with low PTE level an uncommon occurrence.

Table 2.11: Process efficiency scores of R&D investment in 16 China's high-tech sub-sectors in 2001 and 2008

Ind.	*Sub-sector NO.	Abbr.	TE		PTE		SE		RTS	
			2001	2008	2001	2008	2001	2008	2001	2008
medicines	1	CM	0.533	0.314	0.97	0.54	0.55	0.581	Drs	Drs
	2	FTCHM	1	0.551	1	0.959	1	0.575	-	Drs
	3	BABCP	0.429	0.562	1	0.575	0.429	0.977	Irs	Irs
AAS	4	ROA	0.104	0.234	0.237	0.413	0.44	0.566	Drs	Drs
EEACE	6	CTRE	0.363	0.535	0.375	0.787	0.967	0.68	Irs	Drs
	8	CTEE	1	0.252	1	0.255	1	0.987	-	Irs
	11	EVA	0.672	0.389	0.778	0.394	0.863	0.986	Irs	Irs
	12	SDA	0.245	0.335	1	0.469	0.245	0.715	Irs	Irs
	13	IC	0.399	0.786	1	1	0.399	0.786	Irs	Drs
	14	ELC	0.418	0.367	0.544	0.585	0.77	0.628	Drs	Drs
	15	DTSARR	1	0.816	1	1	1	0.816	-	Drs
	16	OEE	0.576	1	1	1	0.576	1	Irs	-
CAOE	17	ENC	1	1	1	1	1	1	-	-
	18	CPE	0.869	0.88	0.926	1	0.939	0.88	Drs	Drs
MEAMI	20	MEAA	1	1	1	1	1	1	-	-
	21	MI	0.689	0.564	0.85	0.977	0.811	0.577	Drs	Drs
	mean		0.644	0.599	0.855	0.747	0.749	0.797		

*The sub-sector No. corresponds with those shown in Table 2.1, and represents the same sub-sectors with the numbers shown in Figure 2.5 and Figure 2.6.

Figure 2.6 shows the shift in the PTE and TE scores of the 16 sub-sectors between 2001 and 2008. This analysis reveals no sub-sector staying in Zones B or C in 2008; more sub-sectors appear in Zone A and B. These

changes indicate that the overall Scale efficiency level across the 16 sub-sectors improved, which may be the consequence of the consistent increase of R&D investment inputs in China. However, a decline of the PTE level across these sub-sectors accompanied the SE improvement, which again highlights the importance of PTE improvement as a key management index for the increasing of overall R&D investment efficiency level within China's high-tech sub-sectors.

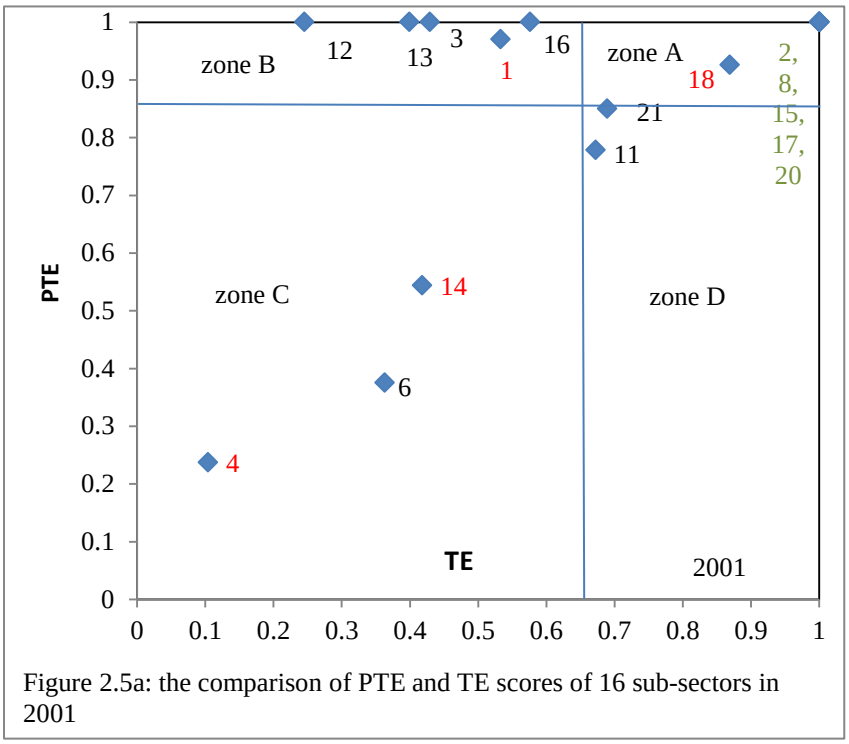


Figure 2.5a: the comparison of PTE and TE scores of 16 sub-sectors in 2001

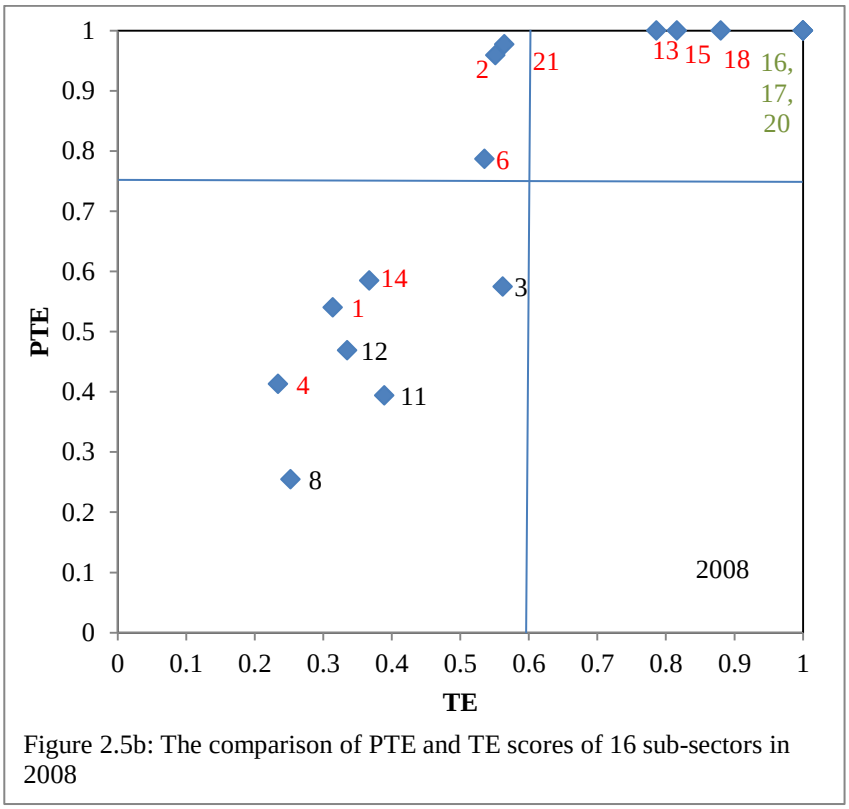


Figure 2.5b: The comparison of PTE and TE scores of 16 sub-sectors in 2008

Figure 2.5: The comparison of PTE and TE scores of 16 sub-sectors in 2001 and 2008

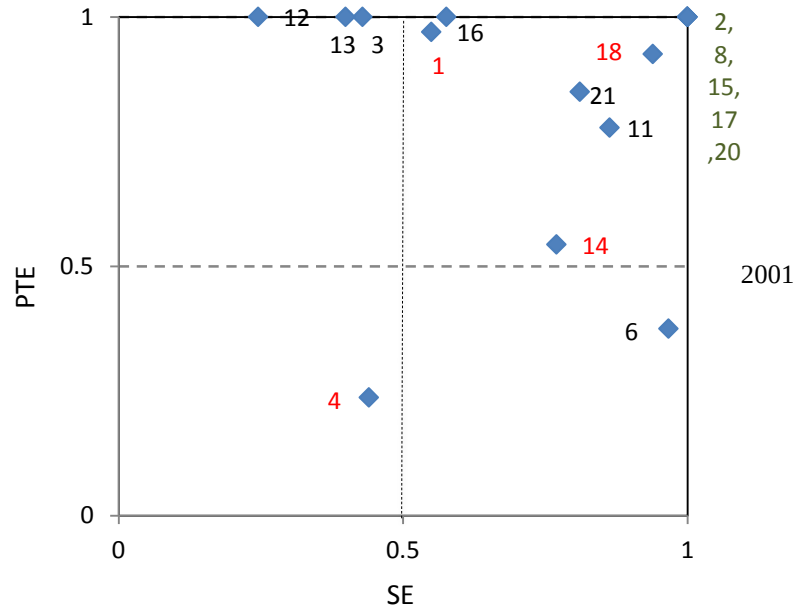


Figure 2.6a: The comparison of PTE and SE scores of 16 sub-sectors in 2001

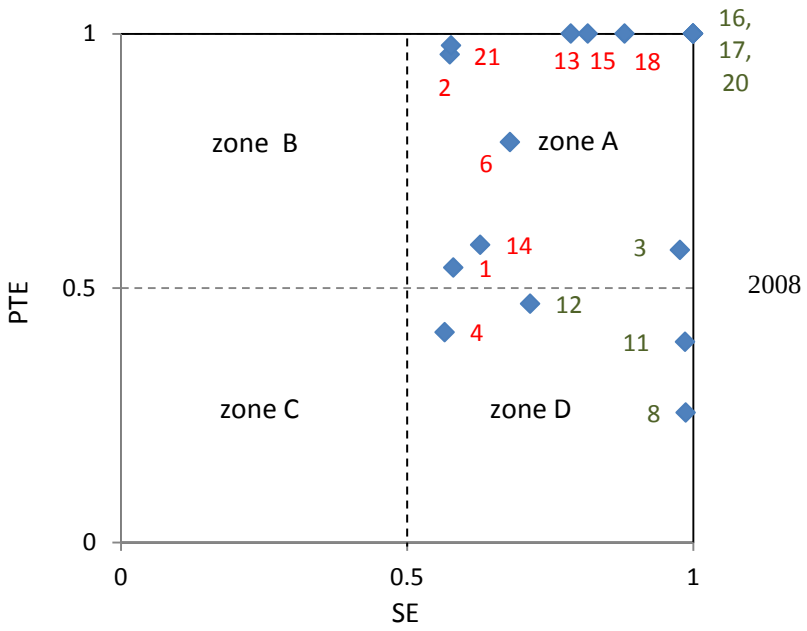


Figure 2.6b: The comparison of PTE and SE scores of 16 sub-sectors in 2008

Figure 2.6: The comparison of PTE and SE scores of 16 sub-sectors in 2001 and 2008

There are three sub-sectors in the Medicines sector: Chemical Medicine, Herbal Medicine, and Biological Products. Chemical Medicine sub-sector (CM) and Herbal Medicine sub-sector (FTCHM), which were separately suffering from the decreasing of PTE and CE experienced the decreasing R&D efficiency. Biological Products sub-sector (BABCP) which was benefit from the great improvement of its CE, improved a little in its TE. Airplanes sub-sector (ORA) which is from Aerospace sector, improved its R&D investment efficiency through the development of both PTE and CE. In Electronics sector, four sub-sectors (CTRE, SDA, IC, and OEE) which most benefited from the improvement of PTE, increased their TE score during year 2001 to 2008. The other four sub-sectors in Electronics sector experienced the decreasing of TE based on different reasons. Entire Computer sub-sector (ENC) from the Computer sector and Medical Equipment sub-sector (MEAA) from the Instrument sector were the most efficient sub-sectors about R&D investment both in year 2001 and 2008.

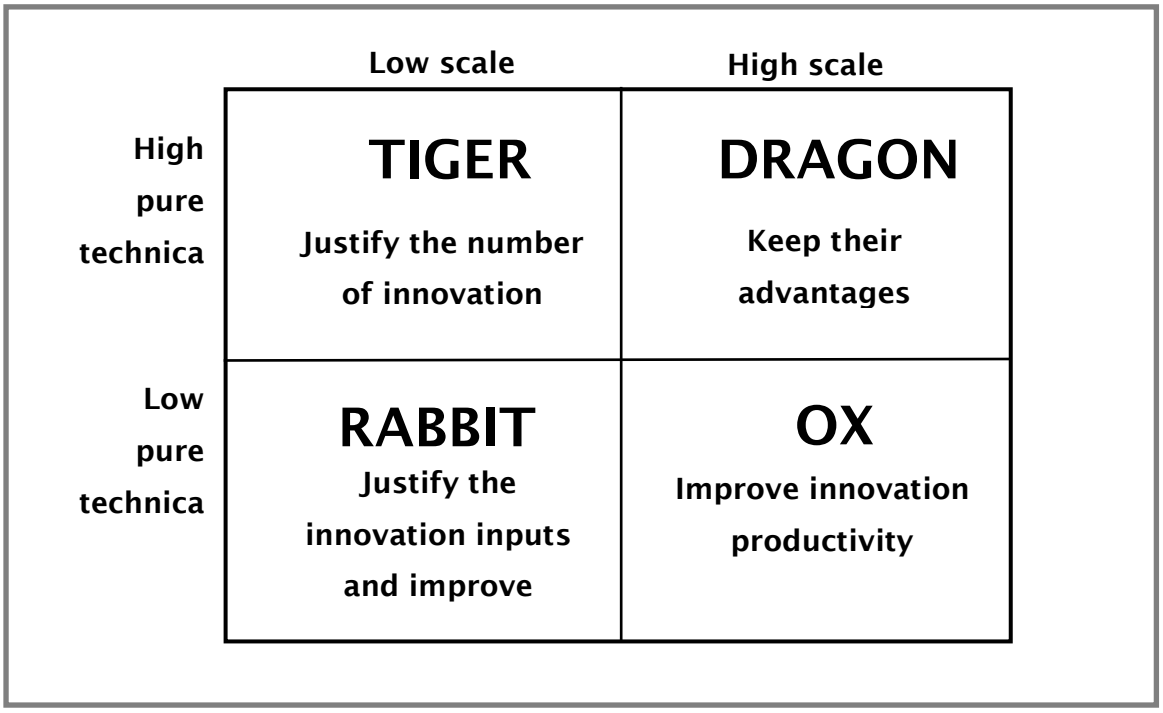


Figure 2.7: Proposed strategy grid for companies/sectors with varying levels of technical efficiency and scale

Based on the above study, a model (see figure 2.7) is designed to help industries evaluate their positions on these key indices of innovation and identify the most appropriate actionable strategies/steps to improve their R&D investment efficiency.

Dragon Zone sectors are in a strong position: for sectors in this zone, the amount of R&D investment input is sufficient, leading to the best returns to the scale; the capacity of resource allocation and innovation productivity is near optimal, leading to highest R&D investment output. This is the desired goal for most if not all sectors each.

Tiger Zone: for sectors in this zone, the capacity of resource allocation and innovation productivity is also approaching the optimum, favouring high R&D investment output, but the level of R&D investment inputs is suboptimal leading to decreasing or increasing returns to the scale scenarios (DRS or IRS). To move to the Dragon zone, companies in the Tiger zone, firstly need to identify the polarity of their scale inefficiency – decreasing returns to the scale (DRS) which implies R&D investment inputs have been used inefficiently, or increasing returns to the scale (IRS) which suggests R&D investment inputs is insufficient to exploit fully the company/sector's capacity. Secondly, based on the earlier analysis, companies/sectors could adopt a different course of action – increasing R&D investment inputs if suffering from IRS, or decreasing R&D investment inputs if the industry is showing signs of DRS effects.

Ox Zone: for companies/sectors in this zone, the amount of R&D investment input is sufficient but not excessive, leading to the best returns to scale. But resource allocation and innovation productivity is relatively weak, producing the observed R&D investment inefficiency. Sectors or companies in this zone need to apply R&D investment more efficiently, and improving innovation productivity is the main approach.

Rabbit Zone: companies or sectors in this zone are likely to have issues both on the scale of R&D investment and innovation productivity. The immediate needs are therefore to judge which scale problem is in effect -

IRS or DRS, then attempt to change the quality and level of the R&D investment inputs, and also concentrate on improving the pure technical efficiency.

For policy makers, the findings and the proposed model suggest that companies or sectors:

(1) Keep the advantage of 'Dragon' industries, which is the most efficient engine for economic growth;

(2) Give policy support to help control the R&D investment inputs in 'Tiger' industries, which are the potential high efficient engine for economic growth;

(3) Help to control the R&D investment inputs in 'Rabbit' industry, that is the fast way to improve their R&D investment efficiency;

(4) Help both 'Rabbit' and 'Ox' industries to improve their resource allocation ability and innovation productivity, which might take a longer time to catch.

2.4 Concluding Remarks

This study applied the CCR (which is designed under the assumption that production exhibits constant returns to scale) and BCC (which assumes that there are variable returns to scale) DEA models to evaluate the relative efficiency of R&D investments in China's high-tech industries. The principal econometric inputs employed were R&D expenditure, R&D personnel full-time equivalent (FTE), and the accumulated patents stock. Three main outputs were selected: the number of applied patents number, the value-added from new products and the sale revenue for new products. The subsequent analysis was conducted at three different levels: across the entire high-tech industry, across the five major high-tech sectors, and then across the 16 high-tech sub-sectors, as defined in the source Chinese government data.

The primary results from this study are that: the R&D investment efficiency in China's high-tech industry was nearly unchanged over test period; most of the sectors showed significant fluctuation on R&D investment efficiency over the period; average SE increased among sub-sectors, and these findings were discussed in more detail in the ensuing sections.

2.4.1 Lack of Immediate Impact of R&D Investment

The first and most striking result of the analysis at the overall high-tech industry level indicates that the R&D investment efficiency in China's high-tech industry was nearly unchanged over the period 1998 to 2009. It is perhaps a little surprising that the overall R&D investment performance of high-tech industry didn't show any increase, even though the R&D expenditure steadily increased during the examination period. Further analysis revealed that the increased R&D expenditure was associated with a dramatic increase (see Figure 2.1) in the number of patent stock, yet there was a limited increase of the economic return from new products over the high-tech industry. This finding suggests that the increase of the R&D inputs has brought the obvious improvement of the technology production efficiency, but that hasn't yet led to an equivalent improvement in the efficiency of the technology commercialization. This may be one reason why the R&D investment of the whole high-tech industry did not perform better during the study period.

2.4.2 Variable and Fluctuating Performance across Sectors

Most of the sectors showed significant fluctuation on R&D investment efficiency over the period. All of them except the Instrument sector were suffered from DRS in most test years. The Computer sector performed the highest on R&D investment efficiency but declined since 2006. Both Electronics and Instrument sectors showed the potential of being the most R&D investment efficient sectors in China. The R&D investment efficiency of the Aerospace sector was lowest among the five sectors in China.

There are three indices observed through DEA analysis: TE score, PTE score and SE score.

For TE score, the Computer sector (CAOE) was highest for many years. The Electronics sector (EEACE) and the Instrument sector (MEAMI) performed well following the Computer sector. Aerospace (AAS) performed lowest of the five high-tech sectors. However the TE score of the Computer sector started to decline in 2006. Compared with the decline of computer sector, Electronics and Instrument sectors experienced an improvement of TE scores over period.

The PTE scores showed a similar pattern to the TE analysis. The Computer sector achieved the highest and most consistent PTE scores during 1998 to 2008. Electronics sector were second highest but unstable over the period. All the other three sectors showed an improvement in their PTE scores. And the Aerospace sector still owned the lowest PET scores, similar to the TE results.

Scale efficiency (SE) scores didn't show any consistent pattern of change across the sectors during this period. SE was highest in the Medicine sector, followed by Instrument and Computer sectors (see Table 2.8 and Fig. 2.4). The average SE scores of the Electronics sector was the lowest of all the high-tech sectors although it has begun to increase since 2005. And at the same time, the SE score of the Computer sector started to decline in 2006. Further analysis of the SE data indicated that China's high-tech sectors suffered from DRS for most of the test period, with the exception of the Instrument sector.

2.4.3 Average SE Increased Among Sub-sectors

16 high-tech second-class sub-sectors were chosen and tested. The result comparison between 2001 and 2008 showed that, their R&D investment efficiencies changed dramatically. Their average TE score decreased with the decreasing average PTE score. The average SE scores across the sub-

sectors however, were increasing. At the same time, sub-sectors were suffering from the decreasing returns to scale.

2.4.4 Summary Conclusion

In summary, China's high-tech industries would still appear to need time to improve their R&D investment efficiency. In the past, many Chinese scholars and government officials have argued that China's high-tech industries should first increase their R&D investment to the level or close to the level of that in developed countries, in order to reach the same scientific and technological level of western countries (Zhong et al., 2011). However, the DEA analysis of this study illustrates that despite a continuous increase of the R&D investment input, the efficiency of the R&D investment has not yet showed a clear and consistent improvement. On the contrary, more sectors and sub-sectors suffered from the decreasing returns to scale, which may be due to the low absorptive capacity for the potential outputs of the increasing R&D inputs.

On the other hand, some scholars and government officials have emphasized that China needs to enhance the capacity for independent innovation. However, comparing the huge increase of the applied patents number with the unchanged R&D investment efficiency, the conclusion is that the problem of China's high-tech industry may not be its lack of independent innovation, but the inefficiency of its technology commercialization processes. Of course, this low commercialization performance may stem from low quality of independent innovation. This hypothesis could be examined in further research, by the study of innovation productivity process in China's high-tech industry.

3. Chapter 3: Patterns of Open Innovation: The Case of Procter & Gamble

Abstract

Open innovation (OI) describes how organizations realize value beyond corporate boundaries by utilizing both internal and external sources of expertise to enhance their innovation and commercialization capabilities. It has become increasingly popular as an enterprise strategy in both industry and academia, and has been adopted, at least in part, by many companies. Despite this popularity, here is a dearth of evaluation of R&D effectiveness and a lack of suitable quantitative indices. To address this problem, this study has adapted and applied Data Envelopment analysis (DEA) and Malmquist Index analysis (MI) to measure innovation performance. These techniques are used to compare the pre- and post-transition levels of performance achievement of Procter & Gamble (P&G), a widely recognized and public early adopter of OI, with a group of its main competitors, which have not adopted OI. Most detailed analysis of the time-course revealed that the R&D efficiency of Procter & Gamble improved rapidly and substantially after its embracing of OI, an effect which is termed as the 'open rise', but that there is also a transient decline in R&D efficiency at the beginning of OI adoption ('open dip') and an unexpected and marked decline ('open drop') after the peak positive effect.

Keywords

Open innovation; performance evaluation; DEA; MI; Proctor & Gamble; open rise; open drop; open dip.

3.1 Introduction

Since the publication of Chesbrough's book in 2003, the concept of open innovation (OI) has continued to receive wide attention from practitioners and researchers (Gassmann et al, 2010). A recent industry survey indicated that OI is one of the tools that the largest number of executives considered using (Rigby and Bilodeau, 2011) and by 2009 there were already more than 150 academic papers on the topic (Dahlander and Gann, 2010). However, the initial studies of OI tended to focus on successful and early adopters (e.g., Huston and Sakkab, 2006; Chesbrough and Crowther, 2006), and to be descriptive conceptually (Huizingh, 2011). Evaluating open versus closed innovation approaches, requires more quantitative approaches to measurement and functional indices of innovation (Enkel et al, 2009). The identification or development of an appropriate metrics system for evaluating the performance of open versus closed innovation should help companies find the balance between open and closed approaches (Enkel and Lenz, 2009), and it has recently been argued that the next stage of studies in OI should include performance measures (Huizingh, 2011).

If suitable performance metrics of indices were available and OI were effective in increasing R&D productivity, there should be a positive differential between OI and pre-OI conditions on measures of R&D efficiency. Because the most important benefit provided by OI is claimed to be the chance to increase the productivity of the adopter's R&D (Ili et al, 2010). In order to assess the change over time, indices of the overall efficiency of the R&D process are needed. Surprisingly, only in recent years have a few examples in the literature discussed R&D efficiency by using quantitative approaches with regard to R&D at the firm level begun to appear (Wang and Huang, 2007). Zhang et al. (2003) examined the effects of different types of ownership to the R&D efficiency through analysing the Chinese firms. Revilla et al. (2003) studied performance of public-private research collaborations through analysis of 281joint projects from 118 Spanish firms and found that R&D efficiency varied

depending on firm size and level of firm knowledge. Guan et al. (2006) studied the relationship between innovation capability and competitiveness through analysing 182 industrial innovative firms. There is no research developed to measure the R&D efficiency performance of the OI-adopted firm.

