Revista Argentina de Clínica Psicológica
2020, Vol. XXIX, N°4, 53-66
DOI: 10.24205/03276716.2020.806

Analyzing Total Factor Productivity of Biotech Firms in the light of FDI Activities in Taiwan: An Application of Hyperbolic Distance Function

Fengsheng Chien[1], Yang Li [2, 3, 4, *], Wei-Song Liu[3] and I-Chien Tsai [5]

Abstract

Conventional Malmquist total factor productivity (TFP) index assumes all decision-making units (DMUs) operating at the optimal scale, while the actual technology employed may not be at constant returns to scale (CRS). In addition, based on variable returns to scale (VRS) the Malmquist TFP index may encounter the problem of infeasibility and. Furthermore, it can only consider either the output expansion or input contraction, but not both. This study employs the hyperbolic distance function, simultaneously expanding outputs and contracting inputs proportionally, to decompose the TFP index of biotechnology firms, which helps overcome the problem of infeasibility. Using data from Taiwan Economic Journal consists of 58 biotechnology firms from 2008 to 2014, empirical results show that the biotechnology firms' TFP has increased over time, mainly due to technological progress and scale efficiency improvement, while technical efficiency change has not been a crucial factor. In addition, 16% of observations face the problem of infeasibility after employing the output distance function to construct the Malmquist TFP index under VRS. We also investigate whether foreign direct investment (FDI) activities influence TFP of Taiwan's biotechnology firms and find that firms with FDI exhibit larger technological change than those without FDI, while the opposite is true for the scale efficiency. We conclude that FDI activities could upgrade the technology of Taiwan's biotechnology firms. We discuss the policy implications of the findings.

Keywords: Biotechnology firms; hyperbolic distance function; total factor productivity; variable returns to scale.

1. Introduction

After completion of the human genome project (HGP) in 2003, biotechnology went into a "post-genome era," with the industry advancing rapidly in its ability to develop new medicines, diagnostic methods, and agricultural products. .

1. School of Finance and Accounting, Fuzhou University of International Studies and Trade, China.
2. Department of International Economics and Trade, School of Economics, Tianjin University of Commerce, China.
3. New Huadu Business School, Minjiang University, China.
4. Research Center of Efficiency and Productivity, Fujian College's Research Base of Humanities and Social Science, Fujian, China.
5. Institute of Business and Management, National Chiao Tung University, Taiwan.
**Corresponding Author: Yang Li*
Email: isu.yangli@nbs.edu.cn

As more new products are brought to market over the next several years, the sector is expected to experience significant growth in revenues. Indeed, many countries have markedly different approaches to carving out a niche in the biotechnology arena, and rapid advances in both the science and commercialization of biotechnology over the past decades have attracted considerable academic research attention. Many studies tried to evaluate how biotech firms use inputs to produce output efficiently and effectively. However, output and input distance functions are commonly used to construct an index to measure total factor productivity (TFP), but they can only consider output expansion or input contraction, but not both. Furthermore, they may encounter the problem of infeasibility for variable returns to scale (VRS) technology (Cooper et al., 2007; Lin and Chen, 2018). The objective of this paper is thus to use an appropriate model that allows VRS technology and simultaneously expands outputs and contracting inputs, to assess the productivity of the biotech industry.

Taiwan government has made great efforts to develop its biotech industry and hopes to become a Green 'Silicon Valley' Island (Chew and Mazlyn, 2002). Eight biotechnology-based parks have been approved recently. The Taiwan government's "Challenge 2018" comprehensive six-year (2008-2014) national development plan calls for a "Two Trillion & Twin Stars" industrial goal, in which "Two Trillion" is the combine annual revenue (in NT$) from semiconductor and color imaging industries, and "Twin Stars" denote the two new fields of digital content and biotechnology for Taiwan to enter. These developments have attracted considerable academic research attention (Chew and Mazlyn, 2002; Chen et al., 2005).

The Malmquist TFP index, proposed by Färe et al. (1994), is commonly used to measure TFP change between two periods by evaluating the ratio of the (input or output) distances of each period relative to a common technology. It has been widely applied in finance (Mukherjee et al., 2001; Yuan and Zhang, 2009; Koutsomanoli-Filippaki et al., 2009; Cui, 2015; Bahrini, 2015; Sun, 2020; Li and Liao, 2020; Otaviya and Rani, 2020), environment (Bing et al., 2010; Chang and Hu, 2010; Zhang and Wang, 2015; Jiang, 2016; Liu et al., 2016; Yu et al., 2016; Liu et al., 2016, Cai and Zhou, 2017; Du et al., 2017; Liu et al., 2020), agriculture (Brummer et al., 2002; Machek and Spicka, 2013; Baležentis, 2014; Gaitán-Cremaschi et al., 2016; Sheng et al., 2017; Li et al., 2018; Sheng et al., 2019), regional study (Zhao and Yang, 2011; Li et al., 2015; Sueyoshi et al., 2017; Li et al., 2020; Yu et al., 2020), biotechnology (Chen et al., 2005; Yang et al., 2009; Sheng et al., 2012; Lu et al., 2015; Liu, 2017; Lu et al., 2017) and so on (Odeck, 2000; Pilyavsky and Staat, 2008; Barros et al., 2011; Liu et al., 2017; Wang et al., 2020; Liang et al., 2020). The primary advantage of the Malmquist TFP change index is the ability to deal with multi-outputs and multi-inputs without information of output and input prices. However, it is constructed by output or input distance functions that can only consider output expansion or input contraction, but not both. Furthermore, the Malmquist TFP index assumes that the technology is constant returns to scale (CRS); in other words, each DMU operates at the optimal scale. Realistically, a DMU may perform under increasing or decreasing returns to scale. Nevertheless, output (or input) distance functions, evaluated relative to variable returns to scale (VRS) technology, may suffer from the problem of infeasibility for a mixed-period calculation (Chew and Mazlyn, 2002; Chen et al., 2005; Lim, 2018).

The hyperbolic distance function can simultaneously expand outputs and contract inputs and also overcome the problem of infeasibility to construct the TFP index based on the VRS frontier. Hence, this study employs hyperbolic distance functions, based on the bottoms-up approach proposed by Balk (2001), to construct a TFP index of Taiwan's biotechnology industry. Our methodology can be applied to biotechnology firms in other countries. We also investigate whether FDI activities affect the TFP index of Taiwan's biotechnology industry and its components. Empirical results show that the TFP of Taiwan's biotechnology firms increased by 8.71% during the study period due to technological progress and scale efficiency improvement, while technical efficiency change did not play a vital role. We also find that FDI activity affect technological change and scales efficiency of Taiwan's biotechnology industry.

The rest of the paper is organized as follows. Following this introduction, section 2 describes the methodologies. Section 3 presents data sources and empirical results. Section 4 concludes this paper.

2. Methodology

It is straightforward to measure productivity by using a single input to produce a single output. The measurement of such productivity is simply output y divided by input x. In other words, it measures how many units of output can be produced by one unit of input. The productivity change from period s to period t is then measured by:

$$\frac{y^t / x^t}{y^s / x^s} = \frac{y^t / y^s}{x^t / x^s} . \qquad (1)$$

The right-hand side is interpreted as the ratio of the output quantity index over the input quantity index. The left-hand side is the ratio of period *t* productivity over period *s* productivity. However, there is no natural way for the case of multiple inputs and/or multiple outputs. Assume that a decision making unit (DMU) uses *N* inputs, $\underset{\sim}{x}^j = \left(x_1^j, \ldots, x_N^j\right) \in \Re_+^N$, to produce *M* outputs, $\underset{\sim}{y}^j = \left(y_1^j, \ldots, y_M^j\right) \in \Re_+^M$, at period *j*. Let $\mathrm{H}(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s)$ be a total factor productivity (TFP) index from period *s* to period *t*. This index is required to satisfy the following property (Balk, 2001; Coelli et al., 2005):

$$\mathrm{H}(\alpha \underset{\sim}{x}^S, \beta \underset{\sim}{y}^S, \underset{\sim}{x}^S, \underset{\sim}{y}^S) = \beta / \alpha \quad \text{for all } \alpha, \beta > 0. \tag{2}$$

It implies Equation (2) is homogenous of degree 1 in output vector $\underset{\sim}{y}$ and –1 in input vector $\underset{\sim}{x}$. Note that this property is automatically fulfilled for the case of a single input and a single output.

