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Are R&D firms more efficient? A two-step switching stochastic frontier approach

Abstract

Are R&D firms more efficient than non-R&D firms? This study employs a two-step switching stochastic frontier approach to examine the RD-efficiency nexus. Different from previous studies, this approach corrects the endogenous R&D choice effect in erecting R&D and non-R&D firms' production frontiers and then estimates their technical efficiency and determinants of inefficiency. Using a sample of 7,590 Taiwanese electronics firms, our empirical works show R&D firms, on average, have a higher technical efficiency than non-R&D firms under the conventional setting. While this result reverses as the endogenous R&D choice effect is considered, pointing out the importance of endogenous R&D choice in examining the RD-efficiency link. Moreover, R&D firms are found to have a higher technology frontier than non-R&D firms, indicating the importance of R&D in promoting technological competence. Finally, the positive contribution of R&D activity to production is mainly sourced from accumulated R&D capital rather than current R&D outlay.

Keywords: efficiency, R&D, stochastic frontier analysis, switching regression.
JEL Classification: L23, O33.

Introduction

Over the past decades, endogenous growth literature has stressed the role played by innovation in promoting economic growth. From micro-level perspective, R&D investment is one of the important strategies to raise a firm's technological capability and productivity. While the positive impact of R&D on productivity is widely recognized in existing literature[1], the R&D-efficiency connection is less well understood.

How does R&D affect a firm's technical efficiency? It depends on the relative strength of two effects: efficiency might be raised through "productivity enhancement effect" and lowered through "technology enhancement effect". Firms engaging in R&D to develop new products or new process can increase their sales or lower production costs, resulting in a higher productivity. From the static viewpoint that technological frontier is fixed, the positive linkage of R&D to productivity accompanies the interchangeable notion that R&D has a positive contribution to technical efficiency. This is the so-called productivity enhancement effect. On the other hand, R&D is the main source of technical progress, suggesting R&D can increase the production frontier curve facing the R&D firm, that is, an upward shift in production frontier. Although R&D can increase firms' productivity, their technical efficiency may even lower if the level of productivity increase is lower than the frontier improvement. Therefore, the technology enhancement effect may have a negative efficiency effect on R&D. The two effects discussed above provide some guidance on the empirical R&D-efficiency nexus: when the R&D activity becomes more productivity enhancement oriented, a positive R&D-efficiency nexus would be revealed. Once the R&D activity inclines to be more technology enhancement oriented and a firm cannot apply the newly developed technologies to production in a timely manner, the efficiency measured as the relative position from actual production point to the frontier would be lower.

Empirical studies on the R&D-efficiency nexus are limited but growing. Dilling-Hansen et al. (2003) adopted the stochastic frontier approach (SFA) model to examine the effect of R&D on technical efficiency in Danish firms and found R&D-active firms (R&D firms) are significantly more efficient than non-R&D active firms (non-R&D firms). However, the linkage might be insignificant in some cases, since the short-term effect of current investment in R&D is hard to prove. This positive association between R&D and efficiency is also found in Aw and Batra (1998) and Wu et al. (2007). Alternatively, some studies suggest R&D activity would not necessarily positively relate to firms' efficiency (Ferrantino, 1992; Perelman, 1995; Kim, 2003) using the same estimation approach.

Although the real effect of R&D on technical efficiency has attracted increasing empirical studies, many ambiguities and uncertainties remain in the literature, suggesting the need for future empirical works. More importantly, there are several failings that are not well dealt with in previous works. First, the irrelevance of R&D activity and efficiency remains ill-interpreted,

[1] The firm-level evidence on the relationship between R&D and productivity, please refer to Wieser (2005) for a comprehensive survey.

because the relative importance of productivity enhancement effect and technology enhancement effect is not clarified clearly. Second, the apparent problem of endogenous R&D choice was not well considered in previous studies, suggesting the inference in the relation between R&D and efficiency is biased. Third, in virtue of the fact that R&D and non-R&D firms are assumed to operate under the same production frontier, once the identical frontier is enhanced by R&D firms, all the non-R&D firms' efficiency measures should be lowered immediately. However, whether R&D and non-R&D firms can be strongly assumed to act under the same production frontier is problematic. Lau and Yotopoulos (1989) pointed out, when certain distinct objective conditions are imposed on different groups of firms, the firms in different groups would not operate under an identical frontier. Those conditions depend on specific circumstances, such as the technological environment. Faria et al. (2005) have highlighted that technological flexibility is important in explaining differences in efficiency, implying that the technological frontier a firm faces might be the result of endogenous choice on technology adoptions.

To tackle these perplexities, this study attempts to research the R&D-efficiency connection, starting from three distinct perspectives. First, the decision on R&D activity should be made according to their own comparative advantage for the rational and profit-maximizing firms. That is, a firm will engage in R&D when the expected benefit is expected to be larger than the cost. For the non-R&D firms, R&D activity may be considered their comparative disadvantage, while other strategies would be the more preferred alternatives for preserving efficiency. Therefore, the decision to undertake R&D activity for a firm would refer to an issue of endogenous selection. R&D activity might improve firms' efficiency, while it should be presumed that R&D firms would be not necessarily more efficient than non-R&D firms, after considering the endogenous effect of the R&D decision.

Second, previous empirical literature regresses the technical efficiency (or inefficiency) on R&D variables (that is: R&D dummy or R&D intensity) to explore the RD-efficiency nexus. Such a specification implies R&D investment is regarded as one of firm-specific characteristics and this variable captures only the short-term effect of R&D investment. Recently, the endogenous growth theory stresses knowledge accumulation as a vital source of economic growth; the R&D activity is also commonly recognized as one of most critical mechanisms in forming new knowledge. Based on the properties of accumulation and lag inherently in R&D activity, it becomes more popular in empirical studies to regard R&D as one type of capital in production function (for example, Adams, 1999; Hall and Mairesse, 1995). Thus, different from previous studies, it is preferred to consider the R&D capital in constructing the production function and the R&D intensity in the inefficiency regression in our empirical works. This consideration would be helpful to clarify the long- and short-term effects of R&D activity on technical efficiency.

