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Full Length Research Paper

Research and development in productivity measurement: An empirical investigation of the high technology industry

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The high tech industry has played a critical role in the economic growth of Taiwan over the past two decades. The main success factor in the high tech industry is posited to be improving R&D efficiency and performance. This study utilizes an empirical study to provide valuable managerial insights when measuring the impact of R&D activities and performance representation in the Taiwanese high tech industry. The multi factor R&D performance model is determined to provide improved performance measures within the framework of the developed model, and is adopted to further examine the R&D performance of high tech firms and industries. The few studies dealing with devising the influence of environmental factors on efficiency measures do not consider that inefficiency results partly from exogenous circumstances. This study develops a two-stage sequential technique for incorporating environmental effects into a method for evaluating R&D performance based data envelopment analysis (DEA) and ordinary least squares (OLS) regression with panel data to obtain an efficiency measurement. The study data comprised 194 high tech firms analyzed from a multi-source database. The empirical results demonstrate that the average pure technical efficiency, overall technical efficiency, and scale efficiency scores across all 194 firms are 0.535, 0.424, and 0.791, respectively. Based on those efficiency scores and two-stage DEA empirical, suggestions regarding resource allocation for inefficient firms are explored and can be used to monitor R&D performance and as a basis for making subsequent innovation activities improvements.

Key words: High tech industry, performance, R&D productivity, two-stage data envelopment analysis, OLS regression.

INTRODUCTION

Recent years have seen rapid growth in the Taiwanese high tech industry. The high tech industry has played a critical role in the economic development of Taiwan. In practice, research and development (R&D) activity have taken the center stage in the economic analysis of the high tech industry (Blonigen, and Taylor, 2000). Numerous studies have pointed out that high tech firms are important generators of economic growth (Jone-Evans and Klofsten, 1997; Bommer and Halajas, 2002). The Taiwanese government has established a series of science parks and provided additional incentives such as research subsidies, infrastructure, favorable tax and trade regime and funding to increase the competitiveness of the local high tech industry. As a result, numerous privately invested high tech firms have developed rapidly and become globally competitive. The high tech industry has enjoyed average annual growth of 18.5% since 1991, and achieved 21.4% annual growth during 2004, in Taiwan. In 1991, the contribution of the high tech industry to national GDP stood at 11.76%, increasing to 14.07%

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by 2003 (MOEA, 2005). Simultaneously, many Taiwanese high tech firms, facing growing international competition, have begun to invest heavily in R&D and innovation in order to develop novel and innovative products that meet the market demand. Additionally, high-tech firms currently face a reducing product life cycle, high uncertainty, and intense competition among new products for market share (Qian and Li, 2003). The current intensely competitive and dynamically changing international environment requires high tech firms to invest heavily in terms of both funds and time in R&D activities if they are to maintain their competitiveness and survive. More specifically, high tech firm survival and competitive advantage depend on R&D ability and hence innovation in extreme competitive environments (Duystersc and Hagedoorn, 2000; Wan, et al., 2005), and this innovativeness can also help capture and maintain market share and improve firm profitability. In the high tech sector, efficiency analysis of R&D is particularly important in the international evolution towards a competitive industrial structure, and market-orientated management is the main reason the high tech firms require R&D performance, and output are necessary in achieving these objectives. In response to R&D performance, a number of studies adopted various approaches to analyze firm R&D performance and productivity.

Traditionally, methods of measuring R&D effectiveness are classified into micro- and macro-level measurement techniques. Macro-level techniques focus on the wider social impact of R&D. Meanwhile, micro-level techniques focus on the impact of firm R&D on firm effectiveness (Werner and Souder, 1997). Both techniques can be used to measure R&D performance, but their objectives are very different. The current study measures individual high tech firms R&D performance and thus focuses on micro measurement, namely firm-specific know-how and R&D knowledge, as both are the outcome and determinant of local R&D performance at the micro level. This is because R&D performance depends on past R&D resource investment, R&D efforts and researchers of the firm. Conversely, R&D efforts are crucial in determining further improvements in R&D capabilities and the representation of innovation activities improvement. Restated, promoting R&D activities can significantly increase firm productivity, accelerate product manufacturing time, reduce costs, improve customer satisfaction, reach sales objectives, and finally will be devoted to subsequent innovation. However, various effects, such as managerial efficiency of R&D activities, influence R&D performance and environmental factors also affect R&D performance. The first event is easy to control and adapt via internal management mechanisms. On the other hand, the second event is an exogenous event, which has information concerning environmental characteristics. Consequently, to determine the influence of environmental factors on R&D performance, this study develops a DEA-based two-stage model to incorporate environmental factors into the process of measuring R&D performance. This study is the first to compare relative efficiency by combining the two methods of traditional radical DEA and OLS regression to measure high tech firm relative R&D performance.

Many studies have pointed out that R&D performance focuses on output or outcome (Lee et al., 1996; Werner and Souder, 1997) rather than adopting an input oriented perspective. However, measuring R&D performance requires not only information about the output and outcome, but also information involving how the input and processes influence R&D effectiveness, such as research personnel. The main problems arise when the focus of performance measurement shifts to R&D activities for which inputs and outputs are difficult to define and measure. This is especially true in R&D and innovation activities, which frequently involve considerable variability and uncertainty. The performance of such complex R&D activities cannot be measured using simple methods or concepts. Furthermore, many high tech firms still lack efficient and accurate evaluation methods for measuring whether their R&D performance has reached an appropriate level. To overcome the limitations of previous studies, this study applied non-parametric DEA methods to measure high tech firm R&D performance that consider the phases from input to outcome, since the non-parametric approach is not limited by any conditions and can easily measure the relative efficiency of decision making units (DMUs).

In fact, till date, no well-established theoretical approaches for determining the input variable selection have been used in these performance measurement models. In addition, Lang and Golden, (1989) argued that DEA is engaged in a performance evaluation mechanism for program planning, at least, some of the inputs selected must be subject to manipulation by the decision-makers. In the same vein, Sexton et al. (1994) refers to the fact that the DEA model allows the assessment of contingent productivity, which takes into account the performance of each DMU despite the various combinations of operating characteristics, given that operating conditions are similar. Therefore, the initial inputs selected for evaluation can be manipulated by the researchers in order to meet the requirement of the specific goals of the research. In this respect, Farrell (1957) stressed the best performing units as bases for performance evaluation. However, in many real-world settings, it is essential to allow some degree correlation in the input variables when rendering a decision on the performance of a DMU. In addition, Odeck (2000) has argued that the DEA possess several advantages as an adequate efficiency measuring approach for measuring the efficiency of high tech firms. The primary advantages includes: (i) Allowing the simultaneous analysis of multiple outputs and multiple inputs, (ii) it does not require an explicit and a priori determination of a production function, (iii) efficiency is measured relative to the highest observed performance rather than against some average and (iv) it does not require information on prices (Odeck, 2000). According to the DEA method, efficiency involves combining available inputs to achieve higher outputs than its possibility with comparable DMUs. Given these advantages and characteristics, DEA is more flexible than other conventional methods of efficiency measurement.

