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Financial crisis and the relative productivity dynamics of the biotechnology industry: Evidence from the Asia-Pacific countries

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Abstract: The dynamics of the corporate-level performance growth can reflect the pattern of the firms' reaction at the financial crisis moment. We employed the generalized metafrontier Malmquist productivity index to measure the impact of the financial crisis on the productivity of the biotechnology industry by using 68 biotechnology firms in the Asia-Pacific countries during 2001–2009. The empirical results showed that the financial crisis did not significantly impact productivity changes in the biotechnology industry in the Asia-Pacific region. This was primarily due to the improvements in efficiencies of scale and factor inputs reducing the overall impact. We observed a significant decreasing trend for technical changes in developed countries after the financial crisis. Therefore, how corporations enhance their technical innovation ability is relatively critical. The technological catch-up, the potential technological relative change, and the change in technical efficiency in less-developed countries were poor after the financial crisis. This suggests that less-developed countries should improve their technical and efficiency levels to enhance productivity.

Keywords: Asia-Pacific, biotechnology, catch-up, generalized metafrontier Malmquist productivity index

The 2007 US subprime crisis, prompted by the excess financial derivative products in the market and a high financial leverage, resulted in a crisis that damaged the global economy. Companies have substantially reduced their investments in the aftermath of the crisis, such as research and development (R&D) spending, logistics costs, and administrative expenditures. However, the dynamics of the corporate-level performance growth can reflect the pattern of the firms' reaction at the financial crisis moment (Rhee and Pyo 2010). The R&D investment has been considered a crucial ingredient in developing the productivity growth and new competitive advantages (Gupta et al. 2007). Mckinsey's 2010 survey comprising 532 industry executives worldwide revealed that 40% of the companies increased R&D budgets and activity levels at the time of the financial crisis (Barrett et al. 2010). This survey identified that the R&D moves made by businesses during the downturn in the economic cycle would serve them well in coming years.

The biotechnology industry invests heavily in the R&D to consistently gain the market share (Gupta et al. 2007; Pedroso and Nakano 2009). R&D spending in the UK biotechnology and pharmaceutical industries amounted to US$7.39 billion, accounting for more than 25% of the country's total R&D spending for 2007 (Development Centre for Biotechnology 2008). According to a report by Ernst & Young (2013), biotechnology R&D spending continued to rise in 2008 (Table 1). The *Yearbook of the Biotechnology Industry* analysed the revenue and operating figures of every listed biotechnology firm worldwide during 2007 and

Table 1. Global Biotechnology R&D expenditures in the business sector (US$ billions)

Year	2006	2007	2008	2009	2010	2011	2012
Revenues	78.3	80.3	89.6	78.3	84.6	83.1	89.8
R&D expense	29.9	26.9	31.7	22.3	22.8	24	25.3
Net income loss	7.4	–3.1	–1.4	3.6	4.7	3.8	5.2
Public companies	743	815	776	622	622	610	598

Data sources: Ernst & Young (2013)

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2008 (Development Centre for Biotechnology 2009). The analysis results showed that the revenue and R&D spending in 2008 increased by 12% and 18%, respectively, compared with that in 2007. Despite large investments that the pharmaceutical companies made in R&D, only 2–3% of the R&D projects end up as commercial products (Pedroso and Nakano 2009).

In the recent years, the biotechnology industry has expanded rapidly in not only Europe and America but also the Asia-Pacific region, particularly in countries such as Australia, China, India, Japan, and the Republic of Korea (Jongsthapongpanth and Bagchi-Sen 2007; Development Centre for Biotechnology 2010). This shows the changes in the distribution of the biotechnology industry; the global biotechnology market is no longer dominated by firms in the Western countries. Huang et al. (2004) and Carey and Bamforth (2005) have suggested that increased development and R&D efforts by the biotechnology industry in various Asia-Pacific countries have resulted in the development of the industry as a whole on a regional level. In addition, governments in Asia have played a critical role in the biotechnology development strategies and inter-firm relationships. Watkinson (2008) explained that tax incentives provided by the Australian government on the R&D spending of organizations have encouraged many domestic and overseas organizations to invest in the R&D in Australia. China has designated the biotechnology industry as one of seven pillar industries in its 12th Five Year Plan (APCO Worldwide 2010). Moon and Jeon (2009) illustrated that, through the Korean government's plan initiated in 2007, the country aims to expand its biotechnology industry to a scale worth US$60 billion by 2016.

Asian countries tend to have a large variance relative to the mean across almost all infrastructure, population, culture, and talent indices. To solve the heterogeneous problem, this study employed the generalized metafrontier Malmquist productivity index (gMMPI) to analyse the impact of the financial crisis on the productivity of the biotechnology industry. We used biotechnology firms in five Asia-Pacific countries (Australia, China, Japan, the Republic of Korea, and Taiwan) as subjects for the sample and obtained data and figures between 2001 and 2009. We categorized the subjects according to their gross domestic product (GDP) figures into either a high-income group or a medium- and low-income group. Next, we used the productivity index to analyse the data and obtain empirical results, which we then used as a basis for discussion.

LITERATURE REVIEW

Research conducted on the performance of biotechnology firms is scant (Färe et al. 1995; Löthgren and Tambour 1999; Danzon et al. 2005; Rothaermel and Thursby 2007; Sheng et al. 2012). Studies on the performance in the biotechnology industry can be categorized as adopting either data envelopment analysis (DEA) or the stochastic frontier approach (Table 2). Using the DEA and the Malmquist model, Chen et al. (2005) estimated the performance of Taiwan's biotech industry during 1998–2001. The DEA results revealed that the proportion of biotech firms with inefficient returns to scale rose during the study period. The Mamlquist models showed that the chemical- and food-related firms had lower technical efficiency levels than the others. Saranga (2007) performed the DEA and the multiple objective DEA to measure efficiency in the Indian pharmaceutical industry and determined that R&D investment had a positive impact on its performance.

Lu et al. (2015) applied the gMMPI to measure productivity growth in 356 biotech enterprises spanning 12 countries and observed that the productivity growth in the biotech industry was driven by changes in technical efficiency. They also indicated that firm age, population density, and GDP mitigated the effect of inefficiency, whereas the average number of labourers employed by all firms significantly increased this effect. Using 10 years of data on 10 Japanese pharmaceutical companies, Hashimoto and Haneda (2008) applied the Malmquist productivity index (MPI) and the DEA to analyse the R&D efficiency. They found that the R&D expenditures could not result in competitiveness. González and Gascón (2004) indicated that productivity growth in Spanish pharmaceutical laboratories could be explained by the scale of technology change (TC) and pure technical efficiency change (TEC). Wang et al. (2011) suggested that competitive advantages of firms are mainly due to their intellectual capital.

