Efficiency and Profitability on Biotech-Industry in Small Economy

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Abstract

In this study, we adopt 'data envelopment analysis' (DEA) methodology to investigate the relative efficiency of biotechnology and medical healthcare firms in Taiwan. In addition, a 'panel smooth transition regression' (PSTR) study is also conducted, using R&D expenditure as the threshold variable.

Of the entire sample of 20 biotechnology firms examined in this study, half are found to have relative efficiency; however, the paid-up capital of these firms is really quite small as compared to the others. Firm performance and R&D expenditure are found to have a non-linear relationship, with the existence of a significant threshold value of US$191,815. If the R&D expenditure of any firm is found to be lower than this threshold value, an increasing in its total assets whilst reducing its operating costs lead to raise its overall profit. However, in those cases where R&D expenditure exceeds the threshold value, the outcome appears to be exactly the reverse.

Key words：*Data Envelopment Analysis (DEA), Panel smooth transition regression (PSTR), R&D expenses*

1. Introduction

Given the rapidly aging global population, and associated increases in chronic diseases and healthcare demand, the biotechnology and medical healthcare industry is likely to see its continuing growth. The biotechnology and medical healthcare industry is an industry which crosses several boundaries, including biomedical, materials, mechanics, electronics and communications. The continuing development of the biotechnology industry has therefore attracted considerable attention throughout the developed countries of the world; indeed, the biotechnology and pharmaceutical industry combined has gradually come to be regarded as the leading enterprise sector in the global market[1].

Throughout the 1990s, the US Government provided total funding of US$15.8 billion for use in biomedical and life sciences research, whilst the industry itself provided a further US$18.6 billion. Over the same period, total government funding in France amounted to US$1.8 billion, with industry funding accounting for a further US$2.8 billion (Gittelman, 2006). As for the biotechnology market in China, according to Chinese government figures, the country achieved an annual average growth rate of 20.5 per cent over the 2000-2008 period; however, with a valuation of US$124.7 billion in 2008, this demonstrates an even higher increase of 25.23 per cent in industry growth over the previous year. In Taiwan, the total amount of biotechnology investment hit a record high of US$844 million in 2007, although this investment figure was reduced slightly in 2008, to US$781 million, largely as a result of the period of macroeconomic recession. Nevertheless, as at February 2009, the Taiwan National Development Fund had approved a total of US$408 million for continuing biotechnological investment (Ministry of Economic Affairs (MoEA), 2009).

Whilst biotechnology applications in the areas of health, agriculture and the environment have been widely discussed in the prior literature, very few studies have attempted to assess the performance of biotechnology industries based upon their R&D inputs. Where such a focus is evident, the studies invariably examine the situation over recent years in the developed biotechnology firms only. In the present study, we not only identify and evaluate the performance of Taiwanese biotechnology firms, but further examine an R&D threshold using a well-defined model as an appropriate indicator of improvement. In such a way, we can simultaneously observe where R&D expenditure has the greatest influence for local biotechnology companies, which can then lead to higher investment funding from the government or venture capital enterprises in an effort to spur on corporate

[1] Refer to Wong (2007)

growth and create powerful international competitive advantages.

We evaluate the efficiency of firms employing 'data envelopment analysis' (DEA) methodology, which has already been applied to a wide range of issues.[2] We also utilize a 'panel smooth transition regression' (PSTR) model to identify the R&D threshold. The PSTR model has yet to be addressed in the domestic literature; thus, we suggest that our use of the model is likely to lead to a more thorough investigation of the underlying issues in Taiwan.

The remainder of this study is organized as follows. Following on from this introductory section, section 2 provides a description of the biotechnology industry in Taiwan, followed in section 3 by a discussion of the prior related literature. A discussion on the research design and methodology adopted for this study is presented in section 4. The empirical results of our DEA and the PSTR model are provided and explained in section 5. Finally, the conclusions drawn from this study are provided in section 6.

2. The Biotechnology Industry in Taiwan

Within life sciences as a whole in Taiwan, biotechnology is defined by the Development Center for Biotechnology (DCB) at the MoEA as "a scientific technology based on knowledge (such as molecular biology, cell biology, immunology and genomics) and techniques (including protein engineering, genetic engineering and fermentation engineering) for the research and development, production and promotion of product quality with the ultimate aim of enhancing the quality of human life" (MoEA, 2009).

The biotechnology industry in Taiwan is essentially divided into three specific sectors, the pharmaceuticals sector, the emerging biotechnology sector, and the medical devices sector. As a result of the extremely strong relationship between biotechnology and drug discoveries, the category of medical treatment cannot be separated from that of predictive medicine, thus Taiwan's biotechnology industry contains both of these sectors.[3]

According to Professor C.H. Chen, the director of Taiwan's Biotechnology and Pharmaceutical Industry Program, "Taiwan provides aggressive incentive measures to encourage investment and create more business opportunities in the biotechnology industry" (Chen, 2007). This is borne out by the announcement by the Taiwanese government in 2009 that the biotechnology industry was to be included in the 'six emerging

[2] Examples include Sarkis and Talluri (2004); Ha (2005), Asmild, Parade, Reese and Tam (2007)

[3] Another common term for the pharmaceuticals and medical devices sector in other countries is the 'life sciences' industry.

industries' project, placing it at the top of the list for industry upgrading.

