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Does R&D Improve Productivity? Evidence from Asian Biotech Firms

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Abstract

Empirical evidence on the contribution of R&D on productivity and efficiency has produced mixed results. Using 141 Asian biotech firms, this study employs the smooth coefficient quantile model to empirically test the hypothesis that firms with different levels of efficiencies have distinct capabilities to absorb the contribution of R&D on productivity. The empirical results support the hypothesis that firm with higher efficiency levels do have larger capability to absorb the contribution of R&D to their productivity. In addition, firms operated on the extremely lower efficiency levels may acquire insignificant or negative influence of R&D on productivity. Other empirical findings include: (i) R&D activity promotes labor productivity and degrades capital productivity for firms associated with extremely higher efficient levels regardless of R&D levels; (ii) if firms operate on the lower efficiency levels, the relationship between R&D and output elasticity of labor appears U-shaped, while it becomes inversely U-shaped between R&D and output elasticity of capital; and (iii) if firms invest enough R&D expenditures, R&D activity augments the labor productivity and lessen the capital productivity, regardless of efficiency levels.

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

1. 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 field went into “post-genome era.” The biotech industry is advanced rapidly to develop new medicines and diagnostic methods. There are significant 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 21st century.

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In addition, the R&D activity lies at the heart of biotechnology firm strategy (Malecki, 1997) and thus, 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 and Coulombe, 2006; Guisado-Gonzalez et al., 2016a), while Graves and Langowitz (1993), Scherer (1983), and Szczygielski et al. (2017) 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.

The innovation process means that an idea is transformed into a commercial product. The process includes a series 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; Chen and Xu, 2018; Wang and An, 2019; Aldieri and Vinci, 2019; Zhao and Wang, 2020). 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; Bahena-Álvarez et al., 2019; Sjödin et al., 2019).

Many literatures explored the relationship between firms' R&D activities and performance (Decarolis and Deeds, 1999; Hall and Bagchi-Sen, 2007). However, they obtain mixed conclusions for the impact of R&D on productivity. *Beck et al. (2014) and* Guisadogonzález et al. (2016b) argued that R&D and productivity are positively related, while Li et al. (2015) and Guo et al. (2016) suggested that R&D contributes negatively to 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 Li, 2003; Terziovski and Morgan, 2006). 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. Many studies found that various factors influence the capacity of absorbing new knowledge (Minbaeva, 2008; Foss et al., 2009; Sun and Anderson, 2010; Martinkenaite and Breunig, 2016; Hart et al., 2016; Distel, 2017; Ter Wal et al., 2017; Enkel et al., 2017; Yao and Chang, 2017). We therefore propose that firms with different levels of efficiencies may have distinct capabilities to absorb the contribution of R&D on productivity.

The above studies employed the maximum likelihood (ML) or the ordinary least squares (OLS) method to estimate the contribution of R&D on productivity. These methods 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, there is a need 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 (2008), 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.

We focus on Asian firms as their countries have had markedly different approaches to carving out niches in the Asian biotech industry. For instance, Singapore proposed "Industry 21" program 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 Korean firms having a 10% market share of the biotech industry in the world by 2010. In Malaysia, the government has 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 in 2006 reported that the Asian biotech industry had the highest growth rate of R&D investment worldwide during 2004 - 2005 (during this period 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 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. Section 4 offers the discussion. The final section gives concluding remarks.

2. Methodology

Quantile regression, introduced by Koenker and Bassett (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 (Cai and Xu, 2008).

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 quantile model, which is capable of investigating the contribution of R&D on biotech firms' productivity at different efficiency levels.