As shown in Table 2, previous studies on the performance in the biotechnology industry have seldom investigated the effect of environmental variables. The ability of management to transform input to output may be affected by several determinants (Lin et al. 2013). Examples of external and internal environmental variables include the firm-characteristic, the industry-characteristic, and the country-characteristic variables (Lu et al. 2015). Fried et al. (1999) also indicated that regulation, location, labour relations, and ownership have an impact on this ability.

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Table 2. Studies of biotechnology industry performance

Author	Data (Year)	Activity	Model	Functional form	Measures	Objective	Environmental variables
González and Gascón (2004)	80 Spain P.L. (1994–2000)	Operating costs	MPI	N/A	Productivity	Influence of firm size in R&D investments	N/A
Chen et al. (2005)	31 Taiwan B.E (1998–2001)	Assets, R&D expenses, and employees	DEA MI	N/A	Efficiency	The efficiency analysis of Taiwan's biotech firms	N/A
Saranga (2007)	44 India B.E. (1992–2002)	Operating costs	DEA	N/A	Efficiency	Influence of R&D investments	N/A
Hashimoto and Haneda (2008)	10 Japan P.F. (1983–1992)	R&D expenditure	DEA MI	N/A	Efficiency Catch-up Frontier shift	The change in R&D efficiency	N/A
Liang et al. (2008)	17 Taiwan B.E (N/A).	Assets, R&D expenses, and employees	DEA	N/A	Efficiency	The effect of integrative strategies	N/A
Wang et al. (2011)	12 mix B.E. (2005–2008)	R&D expenditure Intellectual capital	GRA DEA-MPI	N/A	Rank ordinal Productivity	The impact of intellectual capital	N/A
Lu et al. (2014)	43 Taiwan B.E. (2006–2008)	Assets, R&D expenses, and employees	DDF	N/A	Efficiency	Technological heterogeneity	N/A
Lu et al. (2015)	356 Asian B.E. (2001–2007)	Assets, R&D expenses, and employees	gMMPI	Translog	Efficiency Productivity	Evolution of productivity and its decomposition	The characteristic form country, industry, and firm

B.E. = Biotechnology Enterprise; P.F. = Pharmaceutical Firm; P.L. = Pharmaceutical Laboratories; DEA = Data Envelopment Analysis; gMMPI = Generalized Metafrontier Malmquist Productivity Index; DDF = Directional Distance Function; MI= Malmquist Index; GRA = Grey Relational Analysis; N/A: Non-Available

Regarding financial disruption, the outlook and prospect in capital investment are generally affected by the macroeconomic fluctuations (Isik and Hassan 2003). System-wide financial problems represent an unexplored negative shock for firms (Duchin et al. 2010). Isik and Hassan (2003) employed the Malmquist index to explore the effect of the financial crisis on bank productivity in Turkey during 1992–1996 and revealed a substantial productivity loss. In addition to the financial sector, the financial crisis had an impact on productivity and efficiency in the health, hospitality, and service industries (Meng and Jia 2011; Lu 2015; Samut and Cafrı 2015). Curi and Lozano-Vivas (2015) suggested that the financial sector responded to the financial crisis mainly through the pure efficiency change and technological change in terms of innovation. Tsai and Wang (2004) indicated that the Asian financial crisis had a severe impact on the rate of return of R&D investments in Taiwan between 1997 and 1999. Moreover, Cao et al. (2015) suggested that, during the financial crisis, certain firms exhibited an anti-crisis capability based on their characteristics.

GENERALIZED METAFRONTIER MALMQUIST PRODUCTIVITY INDEX

We provide an explanation of the productivity index model proposed by Chen and Yang (2008) and Lu et al. (2015). First, $P_t^k(x) = \{y_t^k \text{ is obtainable from } x_t^k\}$, where $P_t^k(x)$ is the restricted technology set and the k_{th} group refers to the group frontier. By defining the production function of the production set and group frontier, we can calculate the optimal technical efficiency of an individual firm, whose technical efficiency cannot exceed that of the group it belongs to. Furthermore, by assuming a fixed input, we can establish the optimal technical boundary for the subjects' productivity levels. The distance function can be expressed as Equation (1):

$$D_t^k\left(x_t^k, y_t^k\right) = \inf_{\delta}\left\{\delta > 0 : \left(\frac{y_t^k}{\delta}\right) \in P_t^k\left(x_t^k\right)\right\} \quad (1)$$

According to the recommendations of Färe et al. (1994) for constructing a model of geometric mean comprising the inter-temporal productivity for periods t and $t + 1$ (Caves et al. 1982a, b), we can use Equation (2) to obtain an estimation of the TEC and TC:

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$$MPI_{t,t+1}^{k}\left(x_t, y_t, x_{t+1}, y_{t+1}\right) = \frac{D_{t+1}^{k}\left(x_{t+1}, y_{t+1}\right)}{D_t^{k}\left(x_t, y_t\right)} \times \left[\frac{D_t^{k}\left(x_{t+1}, y_{t+1}\right)}{D_{t+1}^{k}\left(x_{t+1}, y_{t+1}\right)} \times \frac{D_t^{k}\left(x_t, y_t\right)}{D_{t+1}^{k}\left(x_t, y_t\right)}\right]^{0.5} \quad 2)$$

Considering the MMPI analysis proposed by Rao (2006), we can modify Equation (2) and express it as an equivalent formula by using the metafrontier approach; the modified equation is expressed as Equation (3).

The first term on the right-hand side of this equation is the TEC*, which expresses the intertemporal ratio of a firm's productivity level to the distance function of the metafrontier productivity level. The second term on the right-hand side of the equation is the TC*, which expresses the geometric mean of the input–output combinations across different periods. By rearranging Equation (3), we can form the formula for estimating inter-temporal changes in the technology gap ratio (TGR). Rao (2006) called the reciprocal of this "catch-up," which is expressed as Equation (4):

Chen and Yang (2008) considered that the third term on the right-hand side of Equation (4) lacked clarity and therefore rewrote the equation, expressing it as shown in Equation (5). The rewritten equation has incorporated a technology adjustment factor (TAF), which can also be called the "catch-up" (Rao 2006; O'Donnell et al. 2008) and is more effective for converting the group frontier technical standard into the metafrontier technical standard (Equation 5).

