Analyzing Productivity of Asian Biotech Firms

Yang Li and Hsiao-Mei Lin*

Abstract

Literatures offered inconsistent conclusions about the contribution of R&D on productivity and efficiency. This study uses the non-neutral efficiency effect model to empirically analyze the hypothesis that firms with different levels of efficiencies may have distinct capabilities to absorb the contribution of R&D on productivity. The data set, obtained from COMPUSTAT and the Taiwan Economic Journal, consists of 141 Asian biotech firms from 2000 to 2006. The empirical results support the hypothesis and indicate that firm with higher efficiency levels do have larger capability to absorb the contribution of R&D to their productivity, while firms operated on the extremely lower efficiency levels may acquire insignificant or negative influence of R&D on productivity. .Other empirical findings include: (1) R&D will be capable of upgrading labor productivity of firms associated with extremely higher efficient levels regardless of R&D levels, while its contribution to the elasticity of capital declines; (2) If firms operate on the low or median levels of efficiencies, the relationship between R&D and output elasticity of labor appears U-shaped, while it emerges inverse U-shaped between R&D and output elasticity of capital.

Keyword: Quantile regression, smooth coefficient quantile model, Asian biotech firms, R&D, production efficiency quantile

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I. Introduction

Recombinant DNA technology, conduced by Boyer and Cohen in 1973, opened the new version of biotechnology. After completion of human genome project (HGP) in 2003, biology went into “post-genome era.” The biotech industry is advanced rapidly to develop new medicines, and diagnostic methods. There are huge profits in the biotech industry in the post-genome era. Shan and Song (1997) indicated that the biotechnology industry will become a crucial industry in the twenty-first century. In addition, the biotech industry is knowledge intensive. The R&D activity lies at the heart of biotechnology firm strategy (Malecki, 1997). Therefore, R&D plays an important role in the performance of biotech firms. Many literatures have studied the impact of R&D on productivity and efficiency. However, they did not obtain consistent conclusions. Some found that R&D contributes positively to productivity (Griliches, 1994; Acharya et al., 2006), while Scherer (1983) argued that both are negatively related. One of possible reasons is that firms with different levels of efficiencies may have distinct capabilities to absorb the contribution of R&D on productivity. The quantile regression model, offered multiple vectors of parametric estimators corresponding to each conditional quantile of efficiency distribution, provides an alternative description of a production technology. Hence, this method is appropriate for this study to investigate whether or not the contribution of R&D on biotech firms’ productivity varies with different efficiency levels.

Asian countries have had markedly different approaches to carving out niches in the Asian biotech industry. For instance, Singapore proposed “Industry 21” in 1999 with the objective of being one of leaders of biotech industry in the world. In 2002, Taiwan’s government proposed the “Two Trillions, Twin Stars plan” in order to maintain its manufacturing competitive advantages. South Korea’s government drew up ‘Biotech 2000’ in 1993, with the goal of South Korea firms having a 10% market share of the biotech industry in the world in 2010. In Malaysia, the government is primarily focused on the oil palm, rubber, cocoa, and timber in biotech agriculture. Mainland China is investing heavily in biotech with policies such as the “863 plans” and the “15 plans”. Ernst & Young (2006) reported that the Asian biotech industry had the highest growth arte of R&D investment worldwide during 2004－2005 (the growth rate was 23.3%, for Asia,1.77% for the United States, and actually negative for Europe). Furthermore, biotech industry is knowledge intensive and thus, the R&D lies at the heart of its strategy (Malecki, 1997). Hence, it is worthwhile to investigate how R&D activities affect the productivity and efficiency of Asian biotech firms.

The innovation process means that an idea is transformed into a commercial product. The process includes a serious of activities, consisting of research, product development, manufacturing, marketing and so on (Burill and Lee, 1992). It can improve firm’s capacity to utilize external resources and knowledge, and consequently enhances competitive advantage and performance (Abody and Lev, 2000). The R&D investment can not only directly support the innovation activity, but also indirectly sustain it through accumulating knowledge, maintaining and/or advancing core competence, etc (Mansfield, 1984). Many literatures explored the relationship between firms’ R&D activities and performance (Decarolis and Deeds, 1999; Hall and Sharmisha, 2007; Griliches, 1994; Acharya et al., 2006; Scherer, 1983). However, they obtain mixed conclusions for the impact of R&D on productivity. Griliches (1994) and Acharya et al. (2006) argued that R&D and productivity are positively related, while Scherer (1983) suggested that R&D contributes negatively to labor productivity. The similar results also exist in the biotech industry. Some studies found that R&D contributes positively to firms’ performance (Shan et al., 1994; Greis et al., 1995; Deeds and Hill, 1996; Qian and Lee, 2003; Terziovski and Morgan, 2006; Hall and Bagchi-Sen, 2007). Others provided different conclusions. For instance, Decarolis and Deeds (1999) indicated that the impact of R&D on biotech firms’ performance is insignificant; Graves and Langowitz (1993) argued that innovative productivity declines with increasing levels of R&D expenditure.

