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Cross-country analysis of efficiency and productivity in the biotech industry: an application of the generalized metafrontier Malmquist productivity index

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Abstract: The study investigates the productivity of 356 Biotech enterprises spanning 12 countries worldwide from 2001 to 2007 with a newly developed generalized metafrontier Malmquist productivity index (gMMPI) framework. The results suggested that the X inefficiency is prevalent in the current developmental phase of the Biotech worldwide, while the levels of technology vary substantially across enterprises and geographical regions. Moreover, the gMMPI decomposition manifests that the productivity growth in the Biotech is mainly driven by the efficiency change, with an annual rate 20.64%. Meanwhile, the existing technologies continuously try to catch up with the grand technology, and the potential room for a further technological progress has also been advanced.

Key words: efficiency, Malmquist index, productivity index

Briefly, the biotech industry refers to a sector that utilizes the 'organism' and its related technologies to create the economic worth.[1] Since the first biotech enterprise in the United States took the initiative 1973 to formally proclaim the commercialization of the biotech products, the countries worldwide began to awaken to its prospects for development and importance, and successively devoted resources to cultivate this sector. To date, the biotech has been widely applied to diversified domains (medicine, agriculture, food, manufacturing, energy, and environmental protection), and imperceptibly, unobtrusively, and deeply altered and influenced of the lives of people everywhere (health care, food safety, and economic growth). Generally, the biotech industry is recognized as with the characteristics that include its lengthy product development period, a huge and continuous financial consumption, a high innovation uncertainty, a high technological intensity and the entry threshold, the research and development orientation, involving morality controversy, the freedom from economic cycles, etc. Particularly due to the first three characteristics, the requirements from the aspects of the operational efficiency and the productivity change for the biotech business are essential. The academia should provide a review or a new paradigm as a theme for the biotech development.

In the recent years, the global biotech industry can still sustain a position of the continuous expansion. According to an investigation by the Ernst and Young Co., whether in sales, the R&D expenditure, employment, or the number of firms in the industry, most of the listed biotech enterprises in the world revealed the trend of a positive growth between 2005 and 2007. In 2008, the global sales for pharmaceuticals had already reached 773 billion USD; the value of medical instruments attained 286 billion USD; while the market scale for transgenics reached 7.5 billion USD. Despite the unavoidable impact of the '2008 financial tsunami' on various sectors[2], the impact on the biotech industry was relatively limited. The total sales of the listed biotech enterprises in 2008 still showed a continuous growth of 5.7% (89.6 billion USD), and the number of initiatives also increased

[1]According to the UN Convention on Biological Diversity, biotechnology is defined as various production and process technologies that utilize organismic systems, living things, or their derivatives for specific purposes.

[2]The number of listing biotech firms decreased 2.76 % from 798 to 776, the R&D expenditures decreased to 317 USD, the employment was reduced to 200 000 persons in 2008, and the net profits were by 14 USD lower, relative to 2007.

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from 303 to 4717 (Industrial Development Bureau 2009). These have sufficiently described the potential and trend for development.

Though the prospects of the industry are outstanding, numerous countries and enterprises usually face the challenges of its high financial consumption and high uncertainty when launching energy and resources to develop the industry. Currently, not many countries have biotech industries that can possess a certain extent of the operating scale to generate technological advantage; the countries with these capabilities are limited to the United States, Canada, the United Kingdom, Germany, and Japan. We can examine differences in the technological advancement by the region to which the countries belong. Biotechnology firms in the United States are still leaders in the global biotechnology industry; in 2008, the listed biotechnology firms in the United States had accumulated sales of US$ 66.1 billion, which showed a slight growth in sales from 2007, and the R&D expenditure was maintained at approximately US$ 25.3 billion. In 2008, the North American region was the only region in which the biotechnology industry made profits as a whole; and within this region, the biotechnology industry in the United States still outperformed that of Canada. The number of biotechnology firms in Canada is only second to the United States, and Canada also attains good achievements in the categories of the pharmaceuticals and agricultural biotechnology.

The European region is the fastest growing region in the terms of biotechnology. In 2008, the biotechnology firms in the region had accumulated sales of US$ 16.5 billion; which grew by US$ 3.6 billion from 2007. The net loss of the listed biotechnologies firms reduced to US$ 0.7 billion; this reduction in lost profits was due to a number of factors, including a rising exchange rate of the Euro, and an impressive product sales performance. These positive effects also contributed toward the growth in the R&D expenditure, the number of staff, and the number of firms. Many countries in the European region are competing for the market share, including the United Kingdom, Germany, and France. The United Kingdom is the country of origin for the modern biotechnology; Germany is a leading player in biopharmaceuticals; France is actively trying to establish bio-clusters and to develop a unique offering whereby its private firms provide research services; and the biotechnology industries in Denmark and Sweden have also been developing at a rapid rate, thanks to the Medicon Valley in the grand Øresund economic region.

The listed biotechnology firms in the Asia-Pacific region are the smallest in scale, with the total sales in 2008 of approximately 5 billion US$; the R&D expenditures of these firms continued to increase, and their net profits increased by US$ 14 million. Japan is the leading country within the Asia-Pacific region, particularly in the terms of the fermentation technology and medical skills. Nevertheless, other countries in this region, including South Korea, Taiwan, China, Singapore, Australia, and New Zealand, are all the rising stars in the biotechnology industry, and are all striving to level with the more technologically advanced countries (2008 White Book 2009).

The analytical methods most commonly employed to measure the operational efficiencies include the Data Envelopment Analysis (DEA) and the Stochastic Frontier Approach (SFA). The main advantage of using the DEA is that predetermining the estimation functions is not necessary; but at the same time, the results are easily affected by the extreme values (Coelli et al. 2005). Conversely, the SFA is a type of the parameter estimation; the disadvantage of using this method is that the functions in the model need to be predetermined, but its advantage lies in that the model considers both the effects of the efficiency terms and random error. With regard to the application of the DEA (González and Gascón 2004) or the SFA (Chiu et al. 2003) to measure the firm performance in the biotechnology industry, all past studies made the assumption that all firms' technical standards of production were equal. The current trend of development in the biotechnology industry means that we are seeing still more shifts in the production technologies and the staff turnover across different countries and regions, but the state of the economic development, skills and technologies, and the development process in different regions still display large disparities; therefore, there are greater differences between the technical standards of production across different regions.

Hayami (1969) was the first scholar to propose the metaproduction function, and to use this function to study the agricultural production efficiency in developed and undeveloped countries. Then, Hayami and Ruttan (1970) made the important hypothesis that agricultural producers in different countries can be measured against each other using the same production function; that is, the metaproduction function can be regarded as a curve enveloping the

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classical functions. Boskin and Lau (1992) proposed a different method for setting the function; Sharma and Leung (2000) adopted the model proposed by Battese and Coelli (1995), and used it with the SFA to measure the productivity of carp industries in the Southeast Asian countries. Using a stochastic metafrontier model, Battese and Rao (2002) proposed the viewpoint that technical efficiencies in different groups can be compared against each other. Battese et al. (2004) later readjusted the metafrontier model proposed by Battese and Rao (2002), and defined this model as an enveloping metafrontier derived from the stochastic frontier production function of different technical groups that envelops the determined parts of the stochastic frontiers of all groups.

The metafrontier model is repeatedly mentioned and utilized in many studies, particularly in the research related to finance (Bos and Schmiedel 2007; Huang, Chang and Chiu 2009; Yen, Chang and Woo 2008). In the terms of studies related to agriculture, many continents such as Africa (Ayinde, Adewumi and Ojehomon 2009; Binam, Gockowski and Nkamleu 2008), Asia (Boshrabadi, Villano and Fleming 2008; Chen, Huang and Yang 2009; Chen and Song 2008), Australia (Villano, Fleming and Fleming 2008), and many countries on other continents (O'Donnell, Battese and Rao 2008) have conducted the relevant research and produced literature on the metafrontier models. Apart from the application in the industries mentioned previously, the metafrontier is also widely applied in other industries.

Based on the metafrontier concept originally proposed by Battese et al. (2004), Rao (2006) proposed the Metafrontier Malmquist Productivity Index (MMPI). Chen and Yang (2008) and Chen et al. (2009) then made further improvements on the MMPI; the improved model now considers the scale efficiency, and thus became what is known as the generalized Metafrontier Malmquist Productivity Index (gMMPI). Besides working out the technical change and the technical efficiency change, the decomposition of the gMMPI function can further provide details on the technology gap variables. By identifying how the production technologies are catching up with the potential technologies, the information can give rise to a further economic analysis and implications.