Third, it is reasonable to believe the R&D and non-R&D firms do not operate under an identical technological frontier and use the same production technology. Beside the possible differences in economic circumstances between the two firm groups[1], the argument for the separate frontier is quite obvious because the factors comprising the production functions include the intangible R&D capital for R&D firms, but do not for non-R&D firms. R&D activity involves the processes of trial and the basis for creating new know-how in using inputs or innovation. It inherently implies the cost structures and output elasticities of factors (such as capital and input) for R&D firms would differ from non-R&D firms[2]. Thus, the latent risk might be embedded in econometric methods of an empirical study if the separate frontiers are not considered in constructing production functions (Orea and Kumbhakar, 2003). Therefore, a set of econometric methods which carefully and properly consider the endogeneity of the R&D decision and the separate estimations of production functions are particularly desired.

Based on these considerations, this paper aims to provide new empirical evidence on the R&D-efficiency link using a cross-sectional plant-level data of Taiwan's electronics firms. Different from the conventional approach, this study employs a two-step switching stochastic frontier approach which enables us to correct the latent endogenous R&D effect in building R&D and non-R&D firms' production frontiers to estimate their technical efficiency, while inspecting the determinants of technical efficiency simultaneously. Further, in view of the separate frontiers, comparing firms' efficiency across frontiers is limited but emerging.

[1] In Lau and Yotopoulos (1989, p. 242), it was pointed out that when certain distinct economic circumstances are imposed on different groups of firms, the firms in different groups would not operate under an identical frontier.

[2] Li et al. (2002) also argued that both the firms' capital elasticity and labor elasticity should be affected by R&D activity and specified the technological parameters of the input factors in their stochastic production function model are functions of R&D expenditure.

An 'adjustment factor' is thus introduced for disentangling the constraint[1]. The empirical results find: (i) R&D firms overall tend to show a higher technical efficiency than their non-R&D counterparts without considering the endogenous R&D choice, while this result reverses after controlling for the endogenous R&D effect. It implies R&D firms are not necessarily more efficient, depending on the relative strength of productivity enhancement effect and technology enhancement effect. (ii) Even though R&D firms are not more efficient, they are actually found to have a higher frontier than non-R&D firms, supporting the importance of R&D in promoting technological progress; and (iii) the positive contribution of R&D activity to technical efficiency is mainly soured by R&D capital accumulation, but the effect of current R&D investment is the reverse.

The rest of this paper is organized as follows: the econometric specifications and the data source and variables constructions, including the variables in production function and the possible influences of technical efficiency are introduced in section 1. Section 2 presents the analyses of the empirical results. Conclusions are presented in the final section.

1. Empirical specifications, data and variables

1.1. Specifications of empirical models. Based on the original idea of Farrell (1957), the technical efficiency of firms can be measured by a radial distance function represented as the ratio of actual output relative to the output level on the production frontier. In this study, we employ the SFA model developed by Aigner et al. (1977) and Meeusen and van den Broeck (1977) with a translog form. Following the conventional approach that treats R&D and non-R&D firms using the same technology and operating under an identical frontier, the natural logarithmic form of production frontier and efficiency measures can be specified as:

$$\ln Y_i = \alpha_0 + \sum_j \alpha_j \ln X_{ij} + \frac{1}{2}\sum_j \sum_k \alpha_{jk} \ln X_{ij} \ln X_{ik} - U_i + V_i. \quad (1)$$

In equation (1), Y_i represents the output of firm i; X_i denotes the input vector, while the subscripts j and k index input factors (that is: capital, labor or R&D inputs). These variables are all taken in the logarithmic form. Moreover, V_i is assumed to be a stochastic variable and be independent and identically distributed as $N(0, \sigma_v^2)$. Using the setting of Battese and Coelli (1995), U_i represents the technical inefficiency of firms. It is assumed to be independent of V_i and be a non-negative random variable that is independently distributed as truncations at zero of $N(m_i, \sigma_u^2)$ distribution.

$$m_i = Z_i \psi, \quad (2)$$

where[2] term Z_i represents a vector of possible determinants of technical efficiency and ψ denotes the coefficient vector. Equation (2) is the so-called inefficiency regression and we can calculate a firm's technical efficiency (TE) as $TE_i = \exp(-U_i)$.

As discussed above, it is inappropriate to estimate an identical frontier function encompassing every firm when firms use different technologies within an industry. Due to the differences in technological regimes that originate from the nature of relevant knowledge bases, R&D and non-R&D firms use different technologies and operate under distinct frontiers. To reduce the risk of misspecification, the common procedure is to first sort the firms into certain groups and then estimate the frontier functions for the groups separately. However, it is also problematic as this procedure does not use information contained in one class to estimate the technology of firms that belong to other classes, if these firms are coming from the same industry and share some common features (Orea and Kumbhakar, 2003). To correct the problem, a two-step approach combining the switching regression with the stochastic frontier production model is introduced in this study[3]. The first step is to estimate the endogenous choice on R&D and the second step is to estimate technical efficiency for R&D and non-R&D firms, controlling for the potential influence of R&D choice.

Considering a random sample of N firms that contains M R&D firms and N-M (N>M) non-R&D firms, we define the R&D choice undertaken by firm i to be a dichotomous outcome C that is given by:

$$C_i = \begin{cases} 1, \text{if firm } i \text{ is a R \& D firm} \\ 0, \text{otherwise} \end{cases} \quad (3)$$

where C_i signifies the firm categories: R&D and non-R&D firms. Suppose the decision of engaging in R&D activity is determined by a series of firm-

[1] The stochastic metafrontier model developed by Battese et al. (2004) recently provides an alternative approach by which comparable technical efficiencies can be estimated.

[2] Such a specification which estimates the production function and the inefficiency regression simultaneously refers to the single-stage estimation procedure proposed by Battese and Coelli (1995).

[3] There is also literature developing a single-stage approach combining the latent class structure and the stochastic frontier approach, without the need for the *a priori* sample separation information (see Kumbhakar and Tsionas, 2006; Orea and Kumbhakar, 2003; Greene, 2002).

and industry-specific characteristics (W_h), C_i can be specified as:

$$C_i = \sum_h w_h W_{ih} + \xi_i,\ and\ \xi_i \sim N(0,\sigma^2). \quad (4)$$

According to Heckman (1979), after estimating the equation (4) with the probit model, the selectivity terms (inverse Mill's ratio) for R&D and non-R&D firms can be respectively calculated as:

$$S_i^{RD} = \phi(\hat{C}_i) \Big/ \Phi(\hat{C}_i), \quad (5)$$

and $S_i^{NRD} = \phi(\hat{C}_i) \Big/ \left[1 - \Phi(\hat{C}_i)\right]$, (6)

where terms Φ and ϕ are cumulative and the density functions of the standard normal distribution, respectively.