The TAF can be expressed as Equation (6).

In Equation (6), the first term on the right-hand side is the "pure technological catch-up" (PTCU), which is the ratio of the change in the TGR derived from dividing the input and output values into periods $t + 1$ and t. Therefore, this term implies a contraction in the technology gap. The second term on the right-hand side is the "potential technological relative change" (PTRC). This term connotes the rate of improvement in the technical standards when the ratio is either higher or lower than 1; it denotes that a firm's rate of improvement in technical standards is better or worse than the current overall technical standard. Using the preceding formula decomposition method, we can express the MMPI as shown in Equation (7):

Neither of the MPI or MMPI formulae consider the scale efficiency change, which is a factor that may affect the analysis result. Chen and Yang (2008) therefore introduced the inter-temporal scale efficiency change into the MMPI model to offer a more comprehensive analytical model. In period t, firms used the input vector $x_t \in \Re_+^N$ to produce the output vector $y_t \in \Re_+^W$. On the basis of the Quadratic Identity Lemma proposed by Diewert (1976), we determine the cross-period change in the distance function of the metafrontier. Rearranging the MMPI into logarithmic form yields (Equation 8):

Indices of the total factor productivity require several conditions including identity, separability, proportionality, and monotonicity; consequently, Equation (8) may not follow the principle of proportionality.

$$MMPI_{t,t+1}^{k}(x_t, y_t, x_{t+1}, y_{t+1}) = \frac{D_{t+1}^{*}(x_{t+1}, y_{t+1})}{D_t^{*}(x_t, y_t)} \times \left[\frac{D_t^{*}(x_{t+1}, y_{t+1})}{D_{t+1}^{*}(x_{t+1}, y_{t+1})} \times \frac{D_t^{*}(x_t, y_t)}{D_{t+1}^{*}(x_t, y_t)}\right]^{0.5} \tag{3}$$

$$MMPI_{t,t+1}^{k}\left(x_t, y_t, x_{t+1}, y_{t+1}\right) = \frac{D_{t+1}^{k}\left(x_{t+1}, y_{t+1}\right)}{D_t^{k}\left(x_t, y_t\right)} \times \left[\frac{D_t^{k}\left(x_{t+1}, y_{t+1}\right)}{D_{t+1}^{k}\left(x_{t+1}, y_{t+1}\right)} \times \frac{D_t^{k}\left(x_t, y_t\right)}{D_{t+1}^{k}\left(x_t, y_t\right)}\right]^{0.5} \times \left[\frac{TGR_{t+1}^{k}\left(x_{t+1}, y_{t+1}\right)}{TGR_t^{k}\left(x_t, y_t\right)} \times \frac{TGR_t^{k}\left(x_{t+1}, y_{t+1}\right)}{TGR_{t+1}^{k}\left(x_t, y_t\right)}\right]^{0.5} \tag{4}$$

$$MMPI_{t,t+1} = TEC_{t,t+1}^{k} \times TC_{t,t+1}^{k} \times TAF_{t,t+1}^{k} \tag{5}$$

$$TAF_{t,t+1}^{k} = \frac{\dfrac{D_{t+1}^{*}(x_{t+1}, y_{t+1})}{D_{t+1}^{k}(x_{t+1}, y_{t+1})}}{\dfrac{D_t^{*}(x_t, y_t)}{D_t^{k}(x_t, y_t)}} \times \left[\frac{\dfrac{D_t^{*}(x_{t+1}, y_{t+1})}{D_{t+1}^{*}(x_{t+1}, y_{t+1})}}{\dfrac{D_t^{k}(x_{t+1}, y_{t+1})}{D_{t+1}^{k}(x_{t+1}, y_{t+1})}} \times \frac{\dfrac{D_t^{*}(x_t, y_t)}{D_{t+1}^{*}(x_t, y_t)}}{\dfrac{D_t^{k}(x_t, y_t)}{D_{t+1}^{k}(x_t, y_t)}}\right]^{0.5} \tag{6}$$

$$MMPI_{t,t+1} = TEC_{t,t+1}^{k} \times TC_{t,t+1}^{k} \times TAF_{t,t+1}^{k} \times PTCU_{t,t+1}^{k} \times PTRC_{t,t+1}^{k} \tag{7}$$

$$\ln MMPI_{t,t+1}(y_{t+1}^{w}, y_t^{w}, x_{t+1}^{n}, x_t^{n}) = \left[\ln D_{t+1}^{*}(y_{t+1}^{w}, x_{t+1}^{n}, t) - \ln D_t^{*}(y_t^{w}, x_t^{n}, t)\right] - 0.5 \times \left[\frac{\partial \ln D_{t+1}^{*}(y_{t+1}^{w}, x_{t+1}^{n}, t)}{\partial t} + \frac{\partial \ln D_t^{*}(y_t^{w}, x_t^{n}, t)}{\partial t}\right] \tag{8}$$

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$$
\begin{aligned}
\ln gMMPI_{t,t+1}(y^w_{t+1}, y^w_t, x^n_{t+1}, x^n_t) &= \left[\ln D^*_{t+1}(y^w_{t+1}, x^n_{t+1}, t) - (\ln D^*_t(y^w_t, x^n_t, t)\right] - \\
& 0.5 \times \left[\frac{\partial \ln D^*_{t+1}(y^w_{t+1}, x^n_{t+1}, t)}{\partial t} + \frac{\partial \ln D^*_t(y^w_t, x^n_t, t)}{\partial t}\right] + \\
& 0.5 \times \sum_{n=1}^{N}\left[\frac{(-\sum_{n=1}^{N}\xi^{*n}_{t+1} - 1)\xi^{*n}_{t+1}}{\sum_{n=1}^{N}\xi^{*n}_{t+1}} + \frac{(-\sum_{n=1}^{N}\xi^{*n}_{t} - 1)\xi^{*n}_{t}}{\sum_{n=1}^{N}\xi^{*n}_{t}}\right] \times \left(\ln^n_{t+1} - \ln x^n_t\right) \\
& \xi^{*n}_{t+1} = \frac{\partial \ln D^*_{t+1}(y^w_{t+1}, x^n_{t+1}, t)}{\partial \ln x^n};\ \xi^{*n}_t = \frac{\partial \ln D^*_t(y^l_t, x^n_t, t)}{\partial \ln x^n}
\end{aligned} \tag{9}
$$