To identify and understand the changes to the technical efficiency and productivity, this paper will present a study conducted on twelve countries (Australia, China, Japan, South Korea, Taiwan, the United Kingdom, Germany, Denmark, France, Sweden, the United States, and Canada) categorized into three geographical regions (the Asia-Pacific region, the European region, and the North American region). The study gathered data on these countries' productivities between the years 2001 and 2007, and then conducted a cross-regional comparative study.

METHODOLOGY

The metafrontier model

According to the model developed in Battese et al. (2004), let us assume that there are a total N firms belonging to K technological groups in an industry. Then, there are N_k firms in the group k. We know that the metafrontier function that the K groups commonly face can be presented as:

$$Y_{it}^{*} \equiv f(x_{it}, \beta^{*}) = e^{x_{it}\beta^{*}}, i = 1,2,\ldots,N = \sum_{k=1}^{K} N_k, t = 1,2,\ldots,T \quad (1)$$

Here, β^* refers to the estimated parameter vector of the metafrontier production function, and can be estimated under the following constraint condition:

$$x_{ij}\beta^* \geq x_i\beta_{(k)} \quad (2)$$

The k^{th} group on the stochastic frontier is defined as the output of i^{th} firm at time t, or expressed as the following the metafrontier equation:

$$Y_{it} = e^{-U_{it(k)}} \times \frac{e^{x_{it}\beta_{(k)}}}{e^{x_{it}\beta^*}} \times e^{x_{it}\beta^* + V_{it(k)}} \quad (3)$$

In Equation (3), the second term on the right-hand side is the technology gap ratio (TGR), which is the ratio of each firm's stochastic frontier value to the metafrontier value:

$$TGR_{it} = \frac{e^{x_{it}\beta_{(k)}}}{e^{x_{it}\beta^*}} \quad (4)$$

When TGR is between the values of 0 and 1, the closer it is to 1, the smaller the gap between the metafrontier and the group's stochastic frontier. The more similar a particular firm's stochastic frontier value is to the metafrontier, the more highly the firm's technical standard is regarded, and it will therefore demonstrate a higher TGR value. This can be expressed as the following equation:

$$TE_{it}^{*} = TE_{it} \times TGR_{it} \quad (5)$$

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The gMMPI model

An illustration of the concepts and models proposed by Chen and Yang (2008) and Chen et al. (2009) is provided below. Here, the structure of the MMPI model is explained using a distance function. First, we define the production technologies as the process of transforming inputs into outputs; a firm's production (t = 1, 2, ..., T) is produced with the input vector x_t Î R^{+M} in period t and with the output vector y_t Î R^{+L}. Assuming that K technological groups exist in total (k = 1, 2, ..., K), and given an appropriate combination of inputs and outputs, the technological group $P_t^k(x)$ in the same output orientation can be derived as follows:

$$P_t^k(x) = \{y_t^k \text{ is obtainable from } x_t^k\} \quad (6)$$

The upper bound of the technological groups is the group frontier (O'Donnell et al. 2008), which defines the output oriented distance function of k^{th} group (Shephard 1970):

$$D_t^k(x_t^k, y_t^k) = \inf_\delta \left\{\delta > 0 : \left(\frac{y_t^k}{\delta}\right) \in P_t^k(x_t^k)\right\} \quad (7)$$

An equation proposed by Caves et al. (1982) is used here to explain the change in the intertemporal productivity of the Malmquist Productivity Index (MPI) – Equation (8).

In Equation (8), the first term on the right of the equal sign is the technical efficiency change (TEC), and the second term is the technical change (TC). The equation derives a geometric mean through the consideration of the output com binations of period t and period $t+1$. O'Donnell et al. (2008) called the measure of the group frontier in Equation (8) the Group Malmquist Productivity Index (GMPI), and this equation can be simplified and expressed (Equation 9).

According to Battese et al. (2004) and O'Donnell et al. (2008), assuming that the individual technological groups all with the same technologies are not restricted by the output $P^*(x)$, the following equations can be derived (Equations 1a and 11).

The metafrontier is different from the group frontier in that it implies that the obstacles to the technology development can be overcome, and the technical gaps can be closed; therefore, the output oriented distance function can be expressed – Equation (12).

The MPI(MMPI), which Rao (2006) and O'Donnell et al. (2008) defined based on the metafrontier concept, is expressed – Equation (13).

This can be simplified and expressed – Equation (14).

The above TEC^* and TC^* are the bases for measuring the technical efficiency change (TEC) and technical change (TC) using the metafrontier.

The MMPI distance function encompasses two elements: TEC^* and TC^*. However, Chen and Yang (2008) argue that the traditional measuring method MPI ignores the scale efficiency change (SEC), and this is also a likely weakness of the MMPI model; however, the gMMPI model considers the SEC, and includes the intertemporal adjustment of scale efficiency in the MMPI model.

If we assume that the firm technology can be expressed as the input vector $x_t \in R^{+M}$, the output

$$MPI_{t,t+1}^k(x_t, y_t, x_{t+1}, y_{t+1}) = \frac{D_{t+1}^k(x_{t+1}, y_{t+1})}{D_t^k(x_t, y_t)} \times \left[\frac{D_t^k(x_{t+1}, y_{t+1})}{D_{t+1}^k(x_{t+1}, y_{t+1})} \times \frac{D_t^k(x_t, y_t)}{D_{t+1}^k(x_t, y_t)}\right]^{\frac{1}{2}} \quad (8)$$

$$GMPI_{t,t+1} = TEC_{t,t+1}^k \times TC_{t,t+1}^k \quad (9)$$

$$P_t^* = \{P_t^1 \cup P_t^2 \cup \cdots \cup P_t^k\} \quad (10)$$

$$P_t^*(x_t) = \{y_t \text{ is potentially obtainable from } x_t\} \quad (11)$$

$$D_t^*(x_t, y_t) = \inf_\delta \left\{\delta > 0 : \left(\frac{y_t}{\delta}\right) \in P_t^*(x_t)\right\} \quad (12)$$

$$MMPI_{t,t+1}^k(x_t, y_t, x_{t+1}, y_{t+1}) = \frac{D_{t+1}^*(x_{t+1}, y_{t+1})}{D_t^*(x_t, y_t)} \times \left[\frac{D_t^*(x_{t+1}, y_{t+1})}{D_{t+1}^*(x_{t+1}, y_{t+1})} \times \frac{D_t^*(x_t, y_t)}{D_{t+1}^*(x_t, y_t)}\right]^{\frac{1}{2}} \quad (13)$$

$$MMPI_{t,t+1} = TEC_{t,t+1}^* \times TC_{t,t+1}^* \quad (14)$$

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vector $y_t \in R^{+L}$, and the time variable t using an output distance function, by applying the Diewert's (1976) Quadratic Identity Lemma, the intertemporal changes of the distance function can be measured by Equation(15).

The flexibly weighted output distance becomes the change in output. We compared this with the flexibly weighted input distance (input change), and took the natural logarithm to derive the expression (16).

From Equations (15) and (16), we can derive the Equations (17).

Orea (2002) reckons that a number of characteristics are necessary in the construction of a comprehensive index of the total factor productivity; these characteristics include the identity, monotonicity, separability, and proportionality. Equation (16) possesses the first of these three characteristics. Proportionality implies a linear first-order condition of the productivity index, but proportionality may not be presented in the MPI model; and in the VRS, the weighting of input variables may not be one. In the light of this, we adopted the concepts proposed by Orea (2002) and Denny et al. (1981), and replaced the distance elasticity inputs with the distance elasticity shares as the weighting for the input variables. This process can be expressed as Equations (18).

Here, the gMMPI is the general expression of the MMPI; using Equations (15) and (18), the gMMPI can be constructed and expressed as Equations (19).

