China's R&D Production Efficiency and Impact Factors

Shixiong Cheng and Jianping Liu

Abstract：This paper selects Chinese industrial sectors as research objects, based on the R&D capital as divided into the R&D capital in the same sector in the same countries, the R&D capital in the same sector in other countries which we selects in OECD STAN database, the R&D capital in the other sectors in the same countries, the R&D capital in the other sectors in other countries, firstly using the knowledge production function model and stochastic frontier production function method to empirically study the R&D production efficiency in the Chinese industrial sector, then to study how the factors of industry technical level, ownership structure, human capital, degree of trade openness, technology gap ,degree of industry competition, and physical capital stock impact R&D production efficiency. It concludes that except the R&D capital in the other sectors in other countries, the other three R&D capitals have a significant positive impact on R&D production efficiency. Furthermore, the factors of the degree of trade openness, technology gap, and physical capital stock have a significant positive impact on R&D production efficiency，and the human capital and industry competition degree do not have a significant positive impact on R&D production efficiency. As for the industry characteristics, the technical efficiency in high-tech industries is lower than that in non-high-tech industries and the R&D output efficiency differs little between state-owned business and non-state-owned business.

Keywords: R&D input, production efficiency, knowledge production function, stochastic frontier production function

1. Introduction

The development of human society suggests that science and technology is the primary productive force. As an essential support to economic and social development, the level of science and technology determines both the development speed and the international status of one nation. For decades, China's research and development (R&D) inputs have been growing rapidly, with the total R&D expenditure rising around 34 times from 24.8 billion Chinese yuan in 1993 to 861 billion in 2011, and its world ranking leaping from 14th place in 1993 to 3rd in 2011. According to the endogenous economic growth theory, rapid R&D input growth should necessarily lead to increasing technological progress; however, this is not the case in China. Why has a great amount of sci-tech investment failed to considerably boost technical progress? Since R&D input resources are limited in the current system and economic environment of China, If R&D resources are not used effectively, additional investment may be of little help in stimulating economic growth. Therefore, how to make more efficient use of R&D resources in

order to produce more R&D outputs? What are the decisive factors affecting R&D production efficiency? And what exactly is the R&D production efficiency in China's industry? Answering these questions is of both theoretical and practical significance in allocating resources appropriately and increasing R&D production efficiency in China.

The earliest study on efficiency of R&D activities can be traced back to Griliches (1979). He built up an analytical framework, the knowledge production function, and regarded knowledge output as the outcome of knowledge input. Afterwards, this framework was used by most scholars as a common method in analyzing R&D efficiency. Besides this, there are two other methods that are widely used for the study of R&D efficiency. Some scholars advocate a nonparametric method called DEA (Data Envelopment Analysis), as well as its extended method, to measure R&D efficiency (Wang and Huang, 2007). DEA is a method that uses linear programming to measure effective production frontiers based on a set of decision-making units (DMU), including input and output elements. The limitation of DEA is that it merely considers the deterministic production frontier's effect on productivity, neglecting the impact of random shock. Accordingly, many scholars prefer the stochastic frontier analysis (SFA) approach which applies econometric techniques to estimating various production/cost frontiers. Bai et.al (2009) used this method to measure the R&D innovation efficiency in surveyed areas, and investigated the main contributors to innovation efficiency inside the surveyed areas, such as enterprises, tertiary institutions, scientific institutions, local governments, and financial institutions. Reviewing foreign and domestic research, most scholars use provincial panel data to analyze R&D production efficiency in China's industry, only a few choosing industrial panel data. In 2006, choosing 37 sectors in China's industry as study objects, Feng, et. al. (2006) used SFA to measure the R&D production efficiency of China's industry during the five-year period from 1998 to 2002, and showed that the general level of R&D output efficiency in China is still low.

This article intends to improve the extant research of R&D production efficiency in the following three aspects. Firstly, when measuring the efficiency of R&D input, the majority of studies only consider one R&D input channel, while ignoring the intra-industry and inter-industry technology spillover effect. This paper extends the research to open economy; our analysis takes the spillover effect of R&D input into account and expands the single R&D input channel into four channels: 1) the R&D capital in the same sector in the same countries, 2) the R&D capital in the same sector in other countries; 3) the R&D capital in the other sectors in the same countries, 4) the R&D capital in the other sectors in other countries. Secondly, so far as the research data is considered, most studies use panel data from 30 provinces in China rather than panel data of Chinese industries; because of the limited sample size, this leads to a less precise estimate of the frontier.