As a result, Taiwan has established biotechnology parks, aimed at clustering firms within a region with sufficient and appropriate R&D equipment. The parks are located in four regions of Taiwan, Northern (including Nangan Software Park, Taipei and Jungli Industry Park, Taoyuan County), Central (comprising of Jangbin Industrial Park, Changhua County and Taichung Industrial County, Taichung), Southern (including Tainan Technology Industrial Park and Kaohsiung Coastal Industrial Park) and Eastern (Heping Industrial Park, Hualien). As a result of the cooperation of these institutions, resources, technical knowledge and infrastructure can be mutually shared so as to support both economic and biotechnology industry growth. (Table 1)

Total sales revenue for the biotechnology industry in Taiwan came to US$6.47 billion in 2009, with the emerging biotechnology sector accounting for US$1.78 billion, the pharmaceutical sector US$2.15 billion, and the medical devices sector US$2.53 billion. Revenue growth for the various sectors in 2009 stood at about 9 percent for the emerging biotechnology sector, 4 per cent for the medical devices sector, and just 1 per cent for the pharmaceuticals sector. By the year 2009, the total number of biotechnology companies in Taiwan had raised to 1,300, and despite the fact that we were passing the global financial crisis, total sales revenue for the industry, as compared to 2008, was still climbing (Table 1).

3. Literature Review

Pray and Naseem (2003) examined the policy programs of public-private partnerships in the overall impact of biotechnology. They noted that it was particularly important for public-private joint ventures to be promoted in the industrialized countries. Danzon, Nicholson and Pereira (2005) selected data on 900 biotechnology firms in the US, covering the years 1988 to 2000. They found that firms tended to address the scheme using lower probabilities of success, such that they could more easily achieve their goal.

Wolff (2006) observes that the Southeast Asian region has already emerged as an area for future growth in the biotechnology industry and that most of the global biotechnology companies are already outsourcing businesses to the region; these companies are actively seeking to establish an Asian regional headquarters in order to reduce their R&D costs. A survey by Wong (2006) indicated that biotechnology and the life sciences field are the key areas for development in Taiwan, and as such, they have naturally

become targets for investment by the government. The survey revealed that total R&D expenditure in Taiwan has risen dramatically since the early 1990s, and that growth in R&D spending is superior to other advanced industrialized countries. Wong (2007) argued that the process of further development needed to focus not only on greater efficiency, but also on creating more low-risk and cost-effective methods through a new translational research strategy. Chen C. H. (2007) reported that the biotechnology industry in Taiwan is expected to play a vital role in the future economic growth of the island. Chen highlights the fact that the Taiwanese government has already promoted a series of projects in support of biotechnology R&D, including incentives such as the establishment of a wide range of institutions aimed at cultivating biotechnology R&D and the industry as a whole.

Many of the prior studies agree that the biotechnology industry is, without question, an industry with enormous potential on a global scale; numerous studies discuss the relevant issues, such as ways of more rapidly developing and disseminating the benefits of biotechnology. In the present study, we examine the current status of the biotechnology industry in Taiwan, with a primary focus on the efficiency and profitability of the island's biotechnology firms.

4. Research Design and Methodology

In the extant literature for the discussion of operating efficiency, one of the non-parametric approaches is DEA methodology, which has no limitations with regard to functional type and sample size; it is also widely applied to the measurement of performance involving multiple inputs and outputs. On the other hand, the panel regression model is capable of capturing any heterogeneity in the data by means of the individual and time effects. When the observation approaches the threshold variable, this will produce a 'jump' effect; the model in this case, is referred to as the 'panel smooth transition regression (PSTR) model.

4.1 Data Envelopment Analysis Methodology

Data envelopment analysis (DEA) is used primarily to measure relative efficiency amongst a number of producers, with each of these producers usually being referred to as a 'decision making unit' (DMU).[4] The basic foundation, the overall evaluation of efficiency, is essentially dependent upon the realization of the production frontier; that is, we can only compare real output with a theoretical output level in the

[4] Refer to Sarkis and Weinrach (2001) and Sarkis and Talluri (2004) for detailed explanations of the DEA methodology.

production frontier if the production frontier itself is calculated; this can then be followed by subsequent measurement of production efficiency.

Charnes, Cooper and Rhodes (1978) constructed a linear program (the CCR model) which came to be recognized as a theoretically sound framework, and indeed, the first to be referred to as DEA methodology. In a given set of input factors, all inputs can be meaningfully controlled by DMUs with any reduction being calculated without altering the output quantities; in such cases it is safe to assume input-orientation. Alternatively, output-orientation is based on the output factors selected by the DMUs, and as such, any increase in outputs could be evaluated under fixed input quantities. The efficiency measure in operation in the present study involves BCC and CCR models with input- orientation.