In the second step, the stochastic frontier production models for groups of R&D and non-R&D firms can be specified as:

$$\ln Y_i^{RD} = \alpha_0^{RD} + \sum_j \alpha_j^{RD} \ln X_{ij}^{RD} + \frac{1}{2}\sum_j \sum_k \alpha_{jk}^{RD} \ln X_{ij}^{RD} \ln X_{ik}^{RD} + S_i^{RD} - U_i^{RD} + V_i^{RD}$$
$$and U_i^{RD} \sim N(m_l^{RD}, \sigma_u^{RD^2}), m_l^{RD} = Z_l^{RD}\gamma^{RD},\ for\ R\ \&\ D\ firms \quad (7)$$

$$\ln Y_i^{NRD} = \alpha_0^{NRD} + \sum_j \alpha_j^{NRD} \ln X_{ij}^{NRD} + \frac{1}{2}\sum_j \sum_k \alpha_{jk}^{NRD} \ln X_{ij}^{NRD} \ln X_{ik}^{NRD} + S_i^{NRD} - U_i^{NRD} + V_i^{NRL}$$
$$and U_i^{NRD} \sim N(m_l^{NRD}, \sigma_u^{NRD^2}), m^{NRD} = Z_l^{NRD}\gamma^{NRD},\ for\ R\ \&\ D\ firms \quad (8)$$

Equations (7) and (8) are the separate production frontier for R&D and non-R&D firms, which also considers the selectivity terms of the two firms groups in the production functions to correct the effect of endogenous R&D choice on technical efficiency. In this specification, one important point is such a specification implies the operational decisive stages of firms associated with R&D choice and efficiency are not simultaneous but recursive. In other words, it is assumed firms first make R&D choices according to their comparative advantage and the production activities are operated under the determined R&D choice. Therefore, the firms' R&D choice is regarded as one predetermined variable of technical efficiency in this study.

More importantly, the direct comparison of efficiency measures for firms using different technologies and producing under different frontiers is inappropriate. For disentangling the constraint, we introduce an adjustment factor (AF) from Aw and Batra (1998) as follows:

$$AF_i^{NRD} = \frac{x_i^{NRD} \times \alpha_i^{RD}}{x_i^{NRD} \times \alpha_i^{NRD}}. \quad (9)$$

Clearly, the adjustment factor represented as equation (9) is for considering the position of the production frontier of R&D firms relative to non-R&D firms. The idea is to calculate the extra value added that can be generated by non-R&D firms if they combine the R&D firm's technologies with their own inputs in production. Then, this predicted value added is compared with that generated by the non-R&D firms using their own technologies and inputs. We can therefore calculate the adjusted technical efficiency (ATE) for non-R&D firms as follows:

$$ATE_i^{NRD} = TE_i^{NRD} \times AF_i^{NRD}. \quad (10)$$

1.2. Data and variable constructions. The stochastic production frontiers for all electronics firms in Taiwan are estimated using cross-sectional data for all firms in the year 2001. The data are mainly sourced from the Industry, Commerce and Service (ICS) Census conducted by the Directorate-General of Budget, Accounting and Statistics in Taiwan. This survey provides elaborate information on the volume or value of raw data on economic activities, enabling us to construct the variables for the production function and the firm- and industry- specific characteristics. The electronics industry designated in this study is aggregated from the four-digit Standard Industrial Classification (SIC) industries, as listed in Table A.1 in the appendix, and comprises 7,590 firms.

For the variable constructions, the output variable is value-added that is measured as the sum of operating income minus the sum of expenses of raw materials, energy, and electricity. The input factors include physical capital (K), labor employment (L) and R&D capital (R). K is measured as the net amount of operating fixed assets, L is measured as the yearly total wage payment, and R is computed from the R&D investment of firms[1]. These variables for the production functions are all taken in the form of a natural logarithm. As for the internal and external environmental conditions faced by firms, five firm-specific and three industry-specific characteristics are considered in this paper. The firm-specific

characteristics include firm age (F-Age), firm size (F-size), the ratio of capital to labor (F-KL), subcontractor intensity (F-SubI), and R&D intensity (F-RDI). On the other hand, the industry-specific characteristics include four-firm concentration ratio (I-CR4), industry scale (I-Scale), and industry R&D intensity (I-RD) of the 4-digit industries where the firms are located. The definitions, constructions and summary statistics for these variables are provided in Table 1.

Table 1. Definitions and constructions of variables, and summary statistics

Variables	Definition, and construction of the variables	Mean (Std. dev.)	
Y	Value added; measured as the sum of operating income minus the sum of expenses on raw materials, energy, and electricity taken in natural logarithmic form.	NRD[a]:	8.3009 (1.6690)
		RD[b]:	11.2420 (2.0515)
K	Capital input; measured as the net amount of operating fixed assets taken in natural logarithmic form.	NRD:	9.1487 (1.5571)
		RD:	11.8537 (2.0254)
L	Labor input; measured as the yearly total wage payment taken in natural logarithmic form.	NRD:	7.5566 (1.5759)
		RD:	10.5632 (1.8019)
R	R&D capital; measured as the R&D capital taken in natural logarithmic form[c].	NRD:	0.0000 (0.0000)
		RD:	10.0124 (2.3064)
F-Age	Firm age; measured as the sum of the value of 2001 minus the starting year of the firm plus the ratio of 12 minus the starting month to 12 taken in logarithmic form.	NRD:	2.4251 (0.5557)
		RD:	2.4882 (0.6002)
F-Size	Firm size; measured as the number of employment taken in logarithmic form.	NRD:	1.9039 (1.4414)
		RD:	4.4410 (1.6307)
F-KL	Capital intensity; measured as the ratio of the fixed capital stock to labor employment taken in logarithmic form.	NRD:	7.2448 (1.0996)
		RD:	7.4127 (0.9538)
F-Sub	Firm's subcontractor intensity; measured as the subcontractor revenue to total sales.	NRD:	0.2198 (0.4078)
		RD:	0.0383 (0.1784)
F-RDI	Firm's RD intensity; measured as the ratio of R&D investment to sales.	NRD:	0.0000 (0.0000)
		RD:	0.0936 (0.2071)
I-CR4	Four-firm concentration ratio; measured as the percentage of total industry output produced by four largest firms in the 4-digit industry where the firms locate.	NRD:	0.4200 (0.1344)
		RD:	0.4518 (0.1227)
I-Scale	Industrial scale; measured as the industrial scale in terms of total sales in the 4-digit industry where the firms locate taken in logarithmic form.	NRD:	18.9726 (0.8877)
		RD:	19.2075 (0.9127)
I-RDI	Industrial RD intensity; measured as the average RD intensity of firms in 4-digit industry where the firms locate.	NRD:	0.0182 (0.0312)
		RD:	0.0361 (0.0513)