This study aims to measure high tech firm R&D performance, and, particularly, to investigate whether high tech firm R&D productivity efficiency has reached an appropriate scale. Additionally, this study utilizes OLS regression analysis to determine environmental factors and further importing environmental factor to take into account the two-stage DEA model. Furthermore, this study summarized overall R&D performance of individual high tech firms using appropriate measurement models and tools to reduce the useless effort and waste associated with R&D resources. Furthermore, the analytical results presented in this study can provide R&D managers and policy makers with further information in making effective R&D, innovation and resource allocation decisions that can enhance R&D efficiency. The remainder of this paper is organized as follows: Section 2 discusses the relationship between R&D performance measurement and DEA. Section 3 then develops the two-stage DEA methodology for evaluating R&D performance in high tech industry. Next, section 4 identifies the sample size based upon eight DEA input and output variables commonly used to analyze the high tech industry. Section 5 then examines the empirical results obtained using the two-stage DEA approach. Finally, a summary is presented and managerial implications are discussed.

THE R&D PERFORMANCE MEASUREMENT AND DEA

Much of the previous research has focused on developing conceptual models to measure R&D performance. Bremser and Barsky (2004) proposed the balanced scorecard method for measuring R&D performance via the financial, customer, internal business process, and learning and growth perspectives to design an integrated evaluation system. From a system measurement perspective, Brown and Svenson (1998) pointed out that R&D measuring should consider external and internal measurement, focus on enhancing outcomes rather than behavior, and measured outputs should consider cost, quantity and quality, and should be objective rather than subjective. Balachandra, (1997) reviewed over 60 R&D project articles and concluded that successful R&D projects were characterized by a number of features, namely being market related, technology related and organization related. Based on the balanced scorecard framework, Kerssens-van Drongelen and Bilderbeek, (1999) proposed a contingent measurement system design for feedback and feed forward control approach of both R&D function and R&D departments performance at different levels of organizations. In light of R&D and market performance, Thomas and McMillan (2001) demonstrated a significant relationship between R&D metrics and subsequent corporate performance by using a series of science and technology indicators obtained from a unique patented database.

Various methods of effective performance measurement have been developed. Coccia (2001) assessed public research laboratory R&D performance using a system that included inputs, production process (of scientific activity), and outputs. R&D organization performance can be measured according to a series of input and output indicators, which are operated via linear functions (Coccia, 2004) and subsequently further improved the Coccia model (2001) by constructing a new R&D performance model based on discriminant analysis that incorporated a systemic approach that considered financial, scientific, and technological indexes. Regarding comprehensive perspectives, Werner and Souder, (1997) designed an integrated measurement system, which combines both qualitative and quantitative metrics. Schumann et al. (1995) argued that R&D laboratories can be viewed as a system. From a wider system perspective, the R&D lab is more aligned with input, processes and output to improve the understanding of customers' requirements. Similarly, Giffin (1997) proposed process analysis as a method for evaluating R&D performance. Brown and Gobeli (1992) integrated qualitative and quantitative methods for developing and inducing ten R&D productivity indicators with a system for measuring R&D productivity. Dressler et al. (1999) proposed that cost saving ratio (CSR) approach should be used to measure R&D performance. Unfortunately, the previous literature found that most studies emphasized R&D performance conceptual model development or used a method of integration to understand R&D performance without extending to R&D productivity empirical testing. This study employed a large scale survey and developed an empirically derived mode for measuring high tech firm R&D performance.

Various previous studies have examined individual R&D project evaluation and selection method. Almost all of these studies focused on constructing and developing R&D performance evaluation methods. Meanwhile, R&D activity efficiency and productivity measurement has been relatively neglected, in measurement of R&D performance based on comparison of empirical techniques. R&D performance and measurement involves a holistic view of the full range of R&D activities that depends not only on multiple output criteria, but also requires the consideration of multiple output criteria for measuring R&D performance. Previous studies suffer some limitations in relation to R&D performance evaluation and measurement, for example, almost all measurement efforts have focused on R&D output (Szakonyi, 1994). Previously proposed models have been unable to deal with both input and output criteria, and such models have been unable to handle input and output data without any distribution and so on. This study presents an empirical study of multiple inputs and outputs based on quantitative methods, that is, the DEA approach which is a useful mathematical method for overcoming these limitations. Additionally, quantitative measures are relatively straightforward and accurately represent specific areas of R&D activity (Brown and Gobeli, 1992). On the other hand, firm performance is a complex phenomenon that should be measured using multidimensional or multiple criteria. Numerous studies have argued that the use of multiple criteria was more appropriate for performance measurement than the use of single criteria (Bagozzi and Phillips, 1982; Chakravarthy, 1986; Zhu, 2000). As restated, one single indicator was an unsatisfactory R&D performance measurement of high tech firms. DEA was designed to estimate relative efficiency by importing multiple inputs and outputs without any prior underlying functional from assumption, and furthermore to provide useful information for management on improving organizational operation efficiency and avoiding resource wastage. Accordingly, DEA methods of efficiency achievement are appropriate for assessing R&D performance.

Data envelopment analysis provides a clear picture for measuring whether high tech firm R&D achieves productivity or technical efficiency objectives. DEA is a linear programming method based technique and the basic model only requires input and output information. The DEA method enables the identification of a clear relationship between inputs and outputs and can measure relative efficiency by comparing the efficiency achieved by a DMU with those obtained by similar DMUs. Simultaneously, using a DEA approach, the researcher does not handle a production function and does not assume a restricted relationship between inputs and outputs. DEA is a non-parametric methodology that uses a “data oriented approach” for evaluating the performance of DMUs/firms that are regarded as responsible for converting inputs into outputs (Keh and Chu, 2003). The original DEA model is the CCR DEA model developed by Charnes et al. (1978). DEA has also been widely applied to different industries and a number of different DEA models have been developed and improved based on the original DEA model. DEA is based on the principle of using an appropriate linear programming mathematical model to estimate multiple inputs and outputs.

TWO STAGE DEA METHODOLOGY

DEA has become a widely accepted approach for evaluating DMUs productivity or relative efficiency. DEA is also a performance measure and managerial control tool for measuring the degree to which inputs are utilized in obtaining desired outputs and furthermore can easily explain the functional relationship between inputs and outputs. Moreover, the linear programming mathematical model can measure the DEA efficiency frontier and identify the most efficient DMUs. This study used the input-oriented DEA model to measure the best practices frontier. The input oriented DEA model is adopted in this study for three main reasons. First, the increasing high tech firm R&D budgets which have resulted from the growing competition in the global high tech industry during the past decade. Second, extreme competition within industries requiring high tech firms to increase R&D investment and innovation activities to satisfy highly varied customer demands. Third, high tech firms can more easily control inputs such as R&D funds. This study thus adopted the input-oriented DEA model to measure relative high tech firm efficiency.