$$
gMMPI_{t,t+1} = TEC^*_{t,t+1} \times TC^*_{t,t+1} \times SEC^*_{t,t+1} \tag{10}
$$

$$
\begin{aligned}
\ln gMMPI_{t,t+1}(y^w_{t+1}, y^w_t, x^n_{t+1}, x^n_t) &= \left[\ln D^k_{t+1}(y^w_{t+1}, x^n_{t+1}, t) - (\ln D^k_t(y^w_t, x^n_t, t)\right] - \\
& 0.5 \times \left[\frac{\partial \ln D^k_{t+1}(y^w_{t+1}, x^n_{t+1}, t)}{\partial t} + \frac{\partial \ln D^k_t(y^w_t, x^n_t, t)}{\partial t}\right] + \left[\ln TGR^k_{t+1}\left(y^w_{t+1}, x^n_{t+1}, t\right) - \ln TGR^k_t\left(y^w_{t+1}, x^n_{t+1}, t\right)\right] - \\
& 0.5 \times \left[\left(\frac{\partial \ln D^*_{t+1}(y^w_{t+1}, x^n_{t+1}, t)}{\partial t} + \frac{\partial \ln D^*_t(y^w_t, x^n_t, t)}{\partial t}\right) \Big/ \left(\frac{\partial \ln D^k_{t+1}(y^w_{t+1}, x^n_{t+1}, t)}{\partial t} + \frac{\partial \ln D^k_t(y^w_t, x^n_t, t)}{\partial t}\right)\right] \\
& + 0.5 \times \sum_{n=1}^{N}\left[\frac{(-\sum_{n=1}^{N}\xi^{*n}_{t+1} - 1)\xi^{*n}_{t+1}}{\sum_{n=1}^{N}\xi^{*n}_{t+1}} + \frac{(-\sum_{n=1}^{N}\xi^{*n}_{t} - 1)\xi^{*n}_{t}}{\sum_{n=1}^{N}\xi^{*n}_{t}}\right] \times \left(\ln^n_{t+1} - \ln x^n_t\right)
\end{aligned} \tag{11}
$$

$$
gMMPI_{t,t+1} = TEC^k_{t,t+1} \times TC^k_{t,t+1} \times PTCU^k_{t,t+1} \times PTRC^k_{t,t+1} \times SEC^*_{t,t+1} \tag{12}
$$

By adopting the alternative that was proposed by Orea (2002) and entails using the distance elasticity shares of inputs to replace the distance elasticity of inputs, we can ensure that the weight of the input variables fits the linear first-order condition, which can be expressed as Equation (9):

In the preceding equation, the first term (TEC*) and second term (TC*) on the right-hand side are the metafrontiers TEC and TC, respectively. However, Equation (9) differs from Equation (8) in that the factor of the third term on the right-hand side of Equation (9) is the result of scale elasticity and change in the factor input. Therefore, the firm's increasing or decreasing returns to scale also affect the increase or decrease of its input in period $t + 1$. By multiplying with a natural exponent, we can express the gMMPI as Equation (10):

Using a similar approach to that of Equation (6), we can factor into Equation (9) the ratio of the intertemporal changes in TGR to the level of technical improvement and express it as Equation (11):

Equation (11) can be simplified into the following equation by multiplying with a natural exponent:

From Equation (12), we know that the results from the productivity analysis conducted in this study can be obtained by multiplying the following components: TEC, TC, PTCU, PTRC, and the scale efficiency change (SEC*). Hence, this operation is more sophisticated and more effective than the traditional MPI method.

METHODOLOGY

Data sources

We used the biotechnology industry as the study sample and collected data from the OSIRIS databank. However, the method of classifying and categorizing firms in the biotechnology industry and their definitions differ in every country. For this study, we adopted the classifications of the Industry Classification Benchmark (ICB)[1] to determine if a firm belonged

[1]The Industry Classification Benchmark (ICB) is an industry classification taxonomy developed by Britain's FTSE and the United States' Dow Jones indices.

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to the biotechnology industry. We collected data for 68 biotechnology firms in the Asia-Pacific countries of Australia, China, Japan, the Republic of Korea, and Taiwan. The total number of observations was 612. Regarding group categorization for the analysis purposes, this study adopted the same categorization method used by Iyer et al. (2006) and Chen and Yang (2008). First, we categorized the sample countries into two major groups[2] according to their GDPs; Australia and Japan were defined as developed countries (DCs), and China, South Korea, and Taiwan were defined as less developed countries (LDCs). Our sample comprised of 26 firms from DCs and 42 firms from LDCs. Because we collected data across different periods and noted all monetary values in US dollars, we adopted the 2000 US Producer Price Index[3] to deflate the values year on year, thus converting them into real variable values and ensuring an equal basis for analysing variables across various periods.

Variable constructions

Biotechnology industries are highly technology-oriented and require a specialized, professional R&D staff. We set fixed assets, employees, and the R&D capital stocks as our inputs (Yang and Chen 2002; Chiu et al. 2003; Saranga 2007; Chang et al. 2009; Hu et al. 2010; Huang et al. 2010). We obtained data on fixed assets and employees from firms' profit and loss reports, which note them under their fixed assets and the number of workers employed annually. Nevertheless, we used net sales as our output (Chiu et al. 2003). A firm's R&D achievements and the R&D funding that they receive for the current and lag periods all affect the input variable R&D; if we used only the R&D spending accumulated for one particular year as the input variable for that year, it would not demonstrate the true performance achieved by the R&D spending. Therefore, we adopted the method used by Tsai and Wang (2004) and Yang and Chen (2002), in which the R&D capital stock of a two-period lag[4] was estimated and weighted. Finally, we adopted the most common depreciation rate, which was 15% (Chuang and Hsu 1999; Yang and Chen 2002).

Environmental variables

To minimize discrepancies caused by the different internal and external environmental factors for the biotechnology firms, the industries, and the countries, we adopted environmental variables for our analysis. Considering the different internal and external environmental factors for the biotechnology firms in the Asia-Pacific region, we eventually selected the following input environmental variables: firm age (FA); the number of labourers employed by the first 50% of the firms in the group divided by the average number of labourers employed by all firms (IMES); the industry R&D intensity (IRDI), representing the average annual R&D density of all firms; GDP, representing a country's total value of all factors of production; and the average population density (POP), obtained by dividing the total population of a country by its land area (Dietsch and Lozano-Vivas 2000; Staikouras et al. 2008; Thoraneenitiyan and Avkiran 2009; Yang and Chen 2009). Using these variables, we could identify the factors affecting the inefficiency of the environmental variables. The FA figures were calculated by subtracting the year in which the firms were established from each of the 8 years included in the observation period. The GDP, population, and land area figures were obtained from *The World Factbook* prepared by the Central Intelligence Agency in the United States.