Similar to Equation (17), in Equation (19), the first two terms are *TEC** and *TC**, respectively. The difference lies in the third term, *SEC**. Here, *SEC* is affected by two main elements, the scale elasticity and input. The scale elasticity is defined as the scale of a change in the input when the output changes (Ray 1998). When the input scale elasticity deviates from 1, the

$$\ln D^*_{t+1}\left(y^1_{t+1},x^m_{t+1},t\right)-\ln D^*_t\left(y^1_t,x^m_t,t\right)=\frac{1}{2}\sum_{l=1}^{L}\left[\frac{\partial \ln D^*_{t+1}\left(y^l_{t+1},x^m_{t+1},t\right)}{\partial \ln y^l}+\frac{\partial \ln D^*_t\left(y^l_t,x^m_t,t\right)}{\partial \ln y^l}\right]\times\left(\ln y^l_{t+1}-\ln y^l_t\right)$$
$$+\frac{1}{2}\sum_{m=1}^{M}\left[\frac{\partial \ln D^*_{t+1}\left(y^l_{t+1},x^m_{t+1},t\right)}{\partial \ln x^m}+\frac{\partial \ln D^*_t\left(y^l_t,x^m_t,t\right)}{\partial \ln x^m}\right]\times\left(\ln x^m_{t+1}-\ln x^m_t\right)+\frac{1}{2}\left[\frac{\partial \ln D^*_{t+1}\left(y^l_{t+1},x^m_{t+1},t\right)}{\partial t}+\frac{\partial \ln D^*_t\left(y^l_t,x^m_t,t\right)}{\partial t}\right] \quad (15)$$

$$\ln MMPI_{t,t+1}\left(y^1_{t+1},y^1_t,x^m_{t+1},x^m_t\right)=\frac{1}{2}\sum_{l=1}^{L}\left[\frac{\partial \ln D^*_{t+1}\left(y^l_{t+1},x^m_{t+1},t\right)}{\partial \ln y^l}+\frac{\partial \ln D^*_t\left(y^l_t,x^m_t,t\right)}{\partial \ln y^l}\right]\times\left(\ln y^l_{t+1}-\ln y^l_t\right)$$
$$-\frac{1}{2}\sum_{m=1}^{M}\left[\frac{-\partial \ln D^*_{t+1}\left(y^l_{t+1},x^m_{t+1},t\right)}{\partial \ln x^m}+\frac{-\partial \ln D^*_t\left(y^l_t,x^m_t,t\right)}{\partial \ln x^m}\right]\times\left(\ln x^m_{t+1}-\ln x^m_t\right) \quad (16)$$

$$\ln MMPI_{t,t+1}\left(y^1_{t+1},y^1_t,x^m_{t+1},x^m_t\right)=\left[\ln D^*_{t+1}\left(y^1_{t+1},x^m_{t+1},t\right)-\ln D^*_t\left(y^1_t,x^m_t,t\right)\right]-\frac{1}{2}\left[\frac{\partial \ln D^*_{t+1}\left(y^l_{t+1},x^m_{t+1},t\right)}{\partial t}+\frac{\partial \ln D^*_t\left(y^l_t,x^m_t,t\right)}{\partial t}\right] \quad (17)$$

$$\ln gMMPI_{t,t+1}\left(y^1_{t+1},y^1_t,x^m_{t+1},x^m_t\right)=\frac{1}{2}\sum_{l=1}^{L}\left[\frac{\partial \ln D^*_{t+1}\left(y^l_{t+1},x^m_{t+1},t\right)}{\partial \ln y^l}+\frac{\partial \ln D^*_t\left(y^l_t,x^m_t,t\right)}{\partial \ln y^l}\right]\times\left(\ln y^l_{t+1}-\ln y^l_t\right)-$$
$$\frac{1}{2}\sum_{m=1}^{M}\left[\frac{\dfrac{-\partial \ln D^*_{t+1}\left(y^l_{t+1},x^m_{t+1},t\right)}{\partial \ln x^m}}{\sum_{m=1}^{M}\dfrac{-\partial \ln D^*_{t+1}\left(y^l_{t+1},x^m_{t+1},t\right)}{\partial \ln x^m}}+\frac{\dfrac{-\partial \ln D^*_t\left(y^l_t,x^m_t,t\right)}{\partial \ln x^m}}{\sum_{m=1}^{M}\dfrac{-\partial \ln D^*_t\left(y^l_t,x^m_t,t\right)}{\partial \ln x^m}}\right]\times\left(\ln x^m_{t+1}-\ln x^m_t\right) \quad (18)$$

$$\ln gMMPI_{t,t+1}\left(y^1_{t+1},y^1_t,x^m_{t+1},x^m_t\right)=\left[\ln D^*_{t+1}\left(y^1_{t+1},x^m_{t+1},t\right)-\ln D^*_t\left(y^1_t,x^m_t,t\right)\right]-\frac{1}{2}\left[\frac{\partial \ln D^*_{t+1}\left(y^l_{t+1},x^m_{t+1},t\right)}{\partial t}+\frac{\partial \ln D^*_t\left(y^l_t,x^m_t,t\right)}{\partial t}\right]+$$
$$+\frac{1}{2}\sum_{m=1}^{M}\left[\frac{\left(-\sum_{m=1}^{M}\xi^{*m}_{t+1}-1\right)\xi^{*m}_{t+1}}{\sum_{m=1}^{M}\xi^{*m}_{t+1}}+\frac{\left(-\sum_{m=1}^{M}\xi^{*m}_{t}-1\right)\xi^{*m}_{t}}{\sum_{m=1}^{M}\xi^{*m}_{t}}\right]\times\left(\ln x^m_{t+1}-\ln x^m_t\right)$$
$$where,\ \xi^{*m}_{t+1}\frac{\partial \ln D^*_{t+1}\left(y^l_{t+1},x^m_{t+1},t\right)}{\partial \ln x^m};\quad \xi^{*m}_t=\frac{\partial \ln D^*_t\left(y^l_t,x^m_t,t\right)}{\partial \ln x^m} \quad (19)$$

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firm's adjustment of its input-output levels across different periods will then affect its productivity growth. This means that when production is at the IRS/DRS stage and a firm increases or decreases its scale of input, then its *SEC** value will respectively be larger or smaller than 1. The indexed equation can be simplified and expressed as Equation (20).:

$$gMMPI_{t,t+1} = TEC^{*}_{t,t+1} \times TC^{*}_{t,t+1} \times SEC^{*}_{t,t+1} \tag{20}$$

The above equation can be illustrated as Equation (21).

$$\begin{aligned}\ln gMMPI_{t,t+1}\left(y^{1}_{t+1}, y^{1}_{t}, x^{m}_{t+1}, x^{m}_{t}\right) = {} & \left[\ln D^{k}_{t+1}\left(y^{1}_{t+1}, x^{m}_{t+1}, t\right) - \ln D^{k}_{t}\left(y^{1}_{t}, x^{m}_{t}, t\right)\right] - \frac{1}{2}\left[\frac{\partial \ln D^{k}_{t+1}\left(y^{l}_{t+1}, x^{m}_{t+1}, t\right)}{\partial t} + \frac{\partial \ln D^{k}_{t}\left(y^{l}_{t}, x^{m}_{t}, t\right)}{\partial t}\right] \\ & + \left[\ln TGR^{k}_{t+1}\left(y^{l}_{t+1}, x^{m}_{t+1}, t\right) - \ln TGR^{k}_{t}\left(y^{l}_{t}, x^{m}_{t}, t\right)\right] - \frac{1}{2}\left[\frac{\left(\frac{\partial \ln D^{*}_{t+1}\left(y^{l}_{t+1}, x^{m}_{t+1}, t\right)}{\partial t} + \frac{\partial \ln D^{*}_{t}\left(y^{l}_{t}, x^{m}_{t}, t\right)}{\partial t}\right)}{\left(\frac{\partial \ln D^{k}_{t+1}\left(y^{l}_{t+1}, x^{m}_{t+1}, t\right)}{\partial t} + \frac{\partial \ln D^{k}_{t}\left(y^{l}_{t}, x^{m}_{t}, t\right)}{\partial t}\right)}\right] \\ & + \frac{1}{2}\sum_{m=1}^{M}\left[\frac{\left(-\sum_{m=1}^{M}\xi^{*m}_{t+1} - 1\right)\xi^{*m}_{t+1}}{\sum_{m=1}^{M}\xi^{*m}_{t+1}} + \frac{\left(-\sum_{m=1}^{M}\xi^{*m}_{t} - 1\right)\xi^{*m}_{t}}{\sum_{m=1}^{M}\xi^{*m}_{t}}\right] \times \left(\ln x^{m}_{t+1} - \ln x^{m}_{t}\right)\end{aligned} \tag{21}$$

The first two terms on the right of the equals sign are TEC^k and TC^k respectively, which is the group frontier; the third term is the logarithm taken from the intertemporal TGR change. If the ratio is larger than 1, it means that the firm's technology gap diminishes with time, and that the technology catch-up exists. This demonstrates that the currently available technology and technical standards are not a result of the technological catch-up, and this is referred to as pure technological catch-up (PTCU). The fourth term on the right of the equals sign is the ratio of TC^* to TC^k, or the measured rate of the potential improvement in technical standards, based on the change in the current technical standards in production. When the estimated value exceeds 1, it means that the rate of the potential improvement in technical standards outperforms the existing technical standards; thus, the firm's potential in improving and developing its technical standard is increasing. This is referred to as the potential technological relative change (PTRC). The indexed equation can be simplified and expressed as Equation (22).