Notes: a: Means and standard deviations for non-R&D firms. b: Means and standard deviations for R&D firms. c: Refer to appendix of this paper for details.

2. Empirical results[1]

In this section, we employ two alternative approaches to compare technical efficiencies between R&D and non-R&D firms to highlight the importance of endogenous R&D effect on the R&D-efficiency nexus: (i) the conventional stochastic frontier analysis model as shown by equation (1), and (ii) the two-step switching stochastic frontier approach as shown by equation (7) in the previous section.

2.1. Technical efficiency analysis without the endogenous R&D effect. Table 2 displays the estimated results of the conventional stochastic frontier analysis that does not control for the endogenous R&D effect. As shown in the upper panel of Table 2, it is clear the estimated coefficients for variables of input factors are roughly in line with expectations. Looking further at the estimated results for the inefficiency regression shown in the lower panel of Table 2, we can find that firms' age, size, subcontracted intensity, and industrial scales are negatively associated with technical inefficiency, whereas firms' capital labor ratio, firms' R&D intensity, industrial CR4 ratio, and industrial R&D intensity are positively associated with technical inefficiency. The implications of these estimated results will be provided in the discussion of Table 4 in the following sub-section.

Table 2. Estimation of conventional stochastic frontier analysis model[a]

Variable	Coefficient	Std. err.	t-value
Constant	1.3759***	0.1509	9.1163
Variable	Coefficient	Std. err.	t-value
lnK	0.2044***	0.0401	5.1022

[1] As for the calculation process of R&D capital please refer to the appendix of this study for details. Indeed, we do not find a large difference in the empirical results between using the R&D capital or R&D investment as the factor input in production function.

Table 2 (cont.). Estimation of conventional stochastic frontier analysis model[a]

Variable	Coefficient	Std. err.	t-value
lnL	0.6589***	0.0476	13.8344
lnR	-0.0091	0.0134	-0.6792
lnK^2	0.0878***	0.0080	11.0131
lnL^2	0.1086***	0.0096	11.3520
lnR^2	0.0193***	0.0025	7.7086
lnK x lnL	-0.0909***	0.0073	-12.4766
lnK x lnR	-0.0028	0.0021	-1.3205
lnL x lnR	-0.0049**	0.0025	-1.9101
Inefficiency regression			
Constant	-8.1007***	1.7723	-4.5707
F-Age	-0.1335***	0.0487	-2.7390
F-Size	-1.2403***	0.0366	-33.8583
F-KL	1.1207***	0.0717	15.6411
F-SubI	-2.3712***	0.3248	-7.2999
F-RDI	4.2317***	0.2552	16.5826
ICR4	3.4962***	0.4477	7.8088
I-Scale	-0.4143***	0.0472	-8.7870
I-RDI	10.6365***	1.5501	6.8618
σ2	4.9917***	0.3903	12.7896
Γ	0.9700***	0.0024	401.3774
№ of Observation	7,590		
L-LR $\chi2(0.01, 19)^b$=36.19	-6617.0464***		

Notes: ***, ** and * denote coefficients significant at 1%, 5% and 10% statistical levels, respectively. a: all firms are used to estimate the stochastic frontier regardless of the segmentation of production technology. b: Log-Likelihood ratio test; H_0: all the coefficients equal 0; H_1: at least one of the coefficients is not 0.

Turning to the main question, do R&D firms have a higher technical efficiency than non-R&D firms? To obtain a first indication of the R&D-technical efficiency relation, we calculate average technical efficiencies of R&D and non-R&D firms and conduct the difference tests. The results shown in Table 3 are taken as the benchmark model.

Table 3. Mean technical efficiency estimates of R&D and non-R&D firms (conventional SFA model setting)

Industry categories	Groups	Mean TE	Diff. test	No. of obs.
Electronics industry	NRD	0.6769	4.156**	6,449
	RD	0.6886		1,141
Sub-electronics industries				
Electronics and semiconductor equipment	NRD	0.6228	1.770	138
	RD	0.6772		27
Computer and peripherals	NRD	0.6819	3.655*	1,180
	RD	0.7031		278
Telecommunication and machinery appliance	NRD	0.6521	-2.106	450
	RD	0.6231		128
Audio-visual electronics products	NRD	0.6609	3.860**	724
	RD	0.7019		71
Data storage and media electronic product	NRD	0.6479	0.011	79
	RD	0.6519		21
Semiconductor	NRD	0.7047	-3.936**	357
	RD	0.6677		175
Passive electronics component	NRD	0.6711	13.079***	966
	RD	0.7263		145
Printed circuit board	NRD	0.6824	11.920***	594
	RD	0.7479		83
Other electronic components	NRD	0.6867	-0.454	1,961
	RD	0.6779		213

Notes: ***, ** and * denote coefficients significant at 1%, 5% and 10% statistical levels, respectively. The difference test employed in the table is one-way ANOVA test with F-statistics. The positive and negative signs are denoted for comparison; a positive sign denotes that the mean efficiency of R&D firms is higher than that of non-R&D firms, and vice versa.