Consider a deterministic frontier production function

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

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

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

where the quantile coefficient $\alpha^\tau(z)\left(= \alpha + h(z)Q_\tau(u^*)\right)$ 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:

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

where the quantile coefficients $\alpha^\tau(z)\left(= \alpha + h_0(z)Q_\tau(u^*)\right)$ and $\underset{\sim}{\boldsymbol{\beta}}^\tau(z)\left(= \underset{\sim}{\boldsymbol{\beta}} + \underset{\sim}{\boldsymbol{h}}_1(z)Q_\tau(u^*)\right)$ 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 (2008), to estimate the smooth coefficient conditional quantile regression model. Under some regularity conditions, the corresponding estimators are consistent and asymptotic normal (Cai and Xu, 2008). 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) :

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

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

where $\alpha^{(j)}(z_0)$ and $\underset{\sim}{\beta}^{(j)}(z_0)$ 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:

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

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

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

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 $\rho_\tau(b) = (\tau - 1)b$ 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 $c = 0.79\gamma$ where γ is the inter-quartile rage, being robust and able to avoid the influence of extreme values. This paper sets $h_n = 0.79\gamma n^{-1/5}$.

3. Empirical Analysis

3.1 Data and Variables

The data set is obtained from S&P Compustat and Taiwan Economic Journal Data Bank and 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, Philippines, and Indonesia. All nominal variables are deflated by each country's 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. 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:

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

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 $\underset{\sim}{\boldsymbol{x}}$ 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 $\underset{\sim}{\boldsymbol{x}}$ 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.

Figure 1 exhibits the output elasticities of labor $\beta_L^\tau\left(\ln \mathrm{RD}\right)$ at different efficiency levels. The contribution of R&D on the labor productivity reveals the U-shaped relation for firms with lower efficiency levels (for example, $\tau \leq 0.5$). It may suggest that R&D will weaken the labor productivity if inefficient firms cannot invest enough R&D. On the other hand, firms associated with higher efficiency levels (for instance, $\tau \geq 0.75$) experiences a positive relationship between R&D and the labor productivity. In summary, when the R&D expenditures of Asian biotech firms go beyond a threshold, R&D can augment the labor productivity at increasing rate regardless of efficiency levels.