Output and input distance functions introduced independently by Malmquist (1953) and Shephard (1953), allow us to describe a technology of multiple outputs produced by multiple inputs without specifying a behavior objective, such as profit maximization or cost minimization. The Malmquist TFP index, based on output distance functions (or input distance functions), has been widely used within the non-parametric literature recently to measure productivity change over time. It was introduced by Caves et al. (1982a; 1982b) theoretically, and then Färe et al. (1994) extended it empirically by accounting for the existence of inefficiency in the activities of decision-making units (DMUs). One of the nice features of the Malmquist TFP index is that it can construct TFP by using only multi-output and multi-input quantities without the information of output and input prices. In addition, it permits the decomposition of the TFP change index into a technical change component and an efficiency change component.

The Malmquist TFP index assumes that each DMU operates at the optimal scale. Hence, the output (or input) distance functions are estimated relative to constant returns to scale (CRS) technology. However, a DMU might perform under increasing or decreasing returns to scale. Balk (2001) suggested that the actual technology should be relaxed to be variable returns to scale (VRS) and adopted a bottoms-up approach to construct a TFP index. This approach lists all possible sources of productivity growth and inspects the best way to measure them. The productivity change is then derived by combining these sources. Both the Malmquist TFP index and Balk's TFP index do satisfy the property expressed in Equation (2), but they are constructed by output (or input) distance functions, which can only consider output expansion or input contraction, but not both. Furthermore, output (or input) distance functions, based on VRS technology, may encounter the problem of infeasibility for mixed-period calculation.

The hyperbolic distance function, by simultaneously expanding outputs and contracting inputs, can also illustrate a multi-output and/or multi-input technology without identifying a behavior objective. In addition, it can overcome the problem of infeasibility to construct the TFP index based on the VRS frontier. Hence, this study uses hyperbolic distance functions to construct a TFP index based on the bottoms-up approach of Balk (2001).

Färe et al. (1994) defined the hyperbolic distance function as:

$$D_H(\underset{\sim}{x}, \underset{\sim}{y}) = \inf \left\{ \lambda : (\lambda \underset{\sim}{x}, \ \underset{\sim}{y}/\lambda) \in \mathbf{\Phi} \right\}, \tag{3}$$

where $\mathbf{\Phi} = \left\{(\underset{\sim}{x}, \underset{\sim}{y}) : \underset{\sim}{x} \text{ can produce } \underset{\sim}{y}\right\}$ is the technology set. Equation (3) indicates that $D_H(\underset{\sim}{x}, \underset{\sim}{y})$ expands output vector $\underset{\sim}{y}$ and contracts input vector $\underset{\sim}{x}$ simultaneously. Note that the output (input) distance function expands the output vector (contracts the input vector) radially, while the hyperbolic distance function expands the output vector and contracts the input vector hyperbolically. The value of $D_H(\underset{\sim}{x}, \underset{\sim}{y})$ is between 0 and 1. When $D_H(\underset{\sim}{x}, \underset{\sim}{y}) = 1$, it indicates that the observation $(\underset{\sim}{x}, \underset{\sim}{y})$ is on the frontier and hence technically efficient; otherwise, the observation is inside the frontier and thus technically inefficient. The hyperbolic distance function $D_H(\underset{\sim}{x}, \underset{\sim}{y})$ moves the input-output vector $(\underset{\sim}{x}, \underset{\sim}{y})$ to the frontier at the point $\left(D_H(\underset{\sim}{x}, \underset{\sim}{y})\underset{\sim}{x},\ \underset{\sim}{y}\big/D_H(\underset{\sim}{x}, \underset{\sim}{y})\right)$ along the hyperbolic path. It can be shown that $D_H(\rho\underset{\sim}{x}, \rho^{-1}\underset{\sim}{y}) = \rho^{-1}D_H(\underset{\sim}{x}, \underset{\sim}{y})$ for $\rho > 0$.

In addition, if the technology is CRS, then the output distance function equals the square of the hyperbolic distance function (Färe et al., 1994).[1]

2.1 Technological Change

Technological progress from period *s* to period *t* occurs if, given a certain input (output) vector, a DMU under period *t* technology can produce more (use less) than under period *s* technology. Technological regress is just the reverse. For an arbitrary pair $(\underset{\sim}{x}, \underset{\sim}{y})$, the hyperbolic distance function $D_H^j(\underset{\sim}{x}, \underset{\sim}{y})$, evaluated at period *j* (= *s*, *t*) technology $\mathbf{\Phi}^j$, will shift $(\underset{\sim}{x}, \underset{\sim}{y})$ to the frontier of period *j* at the point $\left(D_H^j(\underset{\sim}{x}, \underset{\sim}{y})\underset{\sim}{x},\ \underset{\sim}{y}\big/D_H^j(\underset{\sim}{x}, \underset{\sim}{y})\right)$ along the hyperbolical path. Accordingly, both vectors $\left(D_H^t(\underset{\sim}{x}, \underset{\sim}{y})\underset{\sim}{x},\ \underset{\sim}{y}\big/D_H^t(\underset{\sim}{x}, \underset{\sim}{y})\right)$ and $\left(D_H^s(\underset{\sim}{x}, \underset{\sim}{y})\underset{\sim}{x},\ \underset{\sim}{y}\big/D_H^s(\underset{\sim}{x}, \underset{\sim}{y})\right)$ will be on the frontiers of period *t* and period *s*, respectively. Hence, there is technological progress if $\underset{\sim}{y}\big/D_H^t(\underset{\sim}{x}, \underset{\sim}{y})$ > $\underset{\sim}{y}\big/D_H^s(\underset{\sim}{x}, \underset{\sim}{y})$ and/or $D_H^t(\underset{\sim}{x}, \underset{\sim}{y})\underset{\sim}{x}$ < $D_H^s(\underset{\sim}{x}, \underset{\sim}{y})\underset{\sim}{x}$. Both imply $D_H^s(\underset{\sim}{x}, \underset{\sim}{y})\big/D_H^t(\underset{\sim}{x}, \underset{\sim}{y}) > 1$. Similarly, technological regress means $D_H^s(\underset{\sim}{x}, \underset{\sim}{y})\big/D_H^t(\underset{\sim}{x}, \underset{\sim}{y}) < 1$. To combine input and output cases concurrently, the hyperbolic- based technological change from period *s* to period *t* is naturally defined as:

$$\mathbf{\Delta T}_H^{s,t}(\underset{\sim}{x}, \underset{\sim}{y}) = \left[D_H^s(\underset{\sim}{x}, \underset{\sim}{y})\big/D_H^t(\underset{\sim}{x}, \underset{\sim}{y})\right]^2. \tag{4}$$

The magnitude of technological change depends on the choice of $(\underset{\sim}{x}, \underset{\sim}{y})$. If $\mathbf{\Delta T}_H^{s,t}(\underset{\sim}{x}^s, \underset{\sim}{y}^s) = \mathbf{\Delta T}_H^{s,t}(\underset{\sim}{x}^t, \underset{\sim}{y}^t)$ for all $(\underset{\sim}{x}^s, \underset{\sim}{y}^s)$ and $(\underset{\sim}{x}^t, \underset{\sim}{y}^t)$, then the technological change is neutral. However, both values $\mathbf{\Delta T}_H^{s,t}(\underset{\sim}{x}^s, \underset{\sim}{y}^s)$ and $\mathbf{\Delta T}_H^{s,t}(\underset{\sim}{x}^t, \underset{\sim}{y}^t)$ are in general different. It is possible that there exist technological regress evaluated at $(\underset{\sim}{x}^s, \underset{\sim}{y}^s)$, $\Delta\mathrm{T}_H^{s,t}(\underset{\sim}{x}^s, \underset{\sim}{y}^s) < 1$, and technological progress evaluated at $(\underset{\sim}{x}^t, \underset{\sim}{y}^t)$, $\Delta\mathrm{T}_H^{s,t}(\underset{\sim}{x}^t, \underset{\sim}{y}^t) > 1$

Any average of these two values could be used to obtain a single measure to evaluate the magnitude of technological change from period *s* to period *t*.