As discussed in the first paper, there are two major approaches for evaluating efficiency: SFA (stochastic frontier analysis) and DEA (Data Envelopment analysis) which belongs to non-parametric analysis techniques. Comparing with SFA, DEA is more suitable to measure R&D efficiency. Another candidate of measuring R&D efficiency which also comes from non-parametric analysis techniques is Malmquist Index analysis (MI). Both DEA and MI have previously been applied to assess the efficiency of economic processes with identifiable multiple inputs and outputs (Wang and Huang, 2007; Hashimoto and Haneda, 2008). By adapting these techniques and applying them longitudinally to time series data, the performance of R&D efficiency on the OI adopters can be evaluated to assess that whether adoption of OI strategy has helped firms to achieve the main benefit which is improving R&D productivity.

To explore and validate the efficacy of this approach to metrics, this research undertook a comparative case study of Procter & Gamble (P&G), an early and public adopter of OI strategy, with a clear comment point circa 1999 (Dodgson et al, 2006). For the comparison and validation, and to better understand the relative efficacy of OI versus closed innovation strategies, four leading competitors were identified, based on the categorization of BIS's ranking of top R&D firm.

The remainder of this paper is organized in sections. Section 3.2 makes the literature review about studies on measuring OI performance, P&G's innovation strategy and R&D time lag. Section 3.3 introduces the two techniques utilised in this research – DEA and MI. Section 3.4 describes the data selected in this study. Section 3.5 shows the results of the comparative analysis of P&G case. The final conclusion is summarised in section 3.6.

3.2 Literature Review

3.2.1 Evaluation of OI Performance

Several approaches to the assessment of OI have been put forward in the literature. Ili et al (2010) summarized the previous research and designed management tools to observe the status of OI in the automotive industry. Remneland-Wikhamn and Wikhamn (2011) designed a three-dimensional assessment tool which they utilised to measure the 'OI climate' in an organization. Another attempt at introducing an OI assessment tool was made by Al-Ashaab et al (2011), who developed an operational measurement tool based on the balanced scorecard to measure the outcomes of industry-university collaboration. However, most of these previous studies focus on evaluating the circumstances favouring the adoption of OI. No indices have been proposed or developed to measure the result of OI adoption and the subsequent performance of OI adopters. Previous quantitative studies for OI normally employed financial indices to reflect the firm's performance, such as turnover relating to new products (Laursen and Salter, 2006; Faems et al, 2010). Although a firm's financial indices are useful, this may not disclose the efficiency of OI strategy since they typically don't consider the R&D activities and OI cost in the organizations. Therefore, an appropriate metrics system that could monitor the performance of OI is still needed (Enkel and Lenz, 2009; Huizingh, 2011).

3.2.2 OI Firms

The foregoing studies of OI have referred to many case studies of how firms implement the OI strategy to enhance their innovation and commercial capacity (e.g. Chesbrough, 2003b, 2006a; Sakkab, 2003; Dyer et al., 2004; Tennenhouse, 2004). P&G is one of the most famous companies which adopted OI strategy at an early date and apparently achieved great success through OI adoption. P&G was first studied as an example of adoption of OI in non-high-tech industry by Chesbrough (2003b). After

that, P&G has emerged and been studied as an OI company in a number of papers (for example: Chesbrough, 2006a; Chesbrough, 2006b; Gassmann, 2006; Huizingh, 2011; Lichtenthaler, 2011). There are also some OI studies specially focusing on the case of P&G. Dodgson et al. (2006) analysed Procter and Gamble's 'Connect and Develop' strategy as a case study of the major organizational and technological changes associated with OI, documented the important facilitating role of information and communication technologies for P&G's adoption of OI. P&G's OI strategy and its Connect and Develop model for innovation was systematically reviewed (Huston and Sakkab, 2006), but there is no literature focusing on evaluating the performance of OI strategy on P&G.

In June 1999, P&G launched a specific new strategy to increase growth through innovation called Organisation 2005 (Dodgson et al, 2006). With adoption of Organisation 2005, the firm planned to stimulate innovation by making P&G's internally focused and fragmented communications more outwardly focused and cohesive (Schilling, 2005). Through these efforts, P&G changed its R&D strategy to a 'Connect and Develop' strategy and enjoyed major success in terms of business growth through new, externally sourced products and technology (Gassmann, 2006). The firm announced that they were able to increase their product success rate by 50% and the efficiency of their R&D by 60% by introducing OI strategy (Enkel et al, 2009). With more than 35% of the company's innovations and billions of dollars in revenue produced by radical strategy of OI (Huston and Sakkab, 2006), to measure whether the adoption of OI strategy has triggered such a big impact on P&G's innovation capability, the performance of the R&D investment efficiency in P&G is studied in this research. P&G would therefore seem to have all the attributes required for an effective case study of the performance of OI pre- and post-adoption.

3.2.3 R&D Time Lag

To measure the performance of R&D investment efficiency, both the innovation inputs and outputs must be considered. Because of the time

needed to complete a R&D, introduce products to market (e.g. packaging, pricing and marketing) and gain a market share, there is a sector-dependent time lag for the economic consequences and impacts of R&D to show up following the initial R&D 'priming' investment (Kafouros and Wang, 2012). Previous studies have distinguished two separate lag effects in the total time to market from R&D (Pakes and Schankerman, 1984). The first time lag is the "gestation lag" which refers to the time needed to complete an R&D project. The second one is the "application lag" which refers to the time lag between project completion and commercial application (Kafouros and Wang, 2012).

A number of studies have made estimates of the time lag between an R&D investment and an associated measurable economic outcome. The estimated time lag ranges from 1 to 4 years, with 2 being the median figure. Mansfied et al. (1971) estimated the lag from R&D to innovation was about 3 years for firms. Leonard (1971) reported that the R&D impact on the average began in the second year. Ravenscraft and Scherer (1982) examined the lag between R&D investment and economic benefit, and found mean time lag to be about 4 years. Pakes and Schankerman (1984) estimated the average gestation lag which is usually between 9 months and 1 year. And the total time lag between R&D outlay and its first revenues is 1.2 to 2.5 years. Griliches and Mairesse (1984) reported that the lag effect drops sharply after 2 years based on some evidence. Seldon (1987) measured the time lag of R&D in the forest products industry, and found the best-fitting lag is 2 years for both private and public R&D. lev and Sougiannis (1996) estimated lagged R&D measures for six main industries, and found the benefits of R&D are usually maximized in 2 or 3 years. In another study, Branstetter and Sakaibara (2002) examined the time path of the benefits of research consortia, and had the result that the patenting activity of these consortia is maximized in a 3-year lag.

The variability estimates of the time lag in R&D in this research may reflect that the samples in most studies are different covering different periods, sectors and markets. Several studies indicate that with the growth

of the internet and intense competition, the average time required to compete a project is falling significantly (Kessler, 2003; Kafouros, 2006). Given such factors, one would expect the time lag of R&D to be shorter after the early 1990s when the worldwide web was implemented, and that the R&D lead times should reflect the product life-cycles of different industries.

One obvious difference is between high-tech industry and low-tech industry. The study result of Kafouros and Wang (2012) shows that elasticity of R&D for larger and high-tech firms peaked 1 year after the investment has been made, while it peaked after 2 years for smaller low-tech companies. This appears to indicate that the time lag of R&D may be shorter for high-tech industry compared with low-tech industry. Lev and Sougiannis (1996) estimated the corresponding lag for the computing, electrical, electronics and other industries was 2 years, and Kafouros and Wang (2012), showing the peak of the contribution of R&D is either 1 or 2 years after the investment has been made, supporting that 2 years is reasonable average estimate.

3.3 Method

3.3.1 Data Envelopment Analysis

DEA is an established programming methodology which be applied to assess production efficiency using multiple inputs and outputs (see, e.g., Kozmetsky and Yue, 1998; Yeh, 1996). Ground breaking work by Rousseau and Rousseau (1997, 1998) proved the potential of DEA-analysis to assess R&D activities. Subsequent studies have provided supporting evidence for its use in evaluating innovation efficiency, especially for the high-tech industries (see, e.g., Guan and Chen, 2010; Chen et al., 2006; Zabala-Iturriagagoitia et al., 2007; Zhong et al., 2011). Two standard variations of the DEA model are used in the present study: the CCR model (Charnes et al., 1978) and the BCC model (Banker et al., 1984). Section 2.2.1 in Chapter 2 and Appendix 1 describe the two models in more detail.

3.3.2 Malmquist Index Analysis

Malmquist Index Analysis (MI) (Malmquist, 1953) is designed to solve panel data and show the productivity change in the way of decomposing it into technical change and technical efficiency change. The computation of MI bases on the framework of DEA. Before introducing the detailed model of MI, we define the variables which will be used in the computations.

We define the time periods as $t = 1, \cdots, T$ **and the production technology of** DMU_o**, in time *t* as** P^t **representing the transformation of the inputs** x_o^t **into the outputs** y_o^t **. Thus we have**

$$P^t = \{(x_o^t, y_o^t): x_o^t \text{ can produce } y_o^t\}$$

The distance function (Färe et al., 1994; Shephard, 1970) is defined as

$$D_o^t(x_o^t, y_o^t) = \min\{\theta: (x_o^t, y_o^t/\theta) \in P^t\}.$$

Thus $D_o^t(x_o^t, y_o^t) \leq 1$ **if** $(x_o^t, y_o^t) \in P^t$**. Since** $D_o^t(x_o^t, y_o^t)$ **can be used to measure the efficiency at time *t*, it can be evaluated by the CCR model (3) but in the way of output oriented. That is,**

$$D_o^t(x_o^t, y_o^t)^{-1} = \max_{\theta,\lambda} \ \theta$$

$$s.t. \quad \theta y_o^t \leq Y^t \lambda$$

$$X^t \lambda \leq x_o^t$$

$$\lambda \geq 0 \qquad (5)$$

In order to assess changes in productivity over time, (Färe et al., 1994) defined the mixed period distance functions in the following.

$$D_o^t(x_o^{t+1}, y_o^{t+1}) = \min\{\theta: (x_o^{t+1}, y_o^{t+1}/\theta) \in P^t\}$$

$$D_o^{t+1}(x_o^t, y_o^t) = \min\{\theta: (x_o^t, y_o^t/\theta) \in P^{t+1}\}.$$

Similar to (5), these two functions are evaluated as

$$D_o^t(x_o^{t+1}, y_o^{t+1})^{-1} = \max_{\theta,\lambda} \ \theta$$

$$s.t. \quad \theta y_o^{t+1} \leq Y^t \lambda$$

$$X^t \lambda \leq x_o^{t+1}$$

$$\lambda \geq 0 \qquad (6)$$

$$D_o^{t+1}(x_o^t, y_o^t)^{-1} = \max_{\theta,\lambda} \ \theta$$

$$s.t. \quad \theta y_o^t \leq Y^{t+1} \lambda$$

$$X^{t+1} \lambda \leq x_o^t$$

$$\lambda \geq 0 \qquad (7)$$

Färe et al. (1994) specifies an output-oriented M I which based on Shephard's work (1970), as:

$$M_o(x_o^{t+1}, y_o^{t+1}, x_o^t, y_o^t) = \left[\frac{D_o^t(x_o^{t+1}, y_o^{t+1})}{D_o^t(x_o^t, y_o^t)} \frac{D_o^{t+1}(x_o^{t+1}, y_o^{t+1})}{D_o^{t+1}(x_o^t, y_o^t)}\right]^{\frac{1}{2}} \qquad \textbf{(8)}$$

Malmquist Index (8) could be divided (Färe et al., 1994) into:

$$M_o(x_o^{t+1}, y_o^{t+1}, x_o^t, y_o^t) = Te \times T \times S$$

Where $Te = \frac{D_{o,BCC}^{t+1}(x_o^{t+1}, y_o^{t+1})}{D_{o,BCC}^t(x_o^t, y_o^t)}$

$$T = \left[\frac{D_o^t(x_o^{t+1}, y_o^{t+1})}{D_o^{t+1}(x_o^{t+1}, y_o^{t+1})} \frac{D_o^t(x_o^t, y_o^t)}{D_o^{t+1}(x_o^t, y_o^t)}\right]^{\frac{1}{2}}$$

$$S = \frac{D_o^{t+1}(x_o^{t+1}, y_o^{t+1})}{D_{o,BCC}^{t+1}(x_o^{t+1}, y_o^{t+1})} \frac{D_{o,BCC}^t(x_o^t, y_o^t)}{D_o^t(x_o^t, y_o^t)} \qquad \textbf{(9)}$$

Here $D_{o,BCC}^{t+1}(x_o^{t+1}, y_o^{t+1})$ **and** $D_{o,BCC}^t(x_o^t, y_o^t)$ **are the distance functions computed by the BCC model (4). Te represents the technical efficiency improvement; T represents technology improvement and S represents scale efficiency.**

The Malmquist Index of time period t+1 computed in the previous section is compared to the preceding time period, i.e., t. However, it is difficult to

observe the chronological change throughout the sample period as we only see the successive change for every time period. Therefore, Hashimoto and Haneda (2008) proposed a variant of MI by fixing t to the first time period of sample period in model (8), i.e., t=1.

Then the indices $M_o(x_o^2, y_o^2, x_o^1, y_o^1), M_o(x_o^3, y_o^3, x_o^1, y_o^1), \cdots, M_o(x_o^T, y_o^T, x_o^1, y_o^1)$ are computed accordingly. Note that the indices when t=1 could be all 1.

3.4 Model and Data

3.4.1 Model

To explore the difference between the closed innovation paradigm and the OI paradigm, Chesbrough (2006b) developed two models to encapsulate their action principle (see figure 3.1a). By comparing these two models, it could potentially be found that the main difference between these paradigms is the innovation process.

In the innovation process under the older, closed innovation model, research projects are launched from the science and technology base of the firm. They progress through the process, and some of the projects are stopped, while others are selected for further work. Subsets of these are chosen to go through to the market (Chesbrough, 2006b).

In contrast, in the OI model, projects can be launched from either internal or external technology sources, and new technology can enter into the process at various stages. In addition, projects can go to market by many routes, such as through out-licensing, or a spin-off venture, in addition to going to market through the company's own marketing and sales channels (Chesbrough, 2006b).

The main difference between these two models is the conduct and performance of the innovation process itself. Although the OI model provides broader strategy selection throughout its innovation process, both OI and closed innovation paradigms follow the same principle:

minimise the firm's R&D investment inputs, and maximize the firm's benefit at the same time. In the OI model, R&D inputs could either occur inside or outside of the firm, and the firm could select other ways (out-licensing et al.) to increase the corporate profit in addition to marketing and selling products. The goal of adopting of this strategy is still to improve the R&D investment efficiency i.e. – minimise the R&D inputs and maximise the outputs at the same time. So, by observing the variation of the R&D investment efficiency, the performance of the OI model could be compared with the performance of closed innovation model (see Figure 3.1b).

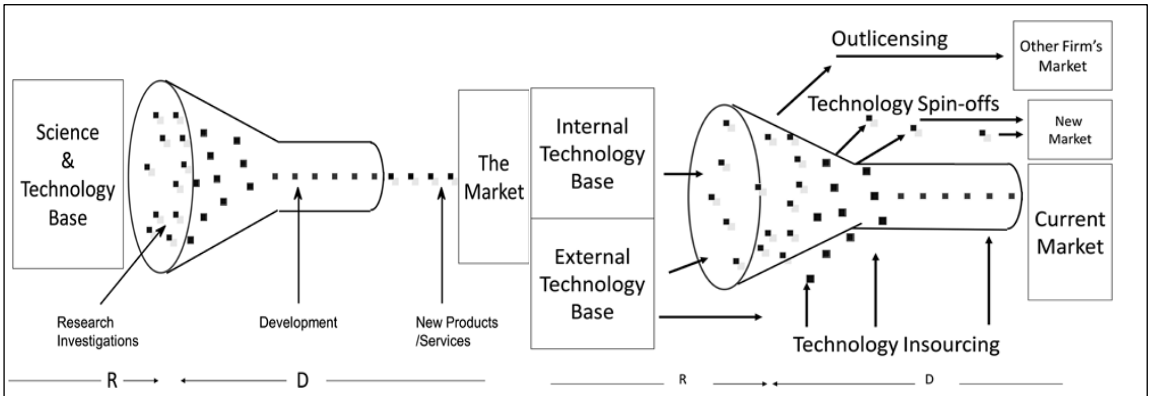


Figure 3.1a: Closed Innovation Model and Open Innovation Model (Chesbrough, 2006b)

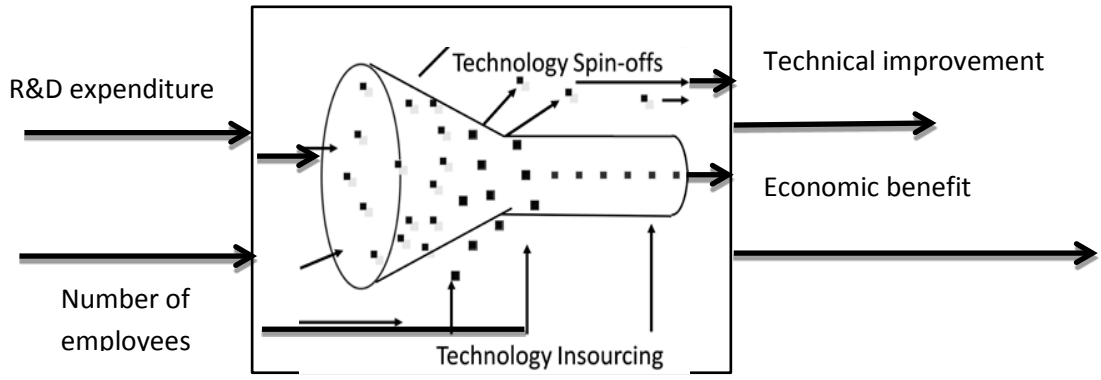


Figure 3.1b: OI Performance Model

Figure 3.1: Closed innovation, open innovation and OI performance models

3.4.2 Inputs, Outputs and Time Lag

R&D investment is often a complex process, with multiple inputs and outputs. One of the advantages of adopting DEA analysis is that multiple inputs and outputs can be measured, more than can be accommodated using conventional econometric techniques (Cooper et al., 2004). This multiple DEA analysis study was begun by selecting the appropriate inputs and outputs based on the previous literature, as illustrated in Figure 3.1b.

As discussed in section 2.2.3.1, the inputs to innovation production activities are mainly physical resources and manpower. Since the analysis was focusing on the industry and sector levels in the emerging market, knowledge capital stock was also adapted as an input in Chapter 2. The research subjects have changed in this research – they are companies from same sector. So the accumulated patent stock which was employed as proxy of knowledge capital stock can only disclose the level of knowledge capital stock inside individual company. However, in OI paradigm, the input of knowledge capital stock is not only from company itself but could also come from outside. Therefore, the accumulated patent stock cannot reflect the real level of knowledge capital stock for one company. The ideal index would be the one which could measure the level of knowledge capital stock truly absorbed by the company no matter it is from inside and outside of the company. However, there is no dataset available for such input.

So the main inputs here are physical resources and manpower, which are usually measured in annual total R&D expenditures and R&D personnel (Wang and Huang, 2007).

The two main inputs selected in this study are R&D expenditure and number of employees. The R&D expenditure refers to the total R&D expense, covering all projects involving both internal and external ones supported by the firm. The R&D expenditure input index has been widely

used, and found to be suitable in previous studies (Guan and Chen, 2010; Zhong et al., 2011; Chen et al., 2006).

Number of employees is adopted in this research as the index of mainly manpower on R&D. R&D personnel is widely employed as the input for measuring R&D efficiency (for example, Zhong et al., 2011). The study in Chapter 2 about the R&D efficiency of China's high-tech industry also employed R&D personnel as the index of mainly R&D manpower. However, two reasons may affect the suitability of R&D personnel as the R&D manpower index in this research. Firstly, the companies studied here are from Nondurable household product industry not the high-tech industry. Their innovation capability does not heavily depend on their R&D department as the high-tech industry. Many of those successful product ideas may come from non-R&D employees, such as employees from marketing. Therefore, only calculating the R&D personnel as the innovation input in this industry may underestimate the real manpower input in R&D. Secondly, since this study is aimed to measure the innovation efficiency within the OI strategy, it should be understood that the manpower put into innovation in the OI model is not as same as the one in the Closed Innovation model. Making P&G for example, the aim for launching Connect & Develop is to acquire 50% of innovation not from inside but outside their company (see Huston and Sakkab, 2006). To achieve this goal, they chose to leverage their own employees. And the innovation becomes no longer the job only for researchers but the job which needs the cooperation from different departments. For example technology support plays an important role in the shift of P&G's OI strategy (see Dodgson et al, 2006). Therefore, R&D personnel inside the company cannot represent the real R&D manpower in OI age. The real manpower in innovation may include most relevant employees especially for the non-high-tech industry. It will be meaningful if the comparison study about manpower input between the R&D personnel and the general number of employees could be developed. However, only limited R&D personnel data is available in certain years from some companies' annual reports, which makes it hard to do the measurement. Therefore, the

number of employees is adopted to represent the human resource inputs in this study. Here the number of employees is an estimate of total company employees excluding interns, co-ops and employees of joint ventures.

The main outputs of R&D activities are technical improvement and economic benefit (see Zhong et al., 2011). The initial, direct outcome of R&D investment is the technical improvement, estimated in this case as the issued patent number. As being discussed in Section 2.2.3.2, although patent cannot include all invention and reflect the quality of invention (see Griliches, 1990), it is still a fairly reliable measure of innovation production (see Acs et al., 2002; Pakes and Griliches, 1984). The number of patent applications which is employed as the index refers to the quantity of accepted patent applications by the patent office in the given year.

The other key outcome is the economic benefit, estimated in this case by the net sales and operating incomes as the final outputs in this study. The aim for companies doing innovation is to improve their capability of producing revenues, which could be reflected on their net sales and operating incomes. The ideal indices may be the sales and operating incomes on new products. However, these kinds of data haven't been publicized by the research subjects - these five companies. And they are not provided by other database. The general net sales and operating incomes may be not as suitable as the ones on new products, while since nondurable household products industry has short product life cycle, these commercial indices reflect the economic benefit on new products to some extent. Therefore, the net sales and operating incomes are employed to measure the economic benefit in this study.

Previous studies indicated that time lags between the inputs and the outputs could be important factors. Following these studies, the preliminary test was given in this study aimed to find the suitable time lag between inputs and outputs, which shows that 1-year lag for the issued patent number and 2-year lag for the net sales and operating incomes are appropriate. (For example, if the dataset of the inputs is in 2003, the

output data of the issued patent number should be in 2004 with 1-year lag, and the outputs data of the net sales and operating incomes should be in 2005 with 2-year lag).

As discussed previously (see Section 2.2.3.3), the robustness of this selection can be tested in two ways: firstly, by choosing two consecutive cross-sectional datasets to provide an approach for a robustness test by longitudinal comparisons (see Guan and Chen, 2010; Zabala-Iturriagagoitia et al., 2007); secondly, by varying the length of time lags to provide a robustness test (e.g., Hollanders and Celikel-Esser, 2007). Cross-sectional dataset already included into the data analysis due to this study utilising panel data. For the other robustness test, two different time lags 1-year (1-year lag for the issued patent number and 1-year lag for the commercial revenue) and 3-year time lags (2-year lag for the issued patent number and 3-year lag for the commercial revenue) were selected and adapted, in order to see whether current introduction of time lag has an effect of the final results. The analysis results show that, although the exact score per company per year has changed, the general performance of each company looks similar which indicates that current introduction of time lag has limited effect on the general analysis results. And because this 2 years' time lag was selected based on preliminary test, it is more suitable to be adapted in this study. The analysis results from the 1-year time lag and the 3-year time lag can been seen in Table A.10-A.12 and Table A.13-A.15 in the appendix.

3.4.3 Case Data Sources

P&G is widely studied as the representative of a class of firms adopting OI strategy at an early date which is followed by an apparently associated sequence of commercial success. Based on previous studies, P&G was chosen as the representative OI firm in this study. To reference its performance to other firms from the same sector, four R&D-intensive companies from the same sector are selected to do the comparison study. The reference companies were picked from the 2010 BIS (Department for

Business, Innovation and Skills in the UK)'s R&D ranking of the top 1000 world companies by their R&D spending. BIS's ranking includes all the R&D intensity companies around the world and ranks them based on their R&D expenditure in 2009. Following the ranking, four companies – Unilever, Henkel, Reckitt Benckiser and Clorox, which are the top R&D intensity companies, were selected (see table 3.1). All the five sample companies are from 'Nondurable household products' sector based on the categorization by BIS's R&D ranking of the top 1000 world companies. (BIS publishes the R&D ranking of the top world companies every year. This data is free to download from BIS's official website).