The CCR-DEA model

This study employs the input-oriented CCR-DEA model to determine the best practice frontier of high tech firm R&D performance. The original CCR-DEA models were proposed by Charnes et al. (1978) as an evaluation tool for DMUs capable of explaining constant returns to scale (CRS) (Charnes, et al., 1978). The CCR-DEA model is used to evaluate the relative technical efficiency of DMUs and to transform inputs into outputs as part of a direct technique that does not make strict assumptions regarding whether data and parameters obey a particular distributions. That is, the DEA model is known in the literature as a non-parametric methodology. Moreover, the CCR-DEA model was applicable only to technologies characterized by constant global returns to scale. The CCR-DEA model formulation is demonstrated as follows:

$$
\begin{aligned}
Min \quad & h_k = \theta - \varepsilon \sum_{i=1}^{m} s_i^- - \varepsilon \sum_{r=1}^{s} s_r^+ \\
s.t \quad & \sum_{j=1}^{n} \lambda_j x_{ij} - \theta x_{ik} + s_i^- = 0, \quad i = 1, \cdots, m \\
& \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ - y_{rk} = 0, \ r = 1, \cdots, s \\
& \lambda_j, s_i^-, s_r^+ \geq 0, \quad j = 1, \cdots, n \quad i = 1, \cdots, m \quad r = 1, \cdots, s \\
& \theta \text{ free}
\end{aligned}
\qquad (1)
$$

where:

i =inputs, $i = 1, \ldots, 4$; $r =$ outputs, $r = 1, \ldots, 4$;

$j =$ DMUs, $j = 1, \ldots, 195$

s_i^- and s_i^+ denote input and output slack variables, respectively,

θ indicates the ratio of minimum input to actual input,

x_{ij} denotes the value of the *i*th input of the *j*th DMU, (*i*=1, …,4)

y_{rj} represents the value of the *r*th output of the *j*th DMU, (*r*=1,…,4)

ε is the non- Archimedean quantity

This model can be used to estimate the input-oriented technical efficiency. Values of $\theta = 1$ and $s_i^- = s_i^+ = 0$ indicate that a DMU attains a100% productivity efficiency and has an efficiency score of 1. Meanwhile, $\theta < 1$ demonstrated that a DMU does not

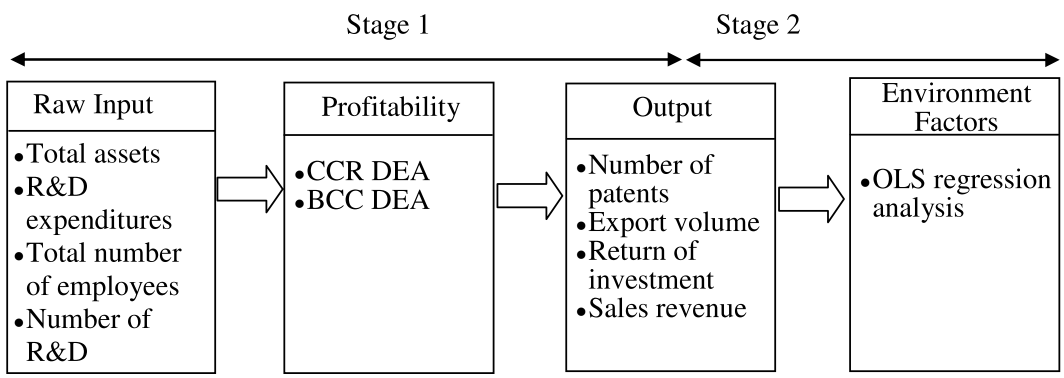

Figure 1. Two-stage DEA model.

attain 100% productivity efficiency. That is, the input is decreased by $x'_{ik} = \theta x_{ik} - s_i^-$ and the output is increased by $y'_{rk} = y_{rk} + s_r^+$ to achieve a DMU of 1.

The BCC-DEA model

The CCR-DEA model is used to measure the technical efficiency of a DMU assuming constant returns to scale (CRS). However, in numerous real world cases, inefficiency results not only from allocation inefficiency, but rather from scale and technical inefficiency. To overcome this difficulty, Banker et al. (1984) extended the CCR-DEA model by imposing an additional constraint of $\sum_{j=1}^{n} \lambda_j = 1$ on the BCC-DEA model. The fundamental premise of the BCC-DEA model is that it compartmentalizes the overall technical efficiency of the CCR-DEA model to yield pure technical efficiency and scale efficiency under variable return to scale (VRS). As a result, the BCC-DEA model can be explained as follows (Banker et al., 1984):

$$
\begin{aligned}
& Min\ h_k = \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \\
& s.t. \quad \sum_{j=1}^{n} \lambda_j X_{ij} - \theta X_{ik} + s_i^- = 0, \quad i = 1,\cdots,m \\
& \qquad \sum_{j=1}^{n} \lambda_j Y_{rj} - s_r^+ = Y_{rk}, \quad r = 1,\cdots,s \\
& \qquad \sum_{j=1}^{n} \lambda_j = 1 \\
& \qquad \lambda_j, s_i^-, s_r^+ \geq 0, \quad j = 1,\cdots,n, \quad r = 1,\cdots,s, \quad i = 1,\cdots,m \\
& \qquad \theta \ \textbf{free}
\end{aligned} \tag{2}
$$

The selection of the CCR-DEA and BCC-DEA models for application to high tech firms is based on two primary considerations. First, since the high tech industry is currently in mature stage, an input-oriented model was more appropriate than an output-oriented one. Second, since the high tech firms in this sample belonged to different size categories, it was important to account for variable scale effects. Consequently, this study utilized the input-oriented DEA model for measuring performance.

In a realistic situation, many exogenous or non-discretionary inputs exist that can not be controlled by high-tech management and decision makers. Consequently, R&D performance evaluation need to metric for external environment factors. However, since the efficiency scores produced by the DEA are fractional data, thus the tobit regression is inappropriate for use in such manner (McDonald, 2009). Banker and Natarajan (2008) and McDonald (2009) shows that using ordinary least squares (OLS) in second stage DEA efficiency analyses is more consistent, unbiased and sufficient estimator than tobit regression. Therefore, it is reasonable to expect that the two-stage DEA-based estimation procedures with OLS were used in the current study, namely, nonparaneter DEA method is used in the first stage to estimate individual high tech firm productivity and the OLS approach is used in the second stage to estimate the environmental variables affecting productivity. In line with the studies of Banker and Natarajan (2008) and McDonald (2009), this study focuses on analyses based on the OLS regression technique using a two stage approach in order to examine the influence of environment on the R&D efficiency of the high tech firms. The environmental factors are not conventional input or output variables and are assumed to be outside of managerial control. To address this problem, the environment variables can be accommodated in the two-stage DEA method by using the OLS regression analysis (Banker and Natarajan, 2008; McDonald, 2009). However, the two-stage DEA method was used to measure whether environmental differences impact high-tech firm R&D performance or not.