These studies employed the maximum likelihood (ML) method or the ordinary least squares (OLS) method to estimate the contribution of R&D on productivity. They can only provide location measures of mean, representing the “averaging” behavior or “central” tendency of a conditional distribution; hence, could not explain the right-tail or left-tail behaviors of a distribution. This study proposes that inefficiency may prevent firms to completely absorb the contribution of R&D on productivity, which could explain why we observed the inconsistent conclusions about the relationship between R&D and productivity. Therefore, it needs to explore the entire efficiency behaviors to fully investigate the relationship between R&D and productivity.

The quantile regression method offers multiple vectors of parametric estimators corresponding to each conditional quantile of firm performance distribution. Moreover, the corresponding estimators are robust to outliers, skew-tailed, or truncated distribution (Coad and Rao, 2006). Hence, it is an appropriate method to inspect whether or not the relationship between R&D and productivity varies with different efficiency levels. In addition, technology change may not be neutral with respect to inputs (Huang and Liu, 1994). The influence of R&D on distinct inputs might be inherently differently. Huang et al. (2007) extended the quantile regression approach to the non-neutral efficiency effect model. They used a local linear fitting scheme, propose by (Cai and Xu, 2006), to estimate the smooth coefficients. This study employs the method proposed by Huang et al. (2007) to analyze how R&D affects the productivity and efficiency of Asian biotech firms. The contribution of this paper is to complement previous studies by exploring the impact of R&D on productivities at different efficiency levels. Hence, we can not only offer a possible explanation why we observed a mixed conclusions about the relationship between R&D and productivity, but also provide a more comprehensive description for the contribution of R&D on the performance of Asian biotech firm.

The rest of the paper is organized as follows. A non-neutral efficiency effect model is set up in section 2 to perform a quantitative assessment. Section 3 consists of the description of the data and the variables, empirical results and discussion. The final section gives concluding remarks.

II. Methodology

Quantile regression, introduced by Koenker and Bassett in 1978, extends the concepts of quantile to regression analysis and extracts the information from whole conditional distributions of response variable. Unlike the OLS estimator based only on the conditional mean function, it assumes that the explanatory variable vector $\underset{\sim}{\boldsymbol{x}}$ may have distinct impacts on the dependent variable y at different locations of the conditional distribution. Consequently, the quantile regression provides different estimators corresponding to each conditional quantile of firm performance distribution. The corresponding estimators are robust to outliers, skew-tailed, or truncated distribution (Coad and Rao, 2006).

The smooth coefficient model provides a flexible specification to study regression with varying coefficients (Li et al., 2002). It is especially a useful tool to explore the technology change to be non-neutral with respect to inputs. Huang et al., (2007) extended the quantile regression methods to the smooth coefficient model, called the smooth coefficient conditional quantile model, which is capable of investigating the contribution of R&D on biotech firms' productivity at different efficiency levels.

Consider a deterministic frontier prduction function

$$\underset{\sim}{\boldsymbol{y}} = \alpha + \underset{\sim}{\boldsymbol{x}}'\underset{\sim}{\boldsymbol{\beta}} + u \tag{1}$$

where $\underset{\sim}{\boldsymbol{x}}$ is an $k \times 1$ vector of exogenous variables; α and $\underset{\sim}{\boldsymbol{\beta}}$ are 1×1 and $k \times 1$ vectors of constants, respectively; the u is a negative random variable which is assumed to account for technical inefficiency in production. Consider the inefficiency variable related to the exogenous variable z. Wang and Schmidt (2002) specified the relation as $u = h(z)\, u^*$ where $h(z) \geqq 0$ called scaling function and $u^* \leqq 0$, called the basic distribution, has a distribution independent of $\underset{\sim}{\boldsymbol{x}}$ and z. The τ^{th} conditional quantile function of y given $\underset{\sim}{\boldsymbol{x}}$ and z is

$$\begin{aligned} Q_\tau\left(y \mid \underset{\sim}{\boldsymbol{x}}, z\right) &= \alpha + \underset{\sim}{\boldsymbol{x}}'\underset{\sim}{\boldsymbol{\beta}} + h(z) Q_\tau\left(u^*\right) \\ &= \alpha^\tau(z) + \underset{\sim}{\boldsymbol{x}}'\underset{\sim}{\boldsymbol{\beta}} \end{aligned} \tag{2}$$

where the quantile coefficient $\alpha^\tau(z)$ is an unspecified smooth function of z. This specification assumes that the (in)efficiency determinant z has the neutral-effect on a firm's production and the degree of impact depends on the firm's efficiency quantile τ. In addition, the determinant z has no effect on the slope vector $\underset{\sim}{\boldsymbol{\beta}}$.