$$gMMPI_{t,t+1} = TEC^{k}_{t,t+1} \times TC^{k}_{t,t+1} \times PTCU^{k}_{t,t+1} \times PTRC^{k}_{t,t+1} \times SEC^{*}_{t,t+1} \tag{22}$$

EXPLANATION OF VARIABLES AND THE EMPIRICAL MODELS

Explanation of variables

We collected data using the OSIRIS databank and adopted the Industry Classification Benchmark ICB for the classification of the biotechnology sample subjects.[3] The main purpose of this study is to compare the biotechnology industries in different countries. After filtering out any incomplete company data from the sample set, the final sample consisted of firms from twelve countries including Australia, China, Japan, South Korea, Taiwan, the United Kingdom, Germany, Denmark, France, Sweden, the United States, and Canada. We then categorized these countries and segmented them into continental regions according to their geographic positions (Rao 2006; O'Donnell et al. 2008; Krishnasamy and Ahmed 2009; Oh and Lee 2010). As in the study conducted by O'Donnell et al. (2008), we also placed Australia in the Asia-Pacific region; our study on the industry productivity change was conducted on countries in three continental regions, including the North American region, the European region, and the Asia-Pacific region.

The sample for this study included a total of 356 firms from the three continental regions, and the analysis was conducted on data from the 2001 to 2007 period. The 356 firms included 55 firms in the Asia-Pacific region (Australia, China, Japan, South Korea, and Taiwan); 68 firms in the European region

[3]Industry Classification Benchmark (ICB) is an industry classification taxonomy developed by the America's Dow Jones Indexes and the Britain's FTSE.

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(the United Kingdom, Germany, Denmark, France, and Sweden); and 233 firms in the North American region (the United States and Canada). In addition, when using US$ million as the unit for measuring the input, output, and other variables, we adopted the 2000 Producer Price Index (PPI) in the United States as the basis for deflation.

Definition of variables

The definitions offered for the output and input variables are provided as follows. The output variables include net sales (González and Gascón 2004; Saranga 2007; Li and Li 2008), which is the item under net sales in a company's income statement. The input variables include fixed assets, staff, and the R&D expenditures. First, fixed assets are the assets listed in a company's income statement that encompass the machinery and equipment, plant, land, and other hardware; fixed assets are the basis for a firm to produce its products. Second, staff is the number of staff employed by a firm on an annual basis. Together, fixed assets and staff are the fundamentals of the production theory (Chiu et al. 2003; González and Gascón 2004; Saranga 2007; Li and Li 2008). Finally, the last input variable is the R&D expenditure. Because the nature of the biotechnology industry technology-and knowledge-intensive, the R&D expenditure is a critical element to the industry, and the studies have proven the benefits that the R&D spending provide to the industry (Chiu et al. 2003; Hsieh et al. 2007; Hashimoto and Haneda 2008; Li and Li 2008).

However, if the R&D expenditure is used as an input variable, then only the expenditure of a particular year is used as the input variable for that year, so this figure does not help to provide a precise measurement of the investment efficiency. The R&D expenditure has a time-lag effect, and this must be considered in the analysis; therefore, this study used the R&D capital stock to estimate investment efficiency. The R&D capital stock can also measure the contribution of innovative efforts to productivity. According to Yang and Chen (2002), the majority of the past studies estimated investment efficiency using an equation which weighted the R&D expenditure of the year and the R&D expenditure of the previous years, and this equation is expressed as Equation (23).

$$K_t = R_t + (1-\delta)R_{t-1} + (1-\delta)^2 R_{t-2} + \ldots = \sum_t R_t (1-\delta)^t = R_t \sum_t \left[\frac{1-\delta}{1+g}\right]^t = \frac{R_t}{g+\delta} \tag{23}$$

R represents the R&D expenditure, δ is the depreciation rate, and g denotes the growth rate of the R&D expenditure. There is no standard depreciation rate, and rates adopted in past studies have included 7.5% (Chen et al. 2009), 12% (Luh and Shih 2005) and 15% (Chuang and Hsu 1999; Griliches and Mairesse 1984; Yang and Chen 2002). Griliches and Mairesse (1984) indicated that different depreciation rates actually have a little impact on the results of estimation; we therefore adopted the most commonly used depreciation rate of 15% for this study. For the estimation of the R&D capital stock, we adopted the method used by Yang and Chen (2002), whereby we used the data from the previous two years for the estimation.

Furthermore, because this study focuses on evaluating biotechnology firms in different countries, the internal and external environmental factors must be excluded to achieve the same basis of comparison for measuring the performance of different firms. In the light of this, we categorized environmental variables into three characteristic levels: the country-characteristic, the industry-characteristic, and the firm-characteristic variables. In doing so, we can exclude the impact on efficiency and productivity created by the internal and external environmental factors, as experienced by the companies, industries, and nations. For the firm-characteristic and industry-characteristic variables, we adopted the same variables as adopted by Yang and Chen (2009), which included the firm age (FA), the R&D intensity (RDI), the industry scale (IS), the ratio of the number of labourers employed by the first 50% of firms in the group to the average number of labourers employed by all firms (IMES), and the average industry R&D intensity (IRDI). The FA represents how long a firm has been operating, and this may affect its technical efficiency; younger firms may be more efficient than the more established firms, and vice versa. The RDI refers to the technical capabilities and skills possessed by a firm, which are the main factors in improving the firm's technical efficiency. The IS and IMES are similar in that their scales can affect the firm's efficiency, so larger firms may be more efficient than the smaller ones. Depending on the overall level of the R&D investment in the industry, the IRDI may affect the ability of new firms to enter into the market, or it may affect the technical efficiency of the existing firms if they do not face new competition

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(Yang and Chen 2009). The country-characteristic variables are dependent on the country's economic level and its population; because the income levels and consumption both affect a firm's output levels and the cost control, we therefore used the gross domestic product (GDP) and the population density (POP) as the variables in this category.

Empirical models

The group frontier in this study was obtained using the SFA model to set the translog function. Chiu et al. (2003) reported the advantage of the flexibility of the function; the more flexible it is, the closer it is to the true function, regardless of the functional form. Tsai and Wann (1995) also mentioned that the Cobb-Douglas and CES functions focus only on simplicity, and overlook the fact that they do not offer the elasticity of substitution. The majority of the past studies (Chiu et al. 2003; Li and Li 2008) adopted translog function for analysis; therefore, we also used the translog function as it is expressed Equation (22).

In this function, g represents each group frontier; i is the firm code; T is the time trend; Y denotes the output variables, L, K, and R are the number of staff, fixed assets, and the R&D capital stock, respectively; a and β are the parameter estimates; V_{it} represents the stochastic variables that are independent and identically distributed $N(0, \sigma_v^2)$; and $U_{it} = \{U \exp[-\eta(t - T)]\}$. According to Battese and Coelli (1992), U_{it} and V_{it} are non-negative random variables that are independent and identically distributed in the terms of technical efficiency; and η denotes the adjusted intertemporal variables.

Battese and Coelli (1995) suggested that the variable (U_{it}), which affects technical inefficiency, can be expressed as a linear function to reflect the characteristics of a country; this can further demonstrate different effects created by resources, social factors, and technology on each firm or country. U_{it} is a non-negative random variable, and follows the normal distribution, as demonstrated Equation (25).

The FA is the firm age (FA), the RDI is a firm's R&D intensity, the IS denotes the industry scale, the IMES is the ratio of the number of labourers employed by the first 50% of firms in the group to the average number of labourers employed by all firms, the IRDI denotes the average industry R&D intensity, GDP is the gross domestic product of a nation, and the POP represents the population density.

Battese et al. (2004) used the absolute minimal distance and the squared minimal distance to calculate β in Equation (22). By setting a stochastic group frontier parameter of $\hat{\beta}_{(k)}$, k = 1. 2. ..., R, the parameter β^* was estimated; this method is also called the linear programming (LP), whereby the parameters of the individual technical groups ($\hat{\beta}_{(k)}$) are induced to work out the optimal solution. Another method using the squared minimal distance and for the estimation of parameter β^* is also referred to as the quadratic programming (QP)[4]; Table 1 shows the results of the stochastic parameter estimation results.