Model specifications

This study employed the commonly used translog function in its analysis. On the basis of the approach used by Battese and Coelli (1995), we set the stochastic frontier production function for the panel data by using Equation (13):

[2]In the Morgan Stanley Capital International Indices (MSCI), Australia and Japan are regarded as developed countries, and China, South Korea, and Taiwan are regarded as emerging and less-developed countries. This categorization demonstrates the difference in the economic environments of these countries.

[3]The August 2010 monthly report of the Directorate-General of Budget, Accounting and Statistics, Executive Yuan, Republic of China, published the wholesale price index (WPI) of every country.

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

This is the formula for estimating R&D capital stock. Here, R_t denotes R&D spending for time period t, g denotes the annual growth in R&D spending, and δ denotes depreciation.

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$$\ln Y_{it} = \alpha_0 + \sum_{j=1}^{3} \alpha_j \ln(x_{jt}) + 0.5 \sum_{j=1}^{3}\sum_{k=1}^{3} \gamma_{jk} \ln(x_{jt}) \ln(x_{kt}) + \varphi_1 t + \varphi_2 t^2 + \sum_{i=1}^{3} \varphi_{1i} t \ln(x_{jt}) + v_{it} - u_{it} \quad (13)$$

where α, γ, and φ are the parameter estimations yet to be determined. Y denotes an output variable, x denotes an input variable, and t denotes the period. U_{it} is the technology inefficiency of production and a nonnegative random variable, which is assumed to be independently distributed and obtained by the half-normal distribution. The formula for U_{it} can be expanded as follows:

$$u_t = \eta_0 + \eta_1 Z_1 + \eta_2 Z_2 + \eta_3 Z_3 + \eta_4 Z_4 + \eta_5 Z_5 + \varepsilon \quad (14)$$

where Z_1 denotes FA, Z_2 denotes IMES, Z_3 denotes IRDI, Z_4 denotes GDP, Z_5 denotes POP, and ε denotes the error term.

Inferring the metafrontier productivity function first necessitates determining the distribution estimate of each sample group by using the stochastic frontier productivity function. The metafrontier production function model can be expressed as (15):

$$\ln Y_{it}^{*} = \alpha_0^{*} + \sum_{j=1}^{3} \alpha_j^{*} \ln(x_{jt}) + 0.5 \sum_{j=1}^{3}\sum_{k=1}^{3} \gamma_{jk}^{*} \ln(x_{jt}) \ln(x_{kt}) + \varphi_1^{*} t + \varphi_2^{*} t^2 + \sum_{i=1}^{3} \varphi_{1i}^{*} t \ln(x_{jt}) \quad (15)$$

We used the linear programming[5] (LP) and quadratic programming (QP) to obtain the metafrontier productivity function's distribution coefficient and used bootstrapping to estimate the standard deviation.

Empirical analysis

Descriptive statistics of sample data

Table 3 displays the descriptive statistics for the input and output changes of the firms from 2001 to 2009. The LDC firms demonstrated net sales of US$23.41 million, higher than the US$18.06 million in net sales of the DC firms. Ostensibly, the LDC firms demonstrated higher performance than did the DC firms. However, examining the ratio of net sales to the number of labourers determined that the net sales produced by each labourer in the DC firms

Table 3. Descriptive statistics on input and output changes

	Unit	Code	DCs	LDCs	t statistics	Overall
Input and output variables						
Net sales	US$ (million)	Net Sales	18.06 (43.55)	23.41 (53.74)	−0.941	21.62 (50.55)
Number of labourer	People	Employees	92.06 (168.85)	170.00 (247.84)	−3.087**	143.87 (227.24)
R&D capital stock	US$ (million)	R&DP	10.85 (19.82)	5.89 (21.31)	2.117*	7.55 (20.93)
Fixed asset	US$ (million)	Fixed Assets	21.93 (46.72)	24.38 (45.12)	−0.476	23.56 (45.61)
Environment variables						
FA	Year	FA	6.28 (4.01)	4.25 (2.38)	5.965***	4.93 (3.17)
IMES	Percentage	IMES	1.87 (0.14)	1.76 (0.06)	10.329***	1.79 (0.11)
IRDI	Percentage	IRDI	1.10 (0.35)	1.02 (1.64)	0.512	1.04 (1.36)
GDP	US$ (thousand)	GDP	33.75 (6.50)	14.18 (5.46)	29.859***	20.74 (10.93)
POP	People/ kilometre	POP	120.96 (160.88)	503.44 (168.96)	−20.456***	375.23 (245.50)

( ) denotes standard deviation

[5] $LP = \min L \equiv \sum_{i=1}^{N}\sum_{t=1}^{T} (X_{it}\beta^{*} - X_{it}\hat{\beta}_{(j)}) \qquad QP = \min L \equiv \sum_{i=1}^{N}\sum_{t=1}^{T} (X_{it}\beta^{*} - X_{it}\hat{\beta}_{(j)})^2$

According to Battese et al. (2004), LP and QP can be calculated using the above two formulae; the result should conform to $\ln f(X_{it}, \beta^{*}) \geq \ln f(X_{it}, \hat{\beta}_{(j)})$.

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was US$0.1962 million, higher than the US$ 0.1377 million in net sales produced by each labourer in the LDC firms. This implies that, although the total productivity of labourers at DC firms was relatively low, their average productivity was actually higher. We observed the opposite for the LDC firms, indicating that the LDC firms tended to operate in a labour-intensive mode. The DCs showed the highest average for their R&D capital stocks at US$10.85 million, nearly double that of the LDCs. This suggests that, compared with other countries, DCs tend to emphasize R&D more and to conduct R&D on a larger scale. The LDC firms showed a higher value of fixed assets (US$24.38 million) than did the DC firms (US$21.93 million). However, the ratio of net sales to fixed assets revealed a reoccurring trend in which DC firms, with less investment in fixed assets, actually produced more net sales than did the LDC firms.