A more general specification, suggested by Huang et al. (2007), assumes that the scaling function $h(\cdot)$ depends on $\underset{\sim}{\boldsymbol{x}}$ and z, say $h\left(\underset{\sim}{\boldsymbol{x}}, z\right) = h_0(z) + \underset{\sim}{\boldsymbol{x}}'\underset{\sim}{\boldsymbol{h}}_1(z)$, called the non-neutral efficiency effect model. The corresponding smooth coefficient conditional quantile function can be written as:

$$Q_\tau\left(y \mid \underset{\sim}{\boldsymbol{x}}, z\right) = \alpha^\tau(z) + \underset{\sim}{\boldsymbol{x}}'\underset{\sim}{\boldsymbol{\beta}}^\tau(z) \tag{3}$$

where the quantile coefficients $\alpha^\tau(z)$ and $\underset{\sim}{\boldsymbol{\beta}}^\tau(z)$ are unspecified smooth functions of z. Equation (3) indicates the inefficiency determinant z has the non-neutral effect on productivity since the slope vector $\underset{\sim}{\boldsymbol{\beta}}^\tau(z)$, the input productivities, is function of z and τ. The non-neutral effect model, proposed by Huang and Liu (1994), is a special case of this model for $\tau = 1$ (Huang et al., 2007).

This study employs the local polynomial method, suggested by Cai and Xu (2006), to estimate the smooth coefficient conditional quantile regression model. Under some regularity conditions, the corresponding estimators are consistent and asymptotic normal (Cai and Xu, 2006). Assume that the coefficients $\alpha^{\tau}(z)$ and $\underset{\sim}{\boldsymbol{\beta}}^{\tau}(z)$ have the (q+1)*th* derivative. Thus, both can be approximated by a linear function at a point z_0 as follows (for continent, we omit superscript τ):

$$\alpha(z) \approx \alpha(z_0) + \sum_{j=1}^{q} \alpha^{(j)}(z_0)(z - z_0)^j \Big/ j! \tag{4}$$

$$\underset{\sim}{\boldsymbol{\beta}}(z) \approx \underset{\sim}{\boldsymbol{x}}'\underset{\sim}{\boldsymbol{\beta}}(z_0) + \sum_{j=1}^{q} \underset{\sim}{\boldsymbol{x}}'\underset{\sim}{\boldsymbol{\beta}}^{(j)}(z_0)(z - z_0)^j \Big/ j! \tag{5}$$

where $\alpha^{(j)}(z_0)$ and $\underset{\sim}{\boldsymbol{\beta}}^{(j)}(z_0)$ are the *j*th derivative evaluated at z_0. Fan and Gijbels (1996) recommended the local linear fit, *i.e.* q = 1. Hence, equation (3) can be expressed as:

$$Q_{\tau}\left(y \middle| \underset{\sim}{\boldsymbol{x}}, z\right) \approx \alpha(z_0) + \alpha^{(1)}(z_0)(z - z_0) + \underset{\sim}{\boldsymbol{x}}'\underset{\sim}{\boldsymbol{\beta}}(z_0) + \underset{\sim}{\boldsymbol{x}}'\underset{\sim}{\boldsymbol{\beta}}^{(1)}(z_0)(z - z_0) \tag{6}$$

The local linear estimator of the smooth coefficient quantile of the τ^{th} order can be obtained by minimizing the following equation:

$$\min_{\alpha, \underset{\sim}{\boldsymbol{\beta}}} \left\{ \sum_{i=1}^{n} \rho_{\tau}\left(y_i - \alpha(z_0) - \alpha^{(1)}(z_0)(z_i - z_0) - \underset{\sim}{\boldsymbol{x}}_i'\underset{\sim}{\boldsymbol{\beta}}(z_0) - \underset{\sim}{\boldsymbol{x}}_i'\underset{\sim}{\boldsymbol{\beta}}^{(1)}(z_0)(z_i - z_0)\right) K_h(z_i - z_0) \right\} \tag{7}$$

where n is the number of observations, $\rho_{\tau}(\cdot)$ is the check function such that $\rho_{\tau}(b) = \tau b$ if $b > 0$ and $\rho_{\tau}(b)$ if $b \le 0$, $K_h(\omega) = K(\omega / h) / h$ is a kernel function, and $h = h_n$ is the smoothing parameter satisfying $h_n \to 0$ and $nh_n \to \infty$ as $n \to \infty$. The choice of h is crucial. Pagan and Ullah (1999) indicates $h_n \propto n^{-1/5}$, i.e., $h_n = cn^{-1/5}$. Many researches proposed different methods to choose c. Silverman (1986) suggested $c = 0.79\psi$ where ψ is the inter-quartile rage, being robust and able to avoid the influence of extreme values. This paper sets $h_n = 0.79\psi n^{-1/5}$.