ANALYSIS OF EMPIRICAL RESULTS

Results of parameter estimation

Table 1 shows the results of the stochastic frontier parameter estimation. In this estimation, the ln(K) values are generally positive, indicating that the firm capital inputs had a positive effect on the output. The cross-product term of the R&D input and time is a positive value, indicating the positive contribution that the R&D expenditure made toward increases in the output year over year. In the Asia-Pacific region, the region's ln(L) and ln(R) values were both positive

$$\ln Y_{it}^g = \alpha_0^g + \beta_{it}^g\left(\ln L_{it}^g\right) + \beta_2^g\left(\ln K_{it}^g\right) + \beta_3^g\left(\ln R_{it}^g\right) + \beta_4^g(T) + \frac{1}{2}\beta_5^g\left(\ln L_{it}^g\right)^2 + \frac{1}{2}\beta_6^g\left(\ln K_{it}^g\right)^2 + \frac{1}{2}\beta_7^g\left(\ln R_{it}^g\right)^2 + \frac{1}{2}\beta_8^g(T)^2 + \beta_9^g\left(\ln L_{it}^g\right)\left(\ln K_{it}^g\right)$$
$$+ \beta_{10}^g\left(\ln L_{it}^g\right)\left(\ln R_{it}^g\right) + \beta_{11}^g\left(\ln K_{it}^g\right)\left(\ln R_{it}^g\right) + \beta_{12}^g\left(\ln L_{it}^g\right)T + \beta_{13}^g\left(\ln K_{it}^g\right)T + \beta_{14}^g\left(\ln R_{it}^g\right)T + V_{it}^g \quad (24)$$

$$U_{it} = \delta_0 + \delta_1(FA_{it}) + \delta_2(RDI_{it}) + \delta_3(IS_{it}) + \delta_4(IMES_{it}) + \delta_5(IRDI_{it}) + \delta_5(IRDI_{it}) + \delta_6(GDP_{it}) +$$
$$+ \delta_7(GDP^2_{it}) + \delta_8(POP_{it}) + \omega_{it} \quad (25)$$

[4] $LP\ objective\ function: \ \min L \equiv \sum_{t=1}^{T}\sum_{t=1}^{N}(x_{it}, \beta^* - x_{it}\hat{\beta}_{(k)}) \quad s.t. \quad x_{it}, \beta^* \geq x_{it}, \hat{\beta}_{(k)}$

$QP\ objective\ function: \ \min L^{**} \equiv \sum_{t=1}^{T}\sum_{t=1}^{N}(x_{it}, \beta^* - x_{it}\hat{\beta}_{(k)})^2 \quad s.t. \quad x_{it}, \beta^* \geq x_{it}, \hat{\beta}_{(k)}$

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and significant. This means that the labour input and R&D input had a positive effect on the regional output. Furthermore, the cross-product term of capital and time indicates the positive contribution made by the capital toward increases in the output year over year. However, the R&D input figures showed a diminishing trend, and this did not accord with the overall estimation results. The reason for this trend was perhaps because the relatively young firms in the Asia-Pacific region regarded the R&D investment as risky due to the long product development period, and thus were unwilling to invest a substantial amount of the R&D during the initial period. In the European region, larger capital inputs had a positive effect on the output. The North American region also displayed a trend of higher capital and R&D inputs resulting in a greater output. These results indicate that the biotechnology firms tend to adopt substantial amounts of capital inputs, and this conforms to the industry characteristic investing heavily. Similarly, by looking

Table 1. Parameter estimation results

Variable	Stochastic Frontier Estimation				Metafrontier Estimation	
	Asia-Pacific Region	European Region	North American Region	overall	MF-LP	MF-QP
Constant	−0.1958	−0.1718	0.1866	0.2225	2.4500***	2.3545***
ln(K)	−0.1076	0.7291***	0.3873***	0.4781***	0.3476	0.7048***
ln(L)	0.5457***	−0.1604	−0.0313	0.0366	−0.5328	−0.5955
ln(R)	0.3362**	−0.1420	0.2397	−0.0306	0.3737	0.2505
0.5*ln(K)*ln(K)	−0.2504***	0.1627***	0.0388	0.0729***	0.0835	0.1174*
0.5*ln(L)*ln(L)	0.0723	0.3287	0.3054	0.2329***	0.3511***	0.3875***
0.5*ln(R)*ln(R)	0.1475***	0.0640	0.0973**	0.0309	0.1233*	0.1654***
ln(K)*ln(L)	0.0605	−0.1336*	−0.0456	−0.0670***	−0.0539	−0.1179
ln(K)*ln(R)	0.1541***	−0.0644	0.0226	−0.0180	−0.0367	−0.0245
ln(L)*ln(R)	−0.1267***	−0.0233	−0.1636***	−0.0391	−0.1342*	−0.1380***
T	−0.0408	0.2387	−0.1151	−0.0287	−0.1908	−0.3582*
0.5*T*T	0.0218	−0.0092	0.0143	0.0050	0.0270	0.0609*
ln(K)*T	0.0979***	−0.0187	−0.0146	−0.0035	0.0293	−0.0120
ln(L)*T	−0.0255	−0.0206	0.0271	−0.0011	0.0121	0.0399
ln(R)*T	−0.0808***	0.0204	0.0200	0.0321***	−0.0098	−0.0058
Constant	0.7410	−1.9802*	−110.1345	−6.0085		
RDI	−2.8678***	−0.4899	−0.4230	−0.6653		
Firm Age	−0.2485***	−1.0988***	−0.2104***	−0.3095***		
IS	0.4732	0.2576*	0.0261	0.0023		
IMES	0.7654	12.5422***	72.3721	6.3885***		
IRDI	1.9600	2.7565***	7.9478	3.8124		
GDP	0.0294	−2.4403***	−0.6069	−0.4737***		
GDP*GDP	−0.0018	0.0470***	0.0086	0.0064***		
Population	−0.0030*	0.0299***	−0.7643	−0.0021*		
σ^2	3.4585***	10.0877***	9.6627***	9.4446***		
γ	1.0000***	0.9516***	0.9589***	0.9548***		
LLF	−348.6474	−541.3565	−2188.8478	−3165.4330		

K = Fixed Asset; L = Staff Number; R = R&D expenditure; T = Time; LLF = Log likelihood function

*, **, *** denotes 10%, 5%, 1% significance level respectively

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at the metafrontier estimation results, we can see that the capital input and the estimated stochastic frontier parameters both showed a positive effect on the output. The estimation of the inefficiency value γ (gamma) in Table 1 was greater than 0.95, indicating that the inefficiency unquestionably influenced the technical efficiency, and that it arose from human factors that could be controlled. The results from the overall sample showed that the GDP, population density, IMES, and firm age values were all significant; the GDP, population density, and firm age alleviated some of the effect of inefficiency, whereas the IMES amplified this effect.

The average GDP per capita serves as an important indicator of a country's economic development status; the countries at higher average levels of income have relatively more established societal and economic environments to help stimulating consumption. The results produced by the overall sample and by the European region are significant; the reason that the GDP alleviates inefficiency is possibly that higher incomes suggest a greater purchasing power, and thus the firms generate higher revenues. The estimation results found by this study are similar to that conducted by Pasiouras et al. (2009). The comparison of the three continental regions showed that the results for the Asia-Pacific and North American regions were not significant, whereas the results for the European region were negative and significant; and those variables reduced the firm inefficiency.

In addition, the population density is also a critical variable; the density of the population may affect the level of improvement on costs and the firm efficiency (Dietsch and Lozano-Vivas 2000). The results for our overall sample were negative and significant; demonstrating that higher population densities were correlated with the reduced inefficiency. These estimation results concur with those of Staikouras et al. (2008). The North American region's POP value was insignificant, but that of the European region was positive and significant, while the value of the Asia-Pacific region' was negative and significant. The results shown by the European and Asia-Pacific regions were completely opposite; the positive and significant values may be attributed to the fact that whilst both of these continental regions have large populations, the overall consumption power of the population in the European region is greater than that of the Asia-Pacific region; and the densely populated areas in the European region are scattered extensively, rather than concentrated in a few regions or cities like those in the Asia-Pacific region. For instance, the densely populated areas in China and Australia tend to be located along the coast. This means that the firms in the European region have to invest more in distributing and marketing to the widely scattered channels, increasing their costs and thus decreasing their profits.