2.2 Technical Efficiency Change

The hyperbolic distance function proportionately magnifies outputs and contracts inputs simultaneously. In other words, it enlarges the observed output vector $\underset{\sim}{y}$ to the potentially expanding output vector $\underset{\sim}{y}\big/D_H(\underset{\sim}{x}, \underset{\sim}{y})$ and reduces the observed input vector $\underset{\sim}{x}$ to the potentially shrinking input vector $D_H(\underset{\sim}{x}, \underset{\sim}{y})\underset{\sim}{x}$ simultaneously. The value of $D_H(\cdot)$, between 0 and 1, equals the ratio of the observed output levels to the potentially expanding output levels, which is analogous to output-oriented technical efficiency. It can also be interpreted as the ratio of potentially shrinking input levels to observed input levels, or similar to input-oriented technical efficiency. To couple output expansion and input contraction simultaneously, we can express the technical efficiency change from period *s* to period *t* as:

[1] Shephard (1970) defined the output distance function as $D_o(\underset{\sim}{x}, \underset{\sim}{y}) = \inf\{\lambda : (\underset{\sim}{x},\ \underset{\sim}{y}/\lambda) \in \mathbf{\Phi}\}$. If the technology is CRS, then $D_o(\underset{\sim}{x}, \underset{\sim}{y})$=$[D_H(\underset{\sim}{x}, \underset{\sim}{y})]^2$.

$$\mathbf{\Delta TE}_H^{s,t}\left(\underset{\sim}{x}^t,\underset{\sim}{y}^t,\underset{\sim}{x}^s,\underset{\sim}{y}^s\right)=\left[D_H^t(\underset{\sim}{x}^t,\underset{\sim}{y}^t)\big/D_H^s(\underset{\sim}{x}^s,\underset{\sim}{y}^s)\right]^2. \tag{5}$$

If the value of $\mathbf{\Delta TE}_H^{s,t}\left(\underset{\sim}{x}^t,\underset{\sim}{y}^t,\underset{\sim}{x}^s,\underset{\sim}{y}^s\right)$ is larger (smaller) than 1, then technical efficiency has improved (deteriorated) from period *s* to period *t*.

2.3 Scale Efficiency Change

Consider an arbitrary point $(\hat{\underset{\sim}{x}},\hat{\underset{\sim}{y}})$. The hyperbolic distance function will move this point to the frontier at $\left(D_H^j(\hat{\underset{\sim}{x}},\hat{\underset{\sim}{y}})\hat{\underset{\sim}{x}},\ \hat{\underset{\sim}{y}}\big/D_H^j(\hat{\underset{\sim}{x}},\hat{\underset{\sim}{y}})\right)$ along the hyperbolical path. All points on the frontier are technically efficient but may not be at the optimal scale. Hence, even though a DMU is technically efficient, it can additionally increase productivity by improving the operating scale along the frontier. Consider now the general scales of $\hat{\underset{\sim}{x}}$ and $\hat{\underset{\sim}{y}}$, say $u\hat{\underset{\sim}{x}}$ and $v\hat{\underset{\sim}{y}}$ for *u*, *v* > 0 and $(u\hat{\underset{\sim}{x}},\ v\hat{\underset{\sim}{y}})\in\mathbf{\Phi}^j$. Their corresponding points on the frontier can be expressed as:

$$\left(D_H^j(u\hat{\underset{\sim}{x}},\ v\hat{\underset{\sim}{y}})u\hat{\underset{\sim}{x}},\ v\hat{\underset{\sim}{y}}\big/D_H^j(u\hat{\underset{\sim}{x}},\ v\hat{\underset{\sim}{y}})\right). \tag{6}$$

Hence, to find a point with the highest returns to scale along the frontier is equivalent to maximize the following ratio:

$$\frac{v\big/D_H^j(u\hat{\underset{\sim}{x}},\ v\hat{\underset{\sim}{y}})}{u\,D_H^j(u\hat{\underset{\sim}{x}},\ v\hat{\underset{\sim}{y}})}=\left[\frac{\sqrt{v}}{\sqrt{u}\,D_H^j(u\hat{\underset{\sim}{x}},\ v\hat{\underset{\sim}{y}})}\right]^2=\left[\frac{1}{D_H^j(\gamma\hat{\underset{\sim}{x}},\ \gamma\hat{\underset{\sim}{y}})}\right]^2, \tag{7}$$

where $\gamma=\sqrt{uv}$. It implies that we look for γ^*, which minimizes $\left[D_H^j(\gamma\hat{\underset{\sim}{x}},\ \gamma\hat{\underset{\sim}{y}})\right]^2$. By construction, we have:

$$\left[D_H^j(\gamma^*\hat{\underset{\sim}{x}},\ \gamma^*\hat{\underset{\sim}{y}})\right]^2\le\left[D_H^j(\hat{\underset{\sim}{x}},\hat{\underset{\sim}{y}})\right]^2. \tag{8}$$

Hence, the hyperbolic scale efficiency for period *j* technology can be defined as:

$$SE_H^j=\frac{\left[\inf_\gamma D_H^j(\gamma\hat{\underset{\sim}{x}},\ \gamma\hat{\underset{\sim}{y}})\right]^2}{\left[D_H^j(\hat{\underset{\sim}{x}},\hat{\underset{\sim}{y}})\right]^2}. \tag{9}$$

According to the definition of the hyperbolic distance function, we obtain:

$$\inf_\gamma D_H^j(\gamma\hat{\underset{\sim}{x}},\ \gamma\hat{\underset{\sim}{y}})=\inf_\gamma\inf\left\{\lambda:\left(\lambda\gamma\hat{\underset{\sim}{x}},\ \gamma\hat{\underset{\sim}{y}}\big/\lambda\right)\in\mathbf{\Phi}^j\right\}. \tag{10}$$

Note that the data can always be enveloped with a VRS model as well as a CRS model. Hence, there exists at least one point on the VRS frontier to satisfy CRS.

We now denote $\mathbf{\Phi}^{*j}$ to be the period *j* CRS technology set, and then $\gamma\mathbf{\Phi}^{*j}=\mathbf{\Phi}^{*j}$ for γ > 0. Therefore, we get:

$$\begin{aligned}\inf_\gamma D_H^j(\gamma\hat{\underset{\sim}{x}},\ \gamma\hat{\underset{\sim}{y}})&=\inf\left\{\lambda:\left(\lambda\hat{\underset{\sim}{x}},\ \hat{\underset{\sim}{y}}\big/\lambda\right)\in\mathbf{\Phi}^{*j}\right\}\\&=D_H^{*j}(\hat{\underset{\sim}{x}},\ \hat{\underset{\sim}{y}})\end{aligned}, \tag{11}$$

where $D_H^{*j}(\hat{\underset{\sim}{x}},\ \hat{\underset{\sim}{y}})$ is the hyperbolic distance function corresponding to the CRS technology. In addition, $D_H^{*j}(\rho\hat{\underset{\sim}{x}},\ \rho^{-1}\hat{\underset{\sim}{y}})=\rho^{-1}D_H^{*j}(\hat{\underset{\sim}{x}},\hat{\underset{\sim}{y}})$ for ρ > 0. Hence, equation (9) can be written as:

$$\left[D_H^{*j}(\hat{\underset{\sim}{x}},\hat{\underset{\sim}{y}})\big/D_H^j(\hat{\underset{\sim}{x}},\hat{\underset{\sim}{y}})\right]^2=\left[D_H^{*j}\left(D_H^j(\hat{\underset{\sim}{x}},\hat{\underset{\sim}{y}})\hat{\underset{\sim}{x}},\ \hat{\underset{\sim}{y}}\big/D_H^j(\hat{\underset{\sim}{x}},\hat{\underset{\sim}{y}})\right)\right]^2. \tag{12}$$