From the environmental variable FA, we observed that the DC firms had been established longer on average than the LDC firms. The DC firms' longer periods of establishment probably reflects that DCs have been investing in their biotechnology industries for a longer period. We found significant discrepancies between the IRDI and IMES values, implying that the first half of the group samples invested more in labour. We categorized the sample countries into two groups by national income so that the DCs displayed substantially higher GDPs than did the LDCs. Finally, the LDCs showed a POP of 503.44, higher than that of the DCs (120.96). This implies that the labour inputs of LDCs were higher than those of DCs.

Parameter estimation

From the parameter estimates of the stochastic frontier production function (Table 4), we observed that only 10 of the 21 parameter estimates were statistically significant; the DCs showed 11 significant values, whereas the LDCs showed seven. Consequently, these independent variables could be used in rationally analysing and determining the output values of the dependent variables. Regarding the estimated pa-

Table 4. Estimation of parameters and standard deviations

Variable	DCs Production function	LDCs Production function	Stochastic frontier production function	LP[a]	QP
Constant	2.036**	–1.018	–0.981	0.544	0.861
$\ln X_1$	0.346	0.485	0.829***	0.790	0.603
$\ln X_2$	1.125***	–0.072	0.535**	0.945***	0.920*
$\ln X_3$	0.659*	0.297	0.452*	0.172	0.334
$(\ln X_1)^2$	–0.205	–0.097	–0.125	–0.218	–0.122
$(\ln X_2)^2$	0.047	–0.066	0.137***	0.234***	0.219***
$(\ln X_3)^2$	0.538***	–0.214*	0.026	0.534***	0.510***
$(\ln X_1)(\ln X_2)$	–0.068	–0.115*	–0.054	–0.120	–0.053
$(\ln X_1)(\ln X_3)$	–0.104	0.146*	–0.025	–0.005	–0.052
$(\ln X_2)(\ln X_3)$	–0.280***	0.203**	0.028	–0.231***	–0.262**
t	–1.340***	–0.021	–0.360**	–0.575***	–0.659*
t^2	0.058	–0.030	0.000	0.040*	0.067*
$(\ln X_1)(t)$	0.304***	0.070*	0.092***	0.152***	0.129*
$(\ln X_2)(t)$	–0.032	–0.012	–0.083***	–0.023	–0.051
$(\ln X_3)(t)$	–0.100**	–0.017	0.006	–0.113***	–0.089
Constant	–0.271	5.512	–80.384	–	–
FA	–0.859***	–0.263	–1.538**	–	–
IMES	–0.528	–8.808	35.588	–	–
IRDI	0.443	0.523*	3.057**	–	–
GDP	0.202***	–1.490*	–0.008	–	–
POP	–0.029***	0.045	–0.023**	–	–
Observations	234	378	612	612	612
Log likelihood function	–165.9375	–343.8083	–549.2042	–	–
Likelihood ratio test 78.917***					

*, **, *** represent 10%, 5% and 1% significance levels, respectively

[a]The standard deviations of LP and QP were estimated using the bootstrapping approach

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rameters of the metafrontier production function, LP and QP showed similar numbers of significant parameters; LP showed seven significant parameters, and QP showed six. We used the log-likelihood ratio (L-LR) test to investigate the null hypothesis that the DCs and LDCs shared the same production frontier (Battese et al. 2004). The statistical value resulting from the L-LR test was 79.917 ($p < 0.01$), suggesting that the DCs and LDCs had different production frontiers (Table 4). The groups' dissimilar stochastic frontiers conformed to the concept of grouping by stochastic frontier; however, each individual group required further analysis to minimize estimation errors engendered by discrepancies in technology standards between the groups.

We identified several facts from observing the overall stochastic frontier production function. We determined a significant positive correlation between the number of labourers and productivity levels. The more employees a firm had, the higher its productivity was. In addition, a significant positive correlation existed between R&D capital stock and the production function; the more a firm invested in R&D, the higher was its productivity. Moreover, we observed a significant positive correlation between the value of fixed assets and the production function; increasing a firm's fixed assets significantly and positively affected its efficiency. Regarding estimated parameters for proving the correlation between time and input, the parameter for fixed assets was not significant; however, the parameters for the remaining inputs were all significant, indicating that changes in time had a strong impact on output.

Multiplying the number of labourers and time produced a positive significance level, indicating that the number of labourers had an increasing positive effect on output. Conversely, multiplying R&D capital stock and time produced a negative significance level. The cause of this adverse trend might be that Asia-Pacific biotechnology firms tend to be smaller in scale, making it relatively more difficult for them to obtain a high technical standard compared with larger firms. The implication is that, over the long term, a larger proportion of the R&D investments of smaller firms generated disproportionate returns, which would explain the adverse trend when multiplying R&D capital stock and time.

We examined the inefficiency effects of the environmental variables, and the results revealed that figures for the overall Asia-Pacific region and the DCs were significantly and negatively correlated with FA figures. This conforms to the findings of Yang and Chen (2009) and implies that, through learning over time, firms can lower their inefficiency effects. The figures for LDCs, as well as those for the overall region, were negatively correlated with the FA figures, although the correlation was not significant. Regarding the IRDI, a positive correlation existed between the inefficient components and the figures of the overall region, the DCs, and the LDCs. Yang and Chen (2009) provided an explanation for this outcome by indicating that high-IRDI industries tend to have higher technical standards that pose tougher entry barriers to external competitors, which in turn make them complacent and less proactive in improving their technical standards. The figures for the overall region and the LDCs were negatively correlated with GDP figures; this result conforms to that of Pasiouras et al. (2009). However, the figures for the DCs were significantly and positively correlated with the GDP, deviating from those for the LDCs and the overall region. This deviation may be engendered by the tendency of firms in higher GDP countries (DCs) to invest more in labourer wages compared with firms in LDCs. Finally, the overall POP figures and the POP figures for the DCs demonstrated a significant negative correlation, signifying that population density had a positive impact on productivity and that higher population density tended to increase efficiency.