A higher IMES means that it may be more difficult for small firms to enter the industry, and may also lead to the larger firms becoming too complacent; consequently, they may not focus on improving their technologies. The results show that the IMES increased inefficiency, and this finding is in line with the results presented by Yang and Chen (2009). A possible reason for this effect is that the more dominant a firm is, the more likely it is to become complacent. Many biotechnology firms tend to utilize only a few technologies and patents (including pharmaceutical products) to gain high profits once they have invented and obtained those patents, medicines, or technologies. However, if they do not manage to innovate and develop other patents or products before the existing ones expire, then their profitability will be greatly affected once the term of the patents expires. With regard to the industry scale (IS), Yang and Chen (2009) originally proposed the opinion that larger firms would benefit from technical efficiencies because of their scale. Our estimated values for the IS show that the relationship is positive but insignificant; however, the implications generally concur with Yang and Chen's (2009) empirical findings. A possible explanation for the difference in the results of the two studies is that once the scale of a firm surpasses a certain point, it may also experience the technical inefficiency. The comparison of the IS and IMES figures shows that they are positive and significant in the European region, but insignificant in the other two regions.

Many past studies have already mentioned the positive effects that the R&D has on the output. The estimated RDI values here were not significant, but the trend still conforms to the previous findings by Yang and Chen (2009). The IRDI represents the average R&D intensity of the industry. Yang and Chen (2009) mentioned that according to some studies, the R&D intensive industries may pose difficulties to new firms trying to enter the market, and this subsequently causes existing firms to be less concerned with improving their technologies. Our IRDI estimation results appear insignificant, but they generally conform to the estimation results of Yang and Chen (2009). While only the Asia-Pacific region presents

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a negative and significant RDI value, it generally accords with the values for the other two regions and the overall sample. Similarly, only the North American region presents an insignificant IRDI value; however, on the whole, the trend is in accordance with those of the other two regions.

The firm age (FA) has often been applied in many studies, and this variable has also produced different results and indicated different effects; in some previous studies, it was verified to increase the inefficiency (Hill and Kalirajan 1993), but some studies found the opposite effect (Yang and Chen 2009). The reason that the firm age may reduce the inefficiency is that the firms can learn from experience, and this learning effect therefore reduces the inefficiency. However, the firm age may actually increase the inefficiency because the technologies adopted by younger firms are relatively newer; so the more obsolete technologies that older firms use may add to their cost, and thus reduce their efficiency (Yang and Chen 2009). The results from our analysis show that the firm age can reduce inefficiency, and this finding accords with that of Yang and Chen (2009). Our results show that the FA values of the different regions and of the overall sample were all negative and significant; therefore, the firm age clearly reduces inefficiency.

Analysis of technical efficiency and technology gap ratio estimations

A likelihood ratio test (LR test) needs to be done prior to conducting the efficiency estimation. The purpose of the LR test is to identify any possible difference between the different groups. Battese *et al.* (2004) mentioned that if different groups possess the same technical standard, then measuring the metafrontier becomes meaningless. The LR test equation is $\lambda = -2\{\ln[L(H_0)] - \ln[L(H_1)]\}$. Here, $\ln[L(H_0)]$ is the stochastic frontier likelihood function of the individual firms in the sample, and $\ln[L(H_1)]$ is the total stochastic frontier likelihood function of all firms in the sample. The calculation shows a significance level higher than 5%; this indicates that differences exist between the firms' technical standards, and the use of the metafrontier model for the analysis is reasonable and appropriate.

From the estimation results in Table 2, the average TGR of years 2001 to 2007 was 0.5593; the highest TGR was demonstrated by the North American region at 0.5845; the second highest TGR was displayed by the European region at 0.5145; and finally, the Asia-Pacific region followed with a TGR of 0.4829. Firms in all three regions have a 45% room for improvement in average, with the Asia-Pacific region possessing the highest potential improvement of 51.71%. With regard to the technical efficiency, the Asia-Pacific region showed an average TE value of 0.3408, the European region's average TE value was 0.5362, and that of the North American region was 0.4339.

The biotechnology firms in the different regions produced a low mean technical efficiency (MTE) value of only 0.2523; the Asia-Pacific region's MTE was the lowest at only 0.1667, followed by the North American region at 0.2616, and finally by the European region at 0.2763, which was only marginally better than that of the North American region. A possible explanation for these results is that for the majority of the countries, biotechnology is still a developing industry, and the proportion of the resource allocation tends to exceed the expected output. This result is probably correlated with the fact that the biotechnology industry invests heavily, and its growth and development tend to take longer to demonstrate results.

By comparing the results of the different regions, we can see that the Asia-Pacific showed a relatively poorer performance in the terms of the TE (0.3408), TGR (0.4829) and MTE (0.1667); this could be attributed to the fact that within this region, Japan is the country whose biotechnology industry is the most established. Japan therefore enjoys superior advantages in the terms of technologies and resources in comparison to the less developed industries of the other four Asia-Pacific countries; hence, their performance is less ideal.

The European region's estimated TE was 0.5362, and its MTE was the highest of all three regions at 0.2763. Its TGR was only second to the North American region at 0.5145. A possible reason for this is that although the firms in the European region may not be as established, they could still learn from the experience of biotechnology firms in the United States, and therefore minimized the errors and resource waste during their development. The estimation results show that the difference in efficiency between firms of the same region was smaller than the differences between firms in different regions.

The North American region's biotechnology industries are the most established and its TE was the highest at 0.4339. Its MTE was by 0.0931 higher than that of the Asia-Pacific region, but just by 0.0147 lower than that of the European region. The region's

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TGR, however, was by 0.07 and 0.1016 higher than those of the European and Asia-Pacific regions, respectively. The biotechnology industries in the North American region, particularly in the United States, are the most established; but even though there are firms possessing a good technical efficiency, there are even more firms whose technical efficiency is poor, and this is perhaps why the average efficiency is undesirable.

With regard to the fluctuation of the TE over time, the Asia-Pacific region's TE first increased and then later decreased; however, compared with the 2001, the

Table 2. Technical efficiencies and technical gap ratios of the regions between 2001 and 2007

Region/year		Technical Gap Ratio (TGR)	Metafrontier Technical Efficiency (MTE)	Technical Efficiency of Groups (TE)
Asia-Pacific Region	2001	0.5164	0.1183	0.2680
	2002	0.5085	0.1818	0.3958
	2003	0.4918	0.1945	0.3911
	2004	0.4842	0.1652	0.3278
	2005	0.4851	0.1737	0.3524
	2006	0.4650	0.1605	0.3343
	2007	0.4710	0.1652	0.3258
	average[a]	0.4829	0.1667	0.3408
European Region	2001	0.3426	0.1836	0.5253
	2002	0.4044	0.2355	0.5802
	2003	0.4910	0.2851	0.5829
	2004	0.5263	0.2786	0.5239
	2005	0.5710	0.3104	0.5409
	2006	0.6080	0.2942	0.4895
	2007	0.6015	0.3176	0.5277
	average[a]	0.5168	0.2763	0.5362
North American Region	2001	0.4905	0.2126	0.4225
	2002	0.5033	0.2212	0.4289
	2003	0.5454	0.2386	0.4197
	2004	0.5917	0.2708	0.4400
	2005	0.6332	0.2863	0.4406
	2006	0.6609	0.2990	0.4407
	2007	0.6801	0.3096	0.4465
	average[a]	0.5845	0.2616	0.4339
Overall sample	2001	0.4676	0.2011	0.4289
	2002	0.4871	0.2205	0.4517
	2003	0.5315	0.2427	0.4449
	2004	0.5651	0.2583	0.4410
	2005	0.5980	0.2730	0.4455
	2006	0.6178	0.2750	0.4328
	2007	0.6271	0.2849	0.4402
	average[*]	0.5593	0.2523	0.4407

*The 'average' represents arithmetic mean

Source: Calculated by this study

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TE value in 2007 represented a small improvement. Conversely, it's TGR showed a trend of diminishing over time, which tells us that the firms' productivities became more and more inefficient, and their technical standards kept decreasing. A possible reason for this is that the R&D capital stock did not generate any substantial growth, and thus affected the firms' technical efficiencies. The European region's TE showed a little change over time, possibly because the R&D capital stock hardly increased between 2001 and 2007, and the number of staff even decreased over this time period. However, the European region's TGR and MTE both showed the trends of increase. The North American region's performance was similar to that of the European region; however, the North American region's TE, MTE, and TGR all showed growth, so the overall technical efficiency and standards improved during the period between 2001 and 2007. This improvement may be attributed to the fact that the input and output had both been growing by a certain amount over time.