Procedure of two-stage DEA analysis

According to Wang and Huang (2007) and Fried et al. (1999), the efficiency measure may be influenced by the external operating environment. After estimating efficiency scores of R&D efforts in the first stage, we thus take into account how the efficiency of R&D efforts is influenced by exogenous operating factors, which are usually beyond the control of the managers. This study employs a two-stage DEA model to model high tech firm R&D performance, as shown in Figure 1. In the first stage, DEA is applied to input and output data to derive an initial evaluation of R&D performance. This stage can be viewed as the R&D profitability stage. The variables considered during the first stage cover eight varieties of input and output quantity data, demonstrating high tech firm ability to obtain revenue and profits. This assessment does not consider the impact of environmental factors on R&D performance (Figure 1).

The second stage input is obtained from the indicators of pure technical efficiency (PTE), overall technical efficiency (OE), and scale efficiency (SE) for R&D obtained in the previous stage. Several of the exogenous environmental factors were considered to be of great impact on R&D performance. The environmental factors impacting high tech firm age, location, networks cooperation and oversea subsidiary were also discussed. As aforementioned, many methods and techniques are used in the evaluation R&D performance or productivity of firm. However, prior researches devote little attention on how to develop efficient and accurate approaches for measuring R&D performance under various environmental factors. In such situations, it may be necessary to use a rigorous and consistent method such as OLS regression to estimate the various environmental factors impact on R&D performance measurement been produced in the first stage. To address this issue, we propose a series of environmental variables in the second stage estimation. Scott (1998) has pointed out that the location of firms and industrial performance are interconnected. In the same vein, Lee (2009) argues that the clustering of firms in high tech industry is widely believed and accepted in both academic and policy circles to facilitate innovative activities and promote regional growth. Some studies stressed that inter-firm cooperation network can act as an important channel to acquire external critical technological know-how and knowledge across different organization levels to improve their R&D capabilities (Löfsten and Lindelöf, 2005; Mancinelli and mazzanti, 2008). Thus, cooperation network is one of important vehicle to acquire complementary resources in improving competitiveness to the high tech firms. In addition, to acquire R&D knowledge and technological know-how, many high tech firms had built an oversea subsidiary as a vehicle in order to access advanced techniques, and knowledge from an advanced country (Wang et al., in press). The impacts of these environmental variables are investigated in our stage 2 OLS regression analysis. As argued by, for instance, Fried et al. (2002), the typical two-stage approach follows a first stage DEA exercise based on inputs and outputs with a second stage regression analysis seeking to explain variation in first stage efficiency scores in terms of a vector of observable environmental variables. In the second stage, therefore, DEA-based model is used to regress the first stage performance measures against a set of environmental variables in order to isolate the impact of luck from those of managerial performance and environmental impacts.

SAMPLE COLLECTION, INPUT AND OUTPUT DEFINITIONS

This study examines the efficiency variations of high tech firms, with quantitative R&D input and output data for these firms being collected, followed by the evaluation R&D efficiency. The advantage of DEA is that it provides multiple inputs and outputs and employs a wide acceptance approach to performance measurement.

DEA Input and output variables

Owing to the lack of clear criteria for selecting the number of variables to be included in the measurement model, this study selected input and output variables based on the previous literature and on the data available, and thus precisely expressed the R&D activities of the high tech industry. To obtain appropriate input and output variables for the R&D performance of high tech firms, in-depth interviews were conducted with top managers of three high tech firms and three scholars of technology management. Subjects were queried regarding what they considered to be the key input and output variables that resulted in high tech firm success or failure in R&D activities. Additionally, they were asked to identify the critical factors influencing productivity efficiency of high tech firm R&D activities. This study, thus, assesses the productivity efficiency of high tech firm R&D not only from a theoretical perspective, but also corresponding with opinion, experiences and professional knowledge background of the top managers and scholars experts of high tech industry.

This study considers individual firm R&D generation activities as a sequential development process. R&D is critical in knowledge- and technology-based innovation processes, especially in the case of high tech firms. That is, R&D performance output can be viewed as resulting from R&D efforts and other resources commitment. In the short-term, R&D efforts may not directly contribute to revenue or profit. However, due to data unavailability, current available data set in high-tech firms do not have direct measures output of R&D efforts. Unlike studies of cost drivers that are based on single firm data, the DEA approach compares the relative efficiency of high-tech firms in the sample. Therefore, although investing R&D efforts may not be necessarily proportional to the increase in innovation output, a high-tech firm deemed to be relatively inefficient under the DEA model when its R&D effort is relatively low after controlling other variables. Further, the sample analyzed in this study is extended over six years of data of a high-tech firms R&D effort, and we believe that using a panel data approach for such a long-period analysis, somewhat, mitigates the R&D efforts and resources commitment differences across high-tech firms. More importantly, we further require the sample to be from high-tech firms that have long-period data on R&D in order to increase consistency of empirical results. According to the R&D efficiency measurement framework, this study only considers direct R&D related inputs. In this study, patents, export volume, return on investment and sale of revenue together with innovation outputs are, thus, considered direct outputs of R&D. Moreover, R&D performance depends on a model of R&D efforts and a set of innovation input factors. That is known as the added value model of R&D performance function at the level of an individual firm, and can be written as:

$$PI_i^t = f(A_i^t, R_i^{t-r}, E_i^{t-r}, N_i^{t-r}) \qquad (3)$$

where PI_i^t denotes a vector of variables measuring the R&D performance of firm *i* at time *t*, A_i^t represents the vector of the total assets of the firm at time *t*, R_i^{t-r} is the vector of R&D expenditures over the period *r* to *t*, E_i^{t-r} denotes the vector of number of employees over the period *r* to *t,* and N_i^{tr} represents the vector of R&D researchers over the period *r* to *t.* This formulation measures firm R&D performance by considering not only firm controllable inputs, but also the influences of firm capital, R&D expenditure, employees and R&D researchers.

The input variables reflected the investment of high tech firms in R&D resources and subsequent innovation activities. The output variables represented quantitative measures of the results high tech firms expected from their own investment in R&D resources and performance. This study included four input variables and four output variables: (1) Total assets: These are the typical inputs in R&D activities (Serrano-Cinca et al., 2005). (2) R&D expenditures, R&D expenditure serve as the indicator of input or firm R&D efforts and innovativeness (Graves and Langowitz, 1996; Bagchi-Sen, 2001; Regers, 2004; Serrano-Cinca et al., 2005; Wan et al., 2005; Becheikh et al., 2006; Wang and Huang, 2007). (3) Total number of employees: The number of employees can be considered a type of R&D and innovation activities input (Sterlacchini, 1999; Koschatzky, et al., 2001; Becheikh et al., 2006) and size is advantageous in exporting activities (Wakelin, 1998). Generally, employee number is used to measure firm size, which is positively correlated with most performance measures. (4) Total number of R&D researchers, R&D researchers is an important part of motivating and engaging in R&D and innovation activities (Koschatzky et al., 2001; Serrano-Cinca, et al., 2005; Wang and Huang, 2007). That is, R&D researchers are directly intent on engaging in being productive and value that enhance activities.