For all samples of the 2-digit electronics industry, the mean technical efficiency of R&D firms is 0.6886, which is slightly higher than that of 0.6769 for non-R&D firms. Besides, the different test shows the difference in technical efficiency is statistically significant at the 5% level, indicating that R&D firms are more efficient than their non-R&D counterparts, on average. This result agrees with the positive association of R&D-efficiency inference already mentioned (e.g. Dilling-Hansen et al., 2003 and Wu et al., 2007). If checking the sub-sector of the 3-digit industry further, it can be found the mean technical efficiency of R&D firms is superior in four sub-industries and is significantly inferior in one sub-industry at the 10% statistical level, compared with non-R&D firms. Meanwhile, there are also four industries with no significant difference in efficiency. The range of mean technical efficiencies is 0.6228 to 0.7479, which indicates a moderate technical efficiency for Taiwan's electronics industry. However, it is worth further consideration before we try to draw any conclusion from these results obtained by the conventional specifications that do not consider the effect of endogenous R&D. Moreover, the moderate technical efficiency for Taiwan's electronics industry suggests a substantial proportion of the total variability is associated with technical inefficiency of production. Thus, identifying the factors influencing technical efficiency is also a crucial issue for firms to improve their technical efficiencies.

2.2. Technical efficiency analysis with endogenous R&D effect. We now turn to the two-step switching stochastic frontier approach proposed by this study. In the first step, a switching regression dealing with the R&D choice is carried out by the Probit model and the results are reported in Panel A of Table 4. In the second step, the separate frontier of the two groups incorporating the selectivity terms

for correcting the endogenous effect of R&D choice are conducted with the SFA model. The estimated results are reported in Panel B of Table 4.

Table 4. Estimations of SFA model with R&D choice effect [a]

Panel A. R&D choice regression – Probit model			
Variable	Coefficient	Std. Err.	t-value
Constant	-5.1972***	0.5171	-10.0513
F-Age	-0.1746***	0.0398	-4.3847
F-Size	0.5298***	0.0147	36.0046
F-KL	0.1652***	0.0219	7.5301
F-SubI	-0.8187***	0.0928	-8.8264
ICR4	0.7007***	0.1724	4.0652
I-Scale	0.0804***	0.0251	3.1991
I-RDI	2.1951***	0.5363	4.0930
No. of observations	7,590		
L-LR χ2(0.01, 8)[b]=20.09	-2040.2340***		

Panel B. Stochastic frontiers model						
Variable	R&D firms			Non-R&D firms		
	Coefficient	Std. err.	t-value	Coefficient	Std. err.	t-value
Constant	2.9202***	0.9395	3.1082	1.7810***	0.2343	7.6012
lnK	0.4346***	0.1249	3.4789	0.1416***	0.0431	3.2863
lnL	0.2306	0.1580	1.4589	0.6689***	0.0539	12.4049
lnR	-0.0052	0.0771	-0.0676	-	-	-
lnK^2	0.1163***	0.0301	3.8615	0.0887***	0.0085	10.4705
lnL^2	0.2661***	0.0369	7.2134	0.0982***	0.0104	9.4449
lnR^2	0.0460***	0.0097	4.7372	-	-	-
lnK x lnL	-0.1634***	0.0302	-5.4090	-0.0851***	0.0080	-10.7067
lnK x lnR	0.0180	0.0119	1.5170	-	-	-
lnL x lnR	-0.0521***	0.0131	-3.9891	-	-	-
S (Selectivity term)	-0.2654***	0.1140	-2.3290	-0.0239	0.0229	-1.0468
Inefficiency regression						
Constant	-6.6085***	2.3697	-2.7888	-4.0399***	1.8864	-2.1416
F-Age	-0.9588***	0.3093	-3.1002	0.5420***	0.1267	4.2777
F-Size	-0.1252*	0.0734	-1.7057	-1.4665***	0.0429	-34.1746
F-KL	0.4733***	0.1097	4.3156	0.6419***	0.1226	5.2372
F-SubI	-1.7100***	0.8347	-2.0486	-1.8309***	0.2321	-7.8869
F-RDI	1.7822***	0.2309	7.7187	-	-	-
ICR4	3.2687***	1.0424	3.1357	2.5454***	0.3690	6.8983
I-Scale	0.1461	0.0914	1.5992	-0.3378***	0.0792	-4.2669
I-RDI	4.1804***	1.4994	2.7881	3.7317***	1.0245	3.6424
σ2	1.5019***	0.3382	4.4408	3.4380***	0.3196	10.7571
Γ	0.9004***	0.0237	37.9255	0.9590***	0.0042	226.5907
No. of observations	1,141			6,449		
L-LR χ2(0.01, 22)[b]=40.29	-1057.1023 ***			-		
L-LR χ2(0.01, 17)[b]=33.41	-			-5457.8328***		
Output elasticity of K	0.2680	(0.1313)		0.3097	(0.0968)	
Output elasticity of L	0.5832	(0.2113)		0.6322	(0.1042)	
Output elasticity of R	0.1187	(0.0777)		-	-	
Output elasticity	0.9699	(0.0672)		0.9419	(0.0250)	

Notes: ***, ** and * denote significance at 1%, 5% and 10% statistical levels, respectively. a: the effect of endogenous R&D choice is taken into account in the R&D and non-R&D firms' production function and the production frontiers are estimated separately. b: Likelihood ratio test; H_0: all the coefficients equal 0; H_1: at least one of the coefficients is not 0. c: figures in parentheses are standard deviations.

Drawing from the results shown in Panel A, a firm with a larger size and/or capital intensity has a higher probability of engaging in R&D activity, while this probability decreases as firm's age and subcontractor intensity increase. As for the impacts of industrial characteristics, industrial CR4 ratio, industrial scale and industrial R&D intensity are found to be associated with a significantly positive coefficient. This result is consistent with expectations suggested by theoretical literature that firms locate in an industry that is more concentrated, R&D intensive, and has a larger market, they also tend to have a higher probability of devoting more to their R&D effort.

Before discussing the estimates shown in Panel B, it is important to examine whether R&D and non-R&D firms share the same technology. A likelihood-ratio (LR) of the null hypothesis that, the frontiers of the two firm groups are the same, is calculated after estimating the stochastic frontier by pooling the firms. The value of the LR statistic is 201.8912, which is significantly higher than the critical value $\chi^2_{(0.01,\ 17)}$=33.41. This result suggests the production frontiers for R&D and non-R&D electronics firms are not the same in Taiwan. Therefore, it might induce a bias when comparing technical efficiency between R&D and non-R&D firms without considering R&D effect, suggesting the need to estimate their frontiers separately.