Table 3.1: the sample firms in this research

Industry description	Open innovation firm	Comparison firms
Nondurable household products	Procter & Gamble, USA	Unilever, UK Henkel, Germany Reckitt Benckiser, UK Clorox, USA

The data's time series is from 1990 to 2011. And much of the data required was available from official government sources and established business databases. The R&D expenditure, the number of employees, net sales and operating incomes were collected from Datastream (Thomson Reuters) and the issued patent number was collected from the database offered by United States patent and Trademark Office (USPTO). Datastream is an established and widely used dataset which provides both current and historical global financial and economic information with various types of data items from both developed and emerging markets. USPTO is the official organization which owns the USPTO search engine to provide search bibliographic details or full text of US patents from 1976. It is the mainstream patent data source in relative studies focusing on cross-market analysis. It is free to use through their website (http://patft.uspto.gov/). All monetary values are adjusted for inflation using the US domestic manufacturing Producer Price Index (with index

year 1989). The basic statistics for the main variables used to study the R&D performance of P&G and its competitors are reported in Table 3.2.

Table 3.2: Descriptive statistics for main variables in P&G cas study

Variables	Mean	Standard deviation	Maximum	Minimum
R&D expenditure	502628.9	499290.7	1628051	25073.56
Number of employees	87725.56	92557.79	308000	4700
Patent applications	124.27	151.7752	599	0
Net sales	19641309	17295408	54362552	1570236
Operating incomes	2831329	2984605	12138044	249768
Sample size of DMU	100			

Data sources: Data of R&D expenditure, number of employees, net sales and operating incomes are from Datastream (Thomson Reuters); data of patent applications is from United States patent and Trademark Office (USPTO). Here the unit of R&D expenditure, net sales and operating incomes is 1000$; the unit of patent applications is item.

3.5 Results

3.5.1 DEA Result

3.5.1.1 Technical Efficiency

In the DEA analyses, the TE scores reflect the overall R&D investment efficiency: the bigger the score, the higher the R&D efficiency: a firm has the highest possible R&D efficiency if its score is 1 in a given year. The detailed results are shown below. Based on the average score for the period 1990 to 1999 (pre-open period), Reckitt Benckiser was the most efficient company on R&D investment among these five companies. Clorox and Henkel were ranked second and third, and Unilever was the least efficient R&D Company, with Procter & Gamble only slightly better than Unilever. For the period 2000 to 2009 (post-open period), Procter & Gamble's average R&D efficiency across the whole period rose significantly, second, only to Reckitt Benckiser. Clorox ranked third, though its average score was higher than for pre-open period. Henkel and Unilever, which both showed the lower R&D efficiency, ranked fourth and last (see Table 3.3).

P&G's average R&D efficiency in the pre-open period was 0.581, the second lowest in relation to the reference companies. If, for example, the average score of the five companies is taken as an index of the industry's R&D performance, P&G's R&D efficiency was behind the average level of the industry (0.686) prior to P&G adopting an OI strategy. The situation changed dramatically after 1999 when P&G launched its OI initiatives. Over the post-open period P&G's average R&D efficiency score of 0.759 was the second highest efficient of all the firms. While with the average score 0.686 and 0.689, the average industry level of R&D efficiency performance was flat during both the pre-open and post-open periods (see Figure 3.2).

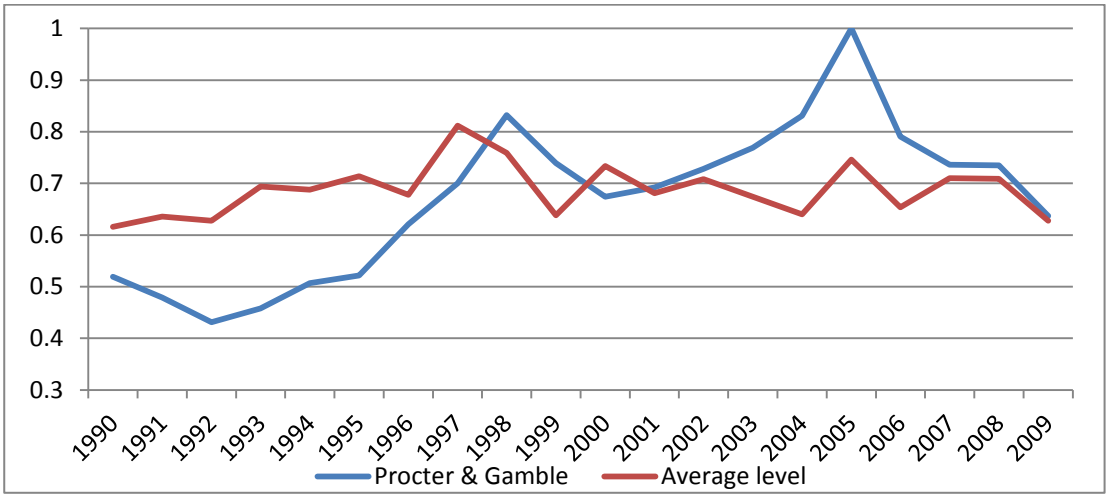


Figure 3.2: The Comparison of R&D Investment Efficiency between Procter & Gamble and Industry Average Level

Table 3.3: DEA technical efficiency index

Firm	Year of R&D activity input										
	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	Average 1990-1999
Unilever	0.482	0.534	0.620	0.611	0.573	0.510	0.483	0.508	0.434	0.447	0.520
Procter & Gamble	0.519	0.479	0.431	0.458	0.507	0.522	0.621	0.700	0.832	0.739	0.581
Henkel	0.506	0.384	0.459	0.764	0.807	1.000	0.714	0.868	0.860	0.672	0.703

Reckitt Benckiser	0.905	0.926	1.000	0.998	0.853	0.717	0.748	0.983	0.791	0.646	0.857
Clorox	0.668	0.857	0.631	0.640	0.700	0.819	0.825	1.000	0.876	0.684	0.770
Average	0.616	0.636	0.628	0.694	0.688	0.714	0.678	0.812	0.759	0.638	0.686

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Average 2000-2009
Unilever	0.455	0.487	0.436	0.387	0.399	0.489	0.447	0.525	0.553	0.511	0.469
Procter & Gamble	0.674	0.692	0.728	0.769	0.831	1.000	0.791	0.736	0.735	0.637	0.759
Henkel	0.980	0.661	0.672	0.594	0.491	0.519	0.452	0.484	0.462	0.421	0.574
Reckitt Benckiser	0.831	0.862	0.959	0.957	0.842	1.000	0.883	1.000	1.000	0.969	0.930
Clorox	0.729	0.703	0.744	0.665	0.637	0.724	0.696	0.806	0.797	0.604	0.711
Average	0.734	0.681	0.708	0.674	0.640	0.746	0.654	0.710	0.709	0.628	0.689

3.5.1.2 Pure Technical Efficiency (PTE)

The PTE scores reflect the pure R&D investment efficiency excluding scale effects. Clorox owned the highest average PTE score during the pre-open period. Unilever and Procter & Gamble followed it, ranking second and third, with Henkel fourth (Table 3.4). Over the post-open period, Procter & Gamble became the most efficient company on PTE with an average score 0.973, with Reckitt Benckiser and Unilever second and third and Clorox last (although it had exhibited the highest average PTE score over the pre-open period, the overall range of PTE scores across these five companies was not that large).

Table 3.4: DEA pure technical efficiency index

Firm	Year of R&D activity input										
	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	Average 1990-1999
Unilever	0.826	0.870	1.000	1.000	1.000	0.905	0.868	0.887	0.762	0.807	0.893
Procter & Gamble	0.951	0.893	0.808	0.829	0.809	0.805	0.913	0.983	1.000	0.920	0.891
Henkel	0.702	0.584	0.651	0.834	0.885	1.000	0.948	0.964	0.932	0.794	0.829

Reckitt Benckiser	0.914	0.936	1.000	1.000	0.862	0.723	0.759	1.000	0.806	0.646	0.865
Clorox	1.000	0.860	0.686	1.000	0.817	1.000	1.000	1.000	0.893	0.690	0.895
Average	0.879	0.829	0.829	0.933	0.875	0.887	0.898	0.967	0.879	0.771	0.874

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Average 2000-2009
Unilever	0.862	0.952	0.845	0.746	0.748	0.905	0.817	0.963	1.000	0.946	0.878
Procter & Gamble	0.892	0.935	1.000	1.000	0.941	1.000	1.000	1.000	0.965	1.000	0.973
Henkel	0.980	0.776	0.884	0.828	0.760	0.823	0.742	0.789	0.757	0.704	0.804
Reckitt Benckiser	0.836	0.878	0.972	0.966	0.882	1.000	0.888	1.000	1.000	0.993	0.942
Clorox	0.739	0.725	0.744	0.712	0.724	0.766	0.755	0.808	0.818	0.658	0.745
Average	0.862	0.835	0.889	0.850	0.811	0.899	0.840	0.912	0.908	0.860	0.868

Figure 3.3 shows a comparison of PTE performance between P&G and the industry level. As for the TE analysis, here the average PTE score of five companies is employed as the index of the industry performance. P&G has showed a higher PTE score than the industry since 1997, although its score declined somewhat during 1998 to 2000. In the post-open period, P&G showed the highest score and a more stable PTE performance. This seems to suggest that the adoption of OI strategy has improved innovation productivity in P&G. But unlike its TE score, which exhibited 'inverted curvilinear performance', P&G's PTE did not decline after the mid-way point in 2005, unlike P&G's TE score, which fell away rapidly.

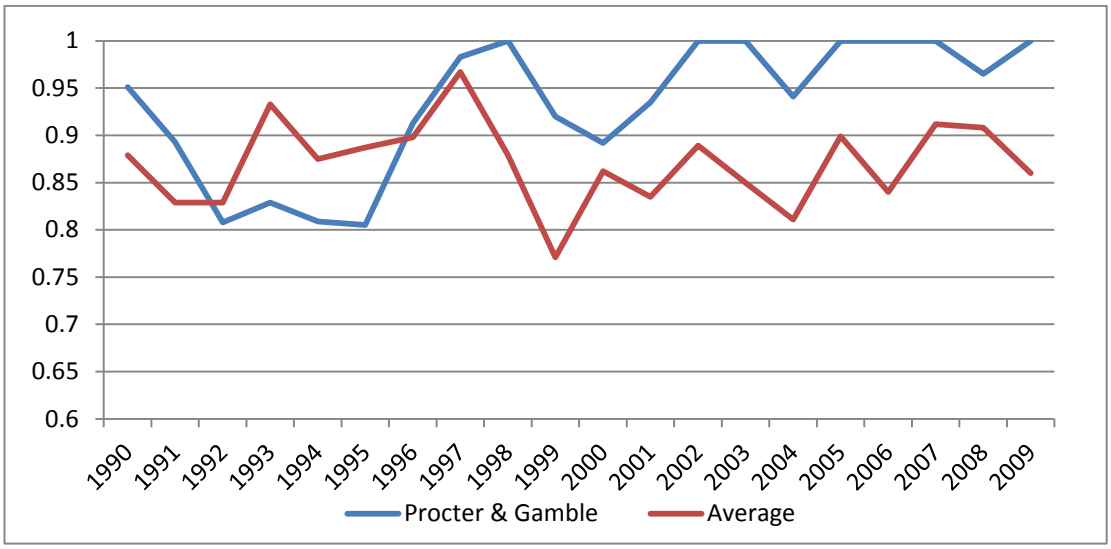


Figure 3.3: The Comparison of PTE score between Procter & Gamble and Industry Average Level

3.5.1.3 Scale Efficiency (SE)

Scale efficiency (SE) scores reflect various classes and levels of returns to scale on R&D investment. There are three possible classes of returns to scale: decreasing (DRS), increasing (IRS) and constant (CRS). CRS is indicated by an SE score of 1; DRS, signified by a decrease in the relative output for a given incremental input, and an associated decline in the consequent profit; IRS, signified by an increase in the relative output for a given incremental input.

In the pre-open period, Reckitt Benckiser and Clorox were first and second on average SE score. Both of them were experiencing increasing return to scale (IRS), indicating that a given level of R&D inputs was producing a relative increase in R&D output in these two companies. Henkel, P&G and Unilever were ranked third, fourth and fifth respectively. All these three companies were suffering from decreasing returns to scale (DRS), indicating that for a given level of increase in the R&D input, less relative R&D output was produced. In the post-open period, Reckitt Benckiser and Clorox were still ranked at first and second for the average SE score, while P&G has moved from fourth to third, and Unilever still had the lowest

average score. During this post-open period, all five companies suffered from DRS at some point. Apart from P&G and Clorox, all companies performed with lower average SE scores compared with the pre-open period (see Table 3.5).

Table 3.5: DEA scale efficiency index

Firm	Year of R&D activity input										
	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	Average 1990-1999
Unilever	0.584 drs	0.614 drs	0.62 drs	0.611 drs	0.573 drs	0.563 drs	0.556 drs	0.572 drs	0.57 drs	0.553 drs	0.582
P&G	0.546 drs	0.537 drs	0.533 drs	0.553 drs	0.626 drs	0.649 drs	0.681 drs	0.713 drs	0.832 drs	0.803 drs	0.647
Henkel	0.72 drs	0.658 drs	0.705 drs	0.916 drs	0.912 drs	1 -	0.752 drs	0.901 drs	0.922 drs	0.847 drs	0.833
Reckitt Benckiser	0.99 irs	0.989 irs	1 -	0.998 drs	0.989 irs	0.991 irs	0.986 irs	0.983 irs	0.981 irs	0.999 -	0.991
Clorox	0.668 irs	0.996 irs	0.92 irs	0.64 irs	0.857 irs	0.819 irs	0.825 irs	1 -	0.981 drs	0.991 irs	0.870
Average	0.702	0.759	0.756	0.744	0.791	0.804	0.760	0.834	0.857	0.839	0.785
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Average 2000-2009
Unilever	0.527 drs	0.512 drs	0.517 drs	0.519 drs	0.533 drs	0.54 drs	0.547 drs	0.545 drs	0.553 drs	0.54 drs	0.533
P&G	0.755 drs	0.74 drs	0.728 drs	0.769 drs	0.884 drs	1 -	0.791 drs	0.736 drs	0.761 drs	0.637 drs	0.780
Henkel	1 -	0.852 drs	0.759 drs	0.717 drs	0.646 drs	0.63 drs	0.61 drs	0.614 drs	0.61 drs	0.597 drs	0.704
Reckitt Benckiser	0.994 irs	0.982 drs	0.986 drs	0.991 drs	0.954 drs	1 -	0.995 drs	1 -	1 -	0.976 drs	0.988
Clorox	0.986 irs	0.97 irs	1 -	0.935 drs	0.881 drs	0.945 drs	0.921 drs	0.998 drs	0.974 drs	0.919 drs	0.953
Average	0.852	0.811	0.798	0.786	0.780	0.823	0.773	0.779	0.780	0.734	0.792

P&G's SE score showed a similar pattern to its TE score, the now familiar inverted curvilinear profile. P&G's SE score increased after 2003 and reached a peak in 2005, followed by a subsequent decline. Figure 3.4, shows the performance of P&G's SE score with the average SE score across

the five companies are compared. Adopting the average SE score as an index of the industry's SE, from the comparison it could be found that P&G had lower Scale Efficiency (SE) than the rest of the industry before 2003, but from 2003-2006 the company made an inverted curvilinear performance and surpassed the whole industry on this index, only to return to lower performance again after 2006 (Figure 3.4).

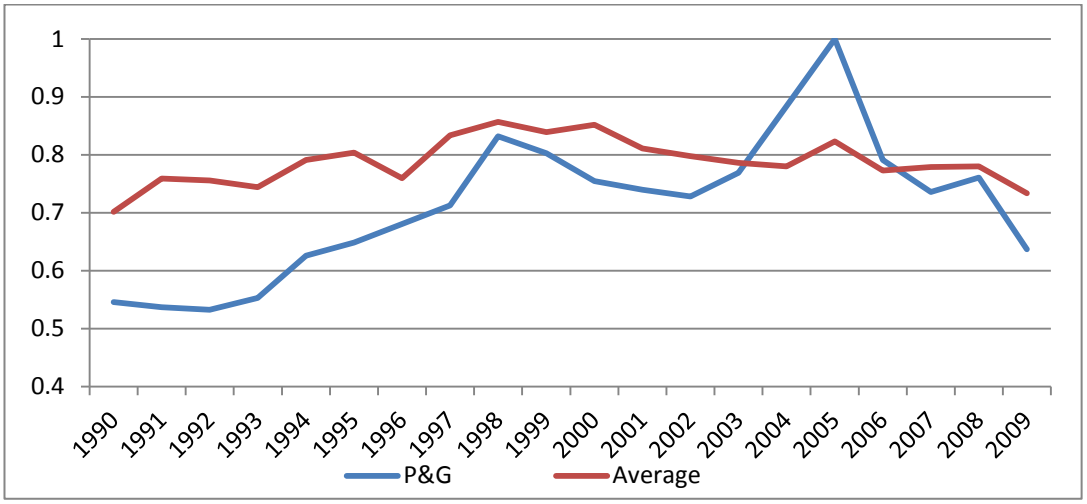


Figure 3.4: The Comparison of SE score between Procter & Gamble and Industry Average Level

3.5.2 MI Results

There are five indices generated by the Malmquist index analysis (MI). This study uses two of the indices: Malmquist index and frontier shift index, which are also known as the total factor productivity change (TEPCH) and technical change (TECHCH) respectively. The Malmquist index reflects the total factor productivity change for individual companies, while frontier shift index reflects 'industry-wide productivity change' (Hashimoto and Haneda, 2008). Therefore, these two indices were adapted to measure separately the total R&D efficiency and the industry-wide R&D productivity.

3.5.2.1 Malmquist Index

The Malmquist index indicates the total R&D efficiency change of a firm over time (Hashimoto and Haneda, 2008). The type of Malmquist index

analysis employed in this study is the cumulative technique. The indices received in each year are all calculated from the reference year 1994 in which the values are all 1. Therefore, the index values from this analysis are different to those in the DEA results, which makes the ranking of the R&D efficiency among the sample companies seem different. In the pre-open period, Henkel ranked first and Reckitt Benckiser ranked last on the average score. With average score 1.097, P&G stayed in the middle among the five companies, while the ranking changed dramatically in the post-open period. P&G and Reckitt Benckiser ranked first and second respectively with average scores of 1.437 and 1.199. In pre-open period, P&G showed a R&D efficiency performance under the average level. It has started to move beyond the industry's average performance since 2000 and led the R&D efficiency for the most years. Intriguingly, the dip of R&D efficiency is found for P&G around 1999 and its R&D efficiency has declined since 2006. Therefore, based on the result, it can be found that the R&D efficiency of P&G had constantly improved since its adoption of OI strategy in year 1999.

Table 3.6: Cumulative Malmquist index

Firm	Year of R&D activity input										
	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	Average 1990-1999
Unilever	1.000	1.084	1.276	1.246	1.210	1.070	1.000	1.057	0.908	0.950	1.080
Procter & Gamble	1.000	0.951	0.852	0.905	1.004	1.093	1.243	1.296	1.533	1.091	1.097
Henkel	1.000	0.864	0.916	1.327	1.404	1.691	1.266	1.697	1.657	1.153	1.298
Reckitt Benckiser	1.000	1.033	1.148	1.131	1.037	0.894	0.889	1.108	0.941	0.778	0.996
Clorox	1.000	1.084	1.050	1.177	1.264	1.498	1.264	1.894	1.614	1.015	1.286
Average	1.000	1.003	1.048	1.157	1.184	1.249	1.132	1.410	1.331	0.997	1.151
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Average 2000-2009
Unilever	0.952	1.092	0.971	0.844	0.850	1.060	0.934	1.097	1.174	1.061	1.004
Procter & Gamble	1.139	1.223	1.405	1.457	1.571	1.807	1.548	1.465	1.448	1.305	1.437

Henkel	1.385	1.143	1.166	1.046	0.852	0.894	0.894	1.051	0.964	0.869	1.026
Reckitt Benckiser	1.033	1.140	1.121	1.046	1.210	1.505	1.099	1.229	1.391	1.220	1.199
Clorox	1.146	1.170	1.248	1.180	0.907	1.185	1.204	1.472	1.400	1.048	1.196
Average	1.131	1.154	1.182	1.115	1.078	1.290	1.136	1.263	1.275	1.101	1.172

It strongly supports the conclusion of previous studies, and demonstrates the significant benefit of OI strategy for P&G. Even compared with the other four firms, the development trend of R&D efficiency for P&G is still obvious, especially compared with its big competitor Unilever which had experienced the flat R&D efficiency across the period based on the Malmquist index (see Table 3.6).

3.5.2.2 Frontier Shift Index

The average frontier shift index across all firms is an appropriate indicator to view R&D efficiency change at the industry level (Hashimoto and Haneda, 2008). Therefore, the industry's R&D efficiency performance can be assessed by the analysis of the average firms' score on frontier shift index.

Table 3.7: Cumulative frontier shift index

Firm	Year of R&D activity input										
	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	Average 1990-1999
Unilever	1.000	0.994	1.107	1.195	1.197	1.117	1.164	1.543	1.246	1.051	1.161
Procter & Gamble	1.000	0.951	0.944	1.183	1.256	1.355	1.243	1.850	1.533	1.091	1.241
Henkel	1.000	0.882	0.962	1.053	1.114	1.342	1.005	1.517	1.315	0.915	1.111
Reckitt Benckiser	1.000	1.033	1.148	1.131	1.037	0.894	0.889	1.108	0.941	0.778	0.996
Clorox	1.000	1.084	1.050	1.177	1.264	1.498	1.264	1.894	1.614	1.015	1.286
Average	1.000	0.989	1.042	1.148	1.174	1.241	1.113	1.582	1.330	0.970	1.159
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	Average 2000-2009
Unilever	1.317	1.343	1.288	1.195	1.330	1.587	1.153	1.228	1.383	1.226	1.305
Procter & Gamble	1.139	1.223	1.405	1.457	1.571	1.807	1.548	1.630	1.596	1.305	1.468
Henkel	1.099	0.907	1.034	1.069	0.763	1.137	1.088	1.270	1.210	0.973	1.055

Reckitt Benckiser	1.033	1.140	1.121	1.046	1.210	1.505	1.099	1.229	1.391	1.220	1.199
Clorox	1.146	1.170	1.248	1.180	0.907	1.185	1.204	1.472	1.400	1.048	1.196
Average	1.147	1.157	1.219	1.189	1.156	1.444	1.218	1.366	1.396	1.154	1.245

Table 3.7 shows that the average scores had a flat performance during the test period, which indicates that the industry's R&D efficiency did not have any great change. This result corresponds to the prior findings from DEA analysis about the industry's performance. Therefore, there is strong evidence to demonstrate that the increase of R&D efficiency on P&G is not triggered by the macro benefit such as the better industry-wide performance.

3.6 Discussion

This study sets out to determine if (1) the indices of innovation could be applied to test whether OI was proving an productive strategy, by (2) analysing the performance of P&G before and after its adoption of OI in 1999, and in doing so (3) explore what other insights such a quantitative view might afford us. The discussion considers first the main observations for each of the individual indices (see Table 3.8), and then the collective implications of these finding for a new potential 'Three-Stage' model of OI adoption.

Table 3.8: Adoption of Open Innovation and Indices of Innovation

Indices	Subject			
	P&G (10 Year Average)		Industry (10 Year Average)	
	Pre-open period	Post-open period	Pre-open period	Post-open period
Technical Efficiency (TE)	0.581	0.759 **(+30.64%)**	0.686	0.689 **(+0.44%)**
Pure Technical Efficiency (PTE)	0.891	0.973 **(+9.20%)**	0.874	0.868 **(-0.69%)**
Scale Efficiency (SE)	0.647	0.78 **(+20.56%)**	0.785	0.792 **(+0.89%)**

Malmquist Index analysis is employed to verify the research result: it disclosed a very similar profile for P&G's R&D performance to that shown by the DEA analysis, showing the 'open rise' after adoption of OI, the 'open drop' after six years, and 'open dip' immediately in the adoption year 1999.

3.6.1 Productivity Pre- and Post-adoption

Technical Efficiency (TE) is the broadest overall index of its R&D effectiveness; Pure Technical Efficiency (PTE) is a pure measure of the effectiveness of the R&D process exclusive of other scale effects; Scales Efficiency (SE) score is a measure of the effect of scale of operation.