This study used four output variables to measure high tech firm R&D output and innovation activities. (1) Number of patents: A patent can be viewed as an indicator of R&D zoutcomes (Graves and Langowitz, 1996; Kim and Oh, 2002). Patent also measures the volume of firm research activities and the impact of firm research on subsequent innovation (Thomas and McMillan, 2001). (2) Export volume, export indicates the higher rate of exports for firms with high R&D efforts input (Wakelin, 1998; Bagchi-Sen, 2001; Regers, 2004). This finding is consistent with the finding of Sterlacchini (1999) and Roper and Love (2002) that R&D intensity increases either the possibility of innovative products being an exporter or the share of exports represented by sales. (3) Return on investment (ROI): The ROI of financial criteria is easiest to calculate for R&D outcomes, which are relatively stable and predictable. Return on investment is the single most important indicator of R&D performance (Walwyn, 2007). (4) Sales revenue, sales revenue represents profitability associated with R&D and innovation activities resulting in new products and services. An important indicator of the realization of product innovations is the share of new products in sales revenue (Koschatzky et al., 2001). Grupp and Maital (2000) examined the R&D activities of the largest Israeli firms, and found an association between perceived innovativeness and significant increases in sales revenues and intended future profitability.

Although some of the variables, such as the sales revenue and ROI may be affected by other factors. The sales revenue is essential to consider the reality of R&D output factors since sales revenue is a major predictor of a firm’s involvement in R&D efforts (Bound et al., 1984; Grabowski and Vernon, 2000), which can be use to explore the product's R&D or services improvement and thus influence the performance. In addition, return on investment (ROI) which takes as an output variable in this study is due to volatility in total assets being greater than total investment in all high tech firms. Therefore, the ROI variable is selected as important indicators not merely on justify investment of the high tech firm reports, but dependent upon the after-tax profits. This was the motivation behind the current investigation to determine how initiating R&D input variables affect and act in response to high tech firm performances. Being a well-connected and significant player in a R&D performance analysis, the relationship between inputs and outputs variables should be based upon observations, in that high-tech firms fully and directly reflect everything in the R&D capacity and efficient behavior. Therefore, we concerned that efforts to develop a simple model using initial R&D variables, turning it into an empirical R&D performance measurement, would be a valuable addition to the high tech industry. In addition, the original fractional and nonlinear DEA model, proposed by Charnes et al. (1978), can obtain be directly from the data without requiring a prior specification of linear relationship or assuming productivity functional forms of relations between inputs and outputs. Particularly, a best-practice function is empirically built from observed inputs and outputs rather than pre-determined criteria or index for each DMU. In order to handle non-linear effects on the DEA model, a fixed and variable DEA model was employed and offered a suitable method for measuring non-linear inputs and outputs. Since the fixed and variable returns-to-scale model can alleviate the non-linear effect between inputs and outputs (Gregorious and Chen, 2006), thus, we apply the fixed and variable returns-to-scale model with input-oriented to evaluate the R&D productivity of high tech firms. The fixed and variable returns-to-scale model can be viewed as a complementary performance evaluation method because it captures the effect of non-linear relationship between the inputs and outputs. Therefore, non-linear might occur in the R&D productivity due to variation of inputs and outputs. But based on the complementary performance evaluation method used in this study, we can alleviate the non-linear effect without the results of DEA analysis being affected. Till date, few applications of DEA and OLS regression analysis have analyzed R&D efficiency in the high tech industry. However, the integrated application of DEA and OLS regression analysis in R&D activities is rare. This study is one of the first studies to analyze high tech firm R&D efficiency using the aforementioned methodologies.

Data collection and description

This study used panel data to measure high tech firm R&D performance. The study sample comprised all over-the-counter (OTC) high tech industry firms listed in the Taiwan Stock Exchange Corporation (TSEC) database and for which continuous financial data was available for the period from 2000 to 2005, a total of 315 firms. The survey sample included firms involved in electronics, computers, integrated circuits, semiconductors, telecommunications and precision equipment firms in which high tech industry is focusing on technology-based and technology-intensity firms. In particular, we summarize the findings from the interview with high-tech industry experts and literature to identify the stage of the high-tech industry. The evidence provides considerable support that the propensity for the high tech industry lies in the mature stage of the industrial life cycle, but not during the declining stage. In the mature stage, product innovations and competitions are incremental and directed toward product differentiation (Adner and Levinthal, 2001), with a heavy reliance on technological-and innovation-based R&D activities. This appears to be one of the reasons why it emerges from the mature stage, in that the importance of R&D efforts in innovation performance measure the degree to which innovative activity tend to be concentrated in the mature stage of the high tech industry life cycle. This stage of life cycle of the high tech industry evolves towards maturity, there is a significant relative advantage in innovative activity such as R&D, technological, manufacturing and management. Thus, an important conclusion drawn from this study is that the high tech industries, which is highly R&D inputs and where most of high tech firms have a higher propensity to innovate are better characterized by the mature stage of the life cycle. On the other hand, standard financial figures are not available for all high tech firms, and further many high tech firms treated such data as secret, making it difficult to gather complete data for all firms. Consequently, secondary data from multiple databases was gathered for validity purposes. Specifically, the annual reports of individual high tech firms published by the Securities and Futures Institute (SFI) of Taiwan, the Taiwan stock market (TEJ, 2005) database published by the Taiwan Economic Journal, the Taiwan business directory and general corporation financial analysis database produced from the survey published by the China Credit Information Service (CCIS, 2005) company, and the annual report on industrial production (MOEA, 2005), were used in this study as supplementary data sources. A final sample of 194 high tech firms was thus, obtained. The available follow-up information came from multiple databases to increase accuracy and reduce error rate.

To handle the time lag issue, Shafer and Byrd (2000) proposed that the time lags in the DEA model can be sovled by using an average level of the inputs over a three year period and by using annual compound growth rate for the outputs over a five year period. Similarly, to address time lag effect and the issue of benefits accruing in multiple time periods in R&D efforts and its output, we used long-period data from the years 2000 to 2005 while the performance measures assessed the compound annual change in the measures over the 6 year period begining in 2000 and ending

Table 1. Descriptive statistics and correlation coefficients of R&D inputs and outputs (n = 194).