This study applies the input-based CCR model in order to determine the optimum frontier under the assumption of 'constant returns to scale' (CRS). This infers that producers are able to linearly scale their inputs and outputs with no discernible increase or reduction in efficiency. The formulation can be written as:

$$Min\theta_{\kappa} - \varepsilon \left(\Sigma_{i=1}^{m} s_i^- + \Sigma_{r=1}^{s} s_r^+\right)$$

$$s.t.\ \Sigma_{k=1}^{n} \lambda_j X_{ij} + s_i^- = b_k X_{ij},\ i = 1, 2, \ldots, m \qquad (1)$$

$$\Sigma_{k=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{rk},\ r = 1, 2, \ldots, s$$

$$\theta_k, \lambda_j, s_r^+, s_i^- \geq 0$$

where ε is a small non-Archimedean number (Charnes et al., 1978).

Let n be the number of firms and m and s be the respective numbers of inputs and outputs. X_{ij} is the i^{th} input of the j^{th} DMU, and y_{rj} refers to the r^{th} output of the j^{th} DMU, with the variable λ_j denoting the weight of the j^{th} DMU. θ_k is the technical efficiency score.

If $\theta_k^* = 1$, and both s_i^- and s_r^+ are equal to zero, then DMU_k lies on the optimal frontier and can be deemed as relatively efficient. Conversely, if $\theta_k^* \neq 1$, and either s_i^- or s_r^+ is non-zero, then DMU_k lies within the envelope line and its efficiency may be strengthened by either bringing down its input costs or

raising its output quantities. In other words, a DMU_k located on the frontier is deemed to be efficient, whereas a DMU_k located within the frontier is considered to be inefficient.

Under the assumption of CRS, only the CCR model is suitable, since all the DMU_k are already working at an ideal scale. However, in those cases where the DMU_k do not work at an ideal scale, the solution to the problem is easily provided by modification of the DEA model with 'variable returns to scale' (VRS) and the inclusion of a convexity constraint which separates overall technical efficiency into 'pure technical efficiency' (PTE) and 'scale efficiency' (SE). We can also include an additional constraint, $\Sigma^{n}_{k=1}\lambda_k = 1$, into Equation (1), and then gauge the performance of the DMU_k; this is given by Equation (2) known as BCC model:

$$Minb_k - \varepsilon\,(\Sigma^{m}_{i=1} s_i^{-} + \Sigma^{s}_{r=1} s_r^{+})$$

$$s.t.\ \Sigma^{n}_{k=1}\lambda_j X_{ij} + s_i^{-} = b_k X_{ik},\ i = 1, 2, \ldots, m \qquad (2)$$

$$\Sigma^{n}_{k=1}\lambda_j y_{rj} - s_r^{+} = y_{rk},\ r = 1, 2, \ldots, s$$

$$\Sigma^{n}_{k=1}\lambda_k = 1$$

$$\theta_k, \lambda_j, s_r^{+}, s_i^{-} \geq 0$$

The above formulations exhibit a VRS efficiency score by b_k^{*} . All of the variables in Equation (2) should restrict non-negative or zero results so as to produce useful values for the calculation of 'returns to scale' (RTS). We examine the scale efficiency ratio based upon a CRS score in comparison to a VRS score. If the score, θ_{κ/b_κ}, is equal to 1, the DMU_k is regarded as efficient; that is to say, $\theta_\kappa^{*} = b_k^{*}$, and as such, CRS is confirmed. Otherwise, if the score is lower than 1 ($\theta_{\kappa/b_\kappa} < 1$), the DMU_k is regarded as inefficient; in this case, the CRS and VRS score will obviously differ, $\theta_\kappa^{*} \neq b_k^{*}$, and as a result, $\Sigma\lambda_\kappa^{*} < 1$ will exhibit 'increasing returns to scale' (IRS) and $\Sigma\lambda_\kappa^{*} > 1$ will exhibit 'decreasing returns to scale' (DRS).

DEA comprises of two radical models, the CCR and BCC measurement models, both of which provide opportunities for investigating technical and scale efficiencies based upon the score of the DMU_k. On balance, the use of the CCR model can initially be used to effectively provide technical efficiency scores for each DMU_k; we can subsequently go on to use the BCC model to further obtain pure technical efficiency and scale efficiency in order to verify the original source of the inefficiency. This also determines which firms are more efficient, and hence, which firms are targets for mergers or joint ventures.

4.2 The PTR and PSTR Models

The panel regression model is capable of capturing any heterogeneity in the data by means of the individual and time effects. Hsiao (2003) notes that various panel data models have been developed within which the regression coefficients are allowed to vary over time and across different cross-sectional units. In the majority of the empirical studies using panel data models, it is generally assumed that most of the parameters are fixed; however, such an assumption may not explicitly reveal the significant relationship between the variables within the model, such that this could give rise to erroneous results.

In order to solve this particular problem, in addition to the application of a random coefficients models, Hansen (1999) developed the 'panel threshold regression' (PTR) model, within which the coefficients are the functions of the other exogenous variables. When the observation approaches the threshold variable, this will produce a 'jump' effect; however, since such a situation is not feasible in practice, we therefore examine the modified general PTR model, which includes the rate of transition and recognizes the changes in the regression coefficients may be more gradual over time, as the system moves from one regime to another. The revised model in this case, is referred to as the 'panel smooth transition regression' (PSTR) model which was first introduced by González, Teräsvirta and van Dijk (2005).