This is the hyperbolic distance of the actual (VRS) frontier point $\left(D_H^j(\hat{\underset{\sim}{x}},\hat{\underset{\sim}{y}})\,\hat{\underset{\sim}{x}},\ \hat{\underset{\sim}{y}}\big/D_H^j(\hat{\underset{\sim}{x}},\hat{\underset{\sim}{y}})\right)$ to the CRS frontier point $\left(D_H^{*j}(\hat{\underset{\sim}{x}},\hat{\underset{\sim}{y}})\,\hat{\underset{\sim}{x}},\ \hat{\underset{\sim}{y}}\big/D_H^{*j}(\hat{\underset{\sim}{x}},\hat{\underset{\sim}{y}})\right)$. Figure 1 shows that the values $D_H^j(\hat{x},\hat{y})$ and $D_H^{*j}(\hat{x},\hat{y})$ are the hyperbolic distances from point *A* to point *B* and from point *A* to point *C*, respectively, while the value $D_H^{*j}(D_H^j(\hat{x},\hat{y})\hat{x},\ \hat{y}/D_H^j(\hat{x},\hat{y}))$ measures the hyperbolic distances from point *B* to point *C*.

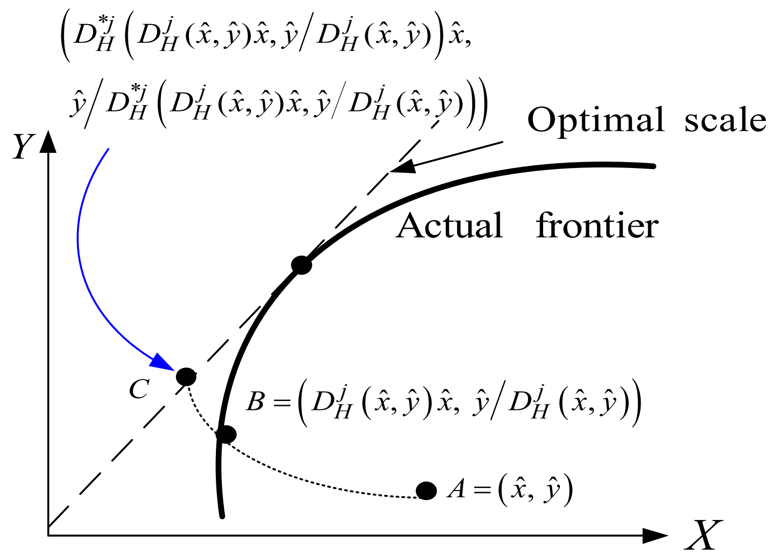

Figure 1 Technical Efficiency and Scale Efficiency

We thus can delineate the scale efficiency change from period *s* to period *t* as:

$$\mathbf{\Delta SE}_H^j\left(\underset{\sim}{x}^t,\underset{\sim}{y}^t,\underset{\sim}{x}^s,\underset{\sim}{y}^s\right)=\frac{\left[D_H^{*j}(\underset{\sim}{x}^t,\underset{\sim}{y}^t)\big/D_H^j(\underset{\sim}{x}^t,\underset{\sim}{y}^t)\right]^2}{\left[D_H^{*j}(\underset{\sim}{x}^s,\underset{\sim}{y}^s)\big/D_H^j(\underset{\sim}{x}^s,\underset{\sim}{y}^s)\right]^2}. \tag{13}$$

If this ratio is larger (less) than 1, then scale efficiency has improved (deteriorated) from period *s* to period *t*. Note that since the numerator and the denominator use the same technology, the scale efficiency change is independent of technological change. Furthermore, it is obvious that if the period *j* technology is CRS, then $\mathbf{\Delta SE}_H^{s,t}(\cdot)=1$.

2.4 Productivity Change

We have so far discussed technological change, technical efficiency change, and scale efficiency change, and it is obvious that these three components comprise independent factors of productivity. Technological progress and technical efficiency improvement imply that a DMU can produce more outputs by using less input quantities. The former indicates that the frontier has shifted, while the latter suggests that the DMU's position relative to the frontier has changed. The promotion of scale efficiency means that the DMU has moved to a better input-output quantity ratio at the frontier. More precisely, if there is no technological change and the DMU operates on the frontier, then the scale efficiency change signifies a movement along the frontier. Hence, we should combine the three components to construct the productivity change index.

Equation (4), (5), and (13) are the technological change index $\mathbf{\Delta T}_H^{s,t}(\underset{\sim}{x},\underset{\sim}{y})$, the technical efficiency change index $\mathbf{\Delta TE}_H^{s,t}\left(\underset{\sim}{x}^t,\underset{\sim}{y}^t,\underset{\sim}{x}^s,\underset{\sim}{y}^s\right)$, and the scale efficiency change index $\mathbf{\Delta SE}_H^j\left(\underset{\sim}{x}^t,\underset{\sim}{y}^t,\underset{\sim}{x}^s,\underset{\sim}{y}^s\right)$, respectively. However, we have not yet specified the input-output vector $(\underset{\sim}{x},\underset{\sim}{y})$ in $\mathbf{\Delta T}_H^{s,t}(\underset{\sim}{x},\underset{\sim}{y})$ and period *j* in $\mathbf{\Delta SE}_H^j\left(\underset{\sim}{x}^t,\underset{\sim}{y}^t,\underset{\sim}{x}^s,\underset{\sim}{y}^s\right)$ and thus consider two alternative ways (or decompositions) to construct movement from period *s* point $(\underset{\sim}{x}^s,\underset{\sim}{y}^s)$ to period *t* point $(\underset{\sim}{x}^t, \underset{\sim}{y}^t)$ in order to identify $(\underset{\sim}{x}, \underset{\sim}{y})$ and period *j*. The first path begins from $(\underset{\sim}{x}^s, \underset{\sim}{y}^s)$ to the actual period *s* frontier point $\left(D_H^s(\underset{\sim}{x}^s, \underset{\sim}{y}^s)\underset{\sim}{x}^s,\ \underset{\sim}{y}^s \big/ D_H^s(\underset{\sim}{x}^s, \underset{\sim}{y}^s)\right)$, corresponding to point *a* in Figure 2. This part is measured by the denominator of the technical efficiency change index $\mathbf{\Delta TE}_H^{s,t}\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right)$. The second portion goes from point *a* at period *s* frontier to point *b* at period *t* frontier, evaluated by the technological change index $\mathbf{\Delta T}_H^{s,t}(\underset{\sim}{x}^s, \underset{\sim}{y}^s)$. The third piece moves along period *t* frontier from point *b* to point *c*, measured by the index of scale efficiency change $\mathbf{\Delta SE}_H^t\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right)$. Finally, we trace the portion from point *c* at period *t* frontier along the corresponding hyperbolic path to point $(\underset{\sim}{x}^t, \underset{\sim}{y}^t)$, as estimated by the numerator of the technical efficiency change index.