In addition, we also used 2003 to divide the research sample into two periods, with a former period (2001 to 2003) and a latter period (2004 to 2007). The reason we also conducted the research analysis in this way was to investigate the possible effects of the Severe Acute Respiratory Syndrome (SARS) outbreak, and the completion of the human Genome Project (HGP) in 2003. When the SARS broke out in China in 2003, it quickly spread to other countries, and the contagion was more serious in a few countries including China, Hong Kong, Taiwan, Canada, and Singapore. As a result of this, firms in the industries related to the preventive medicine, vaccinations, and medical equipment may have benefited. The HGP was a project that made critical breakthroughs in the terms of medical treatment, biotechnology, and medicine. The sequencing of the human genome made it possible for us to develop toward the personalized medical treatment, allowed us to better investigate into genetic diseases, and thus led to a better diagnosis and treatment of those diseases. Consequently, the firms in industries related to preventive medicine, vaccines, and medical equipment may have benefitted. Therefore, we used 2003 as the dividing year to analyze and discuss the development of the biotechnology industry in different countries in these two halves of the research period.

To test whether any differences exist between the estimated average TGR and MTE values of the three continental regions, we conducted a non-parametric Mann-Whitney *U*-test. The purpose of this test is to compare the mean difference between two populations with the same variance, or to compare the differences between two samples.

From Table 3 we can see that between the years 2001 and 2007, all three regions displayed significant differences between their estimated TGR and MTE values. At the 1% significance level, the TGR of the European and North American regions was signifi-

Table 3. *U*-test on the Regional Technical Efficiency and the Technical Gap Ratio

Region	Period	Technical Gap Ratio (TGR)	Metafrontier Technical Efficiency (MTE)	Technical Efficiency (TE)
Asia-Pacific Region	2001–2003 vs. 2004–2007	0.0287	0.0024	0.0223
European Region		−0.1620***	−0.0637***	0.0437
North American Region		−0.1235***	−0.0663***	−0.0181
Asia-Pacific Region vs. European Region	2001–2003	0.0895**	−0.0677**	
	2004–2007	−0.1012***	−0.1339***	
	2001–2007	−0.0339***	−0.1096***	
Asia-Pacific Region vs. North American Region	2001–2003	−0.0091	−0.0559**	
	2004–2007	−0.1643***	−0.1246***	
	2001–2007	−0.1016***	−0.0949***	
European Region vs. North American Region	2001–2003	−0.0987***	0.0118	
	2004–2007	−0.0631***	0.0093	
	2001–2007	−0.0677***	0.0147*	

*, **, *** denotes 10%, 5%, 1% significance level respectively

Source: Computed by this study

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cantly higher than that of the Asia-Pacific region, and the European region's TGR was also significantly higher than that of the North American region. In the terms of the MTE, there was a 5% level of significance between the European and the Asia-Pacific regions, and a 10% level of significance between the European and North American regions. A 1% level of significance was observed between the Asia-Pacific and European regions, and between the Asia-Pacific and North American regions. These outcomes show that the European region's TGR and MTE values were significantly different from those of the North American and Asia-Pacific regions, despite the different levels of significance.

During the former period (2001 to 2003), the Asia-Pacific region's TGR value was higher than that of the European region at the 5% significance level; however, its MTE value was significantly lower than those of the European region and the North American region. During the latter period of the analysis (2004 to 2007), the Asia-Pacific region's TGR and MTE values were both lower than those of the European and North American regions at the 1% significance level. In comparison, the North American region's TGR values in both halves of the research period were significantly higher than those of Europe. During the former period, the active investment and input in the Asia-Pacific region had probably contributed toward the outperformance of its biotechnology industry over that of Europe, but its input and output levels in the latter period fell behind those of Europe; subsequently, its technical efficiency improvement rates also fell behind. Looking at the periods, both the European and North American regions' TGR and MTE values show significant differences at the 1% level which means that both regions demonstrated improvement.

Analysis of productivity estimation

Table 4 shows the estimations of productivity. The overall results show that the gMMPI first decreased, then later increased, with an average change in value of 1.3254. A large proportion of this change was due to the change in the TEC, which means the change in productivity was mainly due to the change in the TEC (by 20.64%). The next largest change was by 10.30% in the SEC, and then in the PTCU by an average of 8.78%.

In the terms of changes in efficiency in each region, the Asia-Pacific region had an average growth rate of 17.94%, largely due to the 24.12% change in the TEC. This is the biggest change of all three regions. The least influential change was the change in SEC, which actually decreased year on year, with an average decrease of 9.64%. The change in the TC also showed a diminishing trend, though the decrease was not as great as the SEC, but only decreased by an average of 6.03%. In the European region, the average growth reached 19.94%, and the main driver behind the improvement in productivity also came from the change in the TEC. The TEC increased by an average of 14.71%, and a more robust growth was seen between 2006 and 2007. However, the SEC only grew by an average of 1.77%, and the TC showed a diminishing trend, with an average decrease of 11.31%; however, the trend of diminishment also slowed over time. The North American region showed the highest growth out of the three regions, growing by 38.28%. Like in the European region, its improvement in productivity came mainly from increases in the TEC, which were increased by an average of 21.59%, the second highest rate of all. The average change of the North American region in the TC showed a diminishing trend, with an average decrease of 9.58%; but its SEC showed a trend of growth, with an average annual growth of 15.71%.

The pure technological catch-up (PTCU) measures the ratio of the intertemporal change in the TGR between the time period t and $t + 1$. If the value is larger than 1, then the TGR intertemporal change is regarded as large, and it means that the current technical production standards are catching up to the potential standards (Chen and Yang 2008). We can see from Table 4 that the entire sample's average PTCU was 1.0878, which means that the catch-up exists. Though the growth rates began to slow after 2005, there was still an average growth of 8.78%. The European region showed the fastest catch-up rate with the 1.1219 average PTCU value, which means that there was 12.09% growth; but after 2005, the growth rate began to slow down. The growth rate demonstrated by the Asia-Pacific region began to slow after 2004, but its average PTCU value was 1.0355, which means that it still achieved a 3.55% growth, and that it demonstrates the potential for growth in terms of technology development. The North American region's average PTCU value was 1.0878, so it showed 8.78% growth; but just as in the Asia-Pacific and European regions, the growth rate in the North American region also slowed down in the latter period.

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Moreover, the potential technological relative change (PTRC) measures the rate of the potential improvement in technological standards as compared with the existing technological standards. If the ratio of the relative change is larger than 1, it means that the potential technological standards are improving at a faster rate than the existing technological standards; thus, the potential and room for the technological development is expanding and increasing (Chen and Yang 2008). Again, from Table 4 we can see that the potential technological change of the overall sample increased. The average PTRC value is 1.0204, which indicates an average growth of 2.04%; this growth rate also showed a gradual increase. In terms of the potential technological changes in each region, the Asia-Pacific region showed an average annual change of 1.0651, which means an average growth of 6.51%; and this growth rate showed a gradual increase. Though the growth rate of the European region slowed over time, its average value was 1.0487, resulting in an average growth of 4.87%; on the whole, there is still room for the potential improvement in technology.

Table 4. Estimation and decomposition of productivity

Region/Period		TEC	TC	SEC	PTCU	PTRC	gMMPI
Asia-Pacific Region	2001~02	1.8431	1.0554	0.7940	1.1214	0.9816	1.5526
	2002~03	1.1940	0.9788	0.7826	1.0186	1.0448	0.9388
	2003~04	1.2372	0.9748	0.9705	1.0352	1.0304	1.3023
	2004~05	1.3435	0.9419	1.0333	1.0256	1.0581	1.4222
	2005~06	1.1015	0.9159	0.7654	0.9596	1.0772	0.8539
	2006~07	1.0721	0.8801	1.0322	1.0937	1.1192	1.1838
	average*	**1.2412**	**0.9397**	**0.9136**	**1.0355**	**1.0651**	**1.1794**
European Region	2001~02	1.1817	0.8626	1.4028	1.2347	1.0818	1.5932
	2002~03	0.9820	0.8732	0.9838	1.2901	1.0681	1.1263
	2003~04	1.0306	0.8836	0.9793	1.1261	1.0564	1.0015
	2004~05	1.2424	0.8862	0.8915	1.0947	1.0553	1.0588
	2005~06	0.9696	0.8985	0.9124	1.0590	1.0328	0.9288
	2006~07	1.4300	0.9075	1.0120	0.9917	1.0120	1.5275
	average*	**1.1471**	**0.8869**	**1.0177**	**1.1219**	**1.0487**	**1.1994**
North American Region	2001~02	1.2130	0.9372	1.3911	1.0494	0.9902	1.6977
	2002~03	1.1896	0.9228	1.1886	1.1128	0.9956	1.5003
	2003~04	1.2620	0.9105	1.0904	1.1184	1.0028	1.2479
	2004~05	1.2372	0.8977	0.9830	1.1062	1.0094	1.1354
	2005~06	1.1462	0.8839	1.1705	1.0713	1.0157	1.3197
	2006~07	1.2461	0.8704	1.1332	1.0624	1.0202	1.4195
	average*	**1.2159**	**0.9042**	**1.1571**	**1.0878**	**1.0055**	**1.3828**
Overall sample	2001~02	1.2543	0.9330	1.3489	1.0867	1.0054	1.6689
	2002~03	1.1552	0.9189	1.1227	1.1351	1.0115	1.3940
	2003~04	1.2216	0.9116	1.0617	1.1125	1.0141	1.2119
	2004~05	1.2529	0.9017	0.9728	1.0929	1.0248	1.1608
	2005~06	1.1048	0.8918	1.0566	1.0514	1.0287	1.1704
	2006~07	1.2544	0.8795	1.0923	1.0534	1.0348	1.4025
	average*	**1.2064**	**0.9052**	**1.1030**	**1.0878**	**1.0204**	**1.3254**