In this paper, the panel data of Chinese industries from 1993 to 2008 is used to measure R&D production efficiency. In order to obtain foreign R&D capital variables, this article revises the Chinese classification of large- and medium-sized industries in light of the International Standard Industrial Classification (ISIC), and uses the tree-digit industry of ISIC as DMU to analyze R&D production efficiency. Thirdly, most researchers consider R&D production efficiency from such dimensions as government funding, market structure, etc, overlooking the influence of factors such as technology gap and human capital. This paper, by contrast, takes an overall consideration of the following factors: human capital, trade openness, the

technology gap, degree of industry competition, physical capital, technological sophistication, and property right structure, etc, to analyze their impact on R&D production efficiency.

2. Model construction

2.1. Knowledge production function

Based on the knowledge production function model constructed by Pakes and Griliches (1984) and Griliches (1990), the general form of the knowledge production function model can be expressed as:

$$Y = f(R, L) \qquad (1)$$

Where R denotes R&D input, L denotes R&D labor supply, and Y denotes R&D output. Most scholars apply the knowledge production function model only in closed economic conditions. Under such conditions, only the R&D capital in the same sector in the same countries can affect R&D production efficiency. However, when the model is extended to open economic conditions, according to Coe and Helpman（1995）, Lichtenberg and Potterie (1998）, Pueyo, Visus and Sanau（2008）, because of the existence of intra-industry and inter-industry technology spillover effects, the R&D capital in the same sector in other countries, the R&D capital in the other sectors in the same country, and the R&D capital in the other sectors in other countries can be seen as means to impact the R&D production efficiency. Therefore, we have:

$$R = \left(R_{it}^{sd}\right)^{\alpha_1} \left(R_{it}^{sf}\right)^{\alpha_2} \left(R_{it}^{od}\right)^{\alpha_3} \left(R_{it}^{of}\right)^{\alpha_4} \qquad (2)$$

Where R^{sd} represents the R&D capital in the same sector in the same countries, R^{sf} represents the R&D capital in the same sector in other countries, R^{od} represents the R&D capital in the other sectors in the same countries[1], and R^{of} represents the R&D capital in the other sectors in other countries. i denotes the industry, t denotes the year, and α_1, α_2, α_3, α_4 are the corresponding coefficients. Using the general Cobb-Douglas production function, the knowledge production function model can be expressed as[2]

$$\log Y_{it} = \alpha_0 + \alpha_1 \log R_{it}^{sd} + \alpha_2 \log R_{it}^{sf} + \alpha_3 \log R_{it}^{od} + \alpha_4 \log R_{it}^{of} + \alpha_5 \log L \qquad (3)$$

2.2. Stochastic frontier production function

According to Kumbhakar and Lovell (2000), the general form of a stochastic frontier production function can be expressed as:

$$\log Y_{it} = \log f(x_{it}) + (v_{it} - u_{it}) \qquad (4)$$

---

[1] Only the R&D capital of the countries for which it was possible to calculate their own R&D stock was weighted. To be exact, the calculation of foreign R&D capital was based on the technology stocks of Belgium, Canada, Czech, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, South Korea, Holland, Norway, Poland, Portugal, Spain, Sweden, Britain, America, etc.

[2] Given that there are too many input variables involved in this paper, the Cobb-Douglas production function is chosen in this paper instead of functions like trans-log production, which may severely reduce the degree-of-freedom of the model.

In Eq. (4), Y_{it} denotes the technical output generated in i industry in time t, and x_{it} denotes all kinds of inputs in i industry in time t, which usually includes R&D inputs and technical labor supply. The error terms v_{it} and u_{it} are in composite structure. v_{it} follows the independent and identical normal distribution N （0，σ_L^2）, representing the impact of random shock impact. u_{it} is the technical inefficiency term, which represents the individual shock impact.