Variable	Mean (S.D)	1	2	3	4	5	6	7	8
Total assets	665327.93 (176237.64)	1							
R&D expenditures	485641.40 (95391.85)	0.801	1						
Total number of employees	2291.06 (1097.16)	0.234**	0.482**	1					
Total number of R&D researchers	171.22 (31.10)	0.408**	0.665**	0.533**	1				
Number of patents	104.74 (33.37)	0.700**	0.821**	0.811**	0.565**	1			
Export volume	11602503 (3029115)	0.276**	0.291**	0.051	0.309**	0.176*	1		
Return on investment	18.72 (0.90)	0.137	0.046	0.025	0.001	0.024	0.098	1	
Sales revenue	16777742 (3625405.90)	0.476**	0.505**	0.088	0.471**	0.311	0.626**	0.104	1

Note: ** and * represent the significant at the 0.01 and 0.05 level, respectively. Values in parenthesis are standard errors.

in 2005 in this study. That is, long-period data do not only increased analytic consistency, but also helped mitigate some of the measurement errors that occured when using data from just a single-period. Table 1 lists descriptive statistics for all input and output variables, including mean, standard deviation, and correlation coefficients. We found that the all of the variables are low correlations to each other excluding number of patents. Thus, this level of correlation indicates that there is little likelihood of collinearity influencing the validity and do not threaten the coefficient estimates in the all estimative mode (Table 1).

EMPIRICAL RESULTS OF TWO-STAGE DEA APPROACH TO R&D PERFORMANCE

In this study, the two-stage DEA methodology was applied to evaluate high tech firm R&D performance measurement and analysis using a sample of 194 Taiwanese high tech firms from 2000 - 2005. Four types of environmental variable were used to regress the first stage performance measures against a set of environmental variables in the second stage.

DEA efficiency measure

The issue of the stage life cycle of high-tech industry is important because it reflects the knowledge and technological requirement for R&D and innovative activity during the various stages of the high tech industry life cycle. According to Audretsch and Feldman (1996), the study the R&D efforts and innovative activity, in which the stage of industry life cycle have significant differences. A major concern is to to identify the stage of industry life cycle of the existing high tech firms, which takes into account R&D productivity as well. To accomplish this, the current study employs expert interviews and literature linkages, through multiple sources, intra-industry information, and various types of R&D efforts among high tech sectors. We measure and evaluate the importance and the performance of R&D for analysis of the R&D productivity.

This study measures high tech firm R&D efficiency using multiple inputs and outputs, in which firms attempt to maximize their outputs for the given R&D inputs resources. This study measures three forms of efficiency. Pure technical efficiency (PTE), overall technical efficiency (OE), and scale efficiency (SE) are adopted as an efficiency index for each high tech firm during the first stage DEA model, based on panel data. Table 2 lists the results for the original DEA efficiency distributions frequency. The optimal efficiencies of each measure of efficiency for high tech firms, namely PTE, OE, and SE

Table 2. Distribution frequency of DEA scores (n = 194).

Score value	PTE (%)	SE (%)	OE (%)
0.1 - 0.19	25 (12.8)	49 (25.3)	3 (1.54)
0.2 - 0.29	30 (28.4)	33 (42.3)	4 (3.61)
0.3 - 0.39	34 (45.8)	31 (58.2)	7 (7.22)
0.40 - 49	22 (57.2)	24 (70.6)	13 (13.9)
0.5 - 0.59	11 (62.8)	11 (76.3)	18 (23.2)
0.6 - 0.69	8 (67.0)	8 (80.4)	14 (30.4)
0.7 - 0.79	9 (71.6)	4 (82.5)	19 (40.2)
0.8 - 0.89	12 (77.8)	10 (87.6)	19 (50.0)
0.9 - 0.99	4 (79.8)	6 (90.7)	78 (90.2)
1	39 (100)	18 (100)	19 (100)

OE□Overall technical efficiency, SE□scale efficiency, TE: pure technical efficiency. Values in parentheses are cumulative frequency.

Table 3. Descriptive statistics of the efficiency indices (n = 194).

Efficiency variables	All firms (194 firms)		Science park firms (122 firms)		Firms not located on science park (72 firms)	
	Mean	S.D	Mean	S.D	Mean	S.D
PTE	0.53	0.31	0.50	0.30	0.60	0.33
OE	0.42	0.29	0.40	0.28	0.45	0.31
SE	0.79	0.23	0.80	0.24	0.78	0.21

Both of overall technical efficiency (OE) and scale efficiency (SE) measure are yield form of CCR DEA model. Pure technical efficiency (PTE) measure is obtained from BCC DEA model.

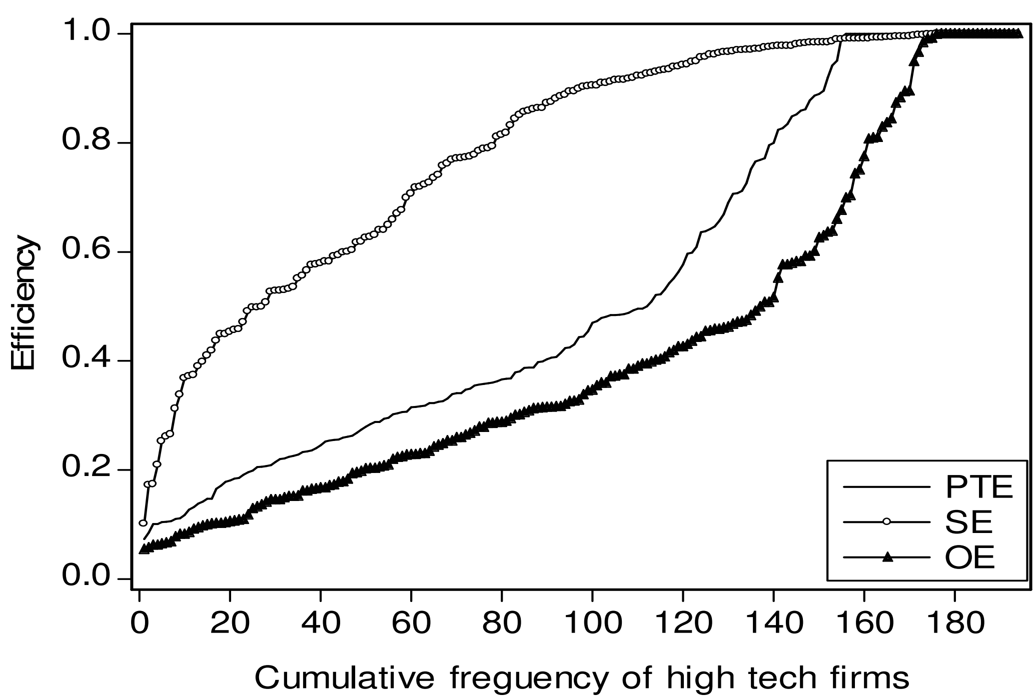

Figure 2. Distribution of various measures of efficiency, where PTE is the pure technical efficiency; SE is the scale efficiency; OE is the overall technical efficiency (n = 194).