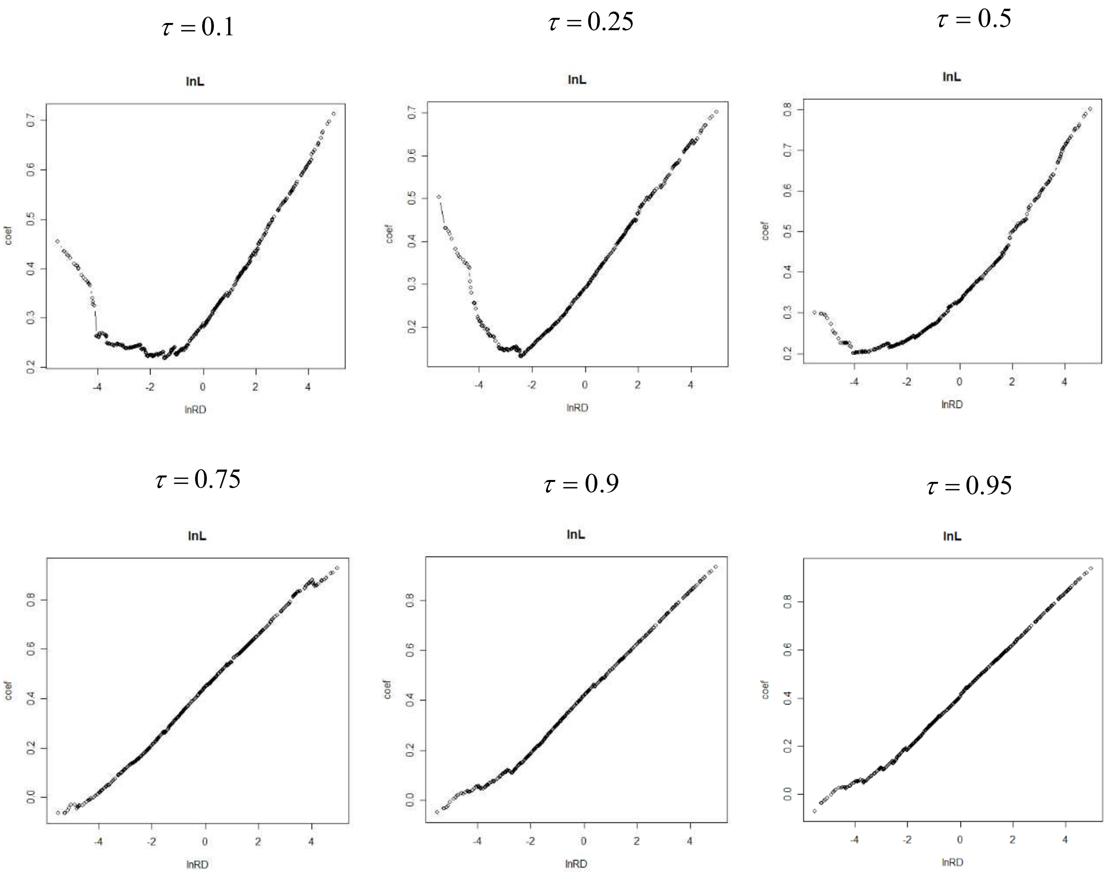

Figure 1 The estimates of R&D on labor productivity at various efficiencies

Figure 2 shows the relationship between R&D and output elasticities of capital $\beta_K^{\ \tau}\left(\ln RD\right)$ at varying efficiency levels. In contrast to Figure 1, the relationship between R&D and the capital productivity is inversely U-shaped for extremely inefficient firms (for example, $\tau \leq 0.5$). In other words, moderate R&D expenditure can enlarge the output elasticity of capital for those Asian biotech firms associated with lower efficiency levels. Nevertheless, R&D lessens the capital productivity for nearly efficient firms (for instance, $\tau \geq 0.75$). We may conclude that if the R&D expenditures surpass a threshold, R&D will abate the capital productivity at increasing rate regardless of efficiency levels.