On the basis of Battese and Coelli's (1992) model, Battese and Coelli (1995) introduced the technology inefficiency function to further explore how external environmental factors affect technical efficiency. They assumed that the technology inefficiency function follows the non-negative truncated normal distribution . Based on the above analysis, the regression model in this paper can finally be expressed as:

$$\log Y_{it} = \alpha_0 + \alpha_1 \log R_{it}^{sd} + \alpha_2 \log R_{it}^{sf} + \alpha_3 \log R_{it}^{od} + \alpha_4 \log R_{it}^{of} + \alpha_5 \log L + v_{it} - u_{it} \qquad （5）$$

Depending on different forms of technical inefficiency items, the stochastic frontier model falls into three categories: 1) the model in which technical inefficiency does not vary with time and the effects of external environmental factors are not considered; 2) the model in which technical inefficiency varies with time and the effects of external environment factors are not considered; 3) the model in which technical inefficiency item varies with external environmental factors. In this paper, all three kinds of models are used for empirical analysis.

3. Construction of variables

3.1. Construction of output variable

The patent is probably the most important indicator of research outcome. Patent statistics offer rich and potentially useful sources of information on R&D activities. But patent is classified according to the International Patent Classification (IPC), however, the IPC is based on technological categories and cannot be directly translated into industrial sectors and because of lacking of IPC sectors data in China, so in our analysis, the new product sales revenue is used as a variable to measure the output of R&D input. Compared with patent index, the new product sales revenue is an explicit index that can be easily measured it is a more sensitive proxy variable that reflects commercialization level and economic value of R&D input and thus can measure the output of R&D better.

3.2. Construction of input variables

The input variables used in this paper include four types of R&D input variables: R&D input in the same sector in the same countries, the R&D input in the same sector in other countries, the R&D input in the other sectors in the same country, and the R&D input in the other sectors in other countries. It uses one kind of labor input, technical employ input. Since the R&D input is a flow index, and R&D activities affect knowledge not only in the current period, but also in the long-term, so the R&D stock indexes should be used in measuring R&D production efficiency. As for the labor input variable, we adopt the index of science and technology personnel, which can be obtained directly from the *China Statistical Yearbook on Science and Technology (1993~2009).* Next we will give an introduction of how to construct four types of R&D capital stocks.

3.2.1. R&D capital in the same sector in same countries

Grilliches (1979) advises that perpetual inventory method be used to estimate R&D capital stock. In order to determine the R&D capital stock in period *t*, we need to: 1) construct the price index of R&D expenditure so that the R&D expenditure per period can be represented by constant price, 2) determine the depreciation rate σ, and 3) calculate the base-period capital stock R_0.

While constructing the price index of R&D expenditure, we suppose that 25% of the R&D expenditure cost is labor cost, and the remaining 75% is the cost of means of production. This assumption is a reasonable one to make if we look at the composition of the expenditure on scientific and technological activities each year. According to figures from the *China Statistical Yearbook on Science and Technology*, service charges account for around 25% of the expenditure on scientific and technological activities for the whole year, and equipment cost accounts for around 75%. This article follows the general practice of setting the depreciation rate at 15%. The base period capital stock can be measured as follows:

$$R_0 = E_0 / (g + \sigma) \tag{6}$$

Where E_0 is the R&D expenditure data in 1993, *g* is the average growth rate of R&D expenditure, and σ represents the depreciation rate in respective industries.

3.2.2. R&D capital in the same sector in other countries

Coe and Helpman (1995) innovatively used the following method to measure the R&D capital in the same sector in other countries as approximated with the variable:

$$R_{ijt}^{sfCH} = \sum_{h \neq j} \frac{M_{iht}}{M_i} R_{ijt}^{sd} \tag{7}$$

Where R_{ijt}^{sd} is the R&D stock in the same sector in same country; M_{iht} is the amount of imports in the industry *i* from the country *h*; M_i is the amount of imports in the industry *i,* and R_{ijt}^{sfCH} is the R&D capital in the same sector in other countries. Subsequently, Lichtenberg and Potterie (1998) improved this method:

$$R_{ijt}^{sfLP} = \sum_{h \neq j} M_{iht} R_{ijt}^{sd} \frac{1}{Y_{iht}} \tag{8}$$

Where R_{ijt}^{sfLP} is the R&D capital stock in the industry *i* in the country *j,* M_{iht} represents the imports of products classified in sector *I* that come from country *h* and arrive in country *j,* and Y_{iht} is the output of sector *i* in country *h*. In this paper, this modified formula is used to measure the R&D capital in the same sector in other countries.