The basic PSTR model of Teräsvirta (1994, 1998) is expressed as follows:

$$y_{it} = \mu_i + \beta_0' \; x_{it} + \beta_1' \; x_{it} g(q_{it}; \gamma, c) + u_{it} \tag{3}$$

where the subscripts i and t respectively index the individual and time for $i = 1,\ldots,N$, and $t = 1,\ldots,T$. The dependent variable y_{it} is a scalar; X_{it} is a k-dimensional vector enous variable, μ_i is the mean or fixed effect for individual, and ε_{it} is the error term. The transition function $g(q_{it};\gamma,c)$ corresponds to a

continuous function with the boundary from zero to one, and q_{it} denotes a transition representing the time varying exogenous variable; μ_i is the mean or fixed effect for an individual; and ε_{it} is the error term. The transition function $g(q_{it};\gamma,c)$ corresponds with a continuous function bounded from zero to 1, with q_{it} denoting the transition variable.

According to Granger and Teräsvirta (1993), Teräsvirta (1994), and Jansen and Teräsvirta (1996), the logistic transition function is determined as follows:

$$g(q_{it};\gamma,c) = (1 + exp(-\gamma \prod_{j=1}^{m}(q_{it}-c_j))^{-1};\ \gamma > 0,\ c_1 \le c_2 \le \ldots \le c_m \qquad (4)$$

$c_1 \le c_2 \le \ldots \le c_m$ denotes an m-dimensional vector of location parameters and the slope of the transition function is written by γ. In general, the transition function may set up $m=1$ and $m=2$. If $m=1$, the result will be the creation of two regimes which implies that with a rise in q_{it}, the coefficients will move from β_0 to $\beta_0+\beta_1$; this is also referred to as the logistic model.

Since we assume that γ is sufficiently large, then $g(q_{it};\gamma,c)$ will be an indicator function $I[q_{it}>c_1]$, with the occurrence of event 'A' producing I[A] = 1, otherwise 0. For $m=2$, which is referred to as the exponential model, the model will be divided into three regimes, with the two similar regimes on either side differing from the central regime. Despite $m=1,2,\ldots$, the value of γ will always influence the slope of the $g(\cdot)$ function.

When $\gamma \to \infty$, the model resembles the Hansen (1999) jump model, as follows:

$$y_{it} = \mu_i + \beta_0' x_{it} + \beta_1' x_{it} \emptyset(q_{it};c) + u_{it} \qquad (5)$$

$$\emptyset(q_{it};c) = \begin{cases} 1 \text{ if } q_{it} \ge c \\ 0 \text{ if } q_{it} \le c \end{cases}$$

Conversely, when $\gamma \to 0$, the model breaks down and approximates to a linear function with no obvious transition structure.

A number of different regimes within the general form of the PSTR model are facilitated by the following equation:

$$y_{it} = \mu_i + \beta_0' x_{it} + \Sigma_{j=1}^{\gamma}\beta_1' x_{it} g(q_{it};\gamma,c) + u_{it} \qquad (6)$$

The transition function $g_j(\ldots)$ is decided by Equation (4), for $j=1,\ldots,r$, where $r+1$ regimes exist with $m=1$

and $\gamma \to \infty$. Hansen (1999) considered the additive PSTR model to be a multiple regime panel smooth threshold model. As noted earlier, Equations (4) and (6) provide an alternative method of testing for remaining heterogeneity.

The PSTR model is constructed with a fixed-effect exogenous regressor under two different translations. Firstly, the model may be deemed as having linear heterogeneity so that the coefficients alter with changes in either individuals or time. Heterogeneity in the regression coefficients supposes that under continuous functions of an observable variable, these coefficients pass through a transition function, fluctuating between finite numbers of different regimes (although often just two). Secondly, the 'non-linear homogenous panel model',[5] is commonly used in the context of a single equation STR model or a univariate 'smooth threshold autoregression' (STAR) model.

5 . Data Source and Empirical Results

This study uses panel data to measure the relationship between R&D expenditure and net sales in the biotechnology and medical firms. The first step involves the adoption of DEA methodology to study the performance of all of the selected firms. In the second step, a PSTR model helps us to determine the potential relationship between R&D expenditure and net sales. Finally, we undertake cross-comparison of the two outcomes from the application of the DEA and the PSTR model.

5.1 Data and Description

In the present study, we focus on the biotechnology and medical healthcare industry, collecting our data from the *Market Observation Post System* and the *Taiwan Economic Journal* (TEJ). Our sample comprises of all biotechnology firms within the target industry listed on the Taiwan Stock Exchange (TSE) and the over-the-counter (OTC) markets, producing a total sample of 43 firms.

In light of our review of the literature in section 3, the input and output variables in our research methodology can be categorized as follows. The input variables include investment by the biotechnology firms in R&D resources and the costs of their production activities. The output variables reflect the quantitative measures of the profit that biotechnology firms expect to make from their contributions (in terms of R&D inputs). Thus, total assets (TA), operating costs (OC) and R&D expenditure are selected as the input factors, and net sales (NS) and earning before interest, tax, depreciation and amortization

[5] Refer to Teräsvirta (1994,1998) for comprehensive details of the model construction.

(EBITDA) are selected as the output factors.