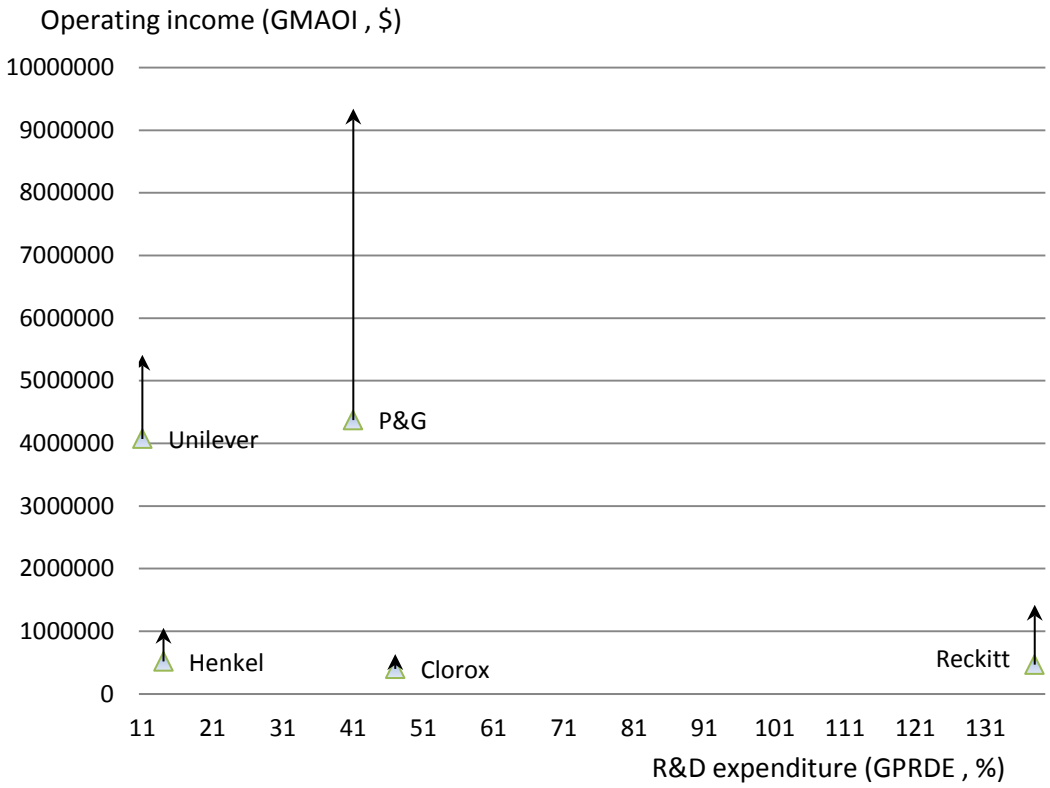
The first finding is that P&G's average scores for all three indices – TE, PTE, and SE - increased in the post-open period when compared with pre-open period, while the average scores for all 3 indices across the industry 'control' group were effectively flat for the whole period, showing none of the profile changes exhibited by P&G. Not all of the profile changes were of the same magnitude. P&G's average Technical Efficiency (TE) increased by approximately 30% in the post-open period compared with the pre-open level, whereas P&G's average Pure Technical Efficiency (PTE) also increased significantly in post-open period compared with pre-open period, but much less dramatically at just 10%. P&G's average Scales Efficiency (SE) score was between the other two indices, showing a 20% increase in the post-open period compared with the pre-open level (see Table 3.8).

The benefit of switching to OI could also be assessed by correlating the operating incomes with R&D expenditure growth. Figure 3.5 shows that with the average R&D expenditure growth rate P&G showed the biggest increase on average operating incomes in the post-open period. This provides a strong evidence to support the success of OI strategy switching.

3.6.2 Post-adoption Response Profile

All three primary 'indices" of innovation – Technical Efficiency, Pure Technical Efficiency and Scale Efficiency - follow a similar 'curvilinear'

developmental sequence, with a characteristic initial dip, followed by a significant rise and then a drop of similar magnitude and ratio, except that the PTE scores did not show any drop. Given the flat and stable performance of the reference competitor group, and the magnitude and duration of the change, the simplest interpretation of the 'Open Rise' at P&G to be that it does indeed reflect a positive effect of the switch to an OI strategy. The transient 'Open Dip' could reasonably be interpreted as a temporary loss of efficiency during transition to the new strategy. The 'Open Drop' observed was unexpected, as was its magnitude, and invites a number of possible interpretations ranging from absorption of the relevant market opportunities to inconsistent execution of partnering activities: in any event, not what adopters of OI are seeking. Further research on indices may identify other cases of the observed 'Open Drop', which so far has not been reported previously.



Y axis shows geometic mean of annual operating incomes (GMAOI). X axis shows the growth percentage of R&D expenditure between geometic means of pre-open R&D expenditure and post-open R&D expenditure (GPRDE). The bottom point of the line shows GMAOI in pre-open period. And the top point shows GMAOI in post-open period. The arrow direction shows that all the firms' GMAOI has increased during pre and post-open periods.
Source: Datastream

Figure 3.5: Correlation of operating incomes and R&D expenditure growth

3.6.3 Other Insights and Implications

As both the DEA and MI analyses revealed, the overall indices of R&D performance exhibited an 'inverted curvilinear' profile. The graphical profile observed for P&G in this study supports the previous conclusion of Laursen and Salter (2006), based on a Tobit regression analysis of the UK manufacturing sector. From which they concluded that 'searching widely and deeply is curvilinear relative to performance', based on the 'inverted curvilinear' relationship they observed between OI and firm performance. The interpretation is that at one extreme the risk may be to set the

research net too wide and catch an unmanageable number of opportunities and at the other to set it too narrow and catch too little. Another implication would be that secondary management indicators of performance trends that correlate with the overall econometric performance indices applied here would be useful additions to the management toolset for informed innovation.

With respect to the individual indices, since PTE reflects pure R&D efficiency exclusive of Scale Efficiency, it can also conclude that the pure R&D efficiency of P&G increased after the OI adoption point, again supporting the notion that the adoption of OI strategy appears to have helped the company improve its pure R&D efficiency. In contrast to the TE result, PTE did not show a continuing and obvious decline in the post-open period, leading us to conclude that other factors, such as scale effects, must be responsible for the overall decline of R&D efficiency at P&G over that period.

Interestingly, the majority of the companies studied – including P&G – tended to suffer from greater decreasing return to scale (DRS) effects in the post-open period than in the pre-open period. The interpretation of this observation is that in a closed innovation scenario, given the limitation of the scope of management to a company boundary and the production principles in use inside that boundary, increasing R&D inputs might be expected to follow the law of diminishing marginal returns and lead to decreasing R&D outputs.

In an OI scenario, firms can access and absorb sources of R&D beyond their internal R&D activities and can thus expand their R&D horizons and maintain scale efficiency, which is account for the 'Open Rise' seen in the SE score after adoption of OI. Since the PTE score did not show 'Open Drop' effect, it maybe that the inverted curvilinear profile of P&G's overall R&D efficiency may be driven or determined by its Scale Efficiency (SE) performance. One explanation might be that external R&D projects normally operate outside the firm by another organization or individuals, and an increase in external R&D projects could entail a risk that the

company who launched the projects loses management control, and lead to a reduction of scale inefficiency.

3.6.4 A Three-Phase Model for OI Adoption

To account for these three observations and their sequence, this study proposes a 'Three-Phase' model of OI adoption (Figure 3.6a), where the initial dip, followed by a cycle of rise and fall (drop), reflects what may be one pattern of company response to the onset of OI.

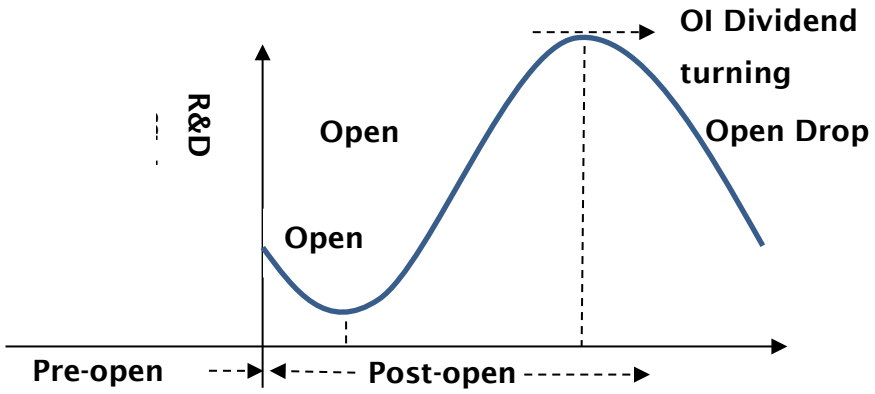


Figure 3.6a: Three-Stage OI Adoption Model

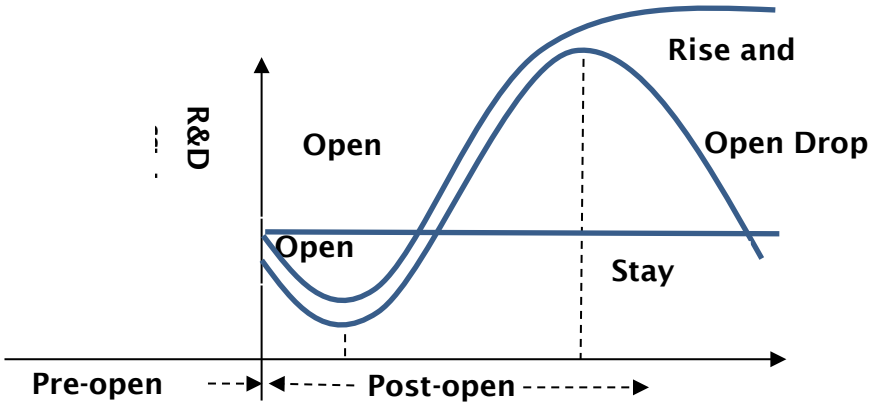


Figure 3.6b: Three alternative scenarios

Figure 3.6: OI adoption model and OI scenarios

This study has already discussed the concepts and potential interpretations of the three 'phases' of the post OI-adoption response, but there are other conceivable response scenarios. For example, two clear alternative scenarios are what might be called 'rise and sustain', where there is no 'open drop' effect, and 'stay flat', where there is no change (Figure 3.6b). There is no data for these at present.

3.7 Concluding Remarks

The result appears to show that not only can OI be effective in transforming R&D performance, but there may be a predictable sequence of effects and a definable range of outcome scenarios. The quantitative methods of this study appear to meet the needs identified in the preceding literature (Huizingh, 2011) for more quantitative approaches to the measurement of OI, which this paper has attempted to address by applying DEA and MI linear programming techniques. Using these techniques, it would appear this study has shown convincing quantitative indices which track increases in OI efficiency in the case of P&G relative to its competitors.

Although the most obvious interpretation of the results is that adopting OI can lead to a dramatic improvement in R&D performance, other explanations are of course possible. For example, a bull market could have an uplift effect; a change of management might have impact, and so forth. However, the temporal apposition of the effect, the existence of parsimonious causal mechanisms, and the lack of similar effects in competitors not making the strategic shift to OI – in effect a control – suggest that there may indeed be an effect worthy of further investigation with a wider range of cases, and perhaps at sector or industry level. The period of adoption also coincided with an extended period of stock market decline: the 'dot bomb' era, also seeming to rule out any general market.

However, although the results of this study show positive improvement on several of the key indices, the pattern is not simple, and OI should not be regarded as a panacea. Even the early adopter of OI still faces a significant

management challenge in implementing OI. So although OI may be a route to more ideas and commercial opportunities from external sources, the companies who are adopting and will adopt OI strategy should recognize that implementation has to be managed and monitored to realize OI efficiency gains. This research appears to suggest that one of key indices to manage is the scale efficiency of R&D within the industrial OI ecosystem, where Scale Efficiency may affect OI efficiency in two distinct phases, at the initial and later stages of execution.

Although more efficient R&D is what the companies seek in moving to OI, moving to OI is not a guarantee for more efficient R&D: if companies are less than totally prepared for the new management challenges likely to emerge from the strategic transition from closed to open, they might for example anticipate problems in R&D source allocation and external project control, which in turn could impact the scale inefficiency in the companies' R&D, and this kind of scale inefficiency might be expected at the beginning of OI adoption.

This study has several potential contributions both in practice and research. Since few studies have been concerned with measuring the performance of OI, this study is one of the first to provide quantitative indices to evaluate the performance of OI. In this comparative study, the relative performance of OI versus closed innovation appears to be a clear win for open, at least in one adoptive organization. This finding and these tools should help companies to find the right balance and monitor the development of OI in their organizations. With the means of measuring the performance of OI, scholars could go beyond the descriptive study and pursue further applicable research about the efficacy of OI in a wider range of companies, sectors, and industries. For practitioners who plan to do OI, the management control might be developed to face the emergence of R&D efficiency deadline at the beginning and later stages of OI adoption. For practitioners who are already opened, they should understand staying in OI does not mean continuous higher R&D efficiency: management of OI efficiency should be paid more attention after the

adoption of OI strategy. To keep their successful story, they might keep innovative not only for OI but also for OI efficiency.

4. Chapter 4: Indices of Innovation: Strategic Application of Open Innovation in the Pharmaceutical Industry

Abstract

With rising costs and flat output for new drug approvals, the pharmaceutical industry is threatened by an uneconomic future. Since the former traditional strategies such as Mergers & Acquisitions and increasing R&D investment did not help to improve the R&D efficiency, the pharmaceutical companies appear to have turned implicitly or explicitly to open innovation as a new strategy. Because of the lack of quantitative econometric studies, there is still a question of whether open innovation is the best prescription for the pharmaceutical industry. A systematic review of the recent literature on open innovation in the pharmaceutical industry highlights questions of its strategic value, level of adoption, and current effectiveness as a strategy. Using DEA and MI, the 'indices of innovation' which have been identified and developed, this study measured whether or not 'open' innovation strategy has helped the industry to improve the R&D efficiency, and other evidence highlighting the relative inefficiency of earlier strategies. One combination of strategies – focused innovation + open innovation – is examined as a potentially effective prescription for the sustained success in the pharmaceutical industry. Future management suggestions have been given to support the transition of pharmaceutical companies moving into the open age.

Keywords

Pharmaceutical industry; open innovation; R&D efficiency; focused innovation.

4.1 Introduction

The Pharmaceutical industry has long been recognized as highly dependent on science, research and development. R&D spending has been growing at an average compounded rate of 12.3% since 1970 (PhRMA, 2009). In 2011, 16.7% of total sales were spent on R&D, higher than most other R&D intensive industries (PhRMA, 2012). However, the rate of approvals of new molecular entities (NMEs) by US Food Drug Administration (FDA) is basically flat for several decades (see Figure 4.1). The industry today is spending much more money to launch one drug into market compared with before: in 1976, it cost US$54 million to develop a new drug (DiMasi, 2001); but now this number has grown to more than US$ 1 billion (DiMasi and Grabowski, 2007). The industry is clearly facing huge challenges in innovation. This cost and innovation pressure is forcing the industry to search for the new way to increase R&D productivity. Many pharmaceutical companies appear to have turned implicitly or explicitly to open innovation as a savior strategy.

The original concept of OI suggested that companies can optimize their productivity by accessing the best sources of expertise regardless of location, and many firms increasingly rely on external sources of innovation by emphasizing that ideas, resources and individuals flow in and out of organizations (Chesbrough, 2003b). In contrast to OI, closed innovation (CI) was the traditional way for firms to innovate and had been a very successful strategy in the past, especially in the pharmaceutical industry. However, with the changing commercial environment, it has or is becoming unsustainable in several industries where a number of "erosion" factors operate (Bianchi at al., 2011). More companies realized that there are more commercial opportunities both inside and outside the firms' boundaries. Because an OI process can involve multiple internal and external technology sources and multiple internal and external technologies commercialization channels (Christensen et al., 2005; Lettl et

al., 2006; West and Gallagher, 2006), firms could operate their innovation process in two directions: inbound and outbound (Lichtenthaler and Ernst, 2009). A wider cultural trend toward OI has been observed and it has taken on greater saliency in light of its successful application in some industries (Ili at al., 2010). OI or variations of it seems, for example, to have taken hold strongly in software industry (West and Gallagher, 2006) and also in consumer goods (Dodgson et al., 2006). Companies from other industries are also talking about the adoption of OI. As a R&D intensive industry, companies from pharmaceutical industry are showing great interests about OI.

Despite the theoretical and practical potential of OI to provide a path for pharmaceutical industry to remain successful into the future, there are surprisingly few studies focussing on the implementation and performance impact OI in Pharmaceutical companies (Hughes and Wareham, 2010; Chiaroni et al., 2009). Based on a systematic literature review of the economics of innovation in the world's leading pharmaceutical companies, this study explores two key questions vital to the future of the industry: Is OI proving an effective strategy for pharmaceutical industry, and how can R&D productivity best be measured?

4.2 Industry Pressures

Previous studies discovered that R&D productivity in Pharmaceuticals has been declining (Scannell et al., 2012), as indicated by ever increasing R&D expenditure but flat R&D output. This section reviews the impact of these and other major pressures.

4.2.1 Rising R&D Expenditure

R&D expenditures have been increasing steadily for decades. Figure 4.1 can show this increasing trend. In Pharmaceutical industry, R&D spending has growen at an average compounded rate of 12.3% since 1970 (PhRMA, 2009). NME costs have grown exponentially at an annual rate of 13.4% since the 1950s, and only 27% of companies have costs per NME below $ 1

billion (Munos, 2009). The 'capitalized' cost per NME launch is $1778 million (Paul et al., 2010).

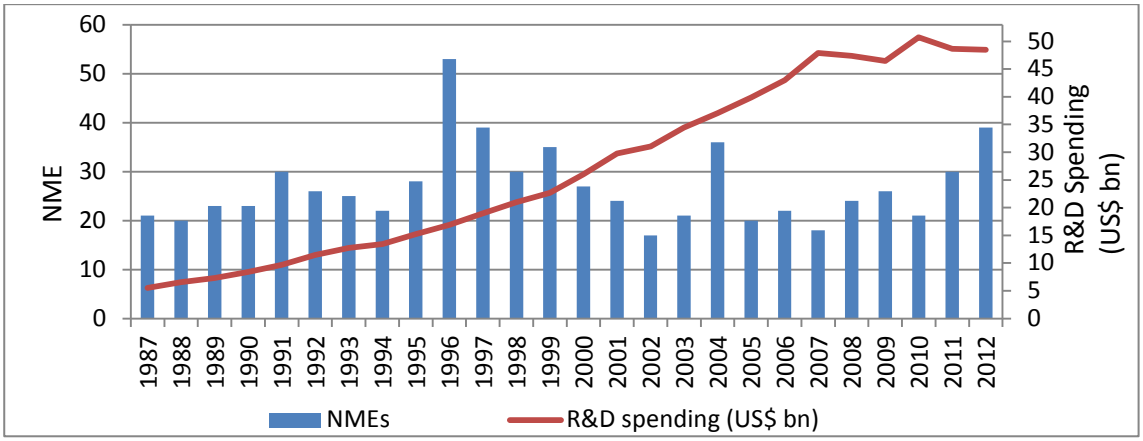


Figure 4.1: NME approvals and drug companies' spending on R&D

4.2.2 Flat NME Performance

Whatever the reasons, the industry major challenge is that R&D expenditure has been rising but the number of new molecular entities (NMEs) has remained flat for three decades. Observing the number of NMEs would yield an estimate of the performance of the R&D output in Pharmaceutical industry. Figure 4.1 shows that the trend line of approvals of NMEs by US Food Drug Administration (FDA) is basically flat with the peak point 53 approvals in 1996. Even the peak point for NMEs in 1996 is not explained by better R&D productivity. There has been speculation that the peak in 1996 was caused by the FDA processing a backlog of applications with the help of the recently approved user fees, which was caused by the enactment of prescription drug user act (PDUFA) in 1992 (Munos, 2009).

4.2.3 Declining Sales Growth

This R&D output challenge is also be observed in sales performance. Although total global pharmaceutical sales have been increasing from 2001 to 2008, the speed of growth has slackened (see Table 4.1). At the

same time, the big pharmaceutical companies face the familiar challenge of patent expiry on their blockbuster products, which seriously affect pharmaceutical present and future sales. Consistent with earlier analyses continuing with the current business model may result in a reduction of 5-10% in sales and 20-30% in net income in 2012-2015 (Munos, 2009).

Table 4.1: Global Pharmaceutical Sales, 2001-2008

	2001	2002	2003	2004	2005	2006	2007	2008
Total World market (current US$ in billions)	393	429	499	560	605	648	715	773
Growth Over Previous year ($Constant US$ Growth)	11.80%	9.20%	10.20%	7.90%	7.20%	6.80%	6.60%	4.80%

Source: IMS Health Market Prognosis (includes IMS Audited and Unaudited markets) (2009).

4.2.4 Regulatory Pressures

Some observers contend that this unsatisfactory R&D performance was caused by regulatory changes. However, countries with a more demanding regulatory apparatus, such as the US and the UK, have also fostered a more innovative and competitive pharmaceutical industry (see the ranking of pharmaceutical companies on market capitalization in Table 4.2). The reasonable interpretation may be that inventing the new drugs is getting harder, since the spring of the 'low-hanging fruit' (mainly in terms of targets) has now dried up ((Talaga, 2009). In view of the fact that increasing internal R&D expenditure is not reflected in a proportional response in sales, new strategies were required.

Table 4.2: The top 10 pharmaceutical companies on market capitalization

Country	Name	Market Capitalization ($M)
USA	Johnson & Johnson	99183
Switzerland	Novartis	82388
USA	Pfizer	80040
Switzerland	Roche	73010
USA	Merck	66615
UK	GlaxoSmithKline	63584
USA	Abbott Laboratories	47863

UK	AstraZeneca	47459
France	Sanofi-Aventis	46324
USA	Amgen	32655

Data resource: 2010 BIS (Department for Business, Innovation and Skills in the UK)'s R&D ranking of the top 1000 world companies by their R&D spending

4.3 Industry Responses

Prior to the emergence of OI, the other strategic alternatives which have been tried do not seem to have worked. The main alternatives adopted - Mergers and acquisitions (M&As) and increasing R&D investment - have proven largely unsuccessful or at least insufficient. This section reviews these and other strategic responses to the pressures identified in the preceding analysis.

4.3.1 Mergers and Acquisitions: No Increase in Net Shareholder Value

M&As have always been a feature of the Pharmaceutical industry landscape from its earliest beginnings. Actually, from the statistics given by Munos (2009), among the 261 organizations which have registered at least one NME since 1950, 137 organizations, over 50% of the total number, have disappeared through M&A.

In recent decades, it appears that M&A strategies have been increasingly been employed in attempts to halt the decline in productivity and profitability. However, M&As do little to close the innovation gap in this industry, serving only to provide temporary bottom-line relief, while the titanic enterprise, though larger, continues to sink. Such strategies do not really deliver breakthrough drugs, but instead often induce a loss of motivation amongst the industrial scientific community because of associated reorganization and downsizing (Lundberg and Reilly, 2009), and frequently a rationalization of the portfolio. Sometimes a partial, if not total, extinction of the 'acquired' partner's drug discovery culture can even happen (Talaga, 2009).

This conclusion is strongly supported by recent econometric research. Ornaghi (2009) studied the effects of mergers on the R&D activity of consolidated firms 1988-2004. His analysis discloses that merged companies have on average, worse performances than the group of non-merging firms. This suggests that M&A are not an effective way to promote an innovation culture or remedy a deficit of innovation, at least for the big pharmaceutical companies, and in fact are often quite the reverse.

Also, because of the particularly strong relationship between innovation capabilities and company revenues in the industry, M&As also affect the company's financial performance. Large firms that merged experienced a similar change in enterprise value, sales, employees, and R&D, showed slower growth in operating profit, compared with similar pharmaceutical firms that did not merge (Danzon et al., 2007). Danzon et al (2007) concluded that for large pharmaceutical firms, mergers are a response to expected excess capacity due to patent expirations and gaps in a firm's product pipeline. And for small firms, mergers are primarily an exit strategy in response to financial trouble.

4.3.2 Increasing R&D Expenditure: Reaching the Limit

There appears little chance that the pharmaceutical industry can maintain its historical success by increasing R&D expenditure. This is determined by the characteristics of Pharmaceutical R&D – more R&D spending but with a smaller success percentage.

The success of the Pharmaceutical industry for much of the last century depended on 'blockbuster' drugs, which remains a major goal the companies in this industry are pursuing. Given the low (21%) probability of blockbusters, the company needs at least 2-5 NME launches per year (Munos, 2009). Therefore, 18-45 Phase 1 starts would be required annually in a typical large company based on the model given by Paul et al., (2010). However, such numbers are rarely achieved even in the very largest companies.