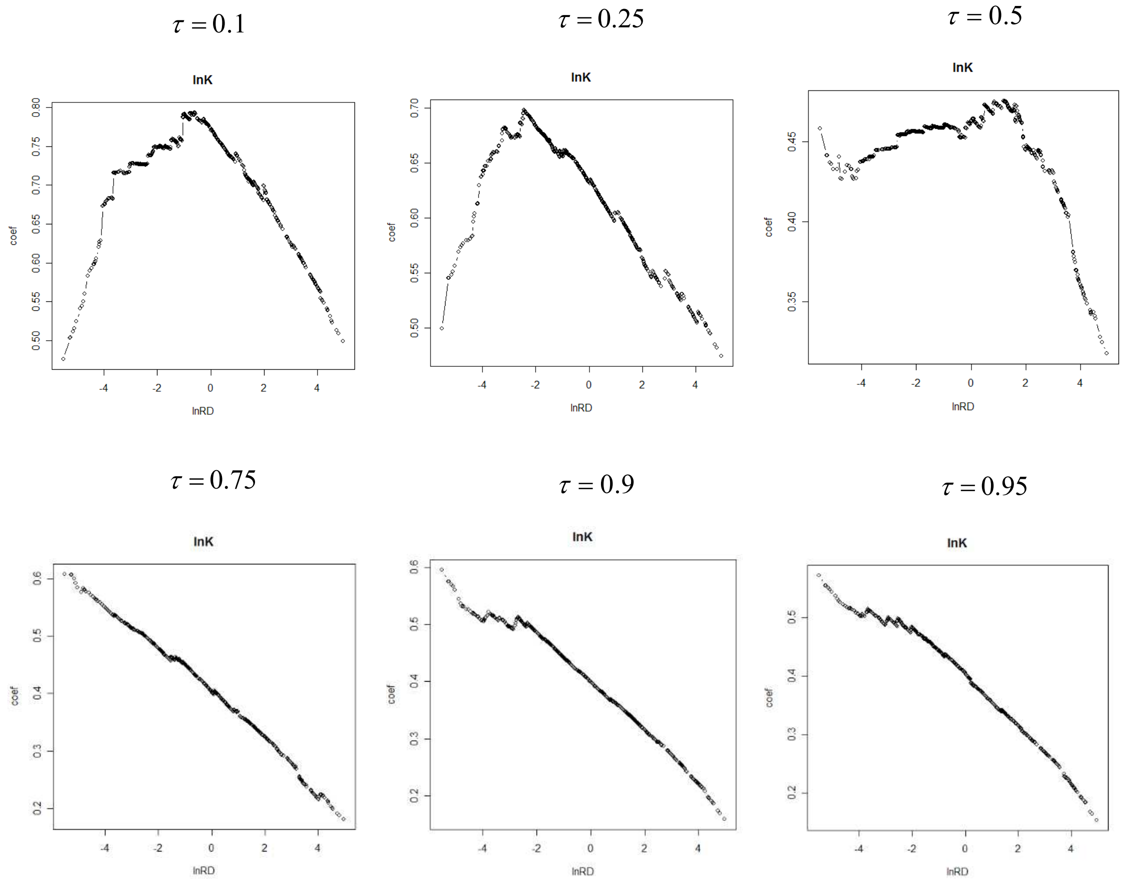

Figure 2 The estimates of R&D on capital productivity at various efficiencies

The estimated effects of R&D expenditure on technology $\beta_t^{\tau}(\ln RD)$ are shown in Figure 3. The contributions of R&D on technology in general appear U-shaped for the Asian biotech firms. Hence, considerable R&D expenditures can upgrade technology of Asian biotech firms. In addition, the impact of R&D on technology for firms with extremely high efficiency levels (τ = 0.95) seems relatively stable.