were 39 (20.1%), 18 (9.3%) and 19 (9.8%), respectively. The high tech firms that have efficiency equal to one, comparatively speaking, is the most efficient. Table 3 lists the summarized statistics for the relative efficiency rating, and Figure 2 lists the different frequency distributions for the various efficiency measures. The original results indicated that the average pure (technique OR technical) efficiency was approximately 53%. That is, the sampled high tech firms can increase their overall production scale by an average of 47% and maintain the existing output level. From Table 2 and Figure 2, approximately 67% of high tech firms have less than 70% pure technical efficiency. Additionally, 80 and 31% of high tech firms achieved less than 70% overall technical efficiency and scale efficiency, respectively. This shows that high tech firms should improve their R&D abilities to achieve optimal productivity, further improve the overall operation efficiency and reduce wastage of R&D resources. To understand the impact of location on high tech firm relative efficiency, this study further analyzes the impact of the science park on R&D productivity to provide a measure of managerial efficiency. The final sample contains 194 high tech firms, consisting of 122 science park firms and 72 non-science park firms, as listed in Table 3. Table 3 lists the descriptive statistics for different R&D efficiency scores. Table 3 revealed that high tech firms located at science parks have slightly lower R&D productivity than the observationally equivalent high tech firms that are not located in science parks, particularly those in PTE and OE (Tables 2 and 3) (Figure 2).

In line with the suggestion of Norman and Stocker (1991), they proposed that efficiency can be measured using three kinds of efficiency units. Robust efficiency units are those with relative efficiency scores using a DMU of 1; marginally inefficient units are those with the relative efficiency score of DMU from 0.9 to 1, and clearly inefficient units are those with the relative efficiency score of distinctly inefficient units below 0.9. An overall efficiency score between 0.9 and 1 indicates that a DMU must determine whether adjusting input and output can achieve relatively acceptable efficiency requirement. When the overall efficiency score is below 0.9, DMU should greatly improve the input and output to achieve overall scale efficiency. The first stage study results presented here found that approximately 10% of the sampled firms (19 firms) achieved robust efficiency. Meanwhile, approximately 50% of the high tech firms sampled only achieved marginal inefficiency. This study is primarily concerned with what external factors of impacting efficiency can be explained by the environmental variables, and which variables exert a more significant effect on R&D performance.

High tech specific factors related to firm efficiency

This study attempts a second stage of analysis for identifying the various efficiency indexes. During the second stage, this study employs a series of efficiency indexes generated from the DEA methodology and adopts them as the dependent variables for recognizing the variables that impact R&D efficiency. The evidence of OLS regression analysis and its applications using second stage DEA efficiency analyses had been demonstrated by Banker and Natarajan (2008) and McDonald (2009). Therefore, this naturally gave rise to the evidence that one might be able to utilize OLS regression approach for estimating environment variables affecting productivity. It is perfectly reasonable to expect that the two-stage DEA-based estimation procedures with OLS were used in the current study. Many external variables may influence R&D performance in high tech industry. For example, as firm age and the environment changes, the high tech firms becomes more and more adequate to the crucial knowledge and technologies in their R&D capabilities and thus affect the performance of the R&D efforts. In this study, we examine the effect of age of high tech firms, which is defined as the number of years the high tech firm had been in operation since it was founded. On the one hand, the well-developed science park can provide many benefits to high tech firms, such as shared local markets and resources, knowledge spillover effects, and low coordination costs (Wang et al., in press). Therefore, high tech firms, located in science parks may impact their R&D activities. The location variable is a dummary variable, it equals to 1 if a high tech is located in the science park. Regarding cooperation network, some researchers pointed out that inter-firm cooperation network can be viewed as a means of complementing internal resources (Löfsten and Lindelöf, 2005; Mancinelli and mazzanti, 2008) in order to enhance the knowledge and technology base of the R&D efforts. Accordingly, the issue on inter-firm cooperation with other firm is described in our environment variables analysis. This variable is a dummy variable and is cosed 1 when the high tech firm is occupied with inter-firm cooperation R&D activitis and 0 when it is not. In addition, a high tech firm builds its oversea subsidiary in order to acquire host resources and absorb foreign firms' R&D knowledge, technique, and experiences. The variable takes on a value of 1 if the high tech firm has built oversea subsidiary that require foreign resource. These variables are the most relevant to R&D performance of the high tech firms, therefore, we use theses four environment variables to estimate their impact on the R&D performances.

In the second stage, the results obtained from OLS regression analysis examine the relationship between efficiency measure (first stage output) and environmental variables and are listed in Table 4. The result for PTE (Table 4) demonstrated that for the OLS, 3 out of 5 variables were statistically significant. Moreover, results of OE identified three statistically significant variables, while the results of SE indicated also three statistically

Table 4. OLS regression coefficients (n = 194).

Independent variables	Dependent variables: proxies for R&D efficiency		
	PTE	**OE**	**SE**
Constant	0.671 (0.073)*	0.538 (0.070)*	0.789 (0.054)*
Age	0.002 (0.002)	0.001 (0.002)	0.003 (0.002)***
Location	-0.096 (0.046)**	-0.080 (0.044)**	-0.008 (0.034)
Network cooperation	0.120 (0.046)*	0.055 (0.044) **	0.066 (0.034)**
Oversea subsidiary	0.050 (0.060)	0.020 (0.058)	0.024 (0.044)

PTE, pure technical efficiency OE, overall technical efficiency; SE, scale efficiency. Three OLS regression equations with dependent variables PTE, OE and SE are estimated separately. Values in parenthesis are standard errors. The superscript sign *, ** or *** indicate significant at the 1, 5 or10% level, respectively.

significant variables. OLS regression coefficients are explained to analyze the directional relationship between efficiency and covariates. The result of empirical indicates that high tech firm age has a positive relation effect on all efficiency measures. However, parameters are only significant for SE in the OLS analysis, implying that each high tech firm needs to invest numerical fixed sunk costs and resources into the systematic R&D efforts to develop new or improved products or processes, whether the firms involved are new or incumbent. The positive coefficients also indicate that inefficiency reduces with age, possibly because of experience or learning effect influencing high tech firm productivity. This phenomenon might indicate that young high tech firms can reduce the inefficiency of R&D activities via learning by doing or imitation, and importing technology from high tech leaders. Additionally, approximately sixty-three percent of the sample, or 122 out of 194 high tech firms, were located in Science Parks. The location dummy for all efficiency measures besides SE was significant and negative. The results indicate that high tech firms located in the science park can obtain a rich high tech cluster effect and additional advantages associated with close proximity to upstream and downstream supply chains. In contrast, although firms located in the Science Park possess rich external resources, including R&D and knowledge spillover effect and low coordination costs, they do not generate additional benefit from shared local markets and resources to achieve optimal scale efficiency level. This disadvantage can be reduced through increasing their knowledge of fluid markets and technologies in the local industrial production within the same science park, specialized service or support industries, and finally, create well-established R&D cooperation mechanisms. This finding reinforces the importance of location in the high tech industry, which has its own specific characteristics resulting from the contribution of R&D activities to productivity and competitiveness. The network cooperation coefficient was positive and significant for all measures. This phenomenon implies that increasing the number of partners through cooperation network can improve high tech firm R&D efficiency. High tech firms could obtain a more direct effect through well-established R&D cooperation network for requiring complementary resources that are difficult to develop by them. Therefore, cooperation network plays a major role in promoting R&D activities. The parameter estimate associated with oversea subsidiary is positive and statistically insignificant for all measures (Table 4).