Even if they cut down their goal to launch one NME per year, which indicates the company may have one blockbuster during five year time period, it is challenging. Because the number of discovery projects from target-to-hit, hit-to-lead and lead optimization is approximately 25, 20 and 15 respectively (Paul et al., 2010), most companies are simply unable to achieve these numbers. Although there is recent benchmark data reflecting that the number of candidates entering Phase 1 trials has increased significantly, it is still insufficient to achieve 2-5 launches per year on Phase 2 and 3 (Mathieu, 2008/2009; Hu et al., 2007; Booth and Zemmil, 2004). The reality is many large pharmaceutical companies estimate they need to produce an average of 2-3 NMEs per year to meet their growth objectives. However, it is actually around 0.45 NMEs per year, resulting over time in a substantial pipeline gap for many companies (Paul et al., 2010).

The interim conclusion must be that - based on the current R&D efficiency and the characteristics in Pharmaceutical industry – traditional business strategies such as purely increasing R&D expenditure or doing M&A will not make the industry sufficiently successful.

4.3.3 Change of Strategy

Since the innovation dynamics of the past century and transplanted business models do not appear to have produced sufficient increases in the pharmaceuticals, a new transformational approach to innovation is needed to raise unsatisfactory levels of R&D efficiency. To realize this, the current emergent hypothesis seems to be that the innovation system in the Pharmaceutical industry should be redesigned, and move from the traditional closed innovation system to the open innovation one.

OI is not a new idea in the pharmaceutical industry: previous studies have demonstrated the long existence of OI-like activities in Pharmaceutical industry. For example, in a 2008 OECD report, the pharmaceutical industry is considered to show levels of open innovation as high as other industries such as chemicals, and information and communication

technology (ICT) (Open Innovation in Global Networks, 2008). The OI trend can also be tracked from the studies of external collaboration activities in pharmaceuticals. Examination of the publication activities of the R&D laboratories of the major European and US pharmaceutical firms during the period 1995-2009, a high percentage of external collaborations is found at the beginning of the period (62.1%, 1998), which increases slightly in the following years (Rafols et al., 2012). Actually since 2000, it appears there is more research being performed outside than in. Many pharmaceutical companies have attempted to tap in to this and are moving more towards an OI model (Judd, 2013).

Bianchi et al. (2011) collected and analysed the data about the adoption of OI by the top 20 worldwide bio-pharmaceutical players in the period 2000-2007. Their study appears to suggest that:

(1) Inbound open innovation is likely to take place mainly in the first three phases of the drug R&D process;

(2) Outbound open innovation is mainly in the second part of the process;

(3) OI activities in core therapeutic areas have decreased while activities in non-core therapeutic areas have increased; this is most evident in the largest firms;

(4) 63.5% of the alliances in inbound OI refer to non-core therapeutic areas, while alliances (mostly co-manufacturing and co-marketing agreements) in outbound OI largely refer to core therapeutic areas;

(5) The vast majority of the in-licensing agreements (69.5%) refer to products in core therapeutic areas;

(6) Establishing organisational modes for OI with universities and research centres is not a relevant phenomenon.

In summary, the precedents in OI activities in the industry do not seem sufficient to justify wholesale adoption of OI by the industry. The reality is more complex.

4.4 Method

4.4.1 Indices of Innovation

As has been argued, many pharmaceutical companies appear to have turned implicitly or explicitly to open innovation as a savior strategy. However, the most important questions – whether OI is the best strategy prescription for the pharmaceutical industry – are still waiting to be answered. In fact, whether OI is working or not is still a serious research question which lacks literature contributions especially from the quantitative evidence through the study of early and current OI adopters (see Enkel et al., 2009; Huizingh, 2011). To evaluate OI, the performance of R&D efficiency on the target firms could be an effective index. Because the most important benefit provided by OI is the chance to increase the productivity of own R&D (Ili et al, 2010). Therefore, the logic here is to evaluate OI strategy through measuring the performance of R&D efficiency. And the suitability and capability of this research design has been demonstrated in Chapter 2 through the study of P&G and its counterparts. As been discussed by Wang and Huang (2007), only in recent decade a few examples in the literature discussed R&D efficiency by using quantitative approaches with regard to R&D at the frim level (see Zhang et al., 2003; Revilla et al., 2003; Guan et al., 2006). And no studies developed to evaluate the performance of R&D efficiency in order to assess the OI performance.

Two major approaches to measure the R&D efficiency have been discussed in previous chapters. SFA (stochastic frontier analysis) and DEA (Data Envelopment analysis) which belongs to non-parametric analysis techniques are major approaches for evaluating efficiency. DEA was employed in this study, based on its obvious advantages and suitability. Malmquist Index analysis (MI) which is another candidate of measuring R&D efficiency from non-parametric analysis techniques was also employed to verify the research results. Both DEA and MI have previously been applied to assess the efficiency of economic processes with

identifiable multiple inputs and outputs (Wang and Huang, 2007; Hashimoto and Haneda, 2008). By adapting these techniques and applying them longitudinally to time series data, the performance of R&D efficiency on the OI adopters can be evaluated to assess that whether adoption of OI strategy has helped firms to achieve the main benefit which is improving R&D productivity.

Therefore this study employed two predictive 'indices of innovation' which were developed in the previous studies, and compared R&D efficiencies before and after adoption of open innovation in the pharmaceutical industry following the model which was developed in Chapter 3 (See Figure 3.1b). With the prediction that if open innovation is working, R&D efficiencies should rise over time, allowing for a delay due to the mean product lead-time for the period for the individual company or for the industry.

4.4.2 Inputs, Outputs and Time Lag

R&D efficiency is the ratio of input in R&D (money, resources, and people) versus its output (new products, patents, publications) (Gassmann and Reepmeyer, 2005). The goal of a highly productive R&D system is to efficiently translate inputs into the most desired and valuable outputs (Paul et al., 2010). R&D investment is often a complex process, with multiple inputs and outputs. One of the advantages of adopting DEA analysis is that multiple inputs and outputs can be measured, more than can be accommodated using conventional econometric techniques (Cooper et al., 2004). This multiple DEA analysis study was begun by selecting the appropriate inputs and outputs based on the previous literature.

As discussed previously in section 2.2.3.1and section 3.4.2, the inputs to innovation production activities are mainly physical resources and manpower, which are usually measured in annual total R&D expenditures and R&D personnel (Wang and Huang, 2007).

The R&D expenditure refers to the total R&D expense, covering all projects involving both internal and external ones supported by the firm. The R&D expenditure input index has been widely used, and found to be suitable in previous studies (Guan and Chen, 2010; Zhong et al., 2011; Chen et al., 2006).

The R&D personnel includes all staff are engaged in either fundamental research, application research or experimental development (Zhong et al., 2011). In Chapter 3, the number of employees was adopted as the index of mainly manpower on innovation in OI age. The reason for adapting this variable is that as a non-R&D intensive industry R&D personnel might not reflect its real innovation capability since human resources from other department are also enrolled into innovation process. And because of the lack of R&D personnel data, the comparison study between R&D personnel and number of employees cannot be made to observe which variable is more suitable. While pharmaceutical industry is very different from the Nondurable household products industry. Because it is the industry with very high level of R&D intensity, R&D personnel should be more suitable variable to measure the mainly manpower on innovation in pharmaceutical industry. However the only available data about human resource input is the number of employees. And there is no data of R&D personnel in these subject companies provided as time series data during the test period. This data issue has been met in previous studies. In Hashimoto and Haneda's study (2008) of measuring the R&D efficiency in Japanese pharmaceutical industry, they dropped off the index of R&D mainly manpower due to the lack of the R&D personnel data, and only employed the R&D expenditure as the R&D input. The reason for that could be: (1) it is not suitable to replace the variable of R&D personnel with other data such as the number of employees, due to the R&D intensive characteristics of pharmaceutical industry; (2) comparing with R&D personnel, R&D expenditure takes the more part of R&D input in pharmaceutical industry and covers the financial expending of R&D manpower on certain level. In consistent with former studies, the financial support for R&D – R&D

expenditure has been employed as the main R&D input in pharmaceutical industry.

The outputs selected here are net sales, operating income and approved patent number. The main outputs of R&D activities are technical improvement and economic benefit. The initial, direct outcome of R&D investment is the technical improvement, estimated in this case as the approved patent number. The approved patent number refers to the quantity of accepted patent applications by the patent office in the given year.

The other key outcome is the economic benefit, estimated in this case by the net sales and operating incomes as the final outputs in this study. The aim for companies doing innovation is to improve their capability for producing revenues, which could be reflected on their net sales and operating incomes. As discussed in Section 3.4.2, the ideal indices may be the sales and operating incomes on new products. However, there is not available for this kind of data. The general net sales and operating incomes may be not as suitable as the ones on new products, but it is the most reasonable variables which could be found to measure the performance of R&D outputs. And their suitability has been demonstrated in former studies (see Chen et al., 2006; Guan and Chen, 2010; Hashimoto and Haneda, 2008; Zhong et al., 2011).

Other input-output structures were also tried, such as adding the number of employees as another input and dropping off the patent number from output list. These research results revealed similar performance to the main finding observed here. This validates the suitability of the variables which were chosen and the reliability of the research findings.

Other studies of time lags between the R&D input and output support that 2 years is the reasonable average estimate across sectors (Kafouros and Wang, 2012; Lev and Sougiannis, 1996; Seldon, 1987;). However for the pharmaceutical industry, the time lags of R&D could be as long as 8 to 13 years. Following these previous studies, the preliminary test was given in

this study aimed to find the suitable time lag between inputs and outputs, which shows that 8-year lag is appropriate. It is in line with previous studies (Hashimoto and Haneda, 2008; Odagiri and Murakami; 1992).

As discussed previously (see Section 2.2.3.3), the robustness of this selection can be tested in two ways: longitudinal comparisons through consecutive cross-sectional datasets (see Guan and Chen, 2010; Zabala-Iturriagagoitia et al., 2007) and robustness text through varying the length of time lags (e.g., Hollanders and Celikel-Esser, 2007). Due to this study utilising panel data, cross-sectional dataset already included into the data analysis. For the other robustness test, two different time lags 7-year and 9-year time lags were selected and adapted, in order to see whether current introduction of time lag has an effect of the final results. The analysis results show that, the general performance of two robustness test is consistent with the one on 8-year time lag, which indicates that current introduction of time lag has limited effect on the general analysis results. And because this 8 years' time lag was selected based on preliminary test, it is more suitable to be adapted in this study. The analysis results from the 7-year time lag and the 9-year time lag can been seen in Table A.16-A.18 and Table A.19-A.21 in the appendix.

4.4.3 Case Data Sources

Certainly up to 2000, the pharmaceutical industry had a fortress mentality based on closed innovation. Since 2000, there is more research being performed outside than in. Many pharmaceutical companies have attempted to tap in to this and are moving more towards an OI model (Judd, 2013), or claim they are. This trend has been found more obviously among the big pharmaceutical companies. Therefore the research subjects are the 10 top pharmaceutical companies around the world including the OI pioneers in this industry.

Table 4.3: Descriptive statistics for main variables in Pharmaceutical study

Variables	Mean	Standard	Maximum	Minimum

		deviation		
R&D expenditure	1431672	1007372	5904504	278875.8
Patent applications	120.83	83.73637	342	18
Net sales	18091873	11929251	44350777	2447593
Operating incomes	4763779	3574869	16347140	488508.1
Sample size of DMU	100			

Data sources: Data of R&D expenditure, number of employees, net sales and operating incomes are from Datastream (Thomson Reuters); data of patent applications is from United States patent and Trademark Office (USPTO). Here the unit of R&D expenditure, net sales and operating incomes is 1000$; the unit of patent applications is item.

The data's time series is from 1994 to 2011, and much of the data required was available from official government sources and established business databases. The R&D expenditure, net sales and operating incomes were collected from Datastream (Thomson Reuters) and the approved patent number was collected from the database offered by United States patent and Trademark Office (USPTO). Datastream is an established and widely used dataset which provides both current and historical global financial and economic information with various types of data items from both developed and emerging markets. USPTO is the official organization which owns the USPTO search engine to provide search bibliographic details or full text of US patents from 1976. It is the mainstream patent data source in relative studies focusing on cross-market analysis. It is free to use through their website (http://patft.uspto.gov/). All monetary values were adjusted for inflation using the US domestic manufacturing Producer Price Index (with index year 1993). The basic statistics for the main variables used to study the R&D performance of P&G and its competitors are reported in Table 4.3.

4.5 Results

4.5.1 Data Envelopment Analysis (DEA) Results

4.5.1.1 Technical Efficiency

In the DEA analyses, the TE scores reflect the overall R&D investment efficiency: the bigger the score, the higher the R&D efficiency: a firm has the highest possible R&D efficiency if its score is 1 in a given year. Overall the average TE score of the industry has declined during the period 1994-2003 with more stability since 2000; most companies show a declining TE score while a few companies have exhibited more positive performances. The detailed results are discussed below.

Table 4.4: DEA technical efficiency index

Firm	Year of R&D activity input												
	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	Average	Pre-open	Post-open
Pfizer	1.000	0.906	1.000	0.714	0.552	0.428	0.280	0.272	0.300	0.217	0.567	0.767	0.267
J&J	0.834	0.740	0.672	0.600	0.561	0.542	0.489	0.421	0.376	0.326	0.556	0.658	0.403
Merck	1.000	0.832	0.562	0.418	0.443	0.444	0.400	0.422	0.520	0.390	0.543	0.617	0.433
TAKEDA	0.415	0.430	0.512	0.472	0.458	0.473	0.489	0.494	0.531	0.354	0.463	0.460	0.467
Abbott	0.483	0.466	0.400	0.396	0.391	0.450	0.449	0.432	0.451	0.427	0.435	0.431	0.440
Bristol	0.507	0.650	0.461	0.482	0.536	0.411	0.365	0.285	0.284	0.269	0.425	0.508	0.301
AstraZeneca	0.557	0.553	0.540	0.562	0.563	0.259	0.278	0.367	0.293	0.247	0.422	0.506	0.296
Novo	0.487	0.532	0.320	0.361	0.273	0.338	0.445	0.469	0.477	0.512	0.421	0.385	0.476
Daichi	0.333	0.287	0.271	0.254	0.339	0.284	0.302	0.302	0.358	0.306	0.304	0.295	0.317
Lilly	0.536	0.414	0.311	0.263	0.218	0.245	0.233	0.247	0.257	0.224	0.295	0.331	0.240
Average	0.615	0.581	0.505	0.452	0.433	0.387	0.373	0.371	0.385	0.327			

Based on the average score for the period of 1994-2003, with an average score of 0.567, Pfizer was the most efficient company on R&D investment

among these ten companies. J&J and Merck were ranked second and third with average scores of 0.556 and 0.543. Lilly was the least efficient R&D Company, with Daichi only slightly better than Lilly. Their average scores were 0.304 and 0.295. If year 2000 is picked up as the start year for the pharmaceutical companies thinking outside (Judd, 2013), the comparison study can be made between the periods 1994-1999 (pre-open period) and 2000-2003 (post-open period). In the pre-open period, Pfizer, J&J and Merck were still ranked first three with average scores of 0.767, 0.658 and 0.617. Lilly and Daichi were the two least efficient R&D companies, with Novo Nordisk (Novo) slightly better. While the ranking changed dramatically for the post-open period, Novo's average R&D efficiency rose from 0.385 in pre-open period to 0.476 in post-open period, becoming the most R&D efficient company. With the average score 0.267, Pfizer ranked ninth among ten companies, only slightly better than Lilly (see Table 4.4).

If the average score of the ten companies was taken as an index of the industry's R&D performance, it could be observed that the R&D efficiency in the pharmaceutical industry has declined from 0.615 in 1994 to 0.327 in 2003 (see Figure 4.2). Among the 10 individual companies, Pfizer showed the biggest drop in R&D efficiency, from 1 in 1994 to 0.217 in 2003. Its R&D efficiency declined dramatically up to 2001, then levelled out. This phenomenon is not only found on Pfizer: Merck also experienced a huge decline up until 1998, but kept its R&D efficiency score around 0.4 after that. A similar situation also happened at Lilly by 1998. Since 1998, Lilly's R&D efficiency stopped declining and came up with a slight increase from 0.218 in 1998 to 0.257 in 2002. J&J also showed a dramatically decline from 0.834 to 0.326 during 1994-2003 but unlike the others, there is no inflection point year which led it to a more stable R&D efficiency. AstraZeneca experienced a huge decline in 1999 on the R&D efficiency, from 0.563 in 1998 to 0.259 1999. This decline may have been triggered by the merger that happened in 1999 (the merger of the Sweden-based Astra AB and the UK-based Zeneca Group). Bristol's R&D efficiency declined from 0.507 in 1994 to 0.269 in 2003.

Except for the companies which were talked about, the other companies (Daichi, Abbott, TAKEDA and Novo) performed more stable on the R&D efficiency. These companies did not show a higher performance at the beginning, while their R&D efficiency did not decline dramatically as the other companies showed. Among them, Novo showed an interesting performance of the R&D efficiency. Its R&D efficiency firstly experienced a decline during 1994 to 1999, whilst increasing after it with the score from 0.338 to 0.512.

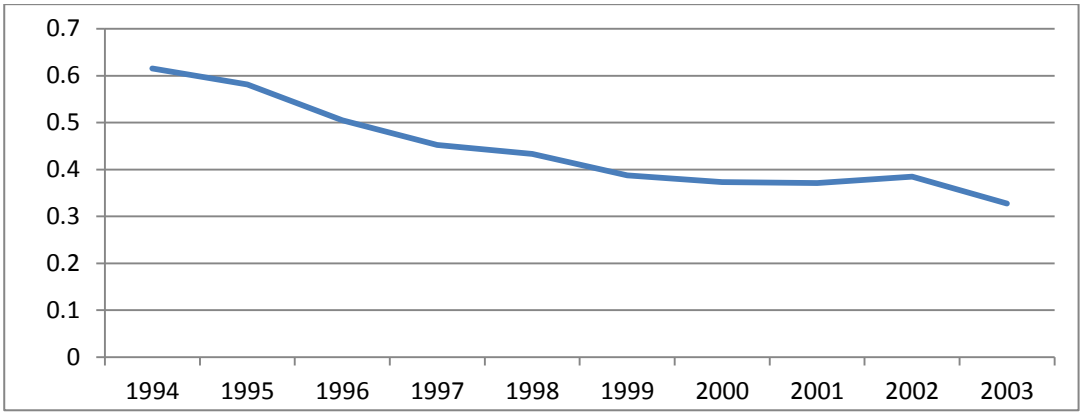


Figure 4.2: The performance of average TE score in Pharmaceutical industry

4.5.1.2 Pure Technical Efficiency (PTE)

The PTE scores reflect the pure R&D investment efficiency excluding scale effects. Overall compared with TE, the PTE scores showed less variation at both industry and company levels, and the gradient of the decline in PTE was more constant. More details are discussed below.

J&J owned the highest average PTE score of 0.927 during the period 1994-2003. Pfizer and Novo followed it with scores 0.888 and 0.788, ranking second and third. Lilly had the lowest PTE score of 0.349, following Daichi with PTE score 0.452. Over both the pre-open period and the post-open period, Pfizer, J&J and Novo were still the top three companies on the average PTE score, with J&J's average score increasing from 0.894 to 0.975. Both Daichi and Lilly performed lower on the average PTE score in the

post-open period than in the pre-open period. They still ranked last two in the post-open period (see Table 4.5).

Taking the average PTE score as the industry's PTE index, it could be observed that – unlike the TE score - the pharmaceutical industry's PTE experienced only a slight decline at the beginning and a slight increase after 2000. When compared with the industry's TE performance, its PTE score was much more stable across the testing years. Compared with the continuous decline for TE, J&J's PTE score increased from 0.84 in 1994 to 1 in 2003. It was the only company to show a continuous increase across the study period. Pfizer, Novo and Merck all exhibited fluctuating PTE performance, their PTE first declining then starting to increase around 1997 to 2000. AstraZeneca's PTE declined dramatically in 1999 (the merger year), while it recovered slightly after 2001. Bristol's PTE score has kept declining since 1998. Abbott showed an increase on PTE from 0.396 in 1998 to 0.53 in 2003, after a slight decline at the beginning. TAKEDA and Daichi's PTE fluctuated during 1994 to 2003. Lilly experienced a slight increase from 1999, after the decline of its PTE since 1994.

Table 4.5: DEA: Pure Technical Efficiency index

Firm	Year of R&D activity input												
	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	Average	Pre-open	Post-open
J&J	0.840	0.900	0.873	0.881	0.891	0.980	0.951	0.975	0.975	1.000	0.927	0.894	0.975
Pfizer	1.000	0.911	1.000	0.903	0.819	0.783	0.735	0.792	1.000	0.934	0.888	0.903	0.865
Novo	1.000	0.944	0.699	0.686	0.440	0.585	1.000	0.908	0.863	0.754	0.788	0.726	0.881
Merck	1.000	0.875	0.613	0.533	0.621	0.693	0.681	0.743	1.000	0.882	0.764	0.723	0.827
TAKEDA	0.503	0.527	0.698	0.658	0.555	0.553	0.617	0.610	0.639	0.380	0.574	0.582	0.562
AstraZeneca	0.625	0.616	0.587	0.603	0.588	0.488	0.433	0.553	0.553	0.512	0.556	0.585	0.513
Bristol	0.516	0.655	0.462	0.513	0.654	0.574	0.515	0.468	0.444	0.384	0.519	0.562	0.453
Abbott	0.510	0.483	0.410	0.398	0.396	0.460	0.452	0.478	0.517	0.530	0.463	0.443	0.494
Daichi	0.498	0.437	0.456	0.470	0.560	0.398	0.435	0.414	0.482	0.374	0.452	0.470	0.426

Lilly	0.571	0.432	0.324	0.264	0.263	0.300	0.305	0.346	0.348	0.337	0.349	0.359	0.334
Average	0.707	0.681	0.616	0.596	0.579	0.567	0.609	0.621	0.687	0.594			

4.5.1.3 Scale Efficiency (SE)

Scale efficiency (SE) scores reflect various classes and levels of returns to scale on R&D investment. There are three possible classes of returns to scale: decreasing (DRS), increasing (IRS) and constant (CRS). CRS is indicated by an SE score of 1; DRS, signified by a decrease in the relative output for a given incremental input, and an associated decline in the consequent profit; IRS, signified by an increase in the relative output for a given incremental input. Overall, the average SE score of the industry showed a small decline, which was also seen for most of individual companies, the majority of which suffered from DRS during the period 1994-2003. The detailed results are discussed below (see Table 4.6).

In the period of 1994-2003, Abbott and Lilly were first and second on average SE score. Pfizer, J&J and Novo were ranked last three among ten companies. TAKEDA's average SE score increased from 0.796 in the pre-open period to 0.842 in the post-open period, while Lilly declined from 0.916 to 0.720 over the same period. Novo's average SE score remained flat at 0.539 in the pre-open period and 0.548 in the post-open period, while J&J decline from 0.742 to 0.414 over the same period. Lilly showed a similar performance decline - suffering from DRS - after 1998, with its SE declining from 0.827 to 0.664 the same year. Companies including Pfizer, J&J, Merck and Bristol declined more dramatically on SE. Pfizer declined from 1 to 0.233. J&J showed the decline from 0.993 to 0.326. Merck's SE score declined from 1 in 1994 to 0.442 in 2003. Bristol's SE score declined from 0.982 in 1994 to 0.607 in 2001.

All these companies suffered from DRS in most years, indicating that for a given level of increase in the R&D input, less relative R&D output was produced. As found before with TE and PTE performance, ASTRAZENECA experienced a huge decline in 1999, and started to suffer from DRS in the

same year. TAKEDA, Daichi and Novo were experiencing increasing return to scale (IRS) across the testing period, which indicates that a given level of R&D inputs was producing a relative increase in R&D output in these three companies. TAKEDA's SE score increased from 0.825 in 1994 to 0.932 in 2003. Daichi also experienced an increase on SE from 0.668 to 0.818 during 1994-2003. Compared with them, Novo had a more fluctuated performance, while its SE also increased from 0.487 in 1994 to 0.679 in 2003 (see Table 4.6).