Generalized metafrontier Malmquist productivity index

Table 5 provides a breakdown of the gMMPI. The table shows that there was a 2.06 increase on average in the gMMPI annually, except for in 2005 and between 2007 and 2008. The yearly increases were significant. The sharpest drop in the gMMPI (17.79% in 2008) can be attributed to 2008 being the year when the financial tsunami hit; consequently, overall performance was adversely affected. In general, significant increases in the gMMPI were demonstrated by increases in the PTCU (1.39%), TC (3.12%), and TEC (14.95%) figures. Despite a drop of 11.15% in the SEC^*, the overall increase in technical efficiency and technological innovation facilitated maintaining the increasing trend in the gMMPI values. Scale efficiency is a measure that pertains to points at the actual technology frontier. Conditional on the output mix, a point moves along the frontier according to changes in the input quantities. By examining SEC^* more closely, we observed that it was subjected to a

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sharp decline between 2002 and 2008. Firms should reduce their inputs to improve production efficiency. The SEC^*, however, showed an increase of 33.8% in 2009, indicating that, after the height of the financial tsunami, the industry scale facilitated an increase in overall production efficiency by improving input standards at the time. This outcome should therefore contribute to firms' strategy development and input-output planning.

The gMMPI values displayed by the LDC biotechnology firms were the lowest when biotechnology firms in categories of different GDPs were considered. On average, the LDC firms showed a 0.04% drop in annual productivity, with the greatest overall drops occurring from 2004 to 2005 and 2007 to 2008. Moreover, on average, the TEC showed a catch-up range of 15.33%, a drop in TC (6.16%) and SEC^* (6.04%), and insignificant improvements in PTCU and PTRC, meaning that an improvement in the TEC did not denote an overall productivity improvement in the biotechnology industry. However, the large reduction in SEC^* between 2007 and 2008 means that scale efficiency began to decrease gradually. In addition, both the PTCU and PTRC exhibited a decreasing trend during 2007 and 2008, which affected the rate and extent of improvement in technical efficiency. Consequently, the average gMMPI for 2007 and 2008 showed a sharp decline.

Compared with the LDC biotechnology firms, the DC biotechnology firms demonstrated higher increases in their gMMPI values, with an average annual increase of 6.53%. This trend can be attributed to the TC and TEC showing marked rises of 22.91% and 14.13%, respectively. Nevertheless, the SEC^* exhibited a contrasting trend, showing a continuous decreasing trend from 2001 to 2009 with an average annual drop of 22.07%. From this result, we can infer that DC firms had no scale efficiency for a prolonged period; it is therefore more critical

Table 5. Breakdown of the Generalized Metafrontier Malmquist Productivity Index

Group type	PTCU	PTRC	TC_k	TEC_k	SE^{C}⊠	gMMPI
DCs						
2002	1.1620	0.9260	1.1919	1.2807	0.7977	1.3782
2003	1.2138	0.8364	1.4688	1.4120	0.5003	0.9790
2004	1.0405	0.8830	1.3822	0.9586	0.7055	1.1860
2005	0.9247	0.8701	1.3872	1.4081	0.6616	1.0257
2006	0.9493	0.9607	1.1895	0.9662	0.8701	1.1574
2007	0.9023	1.0000	1.1278	1.2027	0.8737	0.9699
2008	1.0220	1.0654	0.9448	0.8859	0.9605	0.9569
2009	1.3363	1.0869	0.9578	0.9971	0.9163	1.1998
Average	**1.0121**	**0.9437**	**1.2291**	**1.1413**	**0.7793**	**1.0653**
LDCs						
2002	1.0703	1.2750	0.8131	1.4045	0.6717	1.2338
2003	1.1550	1.2206	0.8431	2.2465	0.7276	1.0688
2004	1.1149	1.1619	0.8635	1.1513	0.7669	0.9651
2005	1.1069	1.0929	0.8944	1.1426	0.7746	0.9463
2006	1.1053	1.0359	0.9180	1.0417	1.0209	1.2059
2007	0.9809	0.9941	0.9524	1.1814	0.8225	0.9822
2008	0.9925	0.9322	0.9928	0.9788	0.8512	0.7674
2009	0.8274	0.8665	1.0035	1.0182	1.3643	1.0330
Average	**1.0147**	**1.0139**	**0.9384**	**1.1533**	**0.9396**	**0.9996**
Overall						
2002	1.1036	1.1481	0.9509	1.3595	0.7175	1.2863
2003	1.1844	1.0285	1.1560	1.8292	0.6140	1.0239
2004	1.0777	1.0224	1.1228	1.0550	0.7362	1.0756
2005	1.0369	1.0072	1.0839	1.2447	0.7311	0.9769
2006	1.0533	1.0108	1.0085	1.0165	0.9706	1.1897
2007	0.9572	0.9959	1.0054	1.1879	0.8380	0.9784
2008	1.0010	0.9707	0.9789	0.9520	0.8828	0.8221
2009	0.8573	0.8794	1.0008	1.0170	1.3380	1.0428
Average	**1.0139**	**0.9915**	**1.0312**	**1.1495**	**0.8885**	**1.0206**

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for DC firms than for LDC firms to determine how to increase their scale efficiency levels. The TC and TEC figures for DCs during 2008 and 2009 were lower than the average value, thereby confirming that the financial tsunami negatively affected the efforts of DCs to attain efficiency improvements and technological innovation.

The aim of this study was to determine the impact of the financial tsunami on biotechnology firms in the Asia-Pacific region by decomposing and analysing productivity index information. Using 2008 to divide the sample into periods before and after the financial tsunami, we ran nonparametric Mann–Whitney U tests on the two periods. The results (Table 6) showed that the PTCU, PTRC, TC, TEC, and SEC* figures all displayed significant changes, with the SEC* displaying an outcome opposite to those of the other variables. The SEC* was higher from 2008 to 2009 than from 2001 to 2007 by 0.2746. The test also revealed that the SEC* after the financial tsunami was significantly higher than that before the financial tsunami, implying that, after the financial tsunami, Asia-Pacific biotechnology firms were able to increase their production efficiency levels by improving their input standards. The remaining variables tested for the Asia-Pacific region all demonstrated higher performance before the financial tsunami, indicating a difference in impact before and after the financial tsunami in terms of the efficiency of Asia-Pacific firms, technological innovation, and technology catch-up. The trend of the SEC* and those of the other figures offset each other; overall, the gMMPI values showed no significant difference.

The results for the LDC group showed that firms performed higher in PTCU, PTRC, and TEC before the financial tsunami. The results were somewhat different for the DC group, indicating that the GDP affected the impact of the financial tsunami on the biotechnology firms. The results showed that the LDC firms performed higher in TC after the financial tsunami whereas the DC firms performed higher in TC before the financial tsunami, although they performed higher after the financial tsunami in all other areas, including PTRC, PTCU, and SEC*. This implies that the DC firms increased productivity after the financial tsunami because they improved their technological innovation levels.