3.2.3. R&D capital in the other sectors in the same countries

In the present work, a weighting schedule that is as suitable as possible to the nature of the spillovers that we are dealing with and to the differences between the countries and industries studied, is proposed. To estimate, for each country and sector, the spillovers from the other sectors of the same country, we used the OECD Input–output Database. To be precise, we used the data from the domestic intermediate goods

flows sub-matrix of the input/output tables. In consequence, for each industry i and country j, the spillovers coming from domestic R&D capital in other industries at moment t, R_{ijt}^{od} , were calculated as:

$$R_{ijt}^{od} = \sum_{k \neq i}(1 - \overline{M_j / Y_j})\omega_{ki}R_{kjt}^{sd} \qquad (9)$$

Where R_{ijt}^{od} is the domestic R&D capital stock from other industries in the industry i of the country j, $(1 - \overline{M_j / Y_j})$ is the domestic output over the domestic market in country j, ω_{ki} is the weighting that represents the portion of the total inputs used in sector i that come from sector k, and R_{kjt}^{sd} is the R&D capital stock in sector k in country j.

3.2.4. R&D input in the other sectors in other countries

Following the method of measurement of domestic R&D capital stock in other industries, we can deduce the formula to calculate the R&D capital in the other sectors in other countries, given by:

$$R_{ijt}^{of} = \sum_{k \neq i}\overline{(M_j / Y_j)}\gamma_{ki}R_{kjt}^{sf} \qquad (10)$$

Where $\overline{(M_j / Y_j)}$ is the proportion of the imported products in the domestic market, and R_{kjt}^{sf} represents R&D stock in the industry k in the country j. The value of γ_{ki} can be directly obtained from the OECD Input-Output Database (2000). We recur to the input–output tables to calculate the weightings but, on this occasion, we use the imported intermediate goods flows sub-matrix of the input–output tables. Once the rows and columns have been converted to ISIC rev. 3, the weightings γ_{ki} are calculated. These represent the imports of country j of intermediate goods inputs from sector k directed to sector i.

3.3. Construction of environmental variables

Besides input variables, there are a large number of other economic and social environmental factors which may affect the R&D production efficiency and may contribute to differences in R&D production efficiency among industries. In this paper, these environment variables are divided into four categories: 1) variables affecting absorptive capacity, 2) variables affecting the degree of competition in the industries, 3) physical capital input variables, and 4) the industry characteristic variables.

3.3.1. Variables affecting absorptive capacity

Cohen and Levinthal (1989) first came up with the concept of the absorptive capacity when they were analyzing enterprise utility. They defined it as a firm's ability to recognize the value of new information, assimilate it, and apply it to commercial ends. As this definition implies, the absorptive capacity can also impact R&D production efficiency. In order to generate more output, countries as well as enterprises need to meet some basic requirements in technological sophistication and infrastructure with the aim to absorb R&D input more effectively. Human capital, technology gap, trade openness, etc. are commonly regarded as the most significant proxy variables in measuring the absorptive capacity. Next we introduce how to construct these variables.

Human capital (H): The variable of human capital is measured by mean years of schooling of employees (Barro, 1991) in most studies. However, this method cannot be applied to China where the data of schooling of employees from various industries is not available. Therefore, this paper adopts the method proposed by Xia Liangke (2010) of using the ratio of scientists and technicians to all employees as proxy variables of human capital variables.

Technology gap (GAP): According to Benhabib and Spiegel (1994), Ge Xiaohan and Chen Ling (2009), we use the relative distance of the technology frontier of a country to measure the technology gap. The relative distance can be defined as the gap between the world technology frontier and the technology level in a given country (such as China):

$$GAP = \left[\frac{\max_j A_j(t) - A_i(t)}{A_i(t)} \right]$$
（11）

Where GAP is the relative distance from the technology frontier, $A_i(t)$ is the technology level in a given country, and maxAj (t) represents the world technology frontier. According to Kang (2002), we can assume that the proportion of physical capital, human capital, and TFP in the production function is not varying with time, so we can use labor productivity to measure the technology level of a nation. In addition, this paper postulates that the technology frontier is the existing technology in the most developed country in the world; therefore, the most developed country, j, is the U.S.A., and the country i is China. In this way, the technology gap can be expressed as the relative labor productivity between the industries in China and America. We use the proportion of total imports to total outputs to measure import openness, and the proportion of total exports to total outputs to measure export openness. The sum of the two variables is the trade openness in the industries.