Table 4.6: DEA scale efficiency index

Firm	Year of R&D activity input												
	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	Average	Pre-open	Post-open
Abbott	0.948 irs	0.967 irs	0.976 irs	0.994 irs	0.988 irs	0.977 irs	0.994 irs	0.903 drs	0.872 drs	0.806 drs	0.943	0.975	0.894
Lilly	0.940 irs	0.959 irs	0.960 irs	0.994 irs	0.827 drs	0.815 drs	0.763 drs	0.714 drs	0.739 drs	0.664 drs	0.838	0.916	0.720
TAKEDA	0.825 irs	0.816 irs	0.734 irs	0.717 irs	0.826 irs	0.855 irs	0.793 irs	0.811 irs	0.832 irs	0.932 irs	0.814	0.796	0.842
Bristol	0.982 irs	0.991 irs	0.997 irs	0.940 drs	0.819 drs	0.716 drs	0.708 drs	0.607 drs	0.639 drs	0.702 drs	0.810	0.908	0.664
AstraZeneca	0.892 irs	0.898 irs	0.920 irs	0.932 irs	0.957 irs	0.530 drs	0.643 drs	0.665 drs	0.530 drs	0.482 drs	0.745	0.855	0.580
Merck	1.000 -	0.951 drs	0.918 drs	0.784 drs	0.713 drs	0.640 drs	0.588 drs	0.568 drs	0.520 drs	0.442 drs	0.712	0.834	0.530
Daichi	0.668 irs	0.656 irs	0.594 irs	0.541 irs	0.606 irs	0.712 irs	0.694 irs	0.730 irs	0.743 irs	0.818 irs	0.676	0.630	0.746
Pfizer	1.000 -	0.994 irs	1.000 -	0.791 drs	0.674 drs	0.547 drs	0.382 drs	0.343 drs	0.300 drs	0.233 drs	0.626	0.834	0.315
J&J	0.993 drs	0.822 drs	0.770 drs	0.682 drs	0.630 drs	0.554 drs	0.514 drs	0.432 drs	0.385 drs	0.326 drs	0.611	0.742	0.414

Novo	0.487 irs	0.563 irs	0.458 irs	0.527 irs	0.620 irs	0.577 irs	0.445 irs	0.516 irs	0.552 irs	0.679 irs	0.542	0.539	0.548
Average	0.874	0.862	0.833	0.790	0.766	0.692	0.652	0.629	0.611	0.608			

4.5.2 Malmquist Index Analysis (MI) Results

Malmquist Index analysis (MI), which has previously been applied for similar analyses in the pharmaceutical industry (Hashimoto and Haneda, 2008) was employed to cross-reference the DEA results. MI generates two key indices, the Malmquist Index and the Frontier Shift Index, which are employed in this research to verify and cross-reference the DEA results. The Malmquist index, in the context of production, expresses a total factor for productivity change, while the frontier shift index reflects 'industry-wide productivity change' (Hashimoto and Haneda, 2008). Therefore, these two indices are adapted to separately measure the total R&D efficiency of a company, and the industry-wide R&D productivity.

4.5.2.1 Malmquist Index

The Malmquist index indicates the total factor R&D efficiency change of a firm over time (Hashimoto and Haneda, 2008). MI which is employed here is the cumulative one, which is different from DEA. The indices for each year are all referenced to the baseline year 1994 where the values are all taken as 1. The values of the indices calculated thus differ from those produced by DEA, which shows a similar picture of performance, but a slightly different ranking of the R&D efficiency among the sample companies. Based on the average score from 1994 to 2003, TAKEDA, Daichi and Abbott showed the highest R&D efficiency. Suffering from relatively huge declines in R&D efficiency, Pfizer, Lilly and Merck ranked the last three among ten companies. Comparing their performance between pre-open and post-open periods, Pfizer, J&J, AstraZeneca and Bristol declined dramatically in R&D efficiency, while Novo showed a bigger increase compared with others during this period, and TAKEDA, Daichi and Abbott all showed slight increases.

Taking the annual average score as the index of the industry's R&D efficiency performance, this shows similar patterns of performance to those found with DEA analysis. The R&D efficiency performance of Pfizer, Lilly and Merck also match those observed in the DEA results: they showed stable performance after huge declines before 2000 and 1998. There was also a huge gap in R&D efficiency between 1998 and 1999 for AstraZeneca. Compared with others, Daichi, Abbott and TAKEDA exhibited more stable R&D efficiency. Consistent with the earlier findings, Novo showed an increasing R&D efficiency after a decline during 1994 to 1999. In summary, the Malmquist index results are very consistent with the findings from DEA on the total R&D efficiency performance on both firm and industry levels (see Table 4.7).

Table 4.7: Cumulative Malmquist index

Firm	Year of R&D activity input												
	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	Average	Pre-open	Post-open
TAKEDA	1	0.999	1.027	1.005	1.053	1.066	1.096	1.038	1.215	0.853	1.035	1.025	1.051
Daichi	1	0.895	0.815	0.688	0.983	0.787	0.846	0.815	1.106	0.876	0.881	0.861	0.911
Abbott	1	0.98	0.746	0.722	0.796	0.868	0.876	0.818	0.927	0.871	0.860	0.852	0.873
Novo	1	1.092	0.631	0.758	0.584	0.642	0.851	0.93	1.011	0.917	0.842	0.785	0.927
Bristol	1	1.237	0.909	0.929	0.974	0.784	0.706	0.562	0.555	0.471	0.813	0.972	0.574
AstraZeneca	1	0.996	0.953	0.959	0.99	0.467	0.499	0.695	0.523	0.436	0.752	0.894	0.538
J&J	1	0.893	0.741	0.677	0.642	0.607	0.561	0.485	0.446	0.402	0.645	0.760	0.474
Pfizer	1	0.913	0.896	0.672	0.563	0.428	0.297	0.271	0.303	0.228	0.557	0.745	0.275
Lilly	1	0.797	0.506	0.433	0.378	0.416	0.399	0.43	0.462	0.402	0.522	0.588	0.423
Merck	1	0.723	0.51	0.403	0.406	0.415	0.382	0.389	0.459	0.386	0.507	0.576	0.404
Average	1.000	0.864	0.721	0.629	0.596	0.467	0.428	0.454	0.439	0.371			

4.5.2.2 Frontier Shift Index

The average frontier shift index across all firms has been viewed an appropriate indicator to view R&D efficiency change at the industry level (Hashimoto and Haneda, 2008). The observed performance on the average frontier shift index indicates that the industry's overall R&D efficiency

declined for several years after 1994, and a more stable performance after year 2000, which supports the prior findings in this research about the industry's performance (see Figure 4.3 and Table 4.8).

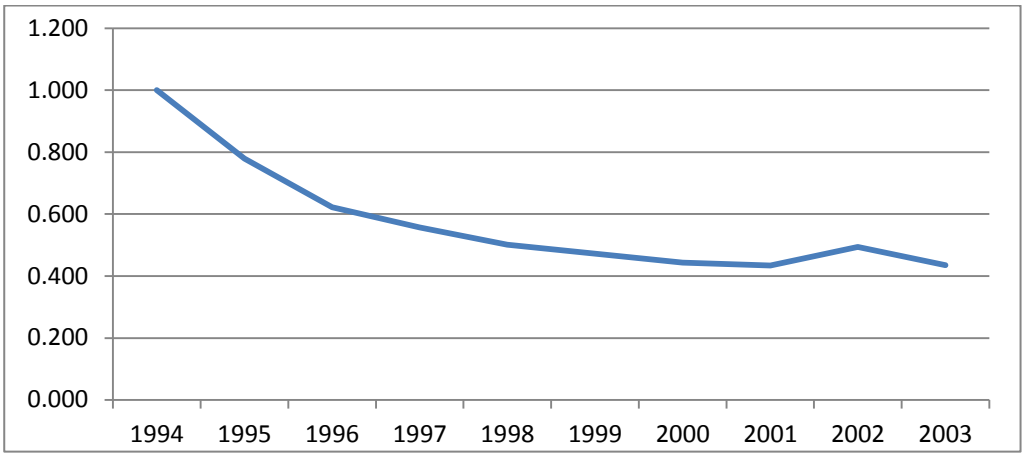


Figure 4.3: The performance of average frontier shift index in the pharmaceutical industry during 1994-2003

Table 4.8: Cumulative frontier shift index

Firm	Year of R&D activity input									
	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	Average
AstraZeneca	1	0.773	0.626	0.607	0.566	0.521	0.494	0.443	0.495	0.455	0.598
Bristol	1	0.732	0.482	0.471	0.494	0.429	0.387	0.361	0.449	0.439	0.524
Lilly	1	0.776	0.579	0.55	0.523	0.485	0.446	0.42	0.505	0.421	0.571
J&J	1	0.754	0.628	0.565	0.536	0.506	0.468	0.422	0.475	0.442	0.580
Merck	1	0.723	0.51	0.449	0.459	0.415	0.382	0.389	0.459	0.386	0.517
Pfizer	1	0.913	0.896	0.672	0.563	0.499	0.48	0.442	0.518	0.466	0.645
Abbott	1	0.678	0.567	0.542	0.47	0.454	0.424	0.413	0.448	0.421	0.542
TAKEDA	1	0.791	0.664	0.586	0.494	0.463	0.454	0.43	0.504	0.435	0.582
Daichi	1	0.68	0.482	0.514	0.48	0.449	0.407	0.434	0.464	0.408	0.532
Novo	1	0.832	0.504	0.472	0.497	0.494	0.452	0.453	0.534	0.447	0.569
Average	1.000	0.779	0.623	0.557	0.501	0.472	0.443	0.434	0.494	0.435	

4.6 Discussion

4.6.1 What the Indices Reveal

So what did the index analyses reveal about the effectiveness of current R&D strategies in the pharmaceutical industry?

The overall picture confirms the long term decline in R&D productivity, but shows some recent slowing of the rate of decline. The pattern of results across the three key DEA indices (TE, PTE and SE) shows that the underlying cause of decline was decreasing returns to scale (DRS), indicating that the addition of resources had proceeded beyond the optimal point. The results of the MI analyses were completely consistent with these findings. The remainder of this section discusses these results in detail, examining the evidence for the relative contributions of open innovation, M&A activity, and increasing R&D investment, before the next section (4.6.2) going on to consider the wider potential impact of OI activities on performance.

4.6.1.1 Patterns of R&D Efficiency and OI in the Industry

The analysis of the average score of the ten pharmaceutical companies showed that the overall R&D efficiency of the pharmaceutical industry declined during the period 1994-2003. Since the industry's pure technical efficiency (PTE) - which reflects R&D efficiency - was more stable, suggesting the decline was related to and perhaps triggered by – the industry's SE status, which showed a continuous decline across the testing period. This appears to indicate that the R&D inputs in the pharmaceutical industry have in this case gone beyond their most efficient level, producing less R&D output per dollar input for the industry as a whole. One interesting finding here is that since the major decline in the industry's R&D efficiency in the period1994-1999, it has slowed down since then, which happens to coincide with the start of the OI adoption phase for many pharmaceutical companies. This suggests but does not prove a causal relationship between OI adoption and R&D efficiency; for

one thing adoption in companies was not simultaneous and the consistency of strategic intent across companies is unclear. Even if it is not triggered by OI directly, this phenomenon may indicate companies are starting to switch their strategies and perceive the opportunities outside in a different light, which could signal a major change in the research paradigm of the pharmaceutical industry.

Common patterns of R&D efficiency performance were observed across some of the companies. Pfizer, Merck and Lilly all experienced a huge decline in their R&D efficiencies at the beginning of the study period, while they all stopped the decline and showed more stability subsequently; though similar in pattern, these effects occurred at slightly different times for each company: 1997, 1998 and 2000 respectively for Merck, Lilly and Pfizer. Starting to benefit from external R&D activities and resulting incoming business opportunities beyond the company boundary could be one possible reason. Other interpretations are also plausible, such as the industry moving back to the traditional model after drying up of the low-hanging fruit. However, this change of the R&D efficiency may be more likely to be triggered by factors affecting an individual company, rather than sector-wide industrial changes. Because no evidence could be found to support that all sample companies followed the similar performance. And since all three companies suffered from the declining SE, the simplest explanation is that the later stable R&D efficiency performance was triggered by the increase of the pure technical efficiency: the increase of PTE since 1997, 1998 and 2000 respectively for Merck, Lilly and Pfizer tends to support this conclusion. These rises in pure technical efficiency seem to suggest that the strategic shift is becoming successful for some companies. This suggests OI a major factor in explaining and halting or slowing the decline in these companies, and the emergence of OI as a potential strategic ploy in pharmaceutical innovation.

4.6.1.2 M&As: Ineffective

The results of the DEA and MI analyses also highlight the relative inefficiency of M&A activity as a strategy. In a recent comparison between

Lilly and selected companies which have been heavily involved in M&As including J&J, Pfizer and Bristol, Munos (2009) found that those companies that have relied heavily on M&A tend to lag behind those that have not on NME output. However, the analysis results did not show that Lilly performed better than other three companies on R&D efficiency (TE). Lilly showed higher R&D scale efficiency than J&J, Pfizer and Bristol which implies its R&D input level is more efficient, while its pure R&D efficiency was lower compared with the others.

On the other hand, AstraZeneca's case also supported the conclusion that M&As have not been synergistic in pharmaceuticals: AstraZeneca's R&D efficiency experienced a big decline in its merger year 1999, and both its PTE and SE scores showed the decline in that year. Compared with PTE, its SE suffered more from the merger, and did not recover its former level subsequently. AstraZeneca suffered from DRS after 1999, which indicated that the increase of its R&D inputs had proceeded beyond its optimal level, and brought less R&D outputs.

Although some conflicting evidence has been found in from the different analyses, these are relatively minor and it seems clear that M&As have not been the best strategic prescription for the embattled pharmaceutical industry. The data shows that the industry cannot be saved only by this traditional business strategy. Since M&As have been adopted by the pharmaceutical industry throughout its history, and on an increasingly large scale in recent decades, if they were effective the industry's R&D efficiency should increase or at least stop declining after 1990s. This did not happen.

4.6.1.3 Increasing the R&D Investment: Ineffective

Simply increasing the R&D investment does not seem to have led to a direct increase in R&D efficiency in the industry. This is observed in the failure of ever-increasing R&D expenditure to alter the flat, static rate of new drug approvals (Figure 4.1). Further evidence for this is also found in the pharmaceutical industry's SE score, which continued declining across

the testing period, indicating that the scale of the industry's R&D inputs was more inefficient. Based on the individual companies' performance, it appears the scale inefficiency did not come from the IRS but DRS, which means that too much R&D resources has been poured into the industry which leads to inefficiency in R&D productivity. Most companies in this research suffered from DRS in most years, and these companies' increases on R&D inputs did not bring them similar or increased R&D outputs compared with their earlier performance.

However, this does not mean that increasing the R&D investment is not necessarily ineffective in all cases. In the present study, TAKEDA, Daichi and Novo were still showing IRS effects, indicating that compared with others these three companies still have a chance to increase their R&D efficiency through increasing R&D inputs. Novo appears to be something of a special case: its R&D inputs are actually below the R&D input level for the best SE (scale efficiency).

4.6.2 Practice and Potential of OI in the Industry

So what do the results with the indices imply when taken in conjunction with other evidence about the effectiveness of current R&D strategies – and OI in particular - in the pharmaceutical industry?

4.6.2.1 OI Precedents in the Industry

Given that results to date on OI adoption in the pharmaceutical industry did not show the clear positive result observed for P&G in the previous study (see Chapter 3), the potential interpretation may be that based on the precedents of OI activities in the industry, there does not seem to be sufficient to justify wholesale adoption of OI by the industry.

The reality is more complex:

(1) OI strategy can be seen as a way to reduce the production/operational cost or accelerate the marketing speed. Companies prefer to collaborate with small-medium 'product' and 'platform' biotech firms to target and

identify projects for pre-clinical testing, but do post-approval activities with large companies because of their mature large-scale R&D operations. These characteristics of the external collaborations suggest a tendency to outsource and diversify the disciplinary base (Rafols et al., 2012), which may indicate that open innovation starts with simple outsourcing deals to reduce overcapacities, cut cost, grow through complementary assets or reduce risks (Gassmann et al., 2010), but not a way to extend R&D ideas beyond the company's boundary. Most outbound OI activities occur in the latter part of the process, perhaps because firms are more likely to invite external organisations for exploiting the results of their innovation activities, ensuring a quicker and wider access to the market, but not for exploring their innovation.

(2) OI can also be applied in non-core areas as a supplementary activity. More OI activities are in non-core areas, which may be because the firms prefer to enter into relationship with a partner holding very dissimilar competencies to capture new ideas from them for extending their business. OI activities in this case are therefore more of a supplement than a necessity.

(3) OI may also be used as a temporary and emergent solution or 'catch-up'. The high percentage of OI activities in the later process reflects inbound activities such as licensing-in, to compensate for the lack of output from basic research toward the start of drug discovery process. These may indicate OI activities are more like to be employed to solve some emergent or tactical problem, such an IP gap, through direct licensing-in activities, but not the long term strategies related to innovation capability such as those in basic research.

In summary, these precedents in OI activity have so far fallen well short of the industry's requirement, especially for addressing the grand challenges of R&D efficiency and overall productivity. However, this situation has continued to evolve, with more OI activities being adopted to address the industry's ever more serious R&D challenge.

4.6.2.2 Current OI Developments in the Industry

Some of the latest OI strategies and activities have begun to reach beyond the original concept and to extend the open concept further, or with more specific variants of it. Large pharmaceutical companies have begun to work more actively together – as well as with small – and medium-sized enterprises and academic institutions – on pre-competitive research (Barnes et al., 2009). Based on the previous studies, several OI activities launched by the big pharmaceutical companies are summarized (see Table 4.9).

Table 4.9: Selected OI initiatives by major pharmaceutical companies

Name	Year	Founder	Type	Remark
Innocentive	2001	Eli Lilly	open source	first internet problem-solving platform (Hunter and Stephens, 2010)
Phenotypic Drug Discovery Initiative (PD2)	2009	Eli Lilly	open source	Innocentive and PD2 are champions of open-source R&D initiatives created and spun out by Lilly (Harnessing open innovation, 2009).
open its internal library	2009	Pfizer	Open source	Pfizer began allowing other organizations to screen against their internal compound library (Hunter and Stephens, 2010).
Sage Bionetworks	2009	Eric Schadt and Stephen Friend (both moving from senior positions at MERCK); Merck	open access	Sage is another open-access platform aiming at building complex, predictive models of disease using logistics and data from Merck and seed money from private sources (Talaga, 2009). The idea is to integrate large-scale biological information into models and then enable other scientists to leverage that information in an open-access way (Harnessing open innovation, 2009).

provide compounds from its library	2010	GSK	Open source	The one spearheaded by GSK in January to freely provide 13,500 malarial compounds from its own library for others to test and develop.
The patent pool	2009	GSK and Alnylam		In the field of neglected tropical diseases, GlaxoSmithKline (GSK) announced the creation of a patent pool, which aims to remove IP as a barrier to research into treatments for neglected diseases. GSK has put more than 800 patents for compounds or processes into this pool, and Alnylam has added a further 1,500 patents (Hunter and Stephens, 2010).
Stevenage Bioscience Catalyst	2009	GSk, EEDA, Wellcome Trust, Technology Strategy Board, BIS	open innovation campus	The UK's first open innovation bioscience campus, pioneering a unique culture to drive early stage biotech, pharma and medtech developments (from its website).
a shift towards an open innovation model	2009	Johnson&Johnson		Johnson&Johnson's Head of Pharmaceutical R&D, Paul Stoffels, announced a shift towards an open innovation model for the company in 2009 (Hunter and Stephens, 2010).

Recently, OI in the pharmaceutical industry has also been pursued through public private partnerships (PPPs) and open source initiatives. PPPs, in theory at least, constitute an attractive OI business model for pharmaceutical companies to address major issues in the field of R&D, combining expertise from various research communities like Academia, Biotechs and/or drug discovery solution providers (Tralau-Stewart, 2008). Several drug development challenges, such as biomarker identification and validation, are increasingly being addressed at a pre-competitive level often through public- private partnerships commented a Nature editorial (Harnessing open innovation, 2009). There are several PPPs listed in Table 4.10.

Table 4.10: Selected public–private partnerships

Name	Website
Biomarkers Consortium	http://www.biomarkersconsortium.org
Critical Path Institute Consortia	http://www.c-path.org/consortia.cfm
EBI Industry Programme	http://www.ebi.ac.uk/industry/ind-prog-

	index.html
Health Commons	http://sciencecommons.org/projects/
Innovative Medicines	Initiative http://imi.europa.eu/index_en.html
Serious Adverse Events Consortium	http://www.saeconsortium.org
Division of Signal Transduction Therapy (also known as the Dundee kinase consortium)	http://www.ppu.mrc.ac.uk/technologies/dstt.php

Resource: Harnessing open innovation, 2009

As the related, but quite distinct 'open' idea, 'Open source' R&D provides a platform to encourage volunteers use online communities to address a problem in which they share an interest. Open source has also sprung up in Pharmaceutical industry in recent years also focusing on precompetitive research through data sharing. Apart the open source activities mentioned previously, there are several other collaborations among industry organizations (Strauss, 2010). However, 'open source' is different in principle to 'open innovation', as the former involves fully shared source information or even product, whereas the latter is typically much more restricted e.g. to specific IP.

The companies in this industry have deliberately established a strategic priority to improve their relationships with external organisations in both inbound and outbound open innovation processes. Both the financial support for the establishment and management of OI and the management preparation for OI activities have begun to appear (Bianchi et al., 2011).

4.6.2.3 The Emerging Strategic Imperatives for OI

As has been described, OI activities have been developing significantly in the pharmaceutical industry over the past decade. The effectiveness and the determinants of adoption of new strategies such as OI can be influenced by a number of specific factors (Chiaroni et al., 2009). For the

pharmaceutical industry, two characteristics – collaboration and connection - may lead the industry into OI strategy.

(1) For collaboration, the R&D challenge in Pharmaceutical industry requires wider and deeper R&D collaboration among various organizations. Since the halcyon days of relatively easy, 'low-hanging fruit' targets which have now dried up, to survive in the future more difficult targets require more sophisticated and multidisciplinary approaches. The remaining new targets are more complicated and less likely to be solved by one company of whatever size, since more information, knowledge and data should be required from various experts and companies. No individual organization has the resources to maximize the potential of molecular data to inform drug development. 'We are going to have to be smarter about identifying the nodes in pathways where we need to intervene and the biomarkers that will tell us whether or not we are targeting the right pathway for a disease with a particular agent' commented a Nature editorial (Harnessing open innovation, 2009). Unlike other high-tech industries (such as the software industry) the information imbalance in the pharmaceutical industry is higher. Therefore, more information with of the right kind should be fluent among different companies and organizations to lower the risks and costs for drug discovery. To do so, initiatives that aim to engage entire research communities to interact with integrated models of disease, to refine them and judge their accuracy are needed (Harnessing open innovation, 2009). Presently, it appears to be very early days.

(2) For connection, a more open and connected ecosystem is needed in Pharmaceutical industry. A closer examination made by Munos (2009) confirms that the expected NME output and the number of companies are closely correlated in a nonlinear manner that explains 95% of the changes in expected NME output by changes in the number of companies. As the number of companies (inclusive of SMEs) increases, the expected NME output increases more than proportionally, suggesting a positive stimulatory effect of SMEs. This is possibly because a larger community of companies could accelerate the acquisition of knowledge and enable all

companies to be more productive in the area. Therefore, if the innovation networks could be organized in the pharmaceutical industry, SMEs will benefit from the development expertise owned by major pharmaceuticals, and large companies will harness the scientific diversity and more productive R&D in SMEs. This would be a potential win-win game lowering the cost and increasing the output for both SMEs and major pharmaceuticals.

4.6.3 The Search for a New Prescription: Emerging Variations

Our DEA and MI analyses also revealed some interesting variations in company strategies that could be described as 'hybrid' rather than 'pure OI' strategies. In contrast to the general decline of R&D efficiency across the sample company group over the period, there were several companies that performed better during the testing period: Daichi, TAKEDA, Abbott showed a more stable performance on the R&D efficiency, while Novo's R&D efficiency had been increasing steadily since 1998. These companies' superior performance may reflect their specific individual strategies relative to other players. Novo Nordisk is highly focused on two particular disease areas, TAKEDA and Daichi are entrenched in and highly focused on their home-country markets, and Abbott sells products and services in addition to drugs (Munos, 2009).