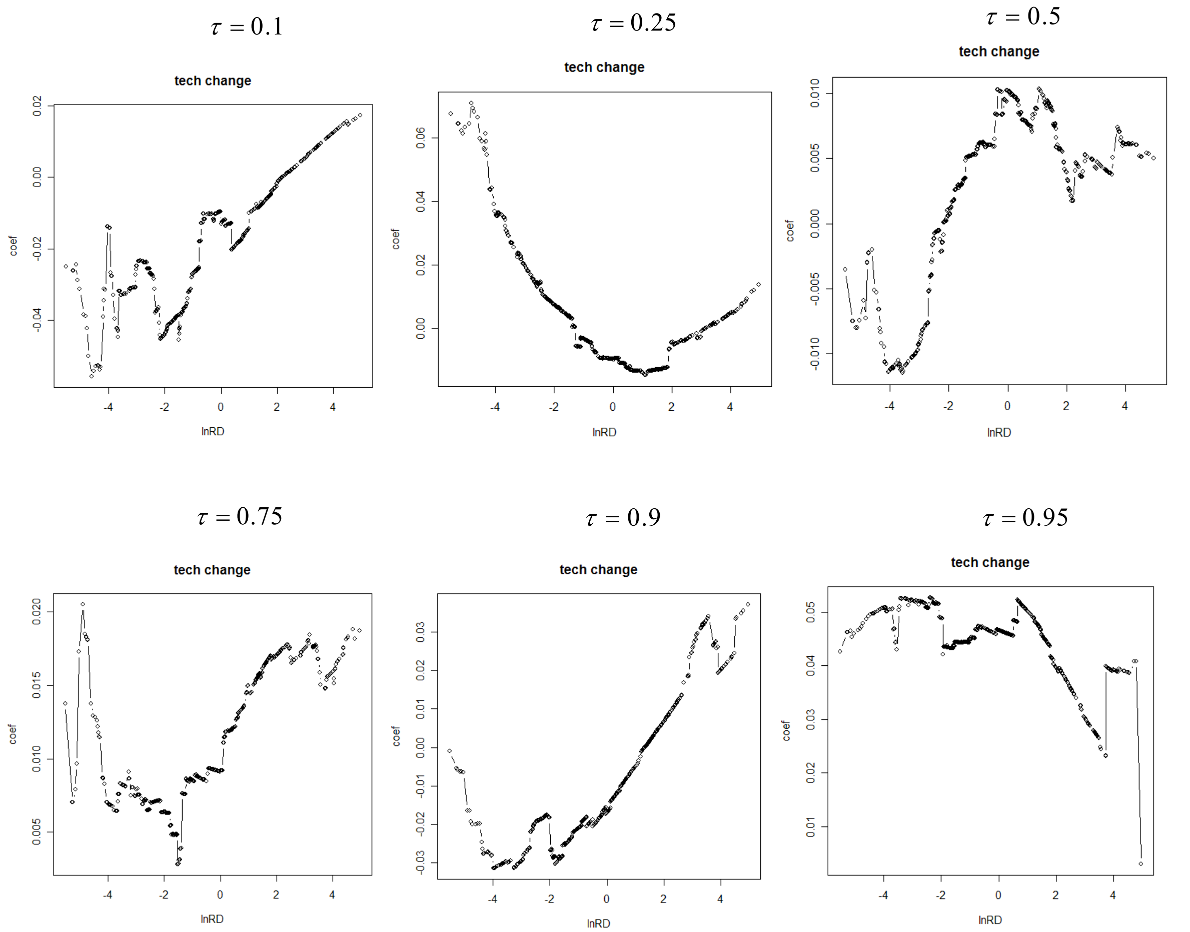

Figure 3 The estimates of R&D on technical change at various efficiencies

We have discussed how R&D influences Asian biotech firms' technology and output elasticities of inputs. Another important issue is the overall impact of R&D on 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 $Q_\tau\left(\ln y \middle| L, K, RD, t\right)$ with respect to ln *RD* can be written as:

$$\frac{\partial Q_\tau}{\partial \ln RD} = \frac{\partial \alpha^\tau\left(\ln RD\right)}{\partial \ln RD} + \frac{\partial \beta_L^\tau\left(\ln RD\right)}{\partial \ln RD} \times \ln L + \frac{\partial \beta_K^\tau\left(\ln RD\right)}{\partial \ln RD} \times \ln K + \frac{\partial \beta_t^\tau\left(\ln RD\right)}{\partial \ln RD} \times t \tag{11}$$

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, when we eliminate the observations with the most extreme values of R&D elasticity in each production efficiency quantile, we find that some firms may experience negative relationship between R&D and productivity. The last two columns of Table 2 show the intervals by excluding 5% and 2.5% of observations with the highest and lowest elasticities of R&D productivity. The intervals corresponding to the extremely lower efficiency levels ($\tau \leq 0.25$) consist of zero and negative values. This may suggest that R&D might insignificantly or negatively influence productivity of Asian biotech firms when they operate on the extremely lower production efficiency quantiles.

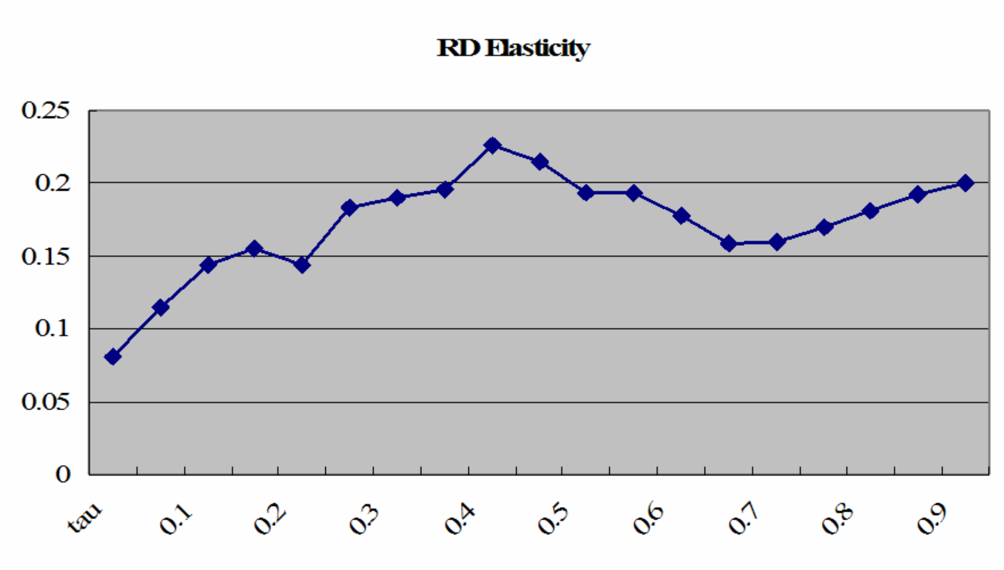

Figure 4 Average Elasticities of R&D Productivity

4. 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 productivity of 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, if firms operate on the extremely lower production efficiency quantiles, 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. We could conclude 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.