3.3.2. Variables affecting the degree of competition in the industries (Firms)

The influence of market structure on R&D production efficiency has always been a major concern in the academic field. Arrow (1962) finds that a competitive environment would motivate the R&D activities of enterprises, so we must consider the impact of degree of competition on R&D production efficiency. Since so far no better index can be found to measure the degree of industry competition than that of Feng, et. al. (2006), we use the number of enterprises to denote the degree of industry competition[3]. The number of enterprises can reflect the market structure and capacity and barriers to entry and exit as well, which are indirect barometers of degree of competition.

3.3.3. Physical capital input variable (K)

Though physical capital input can not affect R&D production efficiency as a R&D input variable directly, it can complement with R&D capital input to determine R&D production efficiency. Perpetual Inventory Method (PIM) is commonly used for measuring physical capital stock, The depreciation rate δ is generally adopted as 5%; the price index of capital stock can be expressed by the price indices of investment in

---

[3] If we can find the micro-data for every firms in each industry, we can use the well-established Herfindahl Index, but in industry level lack of micro-data which used to calculate, so we can only use the number of enterprises to denote the degree of industry competition.

fixed assets; net investment in fixed assets can use original value of production and equipment. Then we can use the price indices of investment in fixed assets to deflate the fixed asset investment to real value in the base period of 1993. Capital stock in the base period can be calculated like formula（11）.

3.3.4. The industry characteristic variables

Firstly, the industry characteristic variable is classified by skill level (high-tech). Technology level is a crucial factor in determining R&D production efficiency and the output performance of R&D inputs varies among industries with different technology levels. For example, in high-tech industries, intensive inputs usually generate large outputs. High production efficiency is a feature that distinguishes high-tech industries from low-tech industries. Consequently, it is necessary to control the technology level as an industry characteristic variable. Based on *National industrial statistics on the 2000 R&D census* and the research by Wu Yanbin (2008), we divide the 34 industries in China into high-tech industry and non-high-tech industry according to the R&D intensity in these industries. Six industries, including the electronic and telecommunications equipment manufacturing industry, the instrumentation and office machinery manufacturing industry, the electrical machinery and equipment manufacturing industry, the transportation equipment manufacturing industry, the general machinery manufacturing industry, and the specialized equipment manufacturing industry enjoy the highest level of R&D intensity. Four industries, including the chemical materials and products manufacturing industry, the pharmaceutical manufacturing industry, the plastic products manufacturing industries, and the metal product industry also boast comparatively high R&D intensity. Among the 34 industries in China, the ten industries above can be classified as high-tech industries, while the others are non-high-tech industries. More specifically, if using dummy variables to indicate industry characteristic variables, high-tech industry then takes the value of 1 and non-high-tech industry takes the value of 0.

Secondly, the industry characteristic variable is classified by property right structure (state). Because of different types of property right structure, ownership may operate differently in terms of management incentives, project audit mechanism, project financing, and budget constraint hardness, etc. Therefore, ownership structure types may have an impact on R&D output efficiency. The proportion of the output value of state-owned industries in the total industrial output value is used to express the proportion of state ownership. Industries with a proportion above 0.42 are classified as industries with a high share of state ownership, and those with a proportion below 0.42 are classified as industries with a low share of state ownership. There are 14 industries with a high share of state ownership: the coal mining industry, the oil and gas exploitation industries, the nonferrous metal mining industry, the logging industry, the food manufacturing industry, the beverage manufacturing industry, the tobacco industry, the petroleum processing and coking industry, the chemical materials and products industry, the pharmaceutical manufacturing industry, the ferrous metal smelting and extended processing industry, the nonferrous metal smelting and extended processing industry, the specialized equipment manufacturing industry, and the transportation equipment manufacturing industry. More specifically, if using dummy variables to indicate industry characteristic variables, industry with a high share of state ownership takes the value of 1 and industry with a low share of state ownership takes the value of 0.