The 'total assets' of the biotechnology firms include their current and fixed assets, such as short-term investments, land, buildings and equipment. 'Operating costs' refer to the costs of their operating activities during the period under examination; this can also refer to the cost of goods sold, service costs, agency costs and other operating costs. 'R&D' is a vital element in ensuring that firms can secure their future growth through the development of new products or processes to improve and expand their operations, particularly in the biotechnology industry (Department of Commerce, MoEA). Thus, these three elements are regarded as the most important inputs in R&D-oriented biotechnology firms.

As regards the output variables, 'net sales' is the amount of sales generated by a firm after the deduction of returns, allowances for damaged or missing goods, and any discounts allowed; this method is more accurate and less influenced by non-operating activities. 'EBITDA', which is net income with interest, taxes, depreciation and amortization added back in, is basically an indicator of the financial performance of a firm which eliminates the effects of financing and accounting decisions; this enables the fair and accurate analysis and comparison of profitability amongst a group of firms.

Since the biotechnology industry is recognized as being highly R&D intensive, and since biotechnology products tend to have a long shelf life, general financial indicators (such as ROA, ROE and EPS) cannot accurately reflect the value of this industry. Thus, net sales and EBITDA are regarded as appropriate factors representing the performance of biotechnology firms. All of the original data on the input and output variables are measured in units of NT$ thousands; for consistency, we present the empirical results in US dollars by dividing the NT$ total by 32.5 (the average exchange rate between 2004 and 2009).

The biotechnology industry in many of the developing countries, including Taiwan, is still at an emerging or growth stage; therefore, some of the numerical financial values are not readily available for all publicly-listed or OTC-traded biotechnology firms. Furthermore, many of these biotechnology firms have been in operation for only a decade, or less, which clearly makes it very difficult to collect complete data for the entire sample of firms over a sufficiently long period of time; hence, the financial statements by the 'market observation post system' (MOPS), the Taiwan Stock Market database published by the TEJ, and the annual reports on biotechnology industry (MoEA, 2009) are used to supplement our research data sources. We were ultimately left with a total sample of 20 firms in the biotechnology and medical healthcare industry on which complete information was available. Sample period runs from the third

quarter of 2004 to the third quarter of 2009, providing a total of 21 periods.[6]

Table 2 presents the correlation matrix of the input and output factors, from which it should be noted that all of the correlation coefficients are positive at the 1 per cent significance level. Consequently, these input and output items exhibit isotonicity relationships; thus, their inclusion within the DEA model is reasonable.

(Table 2)

Table 3, the VIF[7] is found to be lower than 10 and tolerance is clearly greater than 0.4. We can therefore conclude that the efficiency measures of the DEA model have high construct validity.[8]

(Table 3)

5.2 Results of Data Envelopment Analysis

We adopt the DEA approach for the measurement of efficiency in the biotechnology and medical healthcare industry through the identification of efficient frontiers under the assumption of input minimization (referred to as input orientation). The three input variables of total assets, R&D expenditure and operating costs are selected for our analysis, along with the two output variables, net sales and EBITDA.

In applying DEA, our main purpose is to identify those biotechnology firms regarded as 'efficient' in order to examine the relationship between R&D expenditure and net sales for the selected firms under the PSTR model. DEA is carried out on the 20 DMUs for which we assume an efficiency score criterion of greater than 0.7. The technical efficiency (TE) scores for each of the biotechnology firms in the CCR model are presented in Table 4.

The CCR model indicates that a total of 10 DMUs (Nos. 11, 12, 13, 14, 15, 16, 17, 18, 19 and 20) achieve a relative efficiency score of greater than 0.7, with the efficiency score of DMU No. 19 in particular being equal to 1. From our sample of biotechnology firms, all of the remaining DMUs with scores below 0.7 are regarded as being inefficient, which implies that they either need to reduce their inputs for the same level of outputs, or expand their outputs for the same level of inputs in order to become efficient firms. The overall average in the CCR model is 0.678.

[6] The actual calendar period runs from July 2004 to September 2009.
[7] The variance inflation factor (VIF) tests the problem of collinearity.
[8] It is important to note that in the second method, the input variable, RD, is divided is first by 10,000 so as to provide convenient computation.

There are, however, some limitations of the CCR model, particularly since the procedure operates under the assumption of 'constant returns to scale' (CRS). The supposition of CRS is basically appropriate, given that in the light of prior studies, all of the DMUs are at the optimal scale; however, in a dynamic environment, DMUs are not generally found to be at the optimal scale. Banker et al. (1984) argued that the CRS limitation in the CCR model is improved by the BCC model; thus, the outcomes of our analyses using the BCC model are also shown in Table 4.

(Table 4)

The scores are subsequently decomposed into 'pure technical efficiency' (PTE) and 'scale efficiency' (SE). As regards PTE, we find that DMU Nos. 3, 7, 11, 12, 13, 14, 15, 16, 17, 18, 19 and 20 are identified as 'efficient', with a relative efficiency score of greater than 0.7. The mean PTE score in the BCC model, at 0.79, is higher than in the CCR model. In addition, the SE scores for DMU Nos. 1, 3, 4, 5, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19 and 20 are all greater than 0.7 (average 0.799), with DMU No. 19 again being found to achieve a score of 1 in the BCC model.