SUMMARY AND MANAGERIAL IMPLICATIONS

This study applied a two-stage empirical analysis to the relationship between R&D investment and technical efficiency. The analysis yields the following main findings and insights: First, high tech firm R&D performance is assessed in comparison to a sample of 194 firms, including 39 purely technical efficiency firms, 18 scale efficiency firms and 19 overall technical efficiency firms. Due to a lack of external information available on high tech firm R&D productivity, this study captured location, network cooperation, oversea subsidiary and age factors in an aggregate measure to reflect environmental effects in their R&D efficiency. The results demonstrate that high tech firm age positively affects all efficiency measures. Compared to the whole sample, firms located outside science parks have slightly better efficiency than Science Park firms do. After estimating the OLS regressions, the external factors are adjusted to explain the effects of variation in the operating environment. The second stage analysis demonstrates that the environmental variables do indeed influence R&D performance, as measured by a series of R&D input and output variables obtained during the first stage DEA analysis. One interesting finding of this study was that high tech firms located in science parks have slightly lower R&D productivity than observationally equivalent high tech firms located outside science parks. This phenomenon possibly occurs because a science park location does not fully enjoy the elaborate location advantage in R&D productivity, for example, enjoying R&D technology and knowledge spillover effects or learning R&D knowledge efforts from benchmark high tech firms. The sources of inefficiencies indicate that firms do not manipulate location advantage to minimize excessive use of inputs, thus reducing the costs of production associated with their R&D activities. On the other hand, the results indicate that inefficient high tech firms did not efficiently utilize their R&D capacities, including R&D expenditures, number of employees, and number of R&D researchers. Furthermore, an efficient high tech firm that engages in R&D resource allocation or managerial and control R&D strategies could stimulate R&D performance. The DEA approach provides decision makers with a tool for identifying the sources of inefficiencies in R&D productivity given a specific amount of R&D effort.

Based on the first stage results of DEA, this study found that most Taiwanese high tech firms may have failed to reach the maximum level of R&D effort required to set up efficient R&D activities that contributes to the creation of effective R&D productivity and performance. The results have important managerial implications for the role of R&D efforts in the high tech industry. First, the evaluation results can provide high tech managers with a means of identifying good and poor R&D performance. More importantly, management can use these assessments as a basis for taking corrective action based on the productivity of individual high tech firm R&D effort as well as the control of input factors. The most useful benefits of DEA analysis is to identify and find the set of source of inefficiency for individual high tech firm. Based on the reference sets, inefficient high tech firms must improve their R&D production and resource allocation efficiency, particularly in relation to R&D expenditure and research in order to become efficient. Second, due to high tech firms facing shortened product life cycles and intensifying global competition, young high tech firms must invest vast amount of R&D commitment to develop new or improved products or processes, regardless of whether they are new or incumbent firms. The results imply that new high tech firms should be able to fulfill basic requirements to increase the benefits of R&D knowledge and technological learning from advanced or benchmark high tech firms. On the other hand, managers of older high tech firms should improve their R&D resource allocation to achieve a larger impact on R&D efficiency. Third, the OLS analyses provided insights into the impact of location factor for individual high tech firms. Location analyses can help derive the competitive advantage in terms of R&D efficiency for individual high tech firms. One major difference in the location analysis in relation to science park firms and firms located outside science parks was that science park firms had lower past performance in terms of the various efficiency measures. As we can find, there are some previous empirical studies, which have pointed out that the inherent difference may impact the R&D performance or productivity of firms. Several studies, for example, by Audretsch and Feldman (1996) and Shefer and Frenkel (2005) argued that the specific location of the firm has a significant impact on their R&D and innovation activities. In this fashion, the firms' specific advantages should be considered and metric in a series of R&D activities of the high tech firm. Clearly, encouraging open exchange of technology and ensuring that a mechanism for sharing R&D resources among neighboring firms is readily available on a reciprocal treaty basis. In summary, emphasizing both share in R&D technology and R&D resource, and improving share mechanism, may strongly affect the R&D efficiency and ultimately benefit decision-makers and management. Essentially, this study aims to extend theoretical and empirical understanding of R&D productivity in high tech firms, and be useful to managers.

Based on an analysis of the effects of the firms specific advantages on the R&D efforts, we adduce evidence in favor of the view that location agglomeration have significantly impacts on high tech firms R&D productivity. The study's finding is in line with the studies by Audretsch and Feldman (1996) and Shefer and Frenkel (2005), who argued that the specific location of firm has significant impact on their R&D and innovation activities. Therefore, the location agglomeration seem to stimulate R&D capacity and also provide some important implications. The first involves widening the range of possibilities that any individual firm can employ strategic alliances and subcontract activities within the same location agglomeration. The second is enabling of high tech firms' structure to function in an interdependent value chain of high tech industries to make collaborative joint investments or pool resources, such as product development and technological upgrade. Lastly, a well-defined inter-firm cooperation network can be viewed as a supplement and complementary mechanism to reinforce firms R&D capabilities to generate a set of externalities benefiting the whole productive system. The locating agglomeration advantages also provides technology exchange to invest in advanced technology development and accelerate knowledge of a production improvement to quickly become available to many, which will in turn create better quality products. Thus, varieties and synergies in R&D, technology and knowledge can create an R&D cooperation network of a local market when two or more strong linkages exist among the high tech firms within same location agglomeration.

On the one hand, Taiwan is smaller and a resource restricted country that should exploit the greater concentration of their industries in a few strong domains such as high tech industries to successfully obtain an economic advantage through futher centralization of their own R&D capabilities. More specifically, the argument we put forward here is that government can play the role of catalyst to strengthen industry-firm nexus and to shape mainstream industry in developing and improving the locational agglomeration R&D capability. In fact, these concern the high tech firms and industries through which location agglomeration is translated into improved R&D productivity at the firm and industrial levels. This empirical study suffers some limitations. First, since the absence of any universal definitions of R&D inputs or their measurement is given, it is impossible to provide a more exhaustive list of input indicators. Second, other factors and conditions, which are not included in this study, could impact efficiency, and thus a more elaborate measurement model could emerge in the future.

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