4. Data sources

The R&D data for China comes from China Statistical Yearbook on Science and Technology (1993~2009) (see the entry "Intramural expenditure on science and technology activities"), and the R&D data for OECD countries is from Structural Analysis Databases (2009 edition) of OECD, which provides data for industrial R&D expenditure of OECD countries up to 2008. However, the industrial classification standard adopted by China (The national economy industry classification standard GB/T 4754-2002) is inconsistent with the OECD countries (International Standard Industrial Classification (ISIC/Rev.3)). In order to correspond the R&D outputs in the industries of OECD countries with the R&D outputs in the industries of China, firstly, we convert GB/T 4754-2002 and ISIC/Rev.3 standards according to the research of Xiang Tiemei and Huang Jingbo (2008), Li Xiaoping and Lu Xianxiang (2010), abandoning the industries with no data and those that cannot be matched. We obtain 19 corresponding industries. Then we find the R&D output in the industries of OECD countries from the Structural Analysis Databases of OECD countries[4]。

Trade data are from the Stan Bilateral Trade Database of OECD (2008 edition), which provides the data of imports and exports from China's industries to the countries and regions including G7 and OECD over the world. The industries are classified according to ISIC Rev.3 data in current U.S. dollars. The data of input-output efficiency in China and OECD countries all comes from the OECD Input-Output Database (2000). The output value in the industries of China, using GDP deflator index and the actual value of GDP in constant prices in 1990 to get GDP based on constant prices in 1993, which can be obtained from the STAN database of OECD, then converted into US dollars according to the exchange rate from the SNA database of OECD. The industrial output values of OECD countries can be obtained from the STAN database. The values are in European currencies and must be converted into current US dollars, according to the rate of each currency against the US dollar for each year. In regard to R&D expenditure price index, the consumer wages price index for China can be obtained from China Statistical Yearbook and for OECD countries from the MEI database of OECD, and the PPI index in OECD countries comes from the national statistics database of OECD countries. Unless otherwise specified, all other figures in this paper are, without exception, from *China Statistical Yearbook on Science and Technology*, *China Statistical Yearbook*, and the OECD input-output database, STAN, and MEI database.

5. Model estimation results analysis

5.1. Estimation results without considering influential factors

Based on Model (8) established in the previous part, the stochastic frontier model, without considering the influential factors, was initially estimated using Frontier 4.1 software. Considering the fact that the time lag effect commonly exists in the course from R&D input to new product output, we divide our analysis

---

[4] Considering the availability of databases, we select Belgium, Canada, Czech, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, South Korea, Holland, Norway, Poland, Portugal, Spain, Sweden, Britain, America, etc. as examples of OECD countries, which account for around 90% of the world's total R&D input. Accordingly, it is reasonable to use these figures to estimate R&D capital stock in foreign countries. In addition, when the data of a certain industry in a certain year is lost, we can first look for the data of the broad industry it belongs to, and then infer the lost data by estimating the annual average proportion of this industry in the broad industry. If the data of the broad industry is unavailable, we use linear interpolation to calculate the value in the lost year based on average growth rate of previous years.

into two models: one model is with no time lag effect, and the other is subject to first-order time lag effect. With consideration of whether technical inefficiency items vary over time, four models were derived, which are: 1) technical inefficiency items do not vary over time and there is no time lag, 2) technical inefficiency items do not vary over time and there is a first-order time lag, 3) technical inefficiency items vary over time and there is no time lag, 4) technical inefficiency items vary over time and there is a first-order time lag. According to the four models, the model regression results are shown as follows:

Table 1. Estimation results of model without considering the impact of environmental factors

Explanatory variables	Time-invariant with no time lag model	Time-invariant with first order time lag model	Time-variant with no time lag model	Time-variant with first order time lag model
Constant term	-6.242***	-5.839***	-2.392***	-1.830***
	(-5.36)	(-4.61)	(-2.25)	(-1.79)
$logR^{sd}$	0.528***	0.465***	0.492***	0.488***
	(4.37)	(3.37)	(3.68)	(3.56)
$logR^{sf}$	0.102	0.240***	0.249***	0.287***
	(1.46)	(3.48)	(6.77)	(7.49)
$logR^{od}$	1.169***	1.183***	1.042***	0.928***
	(5.15)	(4.76)	(4.33)	(3.89)
$logR^{of}$	0.048	0.063	-0.309	-0.193
	(0.23)	(0.29)	(-1.35)	(-0.71)
$logL$	0.079	-0.032	0.025	-0.016
	(0.78)	(-0.29)	(0.23)	(-0.13)
σ^2	7.645***	7.453**	0.882***	0.870***
	(2.59)	(2.52)	(6.88)	(7.14)
γ	0.969***	0.967***	0.713***	0.691***
	(77.27)	(68.98)	(14.83)	(13.16)
μ			1.587***	1.550***
			(3.64)	(3.93)
η			0.020***	0.024***
			(2.91)	(3.91)
Log likelihood function	-258.305	-251.410	-251.533	-242.067
LR test	134.103	115.321	147.646	134.008
No. of observations	304	285	304	285

Note: The *t*-statistics are in brackets. ***, **, and * indicate the significance at 1, 5 and 10% level (one side), respectively.