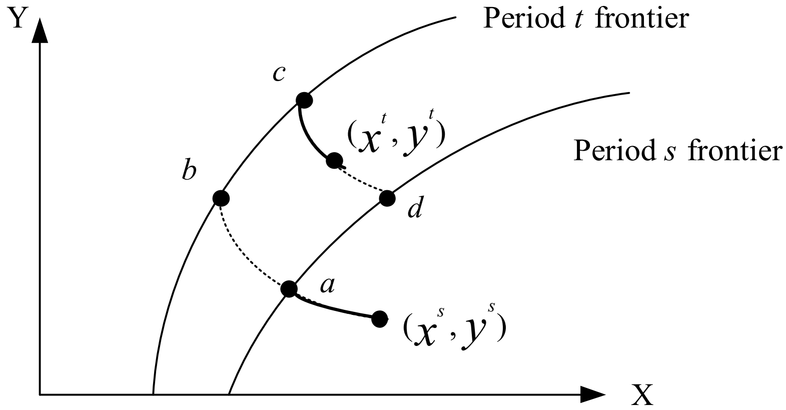

Figure 2 Measuring Productivity Changes

Following the first route, we recognize the suitable $(\underset{\sim}{x}, \underset{\sim}{y})$ and period *j* to be $(\underset{\sim}{x}^s, \underset{\sim}{y}^s)$ and period *t*, respectively. Thus, we define the corresponding productivity change index as:

$$\mathbf{\Delta PROD}_H^1\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right) = \mathbf{\Delta T}_H^{s,t}\left(\underset{\sim}{x}^s, \underset{\sim}{y}^s\right) \times \mathbf{\Delta TE}_H^{s,t}\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right) \times \mathbf{\Delta SE}_H^t\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right). \tag{14}$$

Substituting Equations (4), (5), and (13) into Equation (14), we obtain:

$$\mathbf{\Delta PROD}_H^1\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right) = \left[\frac{D_H^{*t}(\underset{\sim}{x}^t, \underset{\sim}{y}^t)}{D_H^{*t}(\underset{\sim}{x}^s, \underset{\sim}{y}^s)}\right]^2. \tag{15}$$

This is the hyperbolic Malmquist productivity index based on period *t* CRS technology. We denote $D_o^{*t}(\underset{\sim}{x}, \underset{\sim}{y})$ to be the output distance function, evaluated on the period *t* CRS frontier. Since $\left[D_H^{*t}(\underset{\sim}{x}, \underset{\sim}{y})\right]^2 = D_o^{*t}(\underset{\sim}{x}, \underset{\sim}{y})$ and $D_o^{*t}(\underset{\sim}{x}, \underset{\sim}{y})$ is homogenous of degree 1 in $\underset{\sim}{y}$ and -1 in $\underset{\sim}{x}$, we have:

$$\mathbf{\Delta PROD}_H^1\left(\alpha \underset{\sim}{x}^s, \beta \underset{\sim}{y}^s, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right) = \frac{D_o^{*t}(\alpha \underset{\sim}{x}^s, \beta \underset{\sim}{y}^s)}{D_o^{*t}(\underset{\sim}{x}^s, \underset{\sim}{y}^s)} = \frac{\beta}{\alpha} \text{ for } \alpha, \beta > 0. \tag{16}$$

Hence, this index does satisfy the property expressed in Equation (2).

The first part of the second route is the same as the previous one, moving from $(\underset{\sim}{x}^s, \underset{\sim}{y}^s)$ to the frontier point b, $\left(D_H^s(\underset{\sim}{x}^s, \underset{\sim}{y}^s)\underset{\sim}{x}^s,\ \underset{\sim}{y}^s \big/ D_H^s(\underset{\sim}{x}^s, \underset{\sim}{y}^s)\right)$, and measured by the denominator of the technical efficiency change index $\mathbf{\Delta TE}_H^{s,t}\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right)$. The second proportion travels along period s frontier from point b to point d, $\left(D_H^s(\underset{\sim}{x}^t, \underset{\sim}{y}^t)\underset{\sim}{x}^t,\ \underset{\sim}{y}^t \big/ D_H^s(\underset{\sim}{x}^t, \underset{\sim}{y}^t)\right)$, measured by the scale efficiency change index $\mathbf{\Delta SE}_H^s\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right)$. The technological change index $\mathbf{\Delta T}_H^{s,t}(\underset{\sim}{x}^t, \underset{\sim}{y}^t)$ then measures the movement from point d at period s frontier to point c $\left(D_H^t(\underset{\sim}{x}^t, \underset{\sim}{y}^t)\underset{\sim}{x}^t,\ \underset{\sim}{y}^t \big/ D_H^t(\underset{\sim}{x}^t, \underset{\sim}{y}^t)\right)$ at period t frontier. Finally, we must shrink from point c at period t frontier to $(\underset{\sim}{x}^t, \underset{\sim}{y}^t)$, as evaluated by the numerator of $\mathbf{\Delta TE}_H^{s,t}\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right)$. The appropriate $(\underset{\sim}{x}, \underset{\sim}{y})$ and period j for the second decomposition are $(\underset{\sim}{x}^t, \underset{\sim}{y}^t)$ and period s, respectively. Hence, this productivity change index can be defined as:

$$\mathbf{\Delta PROD}_H^2\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right) = \mathbf{\Delta T}_H^{s,t}\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t\right) \times \mathbf{\Delta TE}_H^{s,t}\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right) \times \mathbf{\Delta SE}_H^s\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right). \quad (17)$$

Substituting Equations (4), (5), and (13) into Equation (14), we have:

$$\mathbf{\Delta PROD}_H^2\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right) = \left[\frac{D_H^{*s}(\underset{\sim}{x}^t, \underset{\sim}{y}^t)}{D_H^{*s}(\underset{\sim}{x}^s, \underset{\sim}{y}^s)}\right]^2. \quad (18)$$

This is the hyperbolic Malmquist productivity index based on period s CRS technology. It is apparent that Equation (18) also satisfies the property described by Equation (2).

The first productivity change index $\mathbf{\Delta PROD}_H^1\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right)$ evaluates the technological change index at point $(\underset{\sim}{x}^s, \underset{\sim}{y}^s)$ and the scale efficiency change index along period t frontier, while the second productivity change index $\mathbf{\Delta PROD}_H^2\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right)$ measures the technological change index at point $(\underset{\sim}{x}^t, \underset{\sim}{y}^t)$ and the scale efficiency change index along period s frontier. Both are generally different. We take the geometric average of both indices to avoid these choices. Hence, this study defines the hyperbolic TFP change index from period s to period t as:

$$\begin{aligned}
\mathbf{TFP}_H\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right) &= \left[\mathbf{\Delta PROD}_H^1\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right) \times \mathbf{\Delta PROD}_H^2\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right)\right]^{1/2} \\
&= \left[\mathbf{\Delta T}_H^{s,t}\left(\underset{\sim}{x}^s, \underset{\sim}{y}^s\right) \times \mathbf{\Delta T}_H^{s,t}\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t\right)\right]^{1/2} \times \mathbf{\Delta TE}_H^{s,t}\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right) \\
&\quad \times \left[\mathbf{\Delta SE}_H^t\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right) \times \mathbf{\Delta SE}_H^s\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right)\right]^{1/2} \\
&= \frac{D_H^{*s}(\underset{\sim}{x}^t, \underset{\sim}{y}^t)}{D_H^{*s}(\underset{\sim}{x}^s, \underset{\sim}{y}^s)} \times \frac{D_H^{*t}(\underset{\sim}{x}^t, \underset{\sim}{y}^t)}{D_H^{*t}(\underset{\sim}{x}^s, \underset{\sim}{y}^s)}.
\end{aligned} \quad (19)$$

The hyperbolic TFP change index $\mathbf{TFP}_H\left(\underset{\sim}{x}^t, \underset{\sim}{y}^t, \underset{\sim}{x}^s, \underset{\sim}{y}^s\right)$ is the geometric average of the two hyperbolic productivity change index numbers, Equations (15) and (18), and consists of three components. The first two components

$\left[\Delta\mathbf{T}_H^{s,t}\left(\underset{\sim}{\boldsymbol{x}}^s,\underset{\sim}{\boldsymbol{y}}^s\right)\times\Delta\mathbf{T}_H^{s,t}\left(\underset{\sim}{\boldsymbol{x}}^t,\underset{\sim}{\boldsymbol{y}}^t\right)\right]^{1/2}$ and $\Delta\mathbf{TE}_H^{s,t}\left(\underset{\sim}{\boldsymbol{x}}^t,\underset{\sim}{\boldsymbol{y}}^t,\underset{\sim}{\boldsymbol{x}}^s,\underset{\sim}{\boldsymbol{y}}^s\right)$ measure the technological change ($\Delta\mathbf{T}_H$) and technical efficiency change ($\Delta\mathbf{TE}_H$), while the last component $\left[\Delta\mathbf{SE}_H^t\left(\underset{\sim}{\boldsymbol{x}}^t,\underset{\sim}{\boldsymbol{y}}^t,\underset{\sim}{\boldsymbol{x}}^s,\underset{\sim}{\boldsymbol{y}}^s\right)\times\Delta\mathbf{SE}_H^s\left(\underset{\sim}{\boldsymbol{x}}^t,\underset{\sim}{\boldsymbol{y}}^t,\underset{\sim}{\boldsymbol{x}}^s,\underset{\sim}{\boldsymbol{y}}^s\right)\right]^{1/2}$ evaluates the scale efficiency change ($\Delta\mathbf{SE}_H$). Note that the construction of these three components, $\Delta\mathbf{T}_H$, $\Delta\mathbf{TE}_H$, and $\Delta\mathbf{SE}_H$, is based on the VRS technology.