III. Empirical Analysis

3.1 Data and Variables

The data set, obtained from S&P Compustat and Taiwan Economic Journal Data Bank, consists of 141 firms for the period 2000-2006. This unbalance panel data set includes 714 observations. Sample firms come from 10 Asian countries, consisting of Japan, Taiwan, Mainland China, South Korea, Indian, Singapore, Hong Kong, Malaysia, the Philippines, and Indonesia. Since we have a seven-year panel data, all nominal variables are deflated by each country's own GDP deflator with 2000 as the base year.

The output variable is the total revenue (SALE), which represents the gross income received from all divisions of the company. Two input variables are considered in this research: Total number of employees (L) and fixed assets (K), including buildings, plants, land, equipment and other facilities. The primary objective of this study is to investigate how the R&D expenditures (RD) influence Asian biotech firms' productivity. We propose that the contribution of R&D on input productivities varies with different efficiency levels. The variable of R&D expenditures in this study consists of all costs incurred relating to development of new products or services such as amortization of software costs, company-sponsored research and development and software expenses. Descriptive Statistics of variables are reported in Table 1.

Table 1 Descriptive Statistics

Variable	Mean	S.D.	Minimum	Maximum
***SALE* ($ Millions)**	613.28	1,298.88	0.0005	11,514.40
***L* (Thousands)**	4.09	28.84	0.01	711.74
***K* ($ Millions)**	955.71	2,341.70	0.24	26,203.90
***RD* ($ Millions)**	62.22	161.91	0.0000001	1,450.40

3.2 Empirical Results

The smooth coefficient conditional quantile model, with coefficient being a function of *RD*, is specified in the logarithmic form as:

$$Q_\tau\left(\ln y \middle| L, K, RD, t\right) = \alpha^\tau\left(\ln RD\right) + \beta_L^{\ \tau}\left(\ln RD\right)\ln L + \beta_K^{\ \tau}\left(\ln RD\right)\ln K + \beta_t^{\ \tau}\left(\ln RD\right)t \qquad (10)$$

The variable t is the time trend serving as a proxy to measure technical change. The production efficiency quantile of the firm with output at $Q_\tau\left(\ln y \middle| L, K, RD, t\right)$ using $\underset{\sim}{x}$ units of inputs is equal to τ as it produces more than 100 τ % of firms (or less than 100(1–τ)% of firms) using no more than $\underset{\sim}{x}$ units of inputs (Huang et al., 2007). The specification of equation (10), the non-neutral efficiency effect model, implies that the variable RD not only serves as a factor of production through intercept $\alpha^\tau\left(\ln RD\right)$, but also serves as a factor to augment and/or moderate labor, capital, and technology through $\beta_L{}^\tau\left(\ln RD\right)$, $\beta_K{}^\tau\left(\ln RD\right)$, and $\beta_t{}^\tau\left(\ln RD\right)$, respectively. The computer software, the R package quantreg of Koenker (2004), is used to estimate parameters of equation (10).

The estimated effects of R&D expenditure on input productivities are presented in Figure 1, Figure 2, and Table 2. The output elasticities of labor $\beta_L^\tau\left(\ln \mathrm{RD}\right)$ at different efficiency levels in Figure 1 show that when the R&D expenditures of Asian biotech firms cross a threshold, R&D can augment the labor productivity at increasing rate regardless of efficiency levels. Nevertheless, if inefficient firms cannot invest enough R&D, the contribution of R&D on the labor productivity is negative. In contrast to inefficient firms, the relationship between R&D and labor productivity is almost positive for firms associated with extremely higher efficiencies, for instance, $\tau \geq 0.9$.

Figure 2 represents the relationship between R&D and output elasticities of capital $\beta_K{}^\tau\left(\ln RD\right)$ at varying efficiency levels. Contrary to output elasticities of labor, if the R&D expenditures pass a threshold, R&D will abate the capital productivity at increasing rate regardless of efficiency levels. However, moderate R&D expenditure can enlarge the output elasticities of capital for inefficient Asian biotech firms. This may not be correct for nearly efficient firms since the figure of τ = 0.95 indicates that the relationship between R&D and the capital productivity is negative regardless of R&D levels.