As the estimation results of table 1 suggest, when external environmental factors are excluded from the model, both σ^2 and γ have a high level of statistical significance, regardless of the form of model, indicating that technical non-efficiency is significant among various industries. γ value in the time-invariant model is between 0.691 and 0.969, which demonstrates that most deviation in composite error is caused by the inefficient part. This further proves that the adoption of the stochastic frontier production function model is correct. In time-variant models, the η value is significantly positive, showing that the technical inefficiency decreases over time, or that technical efficiency increases with time. However, a value no more than 0.020 shows that technical efficiency exhibits slow growth. Furthermore, according to Table 1, the following conclusions can be drawn:

Firstly, the coefficient of the R&D capital in the same sector in the same countries is statistically significantly positive, with its estimation of value falling between 0.465 and 0.528, which suggests that the domestic R&D input in the same sector in the same countries plays a significant role in promoting R&D production efficiency. With one percentage increase in investment in R&D, new product sales revenue increases by approximately 0.4 percentage points. This conclusion is consistent with most relevant research findings. Focusing on high-tech industries, Zhu Youwei and Xu Kangning (2006) estimate the domestic R&D capital output elasticity in one industry to be 0.442. With Chinese industrial enterprises as object of study, Zhang et.al (2003) determine that the domestic R&D capital output elasticity in the same sector in China is approximately 0.394. This conclusion also manifests that independent R&D investment is the key factor in enhancing R&D production efficiency. Therefore, independent R&D investment serves as the most direct and efficient way to promote R&D production efficiency in one industry.

Secondly, the coefficient of the R&D capital in the same sector in other countries is statistically significantly positive, which clearly indicates that the R&D capital in the same sector in other countries also exerts significantly positive influence in improving R&D production efficiency. This conclusion agrees with our expectation, proving the existence of significant international intra-industries technology spillover effect, but most research so far neglects this effect. Apparently, through opening up, the foreign R&D capital in the same sector in other countries may exercise an impact on domestic technical production process via international trade, foreign direct investment, and transnational flow of technical personnel, so that R&D capital in the same sector in other countries can also have a significant impact on R&D production efficiency in the same sector in the same countries. Thus through introduction, absorption, assimilation, and re-innovation of foreign R&D capital in the same sector in other countries, the domestic industry can yield great R&D production efficiency.

Thirdly, the coefficient of the R&D capital in the other sectors in the same countries is statistically significantly positive. This result is consistent with our expectation, confirming the existence of significant inter-industry technology spillovers among domestic industries, which has been neglected by most scholars. Therefore, domestic R&D capital of other industries may influence the R&D output efficiency in one industry through intersectional technology spillovers, the forward and backward association of industries, and the intermediate input among industries.

Fourthly, most coefficients of the R&D capital in the other sectors in other countries show no statistical significance. This conclusion demonstrates that Chinese industrial enterprises have failed to take full advantage of foreign R&D input in other industries, which further proves that there is no obvious inter-

industry technology spillover effect from other industries in foreign countries. This phenomenon may be attributed to the huge technological gap between China and countries with advanced technology. In order to realize high utilization of technology from different industries of other countries, China requires great absorptive capacity. However, limited by the current R&D conditions and environment, the technology assimilation ability of Chinese enterprises remains to be improved. Thus, obvious impact of foreign R&D input in other industries has not been observed on R&D production efficiency.

Fifthly, technical labor inputs fail to significantly impact R&D production efficiency. This conclusion is inconsistent with most studies. According to the research of Zhu et.al (2006), the output elasticity of R&D personnel input is 0.231 in high-technology industry. Zhang et.al (2003) conducted research on the output elasticity of domestic R&D labor within Chinese industrial enterprise, giving it a value of 0.297. This conclusion shows that technical labor input does not significantly improve R&D production efficiency. Consulting the data of technical labor inputs in Chinese industries, it is found that industries with intensive technical labor inputs are mostly high-tech industries. High-tech industries have a significant impact on R&D efficiency, on the condition that these industries have a higher level of human capital, that technical staff is equipped with a higher comprehensive quality and educational background, and that there is low staff redundancy. During the past decades, the human capital of high-tech industry still remains at a relatively low level. Compared with developed countries, China still has a long way to go in terms of improving quality of personnel and average educational background. In addition, in terms of staff redundancy, notable improvement has not been observed in R&D production efficiency, even with more input of technical staff.