When examining which variables play vital roles in the biotechnology industry, it is considered important to examine the overall influence of R&D expenditure; we therefore carry out the same procedure without the R&D expenditure variable in the DEA model. The results revealed that only 5 DMUs (Nos. 13, 14, 16, 17 and 19) emerged as efficient in both the CCR and BCC models (Table 4).

The DEA model results presented above provide a number of interesting findings. Firstly, when applying the DEA approach to the measurement of our 20 biotechnology firms in Taiwan, in the CCR model with CRS, ten of the DMUs are found to be efficient, with twelve (fifteen) DMUs being found to achieve the requisite efficiency score in PTE (SE). All three analysis results highlighted the same ten biotechnology firms (DMU Nos. 11, 12, 13, 14, 15, 16, 17, 18, 19 and 20), with DMU Nos. 2, 9 and 10 being the least efficient; we therefore selected these ten DMUs as the 'efficient' sample for our continuing research.

Secondly, our results reveal that the paid-up capital for those biotechnology firms which are classified as 'efficient' was found to be less than US$25 million, whereas the paid-up capital for the other firms regarded as 'inefficient' was invariably found to be greater that US$25 million. This implies that in the biotechnology industry in Taiwan, superior operating performance tends to be achieved by the small- and

medium-sized biotechnology firms (Table 4).

Thirdly, Table 4 also exhibits the efficiency scores both with and without the R&D expenditure variable, clearly showing that research and development significantly improves the performance of the firms in our sample. The efficiency scores for all of the DMUs are found to be superior with the R&D expenditure variable, thereby providing support for our supposition, that R&D enhances firm performance.

5.3 PSTR Results

Following the examination of the 20 biotechnology firms under the DEA model in the previous section, we continue in this section with an exploration of the same relationship, between R&D expenditure and net sales, under the PSTR model. In the first step, we apply the test for homogeneity in order to determine whether or not the model is non-linear. The results in Table 5 reveal that the linearity hypothesis is strongly rejected by the 'likelihood ratio test' (LRT) at the 1 per cent significance level (F = 188.581, p-value = 0.000), such that we can be absolutely certain that at least one transition structure exists in this model and that it is also non-linear.

(Table 5)

In the second step, we compute the test statistics for $m = 1$, where m is a transition function designed to determine the number of regimes required in order to effectively capture all the non-linearity in the relationship. Tables 6 and 7 show that the null hypothesis is not rejected under the LRT Tests (F = –0.000, p-value = 0.517); thus, there is only one transition function ($m = 1$) and two regimes (r = 1) in the model.

(Table 6)

(Table 7)

We then go on to analyze the parameter estimates of the final PSTR model, with the empirical results being described as follows:

$$NS_{it} = \mu_i + \beta_0' \ TA + \beta_1' \ OC + g(RD_{it}; \gamma, c) + u_{it}$$

where the output variable *NS* is a proxy variable for the performance of the firm, and the input variables are *TA* and *OC*; $g(\cdot)$ is the transition function and *RD* is a transfer variable. The parameter estimates are shown in Table 8 whilst the impacts of the exogenous variables on firm performance are shown in Table

9. The threshold value is found to be US$191,815.[9]

(Table 8)

(Table 9)

In the first regime, where R&D expenditure is less than the threshold value of US$191,815, the estimated coefficient on *TA* is found to be 0.4789, which is significant at the 1 per cent level, and which therefore implies a positive effect on *NS*; that is, in those cases where R&D expenditure in the biotechnology and medical healthcare firms is found to be lower than US$191,815, the greater the level of *TA* input, the higher the *NS*.

However, in the second regime, where R&D expenditure is greater than the threshold value of US$191,815, the estimation coefficient on *TA* is found to be −0.9577 which is also significant at the 1 per cent level, but which nevertheless indicates a negative effect on *NS*. This result reveals that when R&D expenditure crosses the threshold value, the firms are likely to reduce their inputs of *TA* in order to achieve their overall purpose of growth in *NS*.

Turning to the relationship between operating costs and net sales, we find that when R&D expenditure lies in a regime below the threshold value, the estimation coefficient on OC is −1.0389, which indicates a significantly negative effect on NS, whereas if it is above the threshold value, the estimated coefficient of 2.0797 indicates a significantly positive effect. When R&D expenditure is below the threshold value, firms may be generally dependent on reducing their operating costs to improve their performance; conversely, when R&D expenditure exceeds the threshold value, the firms are likely to increase their operating cost inputs, such as cost of goods sold and other operating costs.

To summarize, a structural transformation occurs when R&D expenditure exceeds the threshold value of US$191,815. This leads to a jump effect close to the threshold value, with all of the transition functions being bounded between 0 and 1, which approximates to the panel model of Hansen (1999).

6 . Conclusions

Adopting DEA methodology and the PSTR model, we set out in the present study to provide an in-depth examination of the relationship between R&D expenditure and the performance of biotechnology

[9] The original threshold value was calculated as NT$6,234,000; this value was then divided by the average exchange rate of US$1.00 : NT$32.5 during the research period to provide the US$ value.

industry in Taiwan, using quarterly data covering the period from July 2004 to September 2009. The empirical results reported in the previous chapter raise a number of findings of some interest.