From Panel B, as for the production functions, most of the signs and significances of estimated coefficients are consistent with expectations. Of interest is the coefficient of the selectivity variable S_i is significantly negative for the R&D firms' production frontier at the 1% statistical level. Such result implies the existence of negative selection bias in estimating production function, lending support to the need of correcting the endogenous problem. It is thus necessary to control for the latent influence of R&D choice when examining the R&D-efficiency connection, which is neglected in existing works.

Moreover, Panel B also reports the overall output elasticity of R&D firms (0.9699) and non-R&D firms (0.9419) on an average level. For the output elasticity of various inputs, it is revealed that the output elasticity of labor inputs is about two times larger than capital input. One point particularly worth noting here is the positive output elasticity of R&D capital. Specifically, by virtue of the translog production functional form being used, the contribution (marginal effect) of a specific input on

output cannot be merely identified by the estimated parameter of the linear term of the input. Rather, it should be judged by the output elasticity obtained from a first order partial derivative of log-output with respect to the log-input. Then, based upon the values of output and input being both positive and normal, the sign of marginal effect of the specific input on output and the sign of output elasticity will be the same. Thus, in this study, it is plausible to infer the positive output elasticity of R&D capital input implies the existence of the R&D capital effect on enhancing actual production and thus improving technical efficiency, that is, the productivity enhancement effect.

The estimates of the determinants of inefficiency show that all the parameters are statistically significant and display the same signs for R&D and non-R&D firms, except for the effects of firms' age and industrial scale. We firstly discuss the impacts of firm-specific characteristics. For the firm's age, there is still a lack of definite conclusion in previous studies. The impact of age on efficiency is found to be negative in some studies (for example, Hill and Kalirajan, 1993), positive in others (Biggs et al., 1996), or insignificant (Lundvall and Battese, 2000). In this study, we obtain the result that the impact of firm's age (F-age) on inefficiency is significantly negative for R&D firms but significantly positive for non-R&D firms. Presumably, for the R&D firms, the superior efficiency of older firms could be attributed to the learning effect. Alternatively, for the non-R&D firms, the inferior efficiency of older firms could be explained by those younger firms having relatively more advantage in employing advanced technologies.

Firm size is found to have a significantly negative coefficient, especially for the non-R&D firms, implying large electronics firms tend to have a higher technical efficiency than their smaller counterparts. This result is consistent with most of the previous works on the size-efficiency link[1]. It can be attributed to the advantages of market power and scale economies of larger firms (Kim, 2003; Jovanovic, 1982). The coefficient on capital labor ratio is positive and statistically significant, implying more capital input per capita would not improve technical efficiency of electronics firms. At first glance, this result seems to contradict the prediction, but it is also reasonable when properly thought through. As previously mentioned, the output elasticity of capital input is lower (about less than a half) than the labor input. Thus, all other thing being equal, additionally exploiting capital use to substitute labor use would result in a decrease in output[2]. Alternatively, it might arise from the fact that many electronics firms in Taiwan highly stress capital use relative to labor use in their production, that is: more capital intensive production. Yet, such a presumption needs further investigation out of the scope of this study. Moreover, the coefficient of subcontractor intensity is significantly negative for both R&D and non-R&D firms, suggesting a positive impact on firms' technical efficiency. This positive linkage could be interpreted by smoother production schedules, production specialization (Abraham and Taylor, 1996), or reducing market uncertainty. In addition, the subcontractor activity also often serves as one important channel to acquiring production technologies in Taiwan (Aw and Batra, 1998).

As for the industry-specific characteristics, two measures of entry barriers, four-firm concentration ratio and industry R&D intensity, are found to be positively associated with inefficiency, suggesting firms located in industries that are more concentrated and R&D intensive are less efficient. This result is consistent with the expectation that lower market competition may result in incumbent firms paying less attention to improving technical efficiency. Further, the industrial scale displays a positive impact on improving technical efficiency for non-R&D firms, which suggests greater market room would be beneficial to the operations of both incumbents and potential entrants and then contribute to efficiency.

Here, we reserve the discussion of firm's R&D intensity. As shown in Table 4, the variable of firms' R&D intensity reveals a significantly positive sign, which implies a negative association with technical efficiency. Such an outcome could be associated with the unnecessarily R&D-efficiency presumption (Kim, 2003). We regard it as believable because the benefit of innovative activity is usually not the same as setting up a pole and seeing its shadow. Instead, there are the needs for time and accumulation processes, such as the processes of knowledge sifting, fathoming, experimentation and trial (Duranton and Puga, 2001). Therefore, in the relative short term, R&D intensity may demonstrate an effect like extra cost expenditure in production. Meanwhile, in the relative long run, R&D capital represented by the accumulated R&D stock displays a positive output elasticity as mentioned previously, which

[1] Please refer to Taymaz (2005) for a comprehensive survey.

[2] For example, from the results, it is implied exploiting 1% capital use to substitute 1% labor use would result in approximately a 0.3% decrease in output.

implies a contribution to actual production and technical efficiency.

Turning to the major focus of this study, the technical efficiencies of R&D and non-R&D firms are compared again. However, as discussed above, while the frontiers of two firm groups are not identical and are estimated separately, the direct comparison of efficiency measures for firms using different technologies and producing under different frontiers is inappropriate. The adjustment factor calculated according to equation (9) now is needed and reported in Table 5. As shown in Table 5, it can be found, on average, the measure of adjustment factors is greater than unity regardless of the overall electronics industry or sub-industries. As indicated in Aw and Batra (1998), the adjustment factor represents the relative frontier position of the two firm groups. A ratio greater than unity points out, using the same input vector (herein, that of non-R&D firms), the estimated value added of using the technology of R&D firms exceeds using the technology of non-R&D firms. We, therefore, have evidence that the technology frontier of R&D firms is indeed superior to non-R&D firms, lending support to the technology enhancement effect. This result is also consistent with the presumption in Kim (2003) and Perelman (1995) that the production frontier might be pushed upward by R&D activity. More importantly, these adjustment factors can be used to calculate the adjusted technical efficiency and then compare the mean technical efficiency between R&D and non-R&D firms.