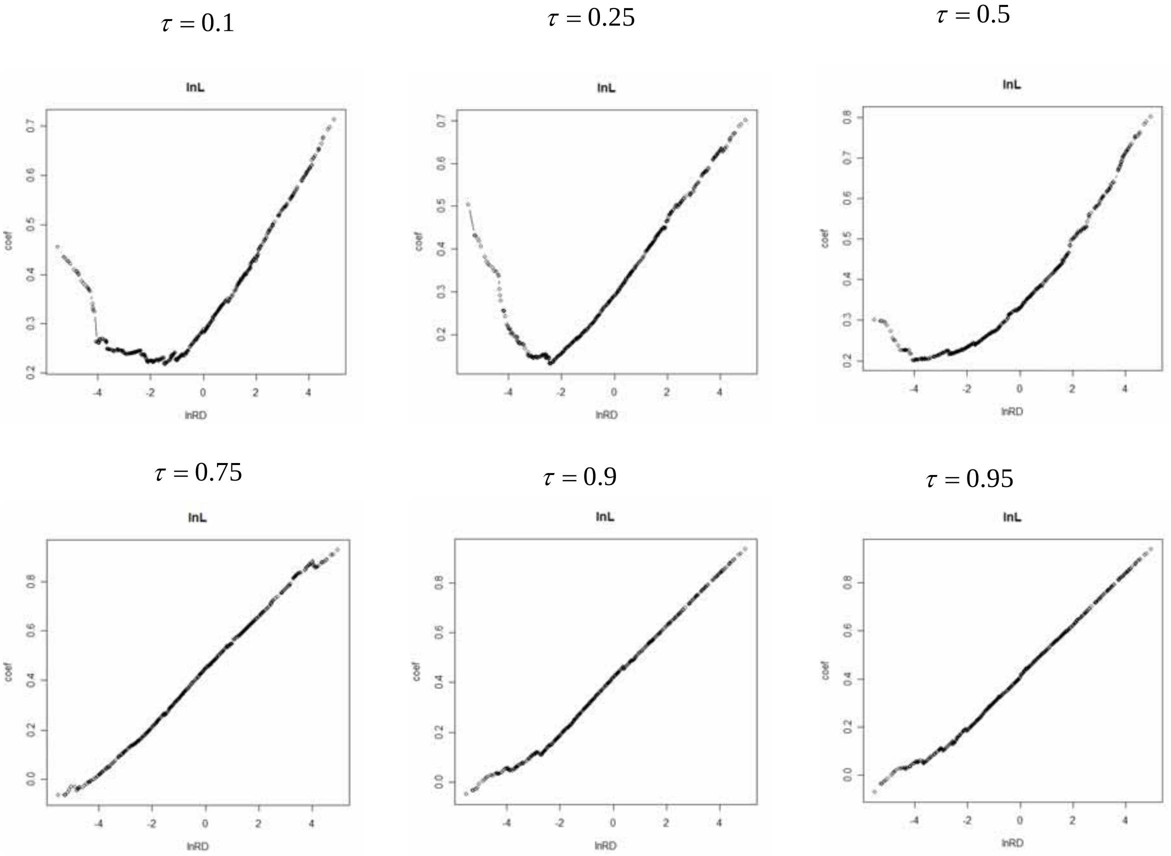

Figure 1 The estimates of R&D on labor productivity at various efficiencies

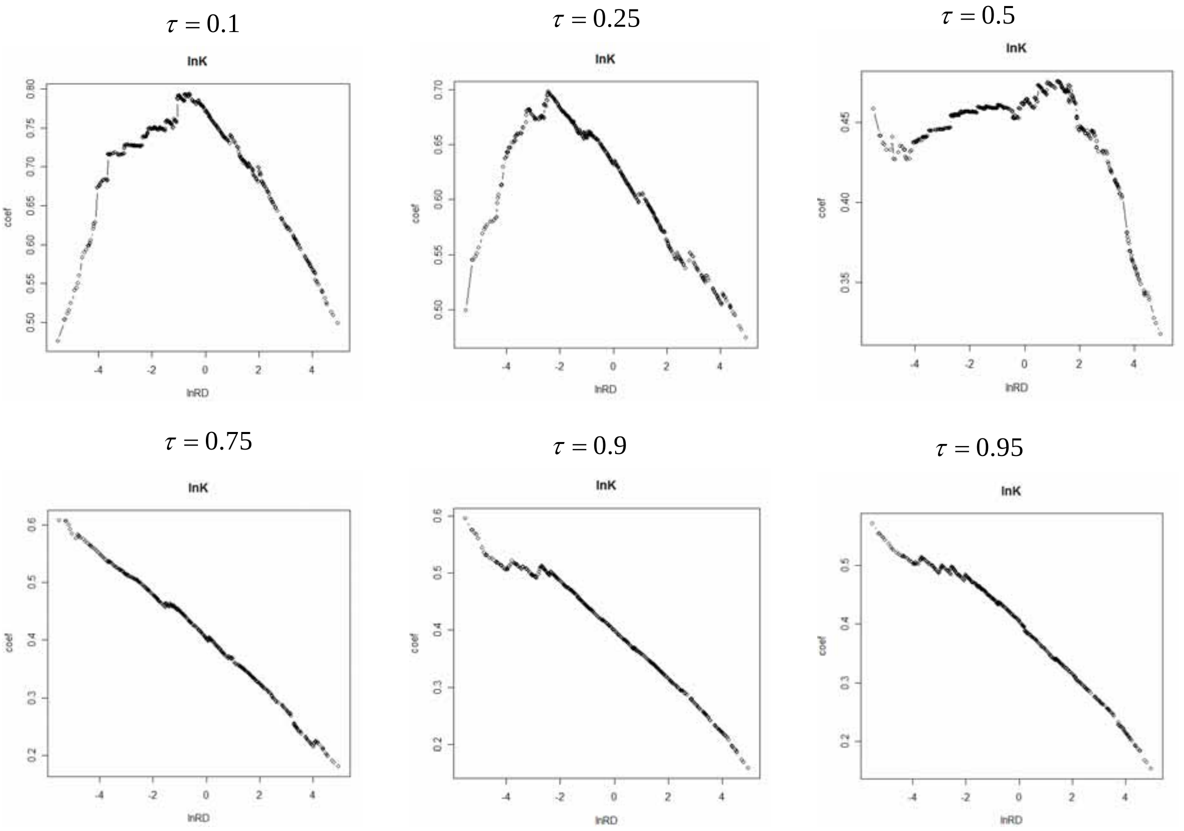

Figure 2 The estimates of R&D on capital productivity at various efficiencies

The estimated effects of R&D expenditure on technology $\beta_t^{\tau}(\ln RD)$ represents in Figure 3. The contributions of R&D on technology appear U-shape around the medium-efficient Asian biotech firms. Considerable R&D expenditures can upgrade technology for firms with extremely low efficiency levels. In addition, the impact of R&D on technology for firms with extremely high efficiency levels seems relatively stable.