Firstly, based upon our adoption of DEA methodology, we find that relative efficiency is achieved by ten of the biotechnology and medical healthcare firms (Bioteque, Chisheng Chemical, Synmosa Biophama, Rossmax, Center Laboratories, United Orthopedic, Dr. Chip Biotech, Yungzip Chemical, Chiajei Tech., and SCI Pharmtech). These firms stand out from the whole sample of 20 firms, clearly demonstrating that R&D expenditure can indeed lead to enhanced performance within the biotechnology firms. It would, therefore, appear that through an overall increase in R&D expenditure, a biotechnology firm can succeed in raising its total revenue.

Surprisingly, however, we also find that the ten firms with relative efficiency have lower levels of paid-up capital (below US$25 million) as compared to the inefficient firms. This may be attributable to the biotechnology environment in Taiwan, which is still going through its developmental stage, such that the small- and medium-sized biotechnology firms are still able to compete and achieve better profitability.

Secondly, we adopt the PSTR model as the means of examining whether a threshold value exists for biotechnology firms when considering their level of R&D expenditure; this is taken as a transition variable. The results reveal that a specific threshold value of US$191,815 does indeed exist. If R&D expenditure is less than this threshold value, the total assets (operating costs) variable is found to have a positive (negative) correlation with net sales, whereas, the outcome is reversed if R&D expenditure exceeds the threshold value.

Within nine of the ten biotechnology firms identified by the DEA methodology as being ‘inefficient’ (Chin Chemical and Pharmaceutical, Grape King Biotech, Standard Chemical and Pharmaceutical, Pihsiang Machinery, Apex Biotech, Shiphar Pharmaceutical, Johnson Health Tech., Microlife and TTY Biopharm), R&D expenditure is found to be greater than the threshold value of US$191,815; only one firm, St. Shine Optical, is found to be below the threshold level.

According to our two selected variables, total assets and operating costs, the nine ‘inefficient’ firms with R&D expenditure above the threshold value may be holding higher proportions of total assets or have excessive operating costs, such as sales costs or service costs. They could try to reduce their equipment

holdings, including buildings, land or other assets, whilst also increasing the sales of products or providing additional services that may enable them to maximize profits. As for the one exception, the case of St. Shine Optical which was found to have R&D expenditure below the threshold value, the proportion of total assets was found to be too low whilst it also had higher operating costs, all of which contributed to the inferior performance of the company.

In contrast, four of the ten biotechnology firms with relative efficiency (Synmosa Biophama, Rossmax, United Orthopedic and Dr. Chip Biotech) were each found to have R&D expenditure which exceeded the threshold value, whilst the remaining six firms (Bioteque, Chisheng Chemical, Center Laboratories, Yungzip Chemical, Chiajei Tech. and SCI Pharmtech) were found to have R&D expenditure below the threshold value. Presumably, these firms could adjust their total assets and operating costs to further strive to achieve 'perfect' revenue levels.

The findings of the present study may provide several insights into a better understanding of the reasons why biotechnology firms in Taiwan do not seem capable of achieving greater profitability, as well as how, through appropriate adjustments to their current R&D expenditure levels, such firms may go on to improve their overall management and profitability performance.

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Appendix

Table A-1 Study sample of biotechnology companies

No.	Company Name	PO Date	Business Scope
	St. Shine Optical	2004	Contact lenses
	Chin Chemical and Pharmaceutical	1962	Generics
	Grape King Biotech	1982	Generics
	Standard Chemical & Pharmaceutical	1995	Generics
	Pihsiang Machinery	2001	Medical devices
	Apex Biotech	2001	Medical devices
	Shiphar Pharmaceutical	2002	Antibiotics, nutraceutical
	Johnson Health Tech.	2003	Medical devices, healthy kits
	Microlife	2001	Medical devices
	TTY Biopharm	2001	Generics, new drug development
	Bioteque	2002	Diagnostic kits
	Chisheng Chemical	1999	Generics
	Synmosa Biophama	2003	New drug development
	Rossmax	2003	Medical devices
	Center Laboratories	2003	Generics
	United Orthopedic	2004	Medical devices
	Dr. Chip Biotech	2004	Bio/Gene chip
	Yungzip Chemical	2001	Generics
	Chiajei Tech.	2002	Nutraceuticals
	SCI Pharmtech	2004	Bulk pharmaceuticals

Table 1 The status of the biotechnology industry in Taiwan, 2008-2009

Variables	Industry			Total
	Emerging Biotechnology	Pharmaceuticals	Medical Devices	
Revenue (US$ million)*				
2008	1,630.77	2,123.08	2,430.77	
2009	1,784.62	2,153.85	2,538.46	6,476.92
No. of Manufacturers				
2008	320	320	544	1,184
2009	380	367	553	1,300
Size of Workforce (No.)				
2008	9,600	11,250	21,923	42,773
2009	9,750	18,000	22,900	50,650
Export Value (US$ million)*				
2008	652.31	415.38	1,015.38	2,083.08
2009	729.23	446.15	1,030.77	2,206.15
Import Value (US$ million)*				
2008	692.31	2,276.92	1,446.15	4,415.38
2009	738.46	2,335.38	1,489.23	4,563.08
Domestic : Export Sales Ratio				
2008	60 : 40	80 : 20	65 : 35	66 : 34
2009	59 : 41	79 : 21	66 : 34	65 : 35
Domestic market demand (US$ million)*				
2008	1,670.77	3,984.62	2,861.54	8,516.92
2009	1,793.85	4,043.08	2,996.92	8,833.85

Note: * The exchange rate used for the calculation is US$1.00 = NT$32.5.