Table 5. Mean adjustment factor calculations for R&D and non-R&D firms

Industry categories	Mean AF	Std. dev.	No. of obs.
Electronics industry	1.1528***	0.0405	6449
Sub-electronics industries			
Electronics and semiconductor equipment	1.1501***	0.0363	138
Computer and peripherals	1.1434***	0.0362	1,180
Telecommunication and machinery appliance	1.1519***	0.0421	450
Audio-visual electronics products	1.1522***	0.0414	724
Data storage and media electronic product	1.1350***	0.0445	79
Semiconductor	1.1528***	0.0421	357
Passive electronics component	1.1532***	0.0394	966
Printed circuit board	1.1468***	0.0412	594
Other electronic components	1.1615***	0.0405	1,961

Notes: ***, ** and * denote coefficients significant at 1%, 5% and 10% statistical levels, respectively.

For the two-digit industry level, comparing the results in Table 6 with those in Table 3, one can clearly note the average technical efficiency of non-R&D firms increases from 0.6769 to 0.7824, after correcting for the effect of endogenous R&D choice. In contrast, the average technical efficiency of R&D firms decreases slightly from 0.6886 to 0.6210. It is worth noting the difference test reveals the average technical efficiency of non-R&D firms is significantly higher than that of R&D firms at the 1% level, showing non-R&D firms have higher technical efficiency than their R&D counterparts after controlling for the endogenous R&D effect. This result sheds light on the importance of endogenous R&D choice when the R&D-technical efficiency connection is examined.

Table 6. Mean technical efficiency estimates for R&D and non-R&D firms (controlling for the R&D choice effects)

Industry categories	Groups	Mean ATE	Diff. test	No. of obs.
Electronics industry	NRD	0.7824	-613.105***	6,449
	RD	0.6210		1,141
Sub-electronics industries				
Electronics and semiconductor equipment	NRD	0.7205	-4.430**	138
	RD	0.6222		27
Computer and peripherals	NRD	0.7859	-138.899***	1,180
	RD	0.6387		278
Telecommunication and machinery appliance	NRD	0.7513	-78.311***	450
	RD	0.5571		128
Audio-visual electronics products	NRD	0.7593	-11.607***	724
	RD	0.6786		71
Data storage and media electronic product	NRD	0.7430	-23.725***	79
	RD	0.5413		21
Semiconductor	NRD	0.8175	-134.442***	357
	RD	0.5725		175
Passive electronics component	NRD	0.7727	-44.837***	966
	RD	0.6542		145

Table 6 (cont.). Mean technical efficiency estimates for R&D and non-R&D firms (controlling for the R&D choice effects)

Industry categories	Groups	Mean ATE	Diff. test	No. of obs.
Printed circuit board	NRD	0.7931	-15.367***	594
	RD	0.7089		83
Other electronic components	NRD	0.7971	-156.993***	1,961
	RD	0.6078		213

Notes: ***, ** and * denote coefficients significant at 1%, 5% and 10% statistical levels, respectively. The difference test employed in the table is one-way ANOVA test with F-statistics. The positive and negative signs are denoted for comparison; a positive sign denotes that the mean efficiency of R&D firms is higher than that of non-R&D firms, and vice versa. a: the means of adjustment factor are reported.

Turning to the further comparison of technical efficiencies between R&D and non-R&D firms among 3-digit industries, it is shown that the number of statistics with a significantly negative sign increases from one to nine, whereas the number of statistics with a significantly positive sign decreases from four to zero. That is, among the nine sub-industries, non-R&D firms tend to have a better technical efficiency than their R&D counterparts in the electronics industry after controlling for the impact of the endogenous R&D effect. However, this result can be explained only from the static perspective, because the utilized dataset is cross-sectional data. The possible interpretation is, in the short run, the increase in productivity is less than the production frontier for R&D firms, resulting in fall of technical efficiency. However, the technology enhancement effect is crucial from the macro and dynamic perspectives.

In sum, the above analyses highlight the importance of the endogenous R&D effect in examining the relationship between R&D and technical efficiency. The efficiency effect of R&D is overestimated in previous studies due to the neglect of the endogenous R&D effect. The non-R&D firms are found to be more efficient in this study, showing non-R&D electronics firms don't necessarily have worse performance in technical efficiency from a static perspective compared with their R&D counterparts in Taiwan. However, we cannot infer R&D has a negative impact on technical efficiency. One reason is this study is a cross-sectional study that can explain the R&D-efficiency relationship for only one point in time rather than over a period of time. The productivity enhancement effect of R&D may be apparent after some time has passed. More importantly, from both macro and dynamic perspectives, R&D serves as the major source in promoting technological capability. The short-term inadvantage in efficiency can be overcome by continuous improvement on productivity. Moreover, from the methodology perspective, the traditional estimates for the R&D-technical efficiency nexus may suffer an estimation bias without dealing with the endogenous R&D effect.

Concluding discussion

Are R&D firms more efficient than non-R&D firms? This study employs a two-step switching stochastic frontier approach to re-examine the R&D-efficiency nexus by adding three additional considerations. First, there are misspecifications in the conventional construction of the production frontier. Specifically, do R&D and non-R&D firms use the same technologies? Instead, it is more persuasive to view R&D and non-R&D firms as operating under different frontiers (technologies). Second, while the production technologies are distinct, selection bias may arise since the choices to engage in R&D activity and what kinds of technology to adopt are rational decisions made by the firms. Thus, it indeed refers to an endogenous selection problem. Moreover, the regression of technical efficiency in the R&D variable only implies that R&D activity can improve, reduce or be irrelevant to technical efficiency, other things being equal. Except the question as to why a firm who has a higher R&D intensity results sometimes has worse technical efficiency is explained insufficiently, it is also incapable of disentangling the perplexity: are R&D firms really more efficient than non-R&D firms?