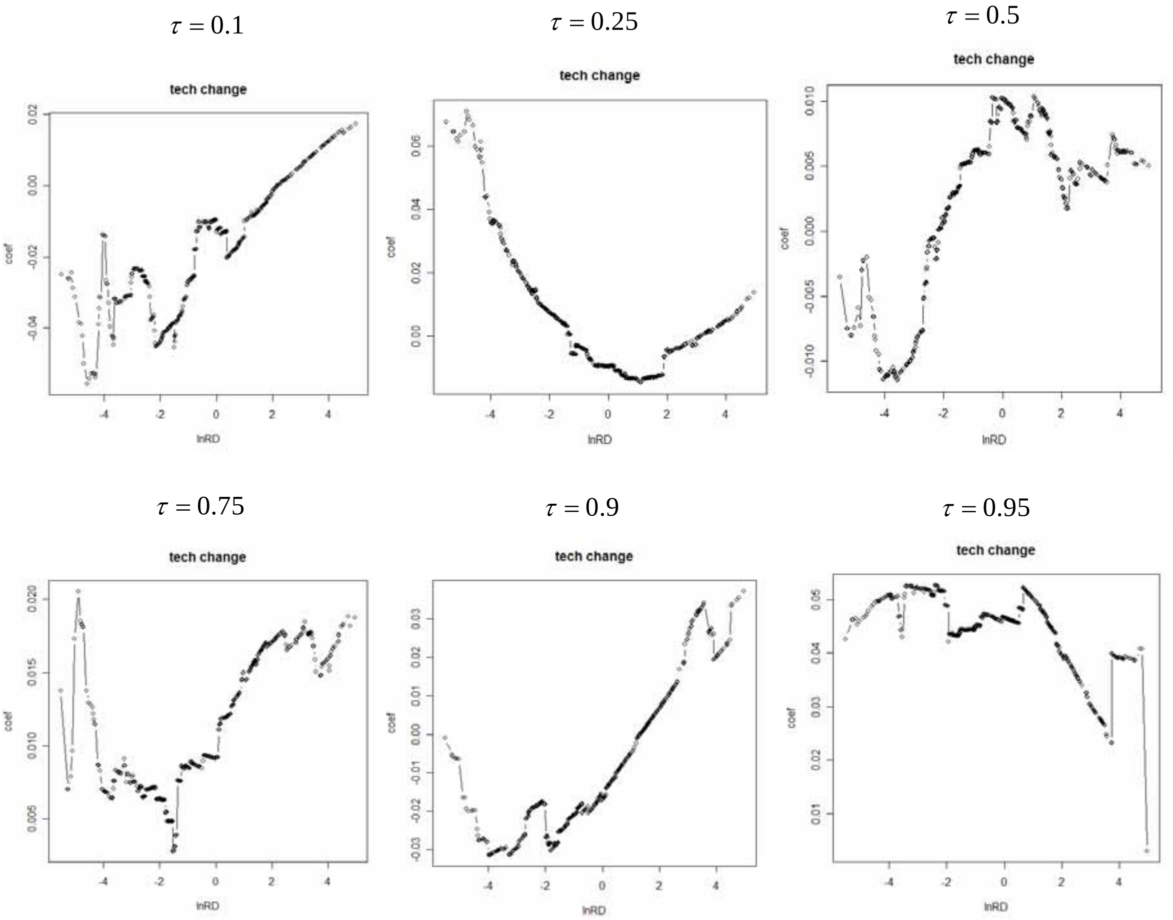

Figure 3 The estimates of R&D on technical change at various efficiencies

We have discussed how R&D influences Asian biotech firms' technology and output elascities of inputs. However, what is the overall impact of R&D on their productivity? This study employs the elasticity of the R&D productivity to investigate how the overall impact of R&D on their productivity changes at various efficiency levels. The elasticity of the R&D productivity at each efficiency level is the derivative of $Q_\tau(\ln y|L, K, RD, t)$ with respect to ln *RD*. It can be written as:

$$\frac{\partial Q_{\tau}}{\partial \ln RD}=\frac{\partial \alpha^{\tau}\left(\ln RD\right)}{\partial \ln RD}+\frac{\partial \beta_{L}^{\tau}\left(\ln RD\right)}{\partial \ln RD}\times \ln L+\frac{\partial \beta_{K}^{\tau}\left(\ln RD\right)}{\partial \ln RD}\times \ln K+\frac{\partial \beta_{t}^{\tau}\left(\ln RD\right)}{\partial \ln RD}\times t \quad (11)$$

Figure 4 shows the estimates of the elasticity of the R&D productivity. It indicates that the overall contribution of R&D is positively related to the efficiency levels. The average elasticities of R&D productivity are all positive for each efficiency level. Nevertheless, Table 2 shows that the 95% confidence intervals of output elasticities of R&D contain zero and negative values for extremely inefficient firms ($\tau \leq 0.3$.). This may suggest that R&D might insignificantly or negatively influence productivity of Asian biotech firms, operated on the extremely lower production efficiency quantile.

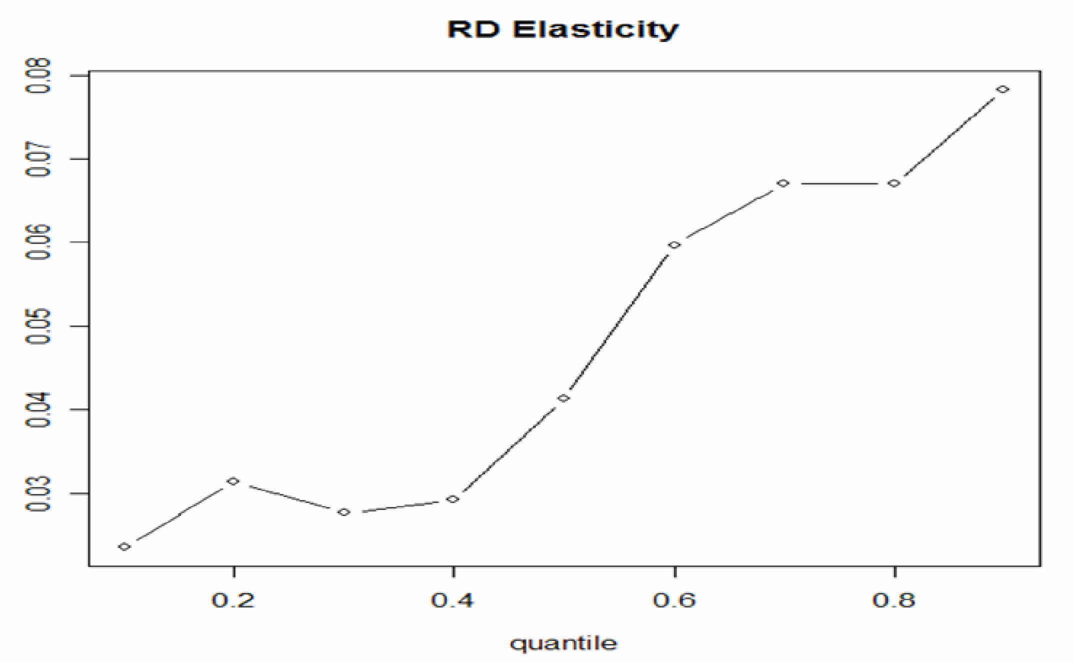

Figure 4 Smooth Coefficient Quantile Estimates of Elasticity of R&D Productivity

3.3 Discussion

This study uses the smooth coefficient quantile model, proposed by Huang et al. (2007), to explore the contribution of R&D on Asian biotech firms' productivity at various efficiency levels. The empirical results indicate that the overall contribution of R&D on Asian biotech firms are positively related their efficiency levels. Firms associated with higher efficiency levels have higher capability to absorb the contribution of R&D to their productivity. However, the 95% confidence intervals of output elasticities of R&D contain zero and negative values for $\tau \leq 0.3$. Hence, if firms operate on the extremely lower efficiency levels, they may experience insignificant or negative influence of R&D on productivity. These results support our hypothesis that inefficiency may prevent firms to completely absorb the contribution of R&D on productivity, and offer a possible explanation why we observed the inconsistent conclusions about the relationship between R&D and productivity. This may indicate that the technical efficiency not only improves the productivity of Asian biotech firms directly, but also reinforces their productivity indirectly through enlarging the capability to absorb the contribution of R&D to productivity.