Compared with the other mainstream pharmaceutical companies, TAKEDA, Daichi and Abbott also showed stable R&D efficiency based on their stable PTE and SE performance. These niche-market and the conglomerate business strategies may help these companies differentiate themselves and survive from the recession in a better state. However, these strategies may be not suitable for other major pharmaceutical companies, or at least could not satisfy their global ambitions and existing drug-focused future. If these strategies do not work, Novo could be exhibiting an interesting alternative model part way between open and closed, that might be termed 'focused innovation'. Novo is the worldwide leader healthcare company in diabetes care (Gasparin, 2010). This business strategy

focusing on one or several disease areas is defined as 'Focused Innovation' in the pharmaceutical industry. Focused innovation may not have helped Novo be as successful as the other big pharmaceutical companies at the beginning, as indicated by Novo's lower R&D efficiency at the beginning compared with others. However, this company really showed an increase since 1998. The result become is more intriguing for the OI hypothesis, when it is taken into account that Novo is also an OI adopter. Gasparin (2010) found that OI is used in different projects in Novo, and continuing to make experiment with OI may be the way to expand the innovative capabilities of the device development within Novo. If Novo had followed the common trend in the pharmaceutical moving to OI around 2000, then it might explain why it experienced the R&D efficiency decline at the beginning while started to increase since 1998. Only adopting focused innovation could not help it to increase its R&D efficiency, while when it came with OI Novo's R&D efficiency showed a continuous increase. In the further analysis, it is found that this 'focused innovation + open innovation' strategy (FI+OI) may help the company improve its pure R&D efficiency because of a huge increase of its PTE since 1998. Since Novo's SE is still far away from the highest R&D efficiency, it still has the space to improve its R&D efficiency through increasing R&D inputs following FI+OI. As previously discussed, as the industry remains to highly dependent on R&D, the pharmaceutical industry is a science business totally different from many other traditional industries. More deep and broad professional collaboration should be developed based on the certain disease areas. Therefore, 'FI+OI' may be one of the prescriptions for sustainable success in the pharmaceutical industry.

4.7 Concluding Remarks

Given the acute lack of recent studies of OI in the industry, and the national and global economic importance of the industry, this study addressed the key question of whether OI is proving an effective strategy

for the pharmaceutical industry, and how R&D productivity can best be measured.

The initial review of the literature confirmed the now well-established picture of escalating R&D spending, rising regulatory barriers, and static new drug approvals, that have opposed R&D efficiency gain for several decades. Previous studies also provided evidence of the ineffectiveness of M&A as a strategy and the clear lack of effect of simply the increasing of R&D investment, both of which were confirmed with the quantitative DEA and MI techniques.

Overall, the results of DEA and MI analyses indicated that:

(1) The 'Indices of innovation' based on DEA and MI as developed and applied in this study were demonstrated to be suitable for measuring innovation performance for OI, and probably other types of innovation

(2) Applying these techniques revealed that the R&D efficiency of the pharmaceutical industry is changing only slowly: the R&D efficiency of industry declined steadily over the period 1994 to 2003 although the rate of decline has slowed since 1999.

(3) Although other interpretations may exist, OI is still a leading candidate as an explanation for some or all of the change in R&D efficiency.

(4) Other strategies for innovation also came to light, including 'hybrid' strategy combinations such as 'focused' innovation - a niche market strategy based on limiting the number of therapeutic areas, combined with elements of open innovation - which may prove a viable future prescription for the pharmaceutical industry.

(5) Although OI activities and new forms of 'open' intervention continue to arise, OI activities to date appear to have fallen far short of the industry's sustainable growth requirements.

The findings of this study have a number of implications for policy:

Given the increasing mobility of expertise of the science base, broader and deeper collaboration is needed to stimulate the improvement of R&D productivity in the pharmaceutical industry. The industry should say goodbye to the old time 'command and control' world of in-house (closed innovation), and open their boundary to embrace 'open' R&D and commercialization opportunities outside (OI). Judging by the present study, there is still a long way for the pharmaceutical industry to go in being successful in exploiting the possibilities of OI in the digital age. Moving into OI, the industry needs to overcome several serious barriers and face up to the severe management challenges involved in fundamental shifts of strategy and core competency. To help the pharmaceutical industry embrace OI and benefit from it, more studies are needed to explore and overcome these barriers.

Finally with respect to the outcome of this industry-level pharmaceutical study, it was perhaps no surprise to find no marked industry-level effects showing to date: the null hypothesis would be no change, with a positive change occurring if or when OI is effective at the industrial level. However, what we have observed so far is that the long-term decline in R&D efficiency over recent decades has started to slow, if only slightly. This is admittedly a somewhat tantalising result at this stage. However, we have also been able to make the prediction that if OI is indeed effective at a sector level, assuming adoption of OI in the period 2000-2005, and allowing for a product lead time of 10 years to elapse, we might reasonably expect to see any marked positive effects beginning to show up after approximately 2015. So ends this paper: if OI is working, the industry's R&D efficiency should begin to rise some time after 2015.

5. Chapter 5: Conclusion

5.1 Review of Findings

5.1.1 Model Selection and Validation

To answer the first question of whether quantitative methods can be identified, adapted, or developed to systematically measure the R&D efficiency of companies or sectors, data envelopment analysis (DEA) was been identified from the literature and then been selected and adapted to measure innovation and economic impact: specifically, changes in R&D efficiency. The suitability and applicability of this technique was first explored in the study of the R&D efficiency in China's high-tech industry. In this research, the R&D efficiency in China's high-tech industry was measured across sectors over approximately one decade. DEA was used to generate quantitative indices for comparison study respectively on three levels: the whole industry, the five sectors and the sub-sectors. This analysis shows that overall R&D efficiency in China's high-tech industry did not change during the test period, despite the sustained R&D investment in China. Most of the sectors fluctuated on R&D efficiency over the period with the Computer sector showing highest performance and Aerospace sector performing lowest. Most sectors and sub-sectors suffered decreasing returns to scale (DRS), presumably reflecting the current R&D investment have beyond the industry's absorbing capability which leads to R&D investment inefficiency. The further analysis suggests that the problem of China's high-tech industry may be from the inefficiency of its technology commercialization processes, with clear implications for state investment policy.

5.1.2 Further Application and Examination

The first study explored and validated the base technique for the R&D efficiency measurement. And DEA has been demonstrated to produce suitable indices for measuring R&D efficiency across China's high-tech industry analysis. The next step question was to understand 'Could such

measures be used to assess changes in OI performance through analysing the performance of R&D efficiency before and after OI adoption'. To answer this question, the case study of Procter and Gamble (P&G) was analysed as a test case for OI. Since P&G is a widely recognised early adopter of OI and highly depends on OI strategy (Huston and Sakkab, 2006; Enkel et al, 2009), it was the most suitable study sample for measuring OI performance. The most important benefit for OI adoption is to increase the R&D productivity (Ili et al., 2010). The relative performance of OI-based and pre-OI strategies could be measured through the analysis of P&G's R&D efficiency in both pre and post open periods. The results of these studies were cross-checked using another metric for economic impact identified in the initial research – the MI analysis, the results of which were consistent with those from the DEA analysis.

A more detailed analysis of the time-course revealed that the R&D efficiency of P&G improved rapidly and substantially after its embracing of OI, an effect termed as the 'open rise', although there was also a transient decline in R&D efficiency at the beginning of OI adoption ('open dip'), and an unexpected and marked decline ('open drop') after the peak positive effect midway through the data period. This is the first time to our knowledge that a seemingly sustained drop in performance is observed after the adoption of an open innovation strategy. This apparent effect warrants further investigation with a wider. The 'open dip' could reasonably be interpreted as a temporary loss of efficiency during transition to the new strategy, while the 'open drop' may have a number of possible interpretations ranging from absorption of the relevant market opportunities to inconsistent execution of partnering activities. This "Three-Stage' model of OI adoption is proposed as a theoretical construct to guide be tested and further refined or refuted in future research.

5.1.3 Deeper Study and Understanding

In the case study of P&G, the 'indices of innovation' have been developed and demonstrated to measure the OI performance. So could such methods be used to test or predict the effectiveness of strategies proposed or

assumed to produce more efficient R&D for the pharmaceutical industry than the previous or current strategies? To answer this question, both DEA and MI have been applied to measuring the R&D efficiency in the 10 top pharmaceutical companies over the past decade (1994-2011). Although a continuous decline of R&D efficiency has been found both in the industry and most companies, there is evidence at both industry and firm levels showing the tapering off of the decline and more stable performance on R&D efficiency after year 2000. Moving to OI is one possible possible interpretation for this change. The research also provides evidence for the failure of former strategies in the pharmaceutical industry such as M&As and increasing the R&D investment. The possibility of other strategies such as niche market or focused innovation (FI) strategies was observed in this study. The success of Novo in increasing R&D efficiency by using multiple strategies rather than a 'pure OI' strategy leads to the further idea of hybrid strategies such as 'focused innovation + open innovation' (FI+OI). Therefore, FI+OI may be an attractive prescription for the continuous success for some companies in the pharmaceutical industry.

5.2 Policy Implications

Throughout this three-step study, the main research question – whether OI is the best strategic prescription for the pharmaceutical industry – has been answered in part. Through the analysis of 'indices of innovation', moving to OI may be one route for the better performance of R&D efficiency in the pharmaceutical industry in the post-open period, but other prescription may also address the industry's challenge. However, how to implement OI is still a question needs to be answered given the lack of relevant knowledge and experience in the industry.

5.2.1 Identify the OI Barriers in the Pharmaceuticals

As OI is still a new idea, implementation and management experience is limited, and barriers may exist when pharmaceutical companies move toward it.

The main barriers for pharmaceutical companies adopting OI strategy appear to be:

(1) How to encourage people and organizations to contribute or share more but at the same time to protect their benefit and privacy?

(2) How to share the benefit and right of the research results produced by OI collaboration?

To overcome these barriers, companies could develop their management capabilities in several respects:

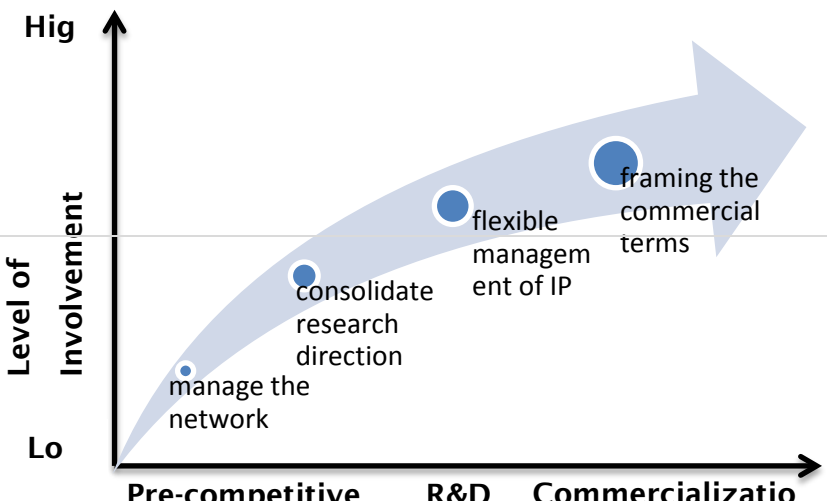
(1) Consolidate Research Direction. Since different partners may have different goals for joining the OI club, they may be using different metrics to measure the outputs (Vargas et al., 2010). Therefore, controlling the direction of research in a network may be very important (Strauss, 2010). To control the direction, the standard method should be developed to judge the success of each stage in OI process. And at the same time, retain and guide incentives for both academic community and companies, such as IP or the right to publish are maintained (Harnessing open innovation, 2009).

(2) Flexible Management of IP. Adopting OI doesn't mean ignoring IP protection. In contrast, in order to encourage collaboration and engagement, IP should be fully protected. IP rights are the currency that fuels OI. If companies are dependent on the benevolence of a benefactor to fund the good ideas, OI activities will fail at the end (Harnessing open innovation, 2009). IP protection in the OI environment will be more challenging compared with closed environment. The first problem that must be solved is the ownership of the IP, which could be decided even in the pre-competitive initiatives stage. In some cases now the pharmaceutical companies want the information to enter the public domain to encourage research. However, both academic groups and SMEs participating in consortia want to retain the right to protect the IP around a particular biomarker (Harnessing open innovation, 2009). Therefore, proactive and flexible methods of IP management must be developed before moving into OI.

(3) Frame the Commercial Terms. Profit and/or share allocation should also be considered at an early stage. Assessing and rewarding the value the different groups bring to the project will be one of the challenges increasingly faced when moving into OI (Judd, 2013). In Hunter and Stephens' study (2010), they give a suggestion for academic-industrial collaboration: there has been some progress in the use of 'boilerplate agreements' (for example, the Lambert Agreements in the UK) that aid discussion by starting from a point that is appropriate to the particular collaborative situation. They believe this is an approach that could be explored more widely for a range of sectors, including pharmaceuticals.

(4) Manage the Network. Pharmaceutical OI has been fostered and cultivated by internet and social networking platforms (Talaga, 2010). 'Innovation technology' such as information and communication technologies helps to support the success of OI (Dodgson et al., 2006). Therefore, managing the relevant communication technology is important to guarantee the success of OI in Pharmaceutical industry. New technology must be effectively deployed to maximize the benefits of OI. For example, the building of expertise networks and databases to allow the best partners to work with each other and dissemination of information about projects across an organization (Hunter and Stephens, 2010). On the other hand, now internet technology is creating more and more new tools and approaches for researchers: aside from the obvious case of Google, companies like Facebook, for example, have mastered how you handle petabyte-scale data distributed over massively parallel architectures and then integrate back to users – that's the kind of problem facing biology and pharmaceutical now (Harnessing open innovation, 2009).

In summary, pharmaceutical companies who intend to adopt OI strategy should be fully prepared and recognize the new challenges from R&D management, IP management and network management (see Figure 5.1).



5.2.2 Overcoming Management Challenges: New Models of OI Adoption

To overcome the challenges and realize the benefit of OI, not only new variants of Open Innovation theories, processes and tools are needed, but also other management practices in companies need updating and even revolutionizing for effective execution in the new model world. To adopt OI strategy requires the efforts of every department in the company. Realizing OI is not just the innovation management job, it should be a general management target. There are also a number of specific management strands required in this approach:

In human resource management, individuals who not only have relevant scientific expertise, but also possess strong external networks and are skilled in working with external organizations should be employed. At the same time, employee roles may need to be redefined to ensure sufficient continuity with external organizations, and to ensure knowledge is being maintained within the enterprise (Hunter and Stephens, 2010).

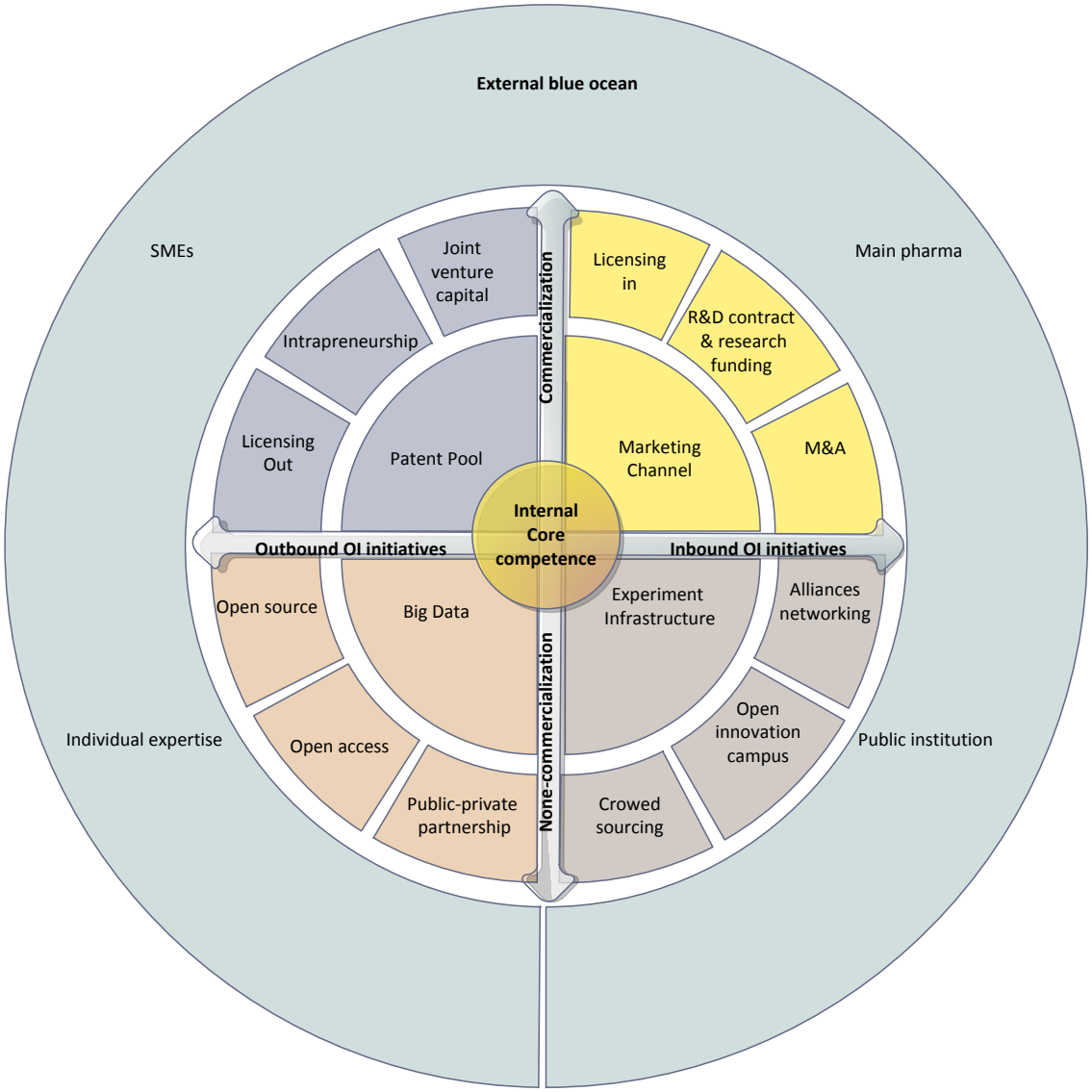
In corporate culture management, senior management must recognize that resources have to be applied to nurture collaborations and monitor their progress to ensure success (Hunter and Stephens, 2010). All staff in the company should understand and positively get involved into this change, and embrace a more open and fully collaboration environment. Culture management is also important between partners. Cultural and commercial differences between partners may constitute a serious hurdle in the negotiation process towards a successful risk sharing agreement in an OI frame (Talaga, 2009).

In operational management, an integrated internal process to develop, manage and implement such type of OI alliances should be set-up. In particular, the management of OI collaboration should be performed in the same manner that Pharmaceutical industry is actually managing its internal project portfolio (Talaga, 2009).

In risk management, a major issue, especially for newcomers, is actually related to the evaluation of the risk and the costs that such business model will imply, at each phase of the process.

Given the trend of moving to OI, there will be more pharmaceutical companies choosing the OI strategy in the future. However, since it is a relatively new concept, not enough theory and tools have been developed and demonstrated, especially in the Pharmaceutical industry. Studying from successful cases in other industries could be one available tactic. But this would have to be based on the full understanding of the characteristics of Pharmaceutical industry. More recent and promising are OI initiatives such as pre-competitive collaboration, covering wide interests in different disease areas, especially for big pharmaceutical companies. For the future success of OI in Pharmaceuticals, more tools and pathways to OI need to be developed in the stages of drug R&D, including tapping into open access or open source initiatives in the pre-competitive stage. Companies could also more focus on their strong innovation areas, to establish more professional but deeper relationships instead of wider but more superficial collaborations with external organizations. In other word, more OI initiatives should be launched in each stage of drug R&D to make the company own both internal and external excellent innovation capability and connection on its limited focusing areas.

The Pharmaceutical-OI adoption model has been developed to give a tool for managing OI activities in the pharmaceutical industry (see Figure 5.2). This model has four main levels, from core competence through to consumer or partner organisations, which were linked by inbound and outbound processes operating through various transfer mechanisms to the market. There are four quadrants to the model which respectively represent the company's core competence – Patent, Channel, Research and Data. For each quadrant, several OI activities which could be developed based on the corresponding core competence are selected to set up the links to the corresponding external resources.



Interpretation: the smallest circle includes the core competence of the big pharmaceutical company. The medium circle includes the OI activities the company could adopt. Based on the category by inbound-outbound and commercial and non-commercial, the activities could classify into four dimensions. Each dimension corresponds to the individual core competence. The elements included into the big circle are the external resources which the big company could benefit from to accelerate its R&D productivity.

Figure 5.2: Pharmaceutical-OI adoption model

5.3 Core Contributions, Limitations and Further Research

5.3.1 Core Contributions

The sequence of research papers reported in this thesis was developed to address the two important research gaps in the study of innovation and its 'open' variant:

(1) The scarcity of attention dedicated to measure the performance of OI, as recently highlighted by several authors (e.g. Huizingh, 2011).

(2) The lack of contributions that systematically and longitudinally assess the extent and the determinants of diffusion of the OI paradigm in a specific industry (Chiaroni et al., 2009).

Through the development of three papers' studies, this thesis explores (a) the feasibility if DEA and MI as quantitative econometric 'indices of innovation', (b) their correlation with a known case of open innovation, and (c) to test the hypothesis that open innovation is increasing R&D efficiency in the pharmaceutical industry. The core contributions emerged from the broad findings and contributions through the study of this thesis:

(1) A set of 'indices of innovation' has been explored and evaluated for measuring innovation performance at several levels and using a variety of data sources.

(2) Understanding of the diffusion of so-called 'open' innovation in a specific industry has been enhanced by developing the possibility of testing whether OI is increasing R&D efficiency or not, and therefore whether it as the potential to be an effective strategic prescription for the pharmaceutical industry.

(3) On the basis of (2), the prediction can be made that if OI (or indeed any other innovation strategy being applied) is working in the pharmaceutical industry, it should show up on the indices within the period of 2015 to 2020.

5.3.2 Limitations of Data and Interpretation

(1) One restriction is that the exact time and degree of OI adoption by the firms is hard to define precisely, there are limited cases studied in this research because of the difficulty to find the suitable cases where these parameters are sufficiently clear.

(2) In line with (1), due to the limitation of available cases and lack of relevant data, the regression framework didn't develop to identify the causal impact of OI by controlling for other elements that might affect the R&D performance. The regression studies are very important to help us better understand the characteristics of OI and guide the practitioners better adopt OI strategy. This kind of studies should be developed when research conditions are fulfilled.

(3) The limitation of data affected the adoption of ideal variables and also the development of comparison studies for variable judgement. The relevant research could go deeper when the relative data are available.

(4) The failure to observe any significant impact of OI on the performance of the industry thus far could be due to product lead times in the pharmaceutical industry being up to the 8-13 years, which prevents a final conclusion at this point on whether or not OI is working in the pharmaceutical industry, but has allowed a clear testable prediction to be made.

(5) This study didn't explore the process performance of OI, which could be very important for understanding and improving the management of OI since innovation is more like one process. Network DEA could be a suitable follow-up technique, which can be employed to develop this line of investigation in the future.

5.3.3 Further Research

The study has addressed two research gaps in OI research: (1) the scarce attention dedicated to measuring innovation performance, in this case in relation to adoption of OI; and (2) The lack of contributions that assess the

adoption and applicability of the OI paradigm specific industries other than high-tech. Studies which could follow on from this work include:

(1) More classic and early OI adopters could be studied and measured through the 'indices of innovation' to provide more evidence of the efficacy or otherwise of OI, or other innovation strategies for R&D.

(2) Both quantitative and qualitative studies could be developed to verify the exist of the three-stage OI adoption model, and also dig the primary interpretations for both 'open dip' and 'open drop'.

(3) Other case studies are needed to support the existing of 'three alternative scenarios ', and more importantly to find the way overcoming the management challenges.

(4) Given more evidence of the advantages of OI adoption, the future performance of R&D efficiency in the pharmaceutical industry should be studied when the firms' data is available.

(5) More case studies both from quantitative and qualitative studies are needed to fill up our knowledge about 'FI+OI' strategy, and more work should be done to support the management practice for this strategy.

(6) The OI performance in other industries could be measured and studied through the 'indices of innovation' developed in this work to contribute our understanding about OI.