In this study, we develop a two-step switching stochastic frontier approach to re-examine the R&D-technical efficiency nexus. The problems concerning the endogenous selection problem of R&D choice, separate frontiers and inverse impact of R&D intensity on efficiency are simultaneously tackled in this framework. The empirical estimates show: (i) the average technical efficiency of R&D firms is larger than that of non-R&D firms without correcting for the endogenous R&D effect, whereas the non-R&D firms have a higher technical efficiency when we consider the potential influence of endogenous R&D effect, suggesting R&D firms are not necessarily more efficient than

non-R&D firms. More importantly, this study highlights the importance of endogenous R&D choice on the R&D-technical efficiency nexus. (ii) R&D firms actually have a higher frontier than non-R&D firms, implying superior technology of R&D firms; and (iii) the positive contribution of R&D activity to technical efficiency is mainly sourced from R&D capital accumulation, but the effect of current R&D investment is the opposite.

Based on these estimates obtained by the two-step approach, several economic implications can be achieved from our empirical study. First, R&D and non-R&D firms use different technologies and operate under different frontiers. Actually, R&D firms face a higher technology frontier and the technology of R&D firms is superior to their non-R&D counterparts. This result can be attributed to the technology enhancement effect of R&D. From the macro and dynamic perspectives, this technology enhancement effect of R&D is particularly relevant to sustained economic growth. Second, R&D is not always beneficial to firms from the static perspective. As discussed earlier, firms are rational and follow profit-maximizing behaviors; the R&D choice is therefore made according to firms' own comparative advantage, by considering the technological environment they are located in. Therefore, we can find the R&D firms are not necessarily more efficient than non-R&D firms.

However, our study does not mean R&D activity has no contribution to technical efficiency. Instead, there are two types of effect embedded in R&D activity impacting efficiency: productivity enhancement effect and technology enhancement effect. It needs to undergo a time lag and knowledge accumulation processes to draw benefit from innovative activity, suggesting the contribution of R&D activity is mainly sourced from the accumulated R&D capital rather than just one period of R&D spending. In the relative short term, R&D intensity only represents an effect like an additional cost or expenditure in production.

Finally, we would like to highlight a point in our methodology. To compare technical efficiency across groups, this paper adopts the adjustment factor approach. This technique not only makes the efficiency comparable between two groups, but also enables us to observe the relative frontier positions of the two groups. Therefore, we do not assume all firms have potential access to the same technology and adopt the metafrontier production function model developed by Battese et al. (2004). Of course, it is also of interest to conduct a metafrontier study on this issue[1].

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[1] Indeed, we have also implemented the estimation using the metafrontier model. The results are similar to our two-step SFA approach. To save space, the estimates of metafrontier model are not shown here. The results are available from the corresponding author on request.

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Appendix A. The inference and calculation of R&D capital

In virtue of the properties of uncertainty, accumulation and lag inherent in R&D activity, the calculation of R&D capital (RK) is an interesting but complicated work. The uncertainty reflects inconsistency between expectations and real outcome of R&D investment. As this paper has no intention of covering the problem of uncertainty, the RK is assumed under a certainty perspective. Further, the accumulation and lag signify a process of time lag and depreciation when transforming R&D investment into productive knowledge − R&D capital, RK. In the literature[1] the common approach assumes the relationship between R&D and RK as follows:

$$RK_t = \sum_{p=0}^{P} u_p RD_{t-p} + (1-\delta) RK_{t-1}, \tag{A1}$$

where, t is the time period, and t=0, 1, 2,…T; p is the lag period, while P is the maximum lag period, and p=0, 1, 2,…P; δ represents a rate of depreciation; u_p denotes a lag operator. Therefore, equation (A1) implies the RK in the current period is the summation of the R&D expenditure of each prior period according to the lag structure and the

[1] E.g., Mansfield (1980), Griliches (1979), Odagiri and Iwata (1986), Bernstein and Nadiri (1988), Goto and Suzuki (1989), and Goel (1990).

depreciated RK of the last period. However, as for the lag structure, there is a lack of definite pattern in hand. Griliches (1979) indicated the peak of R&D transforming into RK is about 3-5 years and then decays rapidly as time progresses. Goto and Suzuki (1989) assumed an average lag pattern of t-θ.

In practice, due to the lack of a definite lag structure, the average lag pattern t-θ is adopted by this paper. Meanwhile, based on most R&D investments in Taiwan being application research but not basic research; the average lag θ should be a short period which is assumed to be 0. Griliches and Mairesse (1984) indicated a tiny influence concerning the specification of lag period. Thus, equation (A1) is adapted as equation (A2), while the RK_{t-1} is specified as equation (A3):

$$RK_t = RD_t + (1-\delta)RK_{t-1}, \tag{A2}$$

$$RK_{t-1} = \sum_{t=0}^{T-1}(1-\delta)^{(T-1)-t} RD_t \ . \tag{A3}$$

In equation (A3), t denotes the age of the firm to 2001. Further, due to the cross-section data used in this paper, the prior four periods of R&D investment are presumed according to the growth rate of R&D expenditure of each four-digit industry calculated from the Industrial Census Report undertaken by the Directorate-General of Budget, Accounting and Statistics in Taiwan. If the firm age is more than four years, the growth rate is assumed to be the average of the last four years. Additionally, in this study, similar to general specifications[1], the depreciation rate is assumed to be 15%. Griliches and Mairesse (1984) also found a weak influence concerning the specification of the depreciation rate.

Table A.1. Electronics industries of ICS census 2001 in Taiwan

SIC	Industries	No. of firms
2548	Electronics and semi-conductor equipment manufacturing	165
2611	Computer manufacturing	157
2612	Monitor and terminal manufacturing	80
2613	Computer and peripheral equipment manufacturing	386
2614	Electronic parts and components manufacturing	584
2619	Other computer peripheral equipment manufacturing	251
2621	Wired communication equipment manufacturing	275
2622	Wireless communication equipment manufacturing	303
2631	Visual electronic product manufacturing	22
2632	Audio electronic product manufacturing	488
2639	Other audio and video electronic product manufacturing	285
2640	Data storage and media electronic product manufacturing	100
2710	Semi-conductor manufacturing	532
2720	Passive electronic component manufacturing	1,111
2730	Printed circuit board manufacturing	677
2791	Electronic tube manufacturing	82
2792	Optical instruments and equipment manufacturing	220
2799	Other electronic parts and components manufacturing not elsewhere classified	1,872

Note: Compiled for this study.

[1] E.g., Cuneo and Mairesse (1984), Griliches and Mairesse (1984), Griliches (1986), Coe and Helpman (1995), Raut (1995), and Hall and Mairesse (1995).