Comparing the DC and LDC groups showed significant differences in the PTRC, TC, and SEC* figures from 2001 to 2009. The DC firms exhibited a higher TC value than that of the LDC firms, indicating that the DC firms were more competitive regarding technological innovation but less competitive in PTRC and SEC*. To further identify possible differences in the productivity index between the periods before and after the financial tsunami, we broke down the sample periods into 2001–2007 and 2008–2009 periods for analytical purposes. The analytical test identified a unique situation, in which the DC firms performed higher in TC than did the LDC firms from 2001 to 2007 and the LDC firms performed significantly higher in PTCU and PTRC than did the DC firms did. However, this trend reversed after the financial tsunami because the LDC firms began to perform higher in TC than the DC firms did and the DC firms started to perform significantly higher in PTCU and PTRC than the LDC firms did. These differing trends in the two periods demonstrate the impact of the financial tsunami on the GDPs of countries. The LDC firms should have focused on technological innovation before the financial tsunami and should presently focus on increasing technological improvement and technical efficiency. Conversely, the DC firms should have been improving their technical efficiency before the financial tsunami and should presently be improving their ability to achieve technological change.

Table 6. Analysis of the Mann-Whitney U test results

Region	Time period	PTCU	PTRC	TCk	TECk	SEC*	gMMPI
DCs	2001–2007 vs. 2008–2009	−0.0635	−0.1525***	0.3459***	0.2944	−0.2146*	0.0931
LDCs	2001–2007 vs. 2008–2009	0.1652***	0.1807***	−0.0942***	0.2440**	−0.2651	0.1568
Asia-Pacific	2001–2007 vs. 2008–2009	0.1079***	0.0868***	0.0618**	0.2448**	−0.2746**	0.1495
DCs vs. LDCs	2001–2009	−0.0027	−0.0702***	0.2907***	−0.0120	−0.1603**	0.0657
DCs vs. LDCs	2001–2007	−0.0747**	−0.1642***	0.3885***	−0.0474	−0.1027**	0.0254
DCs vs. LDCs	2008–2009	0.1540*	0.1689***	−0.0516*	−0.0978	−0.1531	0.0891

The figures in the first three rows are the differences between the average values for periods 2001~2007 and 2008~2009. A positive number means that the average value of period 2001~2007 is bigger than that of period 2008~2009, a negative number means the opposite. The figures in the bottom three rows are the differences between the average values of DCs and LDCs in the given time period.

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CONCLUSION

In recent years, Asia-Pacific countries have been paying increasing attention to their biotechnology industries, and biotechnology has been increasingly applied to products for everyday living. Because of discrepancies between the internal and external environmental factors encountered by biotechnology firms, this study adopted the gMMPI approach to analyse changes in productivity while minimizing estimation errors.

By decomposing and analysing the gimp figures, we could understand changes in productivity among Asia-Pacific biotechnology firms. Overall, the 2008 financial tsunami had a strong impact on their PTCU, PTRC, TC, and TE levels. Although the results of our analytical tests show that firms performed higher before the financial tsunami in these areas, we could not identify significant differences between the gMMPI figures. This may result from the increase in SEC* after the financial tsunami, particularly during 2008–2009. This increase in SEC* subsequently prompted an increase in the gMMPI, which closed the gap between the gMMPI values before and after the financial tsunami. This finding agrees with that presented in the *2010 White Book* by the Biotechnology and Pharmaceutical Industries Program Office of the Taiwan Ministry of Economic Affairs. These congruent findings consider that the impact of the financial tsunami was less evident in the biotechnology industry compared with other industries and that the biotechnology industry began to recover from the second half of 2009. Consequently, the crisis did not significantly affect the change in gMMPI values for biotechnology firms in the Asia-Pacific region.

By carefully inspecting the SEC* test outcomes, we determined implications for different levels of management. SEC* is largely affected by scale elasticity and factor inputs. Through a *t* test, we determined that the number of labourers and the amount of investment on R&D capital stock were considerably great before the financial tsunami and that the average SEC* also began to steadily increase. Therefore, the increase in scale elasticity and factor input engendered an increase in the organizational scale of biotechnology firms after the financial tsunami.

A comparative analysis of the performance levels of DC and LDC firms shows that the LDC figures had a significant impact in terms of the PTCU, PTRC, and TEC areas and that the LDC firms performed higher before the financial tsunami. Conversely, the DC firms performed higher in these areas after the financial tsunami. Therefore, we recommend that, since the financial tsunami, LDC firms should be focusing on increasing efficiency to minimize the impact of the financial tsunami. Because the biotechnology industry continues to expand in LDCs, LDC firms would benefit most from improving their operational efficiency levels and from acquiring and "catching up" on technologies. However, we observed how technological innovation in DC firms deteriorated because of the financial crisis. Therefore, we recommend that DC firms invest more in their R&D to improve their technical standards. We believe that this can benefit firms the most in countries that lead in technology and where technical skills can generate a highly profitable income through technology transfers and patent transactions; therefore, R&D achievements are crucial for improving their overall productivity.

Whether in the DC or LDC group, the SEC* performance of all biotechnology firms showed a gradual decreasing trend over the long term. This is consistent with the finding ofHung, Lu, and Wang (2010), who reported a change in productivity in East Asian countries between 1985 and 2003. Their analysis showed that the scale elasticity was only 0.7933 on average, indicating that many countries in Asia Pacific have been experiencing diminishing scale efficiency levels. The alternative is for them to reduce the level of their input standard and thereby increase their production efficiency levels, which would in turn improve their overall productivity scale efficiency. We therefore suggest that Asia-Pacific countries emphasize vocational training more, thus increasing their labour forces and productivity levels. Firms should update equipment and improve resource utilization to increase their efficiency levels and generate a positive effect on scale efficiency.

The data for this study were collected from the OSIRIS databank. We could not collect data on biotechnology firms in other Asia-Pacific countries such as Singapore and India. We anticipate that data on the biotechnology industries in these countries will become available in the future; hence, more comprehensive analytical results can be presented upon their availability. Regarding grouping by stochastic frontiers, this study concentrated on analysing the selected topics rather than on solving the frontier problems of technology groups. Comparing our method with the grouping methods adopted by previous studies and using the likelihood ratio test enabled us to ensure

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that the concept of grouping by metafrontier was acceptable for our study. We expect to improve the methodology for clustering technologies in future research and to further promote the concept and applications of grouping by metafrontier.

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