For each DMU, we must calculate eight hyperbolic distance functions to measure the hyperbolic productivity change index from period *s* and period *t*. They are $D_H^s(\underset{\sim}{\boldsymbol{x}}^s,\underset{\sim}{\boldsymbol{y}}^s)$, $D_H^s(\underset{\sim}{\boldsymbol{x}}^t,\underset{\sim}{\boldsymbol{y}}^t)$, $D_H^t(\underset{\sim}{\boldsymbol{x}}^t,\underset{\sim}{\boldsymbol{y}}^t)$, $D_H^t(\underset{\sim}{\boldsymbol{x}}^s,\underset{\sim}{\boldsymbol{y}}^s)$, $D_H^{*s}(\underset{\sim}{\boldsymbol{x}}^s,\underset{\sim}{\boldsymbol{y}}^s)$, $D_H^{*s}(\underset{\sim}{\boldsymbol{x}}^t,\underset{\sim}{\boldsymbol{y}}^t)$, $D_H^{*t}(\underset{\sim}{\boldsymbol{x}}^t,\underset{\sim}{\boldsymbol{y}}^t)$, and $D_H^{*t}(\underset{\sim}{\boldsymbol{x}}^s,\underset{\sim}{\boldsymbol{y}}^s)$. The mathematical programming to solve $D_H^{*t}(\underset{\sim}{\boldsymbol{x}}^s,\underset{\sim}{\boldsymbol{y}}^s)$ of DMU *j*, for example, is:

$$D_H^{*t}(\underset{\sim}{\boldsymbol{x}}^s,\underset{\sim}{\boldsymbol{y}}^s) = \min_{\theta_j,\lambda_1,\lambda_2,\cdots,\lambda_H} \theta_j \tag{20}$$

$$\text{s.t} \quad \theta_j x_{nj}^s - \sum_{h=1}^H \lambda_h x_{nj}^t \geq 0, \quad n=1,2,\cdots,N$$
$$-\theta_j^{-1} y_{mj}^s + \sum_{h=1}^H \lambda_h y_{mj}^t \geq 0, \quad m=1,2,\cdots,M$$
$$\lambda_1,\lambda_2,\ldots,\lambda_H \geq 0; \quad \theta_j \text{ is free.}$$

The corresponding $D_H^t(\underset{\sim}{\boldsymbol{x}}^s,\underset{\sim}{\boldsymbol{y}}^s)$, evaluated at the VRS technology, is simply adding the convexity constraint $\sum_{h=1}^H \lambda_h = 1$.

3. Empirical Analysis

3.1 Data and Input-Output Variables

The dataset, obtained from Taiwan Economic Journal, consists of 58 firms for the period 2008-2014. This balance panel dataset includes 406 observations. All nominal variables are deflated by the 2010 GDP deflator as the base year.

We have two output variables: sales and other income. Sales measure the output derived from firms' own business activities, while other income includes revenue other than that obtained from firms' own business activities, such as investment revenue, etc. This study considers three input variables: total number of employees, fixed assets, and raw material expenditures. Table 1 lists the descriptive statistics of the input and output variables.

Table 1 Descriptive Statistics of Input and Output Variables

Variables	Mean	Std. Dev.	Min	Max
Outputs				
Sales (NT$100 million)	20.905	27.311	0.129	169.344
Other Income (NT$100 million)	3.863	9.139	0.000	76.373
Inputs				
Fixed Assets (NT$100 million)	17.935	51.530	0.192	369.396
Staff (Persons)	308.303	340.787	17.000	2,191.000
Raw Materials (NT$100 million)	11.102	18.073	0.0035	135.759

Note: All nominal variables are deflated by the GDP deflator with 2010 as the base year.

3.2 Empirical Results

This study employs the mathematical programming software LINGO 11 to calculate the values of all output and hyperbolic distance functions. The average values of the hyperbolic TFP change index $\mathbf{TFP}_H$ and its components, $\Delta\mathbf{T}_H$, $\Delta\mathbf{TE}_H$, and $\Delta\mathbf{SE}_H$, are reported in Table 2. There are 58 observations in each year. The value in the parentheses of the last row is the number of observations that encountered the problem of infeasibility when we measure their productivity by output distance functions. Over 16% of total observations suffer from this problem when we measure their mixed-period output distance functions based on VRS technology. The hyperbolic TFP change index and its components do exist under CRS and VRS frontiers. We conclude that the hyperbolic distance function could be a better tool to measure productivity change than the output or input distance function for our dataset.

Table 2 Measures of Hyperbolic TFP Change Index and Its Components

	2008 - 2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	Average
$\mathbf{TFP}_H$	1.0146	1.0906	1.2243	1.0865	1.0012	1.1053	**1.0871**
$\Delta\mathbf{T}_H$	0.9837	1.0132	1.6332	0.9553	1.2436	1.2542	**1.1805**
$\Delta\mathbf{TE}_H$	1.0239	1.0780	0.9831	1.1620	0.8375	0.9088	**0.9989**
$\Delta\mathbf{SE}_H$	1.0356	1.0307	1.0065	1.0213	1.0193	1.0077	**1.0202**
Total Number	**58 (9)**	**58 (9)**	**58 (9)**	**58 (13)**	**58 (9)**	**58 (7)**	**348 (31)**

Note: The value in the parentheses is the number of observations encountering the problem of infeasibility when we measure their productivity by output distance functions.

The last column of Table 2 shows the average values of $\mathbf{TFP}_H$ and its components, $\Delta\mathbf{T}_H$, $\Delta\mathbf{TE}_H$, and $\Delta\mathbf{SE}_H$. On average, the TFP of Taiwan's biotechnology firms increased 8.71% during 2013-2019, mainly due to technological progress with a mean growth rate of 18.05%. The contribution of scale efficiencies is also positive with a mean growth rate of 2.02%, while technical efficiency change does not play a critical role with a mean value of 0.9989. In addition, technological change and technical efficiency change vary greatly over the years. For example, the mean value of $\Delta\mathbf{TE}_H$ is between 0.8375 and 1.1620, whereas the range of $\Delta\mathbf{T}_H$ even reaches 0.6779 with average values between 0.9553 and 1.6332. In contrast to $\Delta\mathbf{T}_H$ and $\Delta\mathbf{TE}_H$, the values of scale efficiency change components are all larger than unity. Hence, scale efficiency offers a continuous and steady contribution to TFP of Taiwan's biotechnology firms. This might suggest that analyzing TFP without the scale efficiency component (or assuming that all DMUs operate on the optimal scale) could miss out on some important information.

3.3 The role of Foreign Direct Investment

Foreign direct investment (FDI) not only influences firms' configuration and strategic planning, but also affects their organization, coordination, and integration. It may further impact TFP through different components. One possible explanation why FDI activities may affect the technology of Taiwan's biotechnology industry is because the industry still in the primary stage, and firms with FDI are more likely to obtain advanced technology through their foreign subsidiaries. Another likely reason may result from competitive pressures. We may expect that firms with FDI, in general, face higher competition than those without FDI, because they must directly confront competition in the host country. This competitive pressure may force them to advance technology more aggressively. Hence, in this section, we also investigate whether FDI activities influence TFP of Taiwan's biotechnology firms.