*The 'average' represents arithmetic mean

Source: Computed by this study

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The North American region showed a slow but increasing trend in improvement, with both decreases and increases in the growth rate along the way. The average annual change was 1.0055, meaning that the average growth was 0.55%; therefore, on the whole, there is still room for the potential technological improvement in the North American region.

Looking at the entire research period of 2001 to 2007, at the 1% significance level, significant decreases were observed in the TC value between the Asia-Pacific and the European regions, and between the Asia-Pacific and North American regions. Significant differences emerged in the SEC value between the Asia-Pacific region and the North American region, and between the European and the North American regions at the 5% level of significance. All three regions showed significant differences in the PTCU values at the 5% significance level. Finally, significant differences were also discovered in the PTRC values at the 5% significance level between the Asia-Pacific and the North American regions, and between the European and the North American regions.

By analyzing the results of the former period (2001 to 2003) and the latter period (2004 to 2007), we can see that in the former period, the TC values of the Asia-Pacific region were significantly higher than those of the European and North American regions. This demonstrates that during the former period, the Asia-Pacific region's growth in technical standards exceeded the growth of the other two regions. However, in comparison, the Asia-Pacific region's SEC value was far lower than those of the other two regions, its PTCU was much lower than that of Europe, and its PTRC value was significantly lower than those of the other two regions; which suggest that its potential for technological change was not on par with the other two regions. In the latter period, the Asia-Pacific region's TC value was still significantly higher and its PTCU value significantly lower than those of the other two regions; however, its PTRC value was significantly superior to those of the other two regions, and its rate of the technical improvement continued to outperform those of the European and North American regions. This suggests that the firms in the Asia-Pacific region continually gained from the experience and technologies of the firms in the other two regions and learned from them. In the latter period, the Asia-Pacific region's TC value still showed a significant improvement, but the rate of improvement slowed over time; it also demonstrated significant improvements in its SEC and PTRC values. The European region's PTCU, PTRC, and gMMPI values all deteriorated; only its TC value improved. In the North American region, only the PTTRC value showed a significant improvement; other values, including the TC, SEC and gMMPI, all deteriorated significantly.

CONCLUSIONS

After the United States initiated the commercialization of the biotechnology industry, the industry has since gained a greater recognition in different countries, and those countries have been investing efforts to develop the industry. Likewise, Taiwan has also listed the biotechnology industry as a key industry for development. As different countries continue to develop their biotechnology industries, more attention is being placed on examining the operational efficiencies of biotechnology firms, and thus many studies continue to discuss the efficiencies of biotechnology firms in various countries, and even to conduct the cross-national efficiency comparisons. However, the studies on the biotechnology industry have not been based on the concept of the metafrontier model. This study adapted the model used by Battese et al. (2004) and the research methodology adopted by Chen and Yang (2008) to conduct an analytical study on the biotechnology industries in different countries. Using the new model, we not only analyze the technical efficiencies of different countries, but through the decomposition of the model equations, we are also able to provide explanations for the growth in the biotechnology industry productivity in different countries. The provision of explanations and reasons is currently lacking the related research literature. We compiled and sorted information from the relevant literature, then collected data on 12 countries between the years 2001 and 2007. The countries in the sample are in three regions – the Asia-Pacific, European, and North American region. Using the metafrontier model proposed by Battese et al. (2004), we analyzed the technical efficiencies and the effects of environmental factors. Furthermore, we used the generalized Metafrontier Malmquist Productivity Index (gMMPI) to analyze productivity and to find the causes for the growth in productivity in the different countries, which subsequently improved the efficiency of their respective regions. The conclusions from our research are summarized here.

Firstly, for the results of the metafrontier model analysis, in terms of the effect of environmental factors

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on the overall sample, the GDP, POP, and FA significantly reduced the effect of inefficiency, whereas the IMES significantly increased this effect. In terms of the country characteristics, the GDP and FA in the European region also significantly reduced the effect of inefficiency; however, the result shown by the POP is different from that of the overall sample, possibly because the European region's population distribution differs from those of the other two regions. With regard to the industry and firm characteristics, all three regions displayed different variables that had an insignificant impact; however, the general estimation results concur with the past studies and literature.

The results from the analysis using the metafrontier model show that the overall sample's annual average TGR is 0.5593, with the North American region's TGR being the highest. On the whole, the performance in the technical efficiency was very poor, with the average TE being only 0.4407; the average MTE was also relatively low at only 0.2523, with the European region's MTE being the highest at 0.2763. The three continental regions are completely independent of each other. The Asia-Pacific region did not perform well in any of the indicators of efficiency; its TE, TGR, and MTE values were only 0.3408, 0.4829, and 0.1667, respectively. The North American region's TGR is the best out of the three regions at 0.5845; this figure was significantly higher than those of the European region (0.5168) and the Asia-Pacific region (0.4829). However, the European region's MTE is the best of the three regions, at 0.2763; this region has outperformed the North American region, the most established region in the biotechnology industry. The European region's MTE value is significantly higher than those of the North American region (0.2616) and the Asia-Pacific region (0.1667). The results from the analysis of the different time periods show that apart from the Asia-Pacific region, a significant improvement in performance emerged when dividing the comparison of the European and North American regions into the two time periods of 2001 to 2003 and 2004 to 2007. This demonstrates that these two regions still lead the biotechnology industry.

Secondly, for the gMMPI analysis results, the average change in the gMMPI in our productivity analysis is 32.54%; the majority of this change can be attributed to the change in the TEC (20.64%), which means that the change in productivity is largely due to the changes in the technical efficiency. The second most influential factor in the change of productivity is the SEC, which showed an average change of 10.30%. Finally, the TC deteriorated by an average of 9.48%. Results of the individual regions show that the North American region's efficiency results are consistent with those of the overall sample, where the best performing efficiency indicator was the TEC, followed by the SEC. For the European region, the best performing efficiency indicator was the TEC followed by the PTCU; finally, for the Asia-Pacific region, the best performing efficiency indicator was the TEC followed by the PTRC. With regard to the rate and speed of the change in the PTCU and PTRC, the results showed that the overall PTCU (by 2.04%) displayed a catch-up trend (by 8.78%); indicating as time went on, the technical gap was reduced. The results on the PTRC showed that the potential for the technological change exceeded the existing technical standards; thus, the technical standards consistently improved.

The analysis of productivity during different periods showed that comparing the former period (2001 to 2003) to the latter period (2004 to 2007), the European region only showed significant improvements in the TC, the Asia-Pacific region showed significant improvements in both the SEC and PTRC, and the North American region showed improvement in the PTRC. During the research period (2001 to 2007), a number of significant incidents and projects took place, including the HGP, the SARS, and an outbreak of avian influenza. Though during this period an array of vaccines, medicines, and medical products were formally launched, the majority still remained at the research and development stage, and could not yet be commercialized. Firms could only apply the existing technologies in the production and research to increase and expand the utilization. There is also a lag between the inputs to research and the respective results on output (Hashimoto and Haneda 2008); these are possible reasons for the situations described above.

With the rapid development of the biotechnology industry around the world, each region and country has developed its own characteristics. This comparative study focused on different regions. In the future, a comparison can be made between countries in their respective continents, or between two countries in proximity. This way, the results can serve as an information to help understanding the situation and status within each country, and thus to help the individual firms making the productivity related decisions, and to the help governments to amend and adjust the relevant policies and measures. The sample for this research included data up until 2007. However, the biotechnology industry has been developing at an

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ever faster rate; therefore, it is recommended that the future studies expand the period of the research sample to obtain more results.

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