For firms associated with extremely higher efficient levels, R&D is 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 will be offset 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 operating on the extremely lower production efficiency quantiles may suffer insignificant or negative impact of R&D on productivity. Hence, the top priority of firms with lower efficiency levels to advance productivity is to improve their technical efficiency. Enhancing efficiencies not only promote productivity directly, but also can help firms to truly absorb 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 activity too risky to spend enough R&D expenditures, the capital investment is crucial to advance productivity since the output elasticity of capital is more important than that of labor

Table 2 Elasticity of R&D Productivity

τ	Mean	(5th percentile, 95th percentile)	(2.5th percentile, 97.5th percentile)
0.05	0.0807	(–0.2045, 0.2623)	(–0.2530, 0.2870)
0.10	0.1146	(–0.1051, 0.2443)	(–0.1565, 0.2610)
0.15	0.1447	(–0.0020, 0.2724)	(–0.0140, 0.3097)
0.20	0.1550	(–0.0167, 0.3191)	(–0.0464, 0.3622)
0.25	0.1443	(0.0095, 0.2737)	(–0.0150, 0.3105)
0.30	0.1836	(0.0607, 0.3122)	(0.0424, 0.3379)
0.35	0.1899	(0.0998, 0.2868)	(0.0844, 0.3052)
0.40	0.1960	(0.0986, 0.3004)	(0.0842, 0.3183)
0.45	0.2268	(0.1380, 0.3261)	(0.1245, 0.3413)
0.50	0.2149	(0.1585, 0.2840)	(0.1510, 0.2916)
0.55	0.1937	(0.1373, 0.2572)	(0.1211, 0.2645)
0.60	0.1939	(0.1161, 0.2828)	(0.0966, 0.2892)
0.65	0.1774	(0.0825, 0.2895)	(0.0578, 0.3021)
0.70	0.1589	(0.0409, 0.2806)	(0.0076, 0.2961)
0.75	0.1602	(0.0233, 0.3025)	(0.0024, 0.3284)
0.80	0.1702	(0.0251, 0.3213)	(0.0024, 0.3472)
0.85	0.1814	(0.0016, 0.3728)	(0.0008, 0.4132)
0.90	0.1928	(0.0336, 0.3847)	(0.0047, 0.4040)
0.95	0.2006	(0.1230, 0.3061)	(0.1064, 0.31917.)

5. Concluding Remarks

After the completion of human genome project, biology went into "post-genome era." There are significant 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. Although many studies have examined the impact of R&D on productivity, they did not obtain consistent conclusions. Some studies have found that R&D contributes positively to productivity, while others have argued that both are negatively related. This study has proposed that firms with different levels of efficiencies may have distinct capabilities to absorb the contribution of R&D on productivity. We employ the smooth coefficient quantile model, proposed by Huang et al. (2007), to empirically analyze the proposed hypothesis.

Using the data set obtained from COMPUSTAT and the Taiwan Economic Journal, we have investigated how technical efficiency influences the contribution of R&D on productivity of Asian biotech firms. We find that Asian biotech firms associated with higher efficiency levels have larger capability to absorb the contribution of R&D to their productivity. Moreover, firms operated on the extremely lower production efficiency quantiles may acquire insignificant or negative influence of R&D on productivity. These results offer a possible explanation why we observed the inconsistent conclusions about the relationship between R&D and productivity.

Other notable empirical findings include: (1) for firms associated with extremely higher efficient levels, R&D upgrades labor productivity and reduce capital productivity regardless of R&D levels, while its contribution to the elasticity of capital declines; (2) if firms operate on the lower efficiency levels, the relationship between R&D and output elasticity of labor appears U-shaped, while it reveals inversely U-shaped between R&D and output elasticity of capital; and (3) when the R&D expenditures of Asian biotech firms exceed a threshold, R&D can augment the labor productivity and lessen the capital productivity regardless of efficiency levels.

This study has focused on the biotech industry. The R&D activity is also crucial for other high-tech industries such as 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, Lucca (1988; 1993) proposed that education and learning by doing can enhance economic growth. Hence, given that human capital data of biotech firms is available, then we can 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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