Table 3 shows that the mean value of TFP of firms with FDI (1.2411) is higher than that of those without FDI (1.0442). Firms with FDI exhibit larger technological change $\Delta\mathbf{T}_H$ and technical efficiency change $\Delta\mathbf{TE}_H$ than those without FDI, while the opposite is true for the scale efficiency change component $\Delta\mathbf{SE}_H$. Furthermore, the average values of all three components are greater than unity for those firms with FDI; however, only two components, $\Delta\mathbf{T}_H$ and $\Delta\mathbf{TE}_H$, contribute on average positively to TFP for those without FDI.

Table 3 TFP Index and its Components with Different Types

	Overall Average	**Firms with FDI**	**Firms without FDI**
$\mathbf{TFP}_H$	1.0871	1.1097	1.0361
$\Delta\mathbf{T}_H$	1.1805	1.2411	1.0442
$\Delta\mathbf{TE}_H$	0.9989	1.0022	0.9915
$\Delta\mathbf{SE}_H$	1.0202	1.0076	1.0485
Number of Observations	348	241	107

Although the mean values of **TFP**, $\Delta\mathbf{T}_H$, $\Delta\mathbf{TE}_H$, and $\Delta\mathbf{SE}_H$ indeed display differences between Taiwan's biotechnology firms with FDI and those without FDI, we need additional analysis to identify whether they present significant differences. The non-parametric test is appropriate for both cardinal and ordinal data and does not specify the distribution. This study employs the Mann-Whitney U statistics to test the null hypothesis that the mean TFP of firms with FDI is the same as that of those without FDI. The same procedure can also be applied to other components. The results in Table 4 show that the average TFP and $\Delta\mathbf{TE}_H$ do not exhibit significant differences between firms with FDI and those without FDI at the traditional levels of significance. Nevertheless, the mean value of scale efficiency changes for firms with FDI is significantly lower than that for those without FDI at the 10% level of significance, while the reverse is true for the technological change at the 5 percent significance level. We may conclude that FDI activities could upgrade the technology of Taiwan's biotechnology firms.

Table 4 Mann-Whitney U test of Firms with FDI vs. Those without FDI

	$\mathbf{TFP}_H$	$\Delta\mathbf{T}_H$	$\Delta\mathbf{TE}_H$	$\Delta\mathbf{SE}_H$
Test Statistics	12,677	11,387	12,728	10,855
Z	–0.250	–1.740	–0.192	–2.354
***P*-Value**	0.803	0.082	0.848	0.019

4. Conclusion

Rapid advances in both the science and commercialization of biotechnology over the past decades have attracted considerable academic research attention, with productivity as an important measure to evaluate the performance of DMUs. The Malmquist index, based on output (or input) distance functions, is widely used to measure TFP change, but it can only consider output expansion or input contraction, but not both. In addition, it may suffer the problem of infeasibility for mixed-period calculation under VRS technology.

The hyperbolic distance function is able to simultaneously expand outputs and contract inputs as well as overcome the problem of infeasibility to construct the TFP index under the VRS frontier. Hence, this study applies hyperbolic distance functions and the bottoms-up approach to construct a TFP index to analyze the productivity of 58 Taiwanese biotechnology firms during 2013-2019. The empirical results show that the TFP of Taiwan's biotechnology firms, on average, increased 8.71% during the study period, mainly coming from technological progress and scale efficiency improvement with mean rates of growth of 18.05% and 2.02%, respectively, while technical efficiency change did not play a vital role. Other findings are as follows. (1) Sixteen percent of total observations suffered the problem of infeasibility, as measured by output distance functions, while the TFP change index, based on hyperbolic distance functions, can avoid this problem. (2) The contributions of technological change and technical efficiency change vary greatly over the years, whereas scale efficiency offers a continuous and steady contribution to TFP. (3) The mean value of scale efficiency changes for firms with FDI is significantly lower than that for those without FDI, while it reveals the reverse for technological change.

Our results show that focusing on technological change and scale efficiency would be more appropriate to increase the TPF of the industry. In addition, FDI activities increase technological change but reduce scale efficiency. Hence, policymakers need to take a balanced approach to promote FDI activities considering the tradeoff between technological change and scale efficiency. Furthermore, future studies may employ the hyperbolic distance function used in this study to compute TPF in other sectors and biotechnology sector in different countries.

Acknowledgement: The authors would like to thank the anonymous reviewers for their insightful comments and suggestions. This study is supported by the Fujian Province Social Science Planning Project of China (FJ2019T005).

References

Bahrini, R. The Productivity of MENA Islamic Banks: A Bootstrapped Malmquist Index Approach. International Journal of Islamic and Middle Eastern Finance and Management 2015, 8(4), 508-528.

Baležentis, T. Total Factor Productivity in the Lithuanian Family Farms after Accession to the EU: Application of the Bias-Corrected Malmquist Indices. Empirica 2014, 41(4), 731-746.

Balk, B.M. Scale efficiency and productivity change. Journal of Productivity Analysis 2001, 15, 159-183.

Barros, C.P.; Guironnet, J.P.; Peypoch, N. Productivity Growth and Biased Technical Change in French Higher Education. Economic Modelling 2011, 28(1), 641-646.

Bing, W.; Yanrui, W.; Pengfei, Y. Environmental Efficiency and Environmental Total Factor Productivity Growth in China's Regional Economies. Econ. Res. J. 2010, 5, 95-109.

Brummer, B.; Glauben, T.; Thijssen, G. Decomposition of Productivity Growth Using Distance Functions: The Case of Dairy Farms in Three European Countries. American Journal of Agricultural Economics 2002, 84, 628-44.

Cai, W.G.; Zhou, X.L. Dual Effect of Chinese Environmental Regulation on Green Total Factor Productivity. Economist 2017, 9, 27–35.

Caves, D.W.; Christensen, L.R.; Diewert, W.E. Multilateral comparisons of output, input and productivity using superlative index numbers. Economic Journal 1982a, 92, 73-86.

Caves, D.W.; Christensen, L.R.; Diewert, W.E. The economic theory of index numbers and the measurement of input, output and productivity. Econometrica 1982b, 50, 1393-1414.

Chang, T.P.; Hu, J.L. Total-Factor Energy Productivity Growth, Technical Progress, and Efficiency Change: An Empirical Study of China. Applied Energy 2010, 87(10), 3262-3270.

Chen, M.F.; Hu, J.L.; Ding, C.G. Efficiency and Productivity of Taiwan's Biotech Industry. International Journal of Biotechnology 2005, 7, 307-322.

Chew, L.S.; Mazlyn, M. Riding Asia's biotech wave. Asian Business 2002, January, 20-21.

Coelli, T.J.; Rao, D.S.P.; O'Donnell, C.J; Battese, G.E. An introduction to efficiency and productivity analysis, 2nd ed.; Springer: New York, U.S., 2005.

Cooper, W.W.; Seiford, L.M.; Tong, K. Data envelopment analysis: A comprehensive text with models, applications, references and DEA-solver software, 2nd ed.; Springer: New York, U.S., 2007.

Cui, H.X. Research on Total Factor Productivity of China's Insurance Industry: Based on Comparison between Insurance Group and Independent Insurance Company. Financial Review 2015, 1, 100-126.

Du, J.; Chen, Y.; Huang, Y. A Modified Malmquist-Luenberger Productivity Index: Assessing Environmental Productivity Performance in China. European Journal of Operational Research 2017, 269(1), 171-187.

Färe, R.; Grosskopf, S.; Lovell, C.A K. Production frontiers. Cambridge University Press: Cambridge, U.S., 1994.

Färe, R.; Grosskopf, S.; Norris, M.; Zhang, Z. Productivity growth, technical progress, and efficiency changes in industrialized countries. American Economic Review 1994, 84, 66-83.