Sources: Medical and Pharmaceutical Industry Technology and Development Center, Metal Industry Research & Development Center, Biotechnology and Pharmaceutical Industries Program Office, MoEA (2010).

Table 2 Pearson correlation coefficients of the inputs and outputs

	Operating Costs (I)	Total Assets (I)	R&D Expenditure (I)	EBITDA (O)	Net Sales (O)
Operating Costs (I)	1				
Total Assets (I)	0.589	1			
R&D Expenditure (I)	0.520	0.552	1		
EBITDA (O)	0.654	0.543	0.454	1	
Net Sales (O)	0.952	0.619	0.650	0.719	1

Note: All of the correlations are statistically significant at the 1 per cent level.

Table 3 Collinearity diagnostics

Variables	Tolerance (1/VIF)	VIF
R&D Expenditure	0.570	1.753
Total Assets	0.637	1.570
Operating Cost	0.598	1.672

Table 4 Average DEA efficiency scores from Q3 2004 to Q3 2009

DMU No.	With R&D			Without R&D			Capital* (US$ million)
	Average CCR	Average BCC	Average SE	Average CCR	Average BCC	Average SE	
1	0.605	0.660	0.746	0.366	0.519	0.595	15.51
2	0.399	0.553	0.662	0.383	0.573	0.653	91.72
3	0.613	0.730	0.702	0.488	0.679	0.663	40.07
4	0.474	0.582	0.745	0.416	0.659	0.641	48.03
5	0.539	0.646	0.758	0.414	0.584	0.708	56.01
6	0.496	0.653	0.699	0.341	0.549	0.616	29.39

7	0.576	0.726	0.680	0.441	0.632	0.641	36.34
8	0.477	0.671	0.655	0.469	0.697	0.627	59.80
9	0.440	0.614	0.666	0.408	0.616	0.635	37.61
10	0.447	0.606	0.700	0.446	0.619	0.662	39.48
11	0.750	0.856	0.870	0.488	0.554	0.847	24.09
12	0.906	0.962	0.939	0.612	0.677	0.901	14.77
13	0.847	0.918	0.913	0.717	0.786	0.888	23.67
14	0.801	0.887	0.865	0.700	0.836	0.814	20.65
15	0.759	0.913	0.817	0.510	0.703	0.747	15.24
16	0.947	0.981	0.964	0.817	0.840	0.963	14.27
17	0.973	0.984	0.983	0.836	0.860	0.954	14.83
18	0.777	0.954	0.804	0.515	0.619	0.792	10.17
19	1.000	1.000	1.000	0.754	0.787	0.903	13.79
20	0.736	0.897	0.817	0.507	0.626	0.804	12.42

Note: * Paid-up capital is measured in US$ by dividing the NT$ value by 32.5 (the average exchange rate from July 2004 to September 2009).

*Table 5 Homogeneity test results**

m = 1	Statistic	*p*-value
LRT Tests (LRT)	188.581***	0.000

Note: * H_0: Linear model, against H_1: PSTR model, with at least one threshold variable $r = 1$

*Table 6 Results of the tests for no remaining non-linearity**

m = 1	Statistic	*p*-value
LRT Tests (LRT)	−0.000	0.517

Note: * H_0: PSTR model with $r = 1$, against H_1: PSTR model, with at least one threshold variable $r = 2$.

Table 7 Determination of the number of regimes

$m = 1$	p-value
No. of Thresholds $r(m)$	1(1)
RSS	72463.747
AIC	5.1960
BIC	5.2537

Table 8 Estimation results of the two-threshold PSTR model[a]

	efficient Estimate[b]	Heteroskedasticity S.E.	T-statistic
$= \begin{bmatrix} TA_{it} \\ OC_{it} \end{bmatrix}$	0.478*	0.556	8.611
	−1.039*	1.103	−9.421
$= \begin{bmatrix} TA_{it} \\ OC_{it} \end{bmatrix}$	−0.957*	1.110	−8.622
	2.079*	2.189	9.497
			0.623
			−6.2311e-00
S			72463.74
C			5.196
C			5.253

Notes:

[a] The model estimated is:

$$NS_{it} = \mu_i + 0.4789TA - 1.0398OC + g(RD_{it}; -6.2311\text{e}-008, 0.06243)(-0.9577TA + 2.0797OC) + u_{it}$$

with the rescaling of the original data on R&D expenditure being carried out by dividing by 10,000.

[b] *** indicates statistical significance at 1 per cent level.

*Table 9 The impact of the exogenous variables on firm performance**

Variables	Left Regime (RD < 191,815)		Right Regime (RD < 191,815)	
	Coefficient	Sign	Coefficient	Sign
tal Assets	0.478	+	−0.957	–
erating Costs	−1.039	–	2.079	+

Note: * The threshold is measured in US$ by dividing the NT$ value by 32.5 (the average exchange rate from July 2004 to September 2009).