Appendices

Table A.1: Technical efficiency scores of five high-tech sectors in years 1997-2008 (2-year time lag)

Year	Medicines	AAS	EEACE	CAOE	MEAMI
1997	0.144	0.095	0.648	1	0.227
1998	0.282	0.11	0.557	1	0.296
1999	0.26	0.197	0.608	0.816	0.296
2000	0.186	0.083	0.482	1	0.355
2001	0.297	0.136	0.49	0.782	0.223
2002	0.256	0.098	0.407	1	0.246
2003	0.366	0.163	0.381	1	0.346
2004	0.329	0.168	0.519	1	0.497
2005	0.425	0.139	0.507	0.916	0.417
2006	0.77	0.239	0.764	0.99	0.412
2007	0.497	0.235	0.728	0.95	0.53
2008	0.503	0.581	1	1	0.756

Table A.2: Pure technical efficiency scores of five high-tech sectors in years 1997-2008 (2-year time lag)

Year	Medicines	AAS	EEACE	CAOE	MEAMI
1997	0.154	0.096	1	1	0.248
1998	0.287	0.115	0.931	1	0.343
1999	0.262	0.211	0.929	0.868	0.318
2000	0.194	0.094	0.968	1	0.383
2001	0.3	0.14	0.972	0.881	0.231
2002	0.268	0.131	0.855	1	0.254
2003	0.368	0.191	0.908	1	0.356
2004	0.329	0.168	1	1	0.514
2005	0.439	0.235	0.816	1	0.486
2006	0.835	0.241	0.873	1	0.468
2007	0.512	0.244	1	1	0.585
2008	0.57	0.619	1	1	1

Table A.3: Scale efficiency scores and returns to scale of five high-tech sectors in years 1997-2008 (2-year time lag)

	Medicines		AAS		EEACE		CAOE		MEAMI	
Year	SE	RTS	SE	RTS	SE	RTS	SE	RTS	SE	RTS
1997	0.935	drs	0.992	irs	0.648	drs	1	-	0.915	Irs
1998	0.982	irs	0.955	irs	0.598	drs	1	-	0.863	Irs
1999	0.993	irs	0.937	irs	0.654	drs	0.94	drs	0.932	Irs
2000	0.959	drs	0.874	drs	0.498	drs	1	-	0.926	Irs
2001	0.989	irs	0.974	drs	0.504	drs	0.888	drs	0.963	Irs
2002	0.954	irs	0.746	drs	0.476	drs	1	-	0.967	Irs
2003	0.996	irs	0.858	drs	0.419	drs	1	-	0.973	Irs
2004	0.999	-	1	-	0.519	drs	1	-	0.966	Irs
2005	0.967	drs	0.591	drs	0.622	drs	0.916	drs	0.858	Irs
2006	0.923	irs	0.99	drs	0.875	drs	0.99	drs	0.88	Irs
2007	0.97	irs	0.963	drs	0.728	drs	0.95	drs	0.906	Irs
2008	0.882	irs	0.938	drs	1	-	1	-	0.756	Irs

RTS is returns to scale. irs and drs for increasing and decreasing returns to scale, respectively.

Table A.4: Technical efficiency scores of five high-tech sectors in years 1999-2008 (4-year time lag)

Year	Medicines	AAS	EEACE	CAOE	MEAMI
1999	0.265	0.119	0.611	1	0.414
2000	0.296	0.097	0.584	1	0.624
2001	0.484	0.105	0.658	0.604	0.584
2002	0.446	0.071	0.45	0.976	0.54
2003	0.544	0.188	0.632	1	0.614
2004	0.436	0.161	0.622	1	0.498
2005	0.568	0.092	0.598	1	0.645
2006	0.671	0.144	0.816	1	0.801
2007	0.554	0.217	0.824	1	0.685
2008	0.653	0.406	1	0.824	1

Table A.5: Pure technical efficiency scores of five high-tech sectors in years 1999-2008 (4-year time lag)

Year	Medicines	AAS	EEACE	CAOE	MEAMI
1999	0.292	0.119	1	1	0.446
2000	0.296	0.098	0.957	1	0.63
2001	0.484	0.106	0.9	0.644	0.589
2002	0.446	0.119	0.784	0.985	0.543
2003	0.545	0.19	0.957	1	0.638
2004	0.474	0.165	1	1	0.508
2005	0.581	0.155	0.894	1	0.646
2006	0.686	0.149	0.984	1	0.802
2007	0.561	0.226	1	1	0.708
2008	0.676	0.412	1	1	1

Table A.6: Scale efficiency scores and returns to scale of five high-tech sectors in years 1999-2008 (4-year time lag)

	Medicines		AAS		EEACE		CAOE		MEAMI	
Year	SE	RTS	SE	RTS	SE	RTS	SE	RTS	SE	RTS
1999	0.908	drs	0.999	-	0.611	drs	1	-	0.929	Irs
2000	1	-	0.998	-	0.61	drs	1	-	0.99	Irs
2001	0.999	-	0.995	irs	0.732	drs	0.937	drs	0.993	Irs
2002	0.999	-	0.601	drs	0.574	drs	0.992	drs	0.994	Irs
2003	0.998	drs	0.992	drs	0.661	drs	1	-	0.962	Irs
2004	0.921	drs	0.976	drs	0.622	drs	1	-	0.981	Irs
2005	0.977	drs	0.589	drs	0.669	drs	1	-	0.999	Irs
2006	0.979	drs	0.966	drs	0.83	drs	1	-	0.999	Irs
2007	0.986	drs	0.961	drs	0.824	drs	1	-	0.967	Drs
2008	0.967	drs	0.985	drs	1	-	0.824	drs	1	-

RTS is returns to scale. irs and drs for increasing and decreasing returns to scale, respectively.

Table A.7: Technical efficiency scores of five high-tech sectors in years 1998-2008 (8-year time lag for the Medicines sector and 3-year time lag for others)

Year	Medicines	AAS	EEACE	CAOE	MEAMI
1998		0.072	0.546	1	0.282
1999		0.12	0.475	1	0.289
2000		0.141	0.611	0.72	0.411
2001		0.063	0.403	0.833	0.37
2002		0.125	0.449	0.758	0.345
2003	0.683	0.104	0.426	1	0.416
2004	0.759	0.168	0.471	1	0.372
2005	0.828	0.093	0.617	1	0.534
2006	0.81	0.149	0.707	0.956	0.507
2007	1	0.313	1	0.951	0.752
2008	0.905	0.281	1	0.887	1

Table A.8: Pure Technical efficiency scores of high-tech sectors in years 1998-2008 (8-year time lag for the Medicines sector and 3-year time lag for others)

Year	Medicines	AAS	EEACE	CAOE	MEAMI
1998		0.072	1	1	0.357
1999		0.123	0.818	1	0.317
2000		0.143	1	0.792	0.486
2001		0.106	0.759	1	0.415
2002		0.163	0.794	0.874	0.373
2003	0.726	0.153	0.838	1	0.441
2004	0.765	0.168	1	1	0.387
2005	0.829	0.165	0.936	1	0.556
2006	0.854	0.172	0.808	1	0.525
2007	1	0.322	1	1	0.769
2008	0.911	0.337	1	1	1

Table A.9: Scale efficiency scores of high-tech sectors in years 1998-2008 (8-year time lag for the Medicines sector and 3-year time lag for others)

	Medicines		AAS		EEACE		CAOE		MEAMI	
Year	SE	RTS	SE	RTS	SE	RTS	SE	RTS	SE	RTS
1998			0.997	-	0.546	drs	1	-	0.79	irs
1999			0.972	irs	0.58	drs	1	-	0.909	irs
2000			0.983	irs	0.611	drs	0.909	drs	0.847	irs
2001			0.595	drs	0.532	drs	0.833	drs	0.893	irs
2002			0.769	drs	0.566	drs	0.867	drs	0.924	irs
2003	0.941	drs	0.68	drs	0.508	drs	1	-	0.945	irs
2004	0.992	drs	1	-	0.471	drs	1	-	0.961	irs
2005	0.999	drs	0.561	drs	0.66	drs	1	-	0.96	irs
2006	0.948	drs	0.869	drs	0.875	drs	0.956	drs	0.966	irs
2007	1	-	0.971	drs	1	-	0.951	drs	0.978	irs
2008	0.993	drs	0.833	drs	1	-	0.887	drs	1	-

RTS is returns to scale. irs and drs for increasing and decreasing returns to scale, respectively.

Table A.10: Technical efficiency scores of five companies including P&G (1-year time lag)

Firm	Year of R&D activity input									
	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
Unilever	0.572	0.582	0.663	0.597	0.616	0.553	0.578	0.53	0.465	0.483
Procter & Gamble	0.563	0.51	0.513	0.59	0.619	0.657	0.702	0.832	0.739	0.674
Henkel	0.497	0.472	0.773	0.813	1	0.728	0.891	0.869	0.68	0.986
Reckitt Benckiser	0.963	1	1	0.933	0.802	0.78	0.805	1	0.678	0.818
Clorox	0.857	0.638	0.717	0.744	0.868	0.871	1	1	0.815	0.787
	2001	2002	2003	2004	2005	2006	2007	2008	2009	
Unilever	0.522	0.515	0.476	0.446	0.517	0.592	0.506	0.638	0.575	
Procter & Gamble	0.718	0.799	0.876	0.822	1	0.96	0.951	0.885	0.902	
Henkel	0.664	0.69	0.624	0.52	0.524	0.565	0.466	0.533	0.514	
Reckitt Benckiser	0.849	0.992	1	0.796	1	0.937	1	1	1	
Clorox	0.793	0.821	0.851	0.787	0.848	0.869	0.813	0.91	0.956	

Table A.11: Pure technical efficiency scores of five companies including P&G (1-year time lag)

Firm	Year of R&D activity input									
	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
Unilever	0.869	0.879	1	0.96	1	0.906	0.909	0.852	0.761	0.817
P& G	0.883	0.83	0.779	0.803	0.803	0.89	0.973	1	0.934	0.876
Henkel	0.67	0.608	0.84	0.872	1	0.857	1	0.959	0.77	1
Reckitt Benckiser	0.967	1	1	0.939	0.807	0.791	0.815	1	0.684	0.822
Clorox	0.86	0.725	1	0.862	1	1	1	1	0.824	0.79
	2001	2002	2003	2004	2005	2006	2007	2008	2009	
Unilever	0.896	0.867	0.805	0.75	0.84	0.947	0.81	1	0.931	
P& G	0.916	0.987	1	0.878	1	1	1	1	1	
Henkel	0.727	0.799	0.812	0.715	0.738	0.804	0.676	0.775	0.746	
Reckitt Benckiser	0.87	0.994	1	0.803	1	0.955	1	1	1	
Clorox	0.802	0.87	0.852	0.788	0.848	0.869	0.836	0.91	0.956	

Table A.12: Scale efficiency of five companies including P&G (1-year time lag)

Firm	Year of R&D activity input									
	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
Unilever	0.658 drs	0.662 drs	0.663 drs	0.621 drs	0.616 drs	0.61 drs	0.636 Drs	0.622 drs	0.611 drs	0.592 Drs
P&G	0.637 drs	0.614 drs	0.658 drs	0.735 drs	0.771 drs	0.738 drs	0.721 Drs	0.832 drs	0.791 drs	0.769 Drs
Henkel	0.741 drs	0.776 drs	0.921 drs	0.933 drs	1 -	0.85 drs	0.891 Drs	0.907 drs	0.883 drs	0.986 Drs
Reckitt Benckiser	0.997 drs	1 -	1 -	0.994 irs	0.994 irs	0.986 irs	0.989 Irs	1 -	0.991 drs	0.995 Irs
Clorox	0.996 irs	0.881 irs	0.717 irs	0.864 irs	0.868 irs	0.871 irs	1 -	1 -	0.989 irs	0.996 Irs
	2001	2002	2003	2004	2005	2006	2007	2008	2009	
Unilever	0.583 drs	0.593 drs	0.592 drs	0.595 drs	0.615 drs	0.625 drs	0.624 Drs	0.638 drs	0.618 drs	
P&G	0.783 drs	0.809 drs	0.876 drs	0.937 drs	1 -	0.96 drs	0.951 Drs	0.885 drs	0.902 drs	
Henkel	0.913 drs	0.863 drs	0.768 drs	0.728 drs	0.709 drs	0.704 drs	0.689 Drs	0.688 drs	0.689 drs	
Reckitt Benckiser	0.977 drs	0.998 irs	1 -	0.992 drs	1 -	0.98 drs	1 -	1 -	1 -	
Clorox	0.988	0.943	0.999	0.998	1	1	0.973	1	1	

	irs	irs	drs	drs	-	-	Drs	-	-	

Table A.13: Technical efficiency scores of five companies including P&G (3-year time lag)

Firm	Year of R&D activity input									
	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
Unilever	0.479	0.606	0.607	0.626	0.507	0.477	0.456	0.449	0.459	0.458
P & G	0.488	0.453	0.431	0.456	0.517	0.622	0.695	0.832	0.712	0.649
Henkel	0.329	0.44	0.584	0.728	0.916	0.633	0.765	0.868	0.575	0.744
Reckitt Benckiser	0.888	0.942	1	1	0.82	0.735	0.98	0.836	0.82	0.718
Clorox	0.927	0.538	0.506	0.697	0.765	0.879	1	0.99	0.754	0.708
	2000	2001	2002	2003	2004	2005	2006	2007	2008	
Unilever	0.463	0.459	0.396	0.381	0.413	0.409	0.508	0.496	0.543	
P & G	0.642	0.675	0.712	0.901	0.967	0.958	0.711	0.709	0.601	
Henkel	0.652	0.494	0.604	0.507	0.526	0.446	0.503	0.444	0.413	
Reckitt Benckiser	0.941	1	0.93	0.933	1	1	1	0.947	1	
Clorox	0.736	0.699	0.668	0.616	0.617	0.67	0.798	0.817	0.583	

Table A. 14: Pure technical efficiency scores of five companies including P&G (3-year time lag)

Firm	Year of R&D activity input									
	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
Unilever	0.81	0.976	0.98	1	0.887	0.846	0.813	0.756	0.787	0.827
P&G	0.952	0.857	0.862	0.834	0.871	0.866	0.95	1	0.905	0.874
Henkel	0.545	0.661	0.738	0.871	1	0.927	0.95	0.983	0.777	0.888
Reckitt Benckiser	0.888	0.943	1	1	0.82	0.755	1	0.857	0.847	0.764
Clorox	1	0.552	0.507	1	0.937	1	1	0.991	0.819	0.715
	2000	2001	2002	2003	2004	2005	2006	2007	2008	
Unilever	0.922	0.898	0.765	0.727	0.778	0.744	0.937	0.921	0.981	
P&G	0.889	0.957	0.968	1	1	1	0.996	0.947	1	
Henkel	0.817	0.775	0.873	0.777	0.827	0.743	0.822	0.752	0.706	
Reckitt Benckiser	0.962	1	0.936	0.946	1	1	1	0.968	1	
Clorox	0.74	0.699	0.687	0.702	0.706	0.75	0.807	0.826	0.654	

Table A.15: Scale efficiency scores of five companies including P&G (3-year lag)

Firm	Year of R&D activity input									
	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
Unilever	0.591 drs	0.62 drs	0.62 drs	0.626 drs	0.572 drs	0.564 drs	0.561 drs	0.594 drs	0.583 drs	0.554 drs
P&G	0.512 drs	0.529 drs	0.5 drs	0.546 drs	0.594 drs	0.718 drs	0.731 drs	0.832 drs	0.787 drs	0.743 drs
Henkel	0.604 drs	0.666 drs	0.791 drs	0.836 drs	0.916 drs	0.683 drs	0.805 drs	0.882 drs	0.74 drs	0.838 drs
Reckitt B.	1 -	0.999 drs	1 -	1 -	1 -	0.974 drs	0.98 drs	0.975 drs	0.968 drs	0.94 drs
Clorox	0.927 irs	0.974 drs	0.998 drs	0.697 irs	0.817 irs	0.879 irs	1 -	0.999 drs	0.92 drs	0.99 drs
	2000	2001	2002	2003	2004	2005	2006	2007	2008	
Unilever	0.502 drs	0.51 drs	0.517 drs	0.524 drs	0.531 drs	0.55 drs	0.543 drs	0.538 drs	0.554 drs	
P&G	0.722 drs	0.705 drs	0.736 drs	0.901 drs	0.967 drs	0.958 drs	0.714 drs	0.748 drs	0.601 drs	
Henkel	0.798 drs	0.637 drs	0.691 drs	0.653 drs	0.636 drs	0.601 drs	0.612 drs	0.591 drs	0.585 drs	
Reckitt B.	0.979 drs	1 -	0.993 irs	0.986 drs	1 -	1 -	1 -	0.978 drs	1 -	
Clorox	0.994 irs	1 -	0.972 drs	0.877 drs	0.874 drs	0.894 drs	0.989 drs	0.989 drs	0.892 drs	

Table A.16: Technical efficiency scores of pharmaceutical companies (7-year time lag)

Firm	Year of R&D activity input								
	1995	1996	1997	1998	1999	2000	2001	2002	2003
Pfizer	0.6	0.551	0.55	0.555	0.369	0.442	0.387	0.462	0.437
J&J	0.507	0.656	0.448	0.44	0.545	0.595	0.51	0.481	0.467
Merck	0.66	0.523	0.384	0.397	0.393	0.393	0.349	0.376	0.359
TAKEDA	0.73	0.705	0.658	0.612	0.543	0.544	0.437	0.424	0.422
Abbott	1	0.805	0.54	0.425	0.455	0.458	0.405	0.442	0.73
Bristol	0.925	0.897	1	0.933	0.771	0.414	0.397	0.391	0.39
AstraZeneca	0.478	0.452	0.396	0.444	0.429	0.435	0.412	0.461	0.438
Novo	0.552	0.563	0.591	0.508	0.644	0.691	0.66	0.811	0.884
Daichi	0.733	0.71	0.661	0.576	0.851	0.539	0.547	0.568	0.669
Lilly	0.454	0.53	0.329	0.327	0.318	0.441	0.44	0.486	0.45

Table A.17: Pure technical efficiency scores of pharmaceutical companies (7-year time lag)

Firm	Year of R&D activity input								
	1995	1996	1997	1998	1999	2000	2001	2002	2003
Pfizer	0.682	0.611	0.578	0.583	0.451	0.489	0.439	0.553	0.561
J&J	0.517	0.664	0.454	0.512	0.653	0.596	0.519	0.482	0.468
Merck	0.682	0.543	0.39	0.404	0.399	0.397	0.351	0.376	0.359
TAKEDA	0.819	0.904	0.873	0.881	0.891	0.98	0.951	0.975	1
Abbott	1	0.875	0.614	0.537	0.621	0.694	0.681	0.744	1
Bristol	0.947	0.898	1	0.934	0.822	0.781	0.735	0.792	1
AstraZeneca	0.507	0.467	0.404	0.458	0.443	0.44	0.435	0.478	0.517
Novo	0.653	0.836	0.927	0.709	0.742	0.866	0.821	0.863	1
Daichi	1	1	1	1	1	0.649	0.635	0.647	0.724
Lilly	1	1	0.736	0.579	0.609	1	0.876	0.901	0.718

Table A.18: Scale technical efficiency scores of pharmaceutical companies (7-year time lag)

Firm	Year of R&D activity input								
	1995	1996	1997	1998	1999	2000	2001	2002	2003
Abbott	0.879 irs	0.902 irs	0.952 irs	0.951 irs	0.817 drs	0.902 drs	0.881 drs	0.836 Drs	0.778 drs
Lilly	0.981 irs	0.988 irs	0.987 drs	0.86 drs	0.834 drs	0.999 irs	0.984 drs	0.999 Irs	0.998 irs
TAKEDA	0.967 irs	0.963 irs	0.986 irs	0.984 irs	0.986 irs	0.992 irs	0.996 irs	0.998 Irs	0.999 -
Bristol	0.891 drs	0.779 drs	0.754 drs	0.695 drs	0.609 drs	0.556 drs	0.459 drs	0.435 Drs	0.422 drs
AstraZeneca	1 -	0.921 drs	0.879 drs	0.791 drs	0.732 drs	0.66 drs	0.594 drs	0.594 Drs	0.73 drs
Merck	0.976 irs	0.999 irs	1 -	0.999 irs	0.938 drs	0.53 drs	0.541 drs	0.493 Drs	0.39 drs
Daichi	0.942 irs	0.967 irs	0.98 irs	0.971 irs	0.969 irs	0.987 irs	0.946 drs	0.964 Drs	0.848 drs
Pfizer	0.846 irs	0.674 irs	0.638 irs	0.717 irs	0.869 irs	0.797 irs	0.804 irs	0.94 Irs	0.884 irs
J&J	0.733 irs	0.71 irs	0.661 irs	0.576 irs	0.851 irs	0.831 irs	0.862 irs	0.877 Irs	0.924 irs
Novo	0.454 irs	0.53 irs	0.447 irs	0.564 irs	0.523 irs	0.441 irs	0.503 irs	0.54 Irs	0.627 irs

Table A.19: Technical efficiency scores of pharmaceutical companies (9-year time lag)

Firm	Year of R&D activity input								
	1994	1995	1996	1997	1998	1999	2000	2001	2002
Pfizer	0.607	0.624	0.634	0.696	0.656	0.366	0.465	0.485	0.415
J&J	0.818	0.602	0.626	0.705	0.582	0.532	0.6	0.533	0.45
Merck	0.764	0.471	0.407	0.41	0.489	0.452	0.444	0.386	0.362
TAKEDA	1	0.739	0.662	0.6	0.607	0.551	0.486	0.525	0.551
Abbott	1	0.716	0.622	0.652	0.676	0.605	0.605	0.745	0.668
Bristol	1	1	0.874	0.75	0.77	0.643	0.396	0.512	0.434
AstraZeneca	0.631	0.464	0.447	0.434	0.47	0.517	0.529	0.492	0.56
Novo	0.679	0.522	0.452	0.664	0.727	0.687	0.747	0.808	0.855
Daichi	0.988	0.882	0.596	0.858	0.871	0.898	0.606	0.73	0.733
Lilly	0.685	0.403	0.48	0.401	0.342	0.344	0.476	0.461	0.612

Table A.20: Pure technical efficiency scores of pharmaceutical companies (9-year time lag)

Firm	Year of R&D activity input								
	1994	1995	1996	1997	1998	1999	2000	2001	2002
Pfizer	0.638	0.665	0.644	0.697	0.659	0.463	0.553	0.567	0.52
J&J	0.827	0.605	0.626	0.741	0.637	0.584	0.6	0.535	0.45
Merck	0.765	0.472	0.411	0.41	0.489	0.456	0.445	0.386	0.38
TAKEDA	1	0.945	0.938	0.93	1	0.985	0.993	0.991	1
Abbott	1	0.717	0.652	0.712	0.761	0.729	0.772	1	0.928
Bristol	1	1	0.925	0.837	0.807	0.742	0.792	1	0.934
AstraZeneca	0.648	0.47	0.448	0.447	0.476	0.518	0.553	0.576	0.63
Novo	0.701	0.576	0.61	0.76	0.765	0.721	0.783	0.85	0.895
Daichi	1	0.939	0.71	1	1	1	0.658	0.785	0.792
Lilly	1	0.765	0.737	0.668	0.524	0.597	1	0.863	0.913

Table A.21: Scale technical efficiency scores of pharmaceutical companies (9-year time lag)

Firm	Year of R&D activity input								
	1994	1995	1996	1997	1998	1999	2000	2001	2002
Abbott	0.95 irs	0.939 irs	0.983 irs	0.999 -	0.996 irs	0.792 Drs	0.842 drs	0.855 drs	0.799 drs
Lilly	0.989 irs	0.996 irs	0.999 irs	0.951 drs	0.914 drs	0.91 Drs	1 -	0.997 drs	1 -
TAKEDA	0.998 irs	0.999 irs	0.991 irs	0.999 -	0.999 -	0.993 Irs	0.996 irs	0.999 -	0.953 drs
Bristol	1 -	0.782 drs	0.706 drs	0.645 drs	0.607 drs	0.559 Drs	0.49 drs	0.529 drs	0.551 drs
AstraZeneca	1 -	0.998 drs	0.953 drs	0.916 drs	0.889 drs	0.83 Drs	0.784 drs	0.745 drs	0.719 drs
Merck	1 -	1 -	0.945 drs	0.896 drs	0.955 drs	0.867 Drs	0.5 drs	0.512 drs	0.464 drs
Daichi	0.973 irs	0.986 irs	0.998 drs	0.972 drs	0.987 drs	0.997 Irs	0.957 drs	0.854 drs	0.889 drs
Pfizer	0.968 irs	0.905 irs	0.742 irs	0.873 irs	0.95 irs	0.952 Irs	0.954 irs	0.951 irs	0.955 irs
J&J	0.988 irs	0.939 irs	0.84 irs	0.858 irs	0.871 irs	0.898 Irs	0.922 irs	0.93 irs	0.926 irs
Novo	0.685 irs	0.527 irs	0.651 irs	0.6 irs	0.652 irs	0.577 Irs	0.476 irs	0.534 irs	0.67 irs

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