Gaitán-Cremaschi, D.; Meuwissen, M.; Oude Lansink, A. Total Factor Productivity: A Framework for Measuring Agri-Food Supply Chain Performance towards Sustainability. Applied Economic Perspectives and Policy 2016, 39(2), 259-285.

Jiang, L.P. A Comparative Study of the Total Factor Productivity of Chinese Industry under Environmental Regulation. Knowl. Econ. 2016, 8, 25–26.

Koutsomanoli-Filippaki, A.; Margaritis, D.; Staikouras, C. Efficiency and Productivity Growth in the Banking Industry of Central and Eastern Europe. Journal of Banking and Finance 2009, 33(3), 557-567.

Li, T.; Baležentis, T.; Cao, L.; Zhu, J.; Štreimikienė, D.; Melnikienė, R. Technical Change Directions of China’s Grain Production: Application of the Bias-Corrected Malmquist Indices. Technological and Economic Development of Economy 2018, 24(5), 2065-2082.

Li, T.; Liao, G. The Heterogeneous Impact of Financial Development on Green Total Factor Productivity. Frontier in Energy Research 2020, 8, 29.

Li, K.; Qu, J.; Wei, P.; Ai, H.; Jia, P. Modelling Technological Bias and Productivity Growth: A Case Study of China’s Three Urban Agglomerations. Technological and Economic Development of Economy 2020, 26(1), 135-164.

Li, J.; Zhang, J.; Gong, L.; Miao, P. Research on the Total Factor Productivity and Decomposition of Chinese Coastal Marine Economy: Based on DEA-Malmquist Index. Journal of Coastal Research 2015, 73(sp1), 283-289.

Liang, Z.; Chiu, Y.H.; Li, X.; Guo, Q.; Yun, Y. Study on the Effect of Environmental Regulation on the Green Total Factor Productivity of Logistics Industry from the Perspective of Low Carbon. Sustainability 2020, 12, 175.

Liu, H.H. Using DEA and Malquist Productivity Index to Analyze the Operational Efficiency of Taiwan Biotechnological Industry. Asian Economic and Financial Review 2017, 7(8), 809-822.

Lim, D.J. Technology forecasting using DEA in the presence of infeasibility. International Transactions in Operational Research 2018, 25(5), 1695-1076.

Lin, R.; Chen, Z. Modified super-efficiency DEA models for solving infeasibility under non-negative data set. INFOR: Information Systems and Operational Research 2018, 56(3), 265-285.

Liu, G.; Wang, B.; Cheng, Z.; Zhang, N. The drivers of China’s regional green productivity, 1999–2013. Resources, Conservation & Recycling 2020, 153, 104561.

Liu, G.T.; Wang, B.; Zhang, N. A Coin Has Two Sides: Which One Is Driving China’s Green TFP Growth? Econ. Syst. 2016, 40, 481-498.

Liu, X.; Zhou, D.Q.; Wang, Q.W. Dynamic Carbon Emission Performance of Chinese Airlines: A Global Malmquist Index Analysis. J. Air Transp. Manag. 2017, 65, 99-109.

Liu, H.W.; Zheng, S.L.; Zuo, W.T. The Influence Mechanism of Environmental Regulation on TFP of Enterprises. Sci. Res. Manag. 2016, 37, 33-41.

Lu, Y.H.; Chen, K.H.; Wu, C.C. Cross-Country Analysis of Efficiency and Productivity in the Biotech industry: An Application of the Generalized Metafrontier Malmquist Productivity Index. Agricultural Economics-Czech 2015, 61, 116-134.

Lu, Y.H.; Wang, S.C.; Yuan, C.H. Financial Crisis and the Relative Productivity Dynamics of the Biotechnology Industry: Evidence from the Asia-Pacific Countries. Agric. Econ.-Czech 2017, 63, 65–79.

Machek, O.; Spicka, J. Measuring Performance Growth of Agricultural Sector: A Total Factor Productivity Approach. International Journal of Economics and Statistics 2013, 1(4), 200-208.

Malmquist, S. Index numbers and indifference surfaces. Trabajos de Estatistica 1953, 4, 209-242.

Mukherjee, K.; Ray, S.C.; Miller, S.M. Productivity Growth in Large US Commercial Banks: The Initial Post-Deregulation Experience. Journal of Banking and Finance 2001, 25(5), 913-939.

Odeck, J. Assessing the Relative Efficiency and Productivity Growth of Vehicle Inspection

Services: An Application of DEA and Malmquist indices. Eur. J. Oper. Res. 2000, 126, 501-514.

Otaviya, S.; Rani, L. Productivity and Determinant of Islamic Banks Evidence from Indonesia. Journal of Islamic Monetary Economics and Finance 2020, 6(1), 189-212.

Pilyavsky, A.; Staat, M. Efficiency and Productivity Change in Ukrainian Health Care. J. Product. Anal. 2008, 29, 143–154.

Sheng, Y.; Jackson, T.; Zhao, S.; Zhang, D. Measuring Output, Input and Total Factor Productivity in Australian Agriculture: An Industry-Level Analysis. Review of Income and Wealth 2017, 63, 169-193.

Sheng T.C.; Liu, K.P.; Yang, Y.L. Estimating the Three-Stage Cost Malmquist Productivity Index in the Taiwan Biotech and Biopharmaceutical Industry. Journal of Modern Accounting and Auditing 2012, 8, 679–687.

Sheng, Y.; Tian, X.H.; Qiao, W.Q.; Peng, C. Measuring Agricultural Total Factor Productivity in China: Pattern and Drivers over the Period of 1978-2016. Australian Journal of Agricultural and Resource Economics 2019, 59, 1-22.

Shephard, R.W. Cost and Production Functions, Princeton University Press: Princeton, U.S., 1953.

Shephard, R.W. Theory of cost and production functions. Princeton University Press: Princeton, U.S., 1970.

Sueyoshi, T.; Goto, M.; Wang, D. Malmquist Index Measurement for Sustainability Enhancement in Chinese Municipalities and Provinces. Energy Economics 2017, 67, 554-571.

Sun, Z. Research on the Factors Affecting the Total Factor Productivity of Chinese Life Insurance Companies. Archives of Business Research 2020, 8(1), 38-50.

Wang, C.N.; Tibo, H.; Nguyen, H.A. Malmquist Productivity Analysis of Top Global Automobile Manufacturers. Mathematics 2020, 8, 580.

Yang, Y.L.; Sheng, T.C.; Huang, C.J. Estimating the Cost Malmquist Productivity Index in the Taiwan Biotech and Biopharmaceutical Industry. Taiwan Journal of Applied Economics 2009, Special Issue for Productivity and Efficiency, 88, 60-85.

Yu, H.; Liu, Y.; Zhao, J.; Li, G. Urban Total Factor Productivity: Does Urban Spatial Structure Matter in China? Sustainability 2020, 12, 214.

Yu, C.; Shi, L.; Wang, Y.; Chang, Y.; Cheng, B. The Eco-Efficiency of Pulp and Paper Industry in China: An Assessment Based on Slacks-Based Measure and Malmquist-Luenberger Index. Journal of Cleaner Production 2016, 127, 511-521.

Yuan, X.L.; Zhang, B.SH. Study on the Factors Affecting the Total Factor Productivity of China's Commercial Banks: A Malmquist Index Analysis Based on DEA Model. The Journal of Quantitative and Technical Economics 2009, 4, 93-104.

Zhang, N.; Wang, B. A Deterministic Parametric Metafrontier Luenberger Indicator for Measuring Environmentally-Sensitive Productivity Growth: A Korean Fossil-Fuel Power Case. Energy Economics 2015, 51, 88-98.

Zhao, Z.; Yang, C. Estimation and Explanation of China’s Total Factor Productivity: 1979–2009. Res. Financ. Econ. Issues 2011, 9, 3-12.

Zofío, J.L.; Lovell, C.A.K. Graph efficiency and productivity measures: An application to US agriculture. Applied Economics 2001, 33, 1433-1442