Table 2 Descriptive Statistics of Elasticity of R&D Productivity

quantile	mean	S.D.	min	max	95% C. I.
0.1	0.0235	0.0124	0.0046	0.0356	(–0.0013, 0.0483)
0.2	0.0314	0.0193	0.0064	0.0469	(–0.0072, 0.0700)
0.3	0.0276	0.0161	0.0061	0.0403	(–0.0046, 0.0437)
0.4	0.0292	0.0138	0.0052	0.0388	(0.0016, 0.0568)
0.5	0.0368	0.0089	0.0175	0.0519	(0.0170, 0.0566)
0.6	0.0532	0.0088	0.0215	0.0685	(0.0346, 0.0708)
0.7	0.0658	0.0055	0.0362	0.0726	(0.0548, 0.0768)
0.8	0.0615	0.0077	0.0309	0.0741	(0.0461, 0.0769)
0.9	0.0707	0.0150	0.0241	0.0916	(0.0407, 0.1007)

For firms associated with extremely higher efficient levels, R&D will be capable of upgrading their labor productivity regardless of R&D levels, while its contribution to the elasticity of capital declines. These findings may suggest that the human resource management as well as R&D activities is important for these firms. Even if they have higher ability to assimilate the contribution of R&D activities, the effect may decline largely when they experience a higher turnover of staff. Furthermore, a group with higher cohesiveness, due to less anticipated staff turnover, will have higher levels of professional and social interaction, social influence and satisfaction (Shaw, 1981).

Firms with low or median levels of efficiencies can enhance productivities by improving their efficiencies if they do not have enough resource to inflate R&D expenditure. Expanding efficiencies can enlarge the influence of current R&D on productivity. For $\tau \leq 0.5$, the relationship between R&D and output elasticity of labor appears U-shaped, while it emerges inverse U-shaped between R&D and output elasticity of capital. In other words, the contributions of mild R&D expenditures focus on the marginal productivity of capital, while it may contribute mainly on the labor productivity if the R&D expenditure exceeds a threshold. Hence, a suitable human resource management is also critical if these firms invest enough R&D activities. On the other hand, if they view R&D investment as a risky activity, do not want to invest too much R&D. The capital investment is crucial to advance productivity since the output elacticity of capital is more important than that of labor.

IV. Concluding Remarks

After completion of human genome project, biology went into "post-genome era." There are huge profits in the biotech industry in the post-genome era. Asian countries have had markedly different approaches to develop their biotech industry. R&D plays an important role in the performance of biotech firms. Many literatures examined the impact of R&D on productivity and efficiency. However, they did not obtain consistent conclusions. Some found that R&D contributes positively to productivity, while other argued that both are negatively related. This study proposes that firms with different levels of efficiencies may have distinct capabilities to absorb the contribution of R&D on productivity. We employ the non-neutral efficiency effect model, proposed by Huang et al. (2007), to empirically analyze the proposed hypothesis.

This study employs the data set, obtained from COMPUSTAT and the Taiwan Economic Journal, to investigate how technical efficiency influences the contribution of RD on productivity of Asian biotech firms. The empirical results show that Asian biotech firms associated with higher efficiency levels have larger capability to absorb the contribution of R&D to their productivity, while firms operated on the extremely lower efficiency levels may acquire insignificant or negative influence of R&D on productivity. These results support our hypothesis that inefficiency may prevent firms to completely absorb the contribution of R&D on productivity, and offer a possible explanation why we observed the inconsistent conclusions about the relationship between R&D and productivity.

Other empirical findings include: (1) For firms associated with extremely higher efficient levels, R&D will be capable of upgrading their labor productivity regardless of R&D levels, while its contribution to the elasticity of capital declines; (2) If firms operate on the low or median levels of efficiencies, the relationship between R&D and output elasticity of labor appears U-shaped, while it emerges inverse U-shaped between R&D and output elasticity of capital; (3) When the R&D expenditures of Asian biotech firms cross a threshold, R&D can augment the labor productivity at increasing rate regardless of efficiency levels.

This study focuses on the biotech industry. The R&D activity is also crucial for other high tech industries, e.g., the IT industry. This model can be used to investigate whether or not IT firms with different levels of efficiencies have distinct capabilities to absorb the contribution of R&D on their productivity. Furthermore, if the information about the human capital of biotech firms is available, we will be able to obtain a more complete picture of biotech firms' productivity and offer clearer description about the contribution of R&D on productivity from human resource and human capital.

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