5.2. Estimation results of model considering efficiency influential factors

In order to consider the impact of other factors on technical inefficiency, the models constructed by Battese and Coelli (1995) were applied, including the model without time lag and with first-order lag. Moreover, environmental factors on technical inefficiency were also taken into account to analyze their impact. These factors include human capital, trade openness, technology gap, degree of industry competition, physical capital, technology level of industry, and structure of property rights. The model estimation results are shown in table 2.

Table 2. Estimation results of model with consideration of the impact of environmental factors

Explained variables	Model with no time lag	Model with first order time lag	Explained variables	Model with no time lag	Model with first order time lag
Constant term	3.315***	3.313***	TROP	-0.761**	-0.610*
	(2.99)	(3.08)		(-2.29)	(-1.76)
$\log R^{sd}$	0.568***	0.535***	Firms	0.048	-0.016
	(4.41)	(4.60)		(1.00)	(-0.32)
$\log R^{sf}$	0.268***	0.279***	K	-0.198***	-0.206***
	(13.19)	(15.27)		(-3.03)	(-3.20)
$\log R^{od}$	0.194*	0.213**	High-tech	0.371***	0.398***
	(1.98)	(1.94)		(4.24)	(4.04)

$logR^{of}$	-0.073	-0.056	State	-0.080	-0.091
	(-0.81)	(-0.58)		(-0.78)	(-0.80)
logL	0.102	0.107	σ^2	0.349***	0.359***
	(0.90)	(0.96)		(10.95)	(9.86)
Constant term	2.932***	3.276***	γ	0.756***	0.824***
	(2.01)	(2.32)		(3.78)	(5.04)
H	-0.541*	-0.237*	Log likelihood function	-262.780	-247.216
	(-1.71)	(-1.94)	LR test	125.153	123.709
GAP	0.662***	0.713***	No. of observations	304	285
	(7.64)	(7.30)			

Note: The *t*-statistics are in brackets. ***, **, and * indicate the significance at 1, 5 and 10% level (one side), respectively.

In table 2, it can be seen that whatever the model is, γ values are greater than 0.7 and have a statistical significance. This indicates that the error term of the stochastic frontier production function mainly originates from technical inefficiency items. Technical inefficiency is the major obstacle hindering innovation from reaching the frontier. It also proves the correctness of the model by Battese and Coelli (1995). Based on the estimation results in table 2, the conclusions drawn with the frontier production function reach consensus with that shown in table 1. Except for the foreign R&D input from other industries and technical labor, which have no effect on R&D production efficiency, other input variables, including the R&D capital in the same sector in the same country, the R&D capital in the same sector in other countries, and the R&D capital in the other sectors in the same country, all have a positive effect on boosting R&D production efficiency. Some other conclusions can also be derived from table 2.

Firstly, human capital has a statistically significant negative impact on technical inefficiency. This result indicates that human capital plays a significant role in promoting technical efficiency. Generally speaking, a higher level of human capital indicates that the technical employees engaging in this industry receive more education, and that the industry possesses a stronger capability to absorb foreign advanced technology and innovate. Therefore, the level of human capital is a crucial factor in determining R&D output efficiency.

Secondly, the degree of trade openness has a statistically significant negative effect on technical inefficiency, which means that in industries with a higher degree of trade openness, R&D production efficiency also tends to be higher. New trade theory and endogenous growth theory always consider international trade as a channel for international technology spillovers. It is believed that international trade plays a significant role in productivity growth. This research also holds that international trade has functioned as a channel for improving R&D production efficiency. Import and export trade stimulate transnational flows of technology and knowledge worldwide, during the process of which a country can not only strengthen its absorption ability, but also enhance R&D production efficiency.

Thirdly, the variable coefficient of the technology gap is shown to be positive and significant. Thus, it can be concluded that the larger the technology gap is, the lower the R&D production efficiency will be. If there is a huge technological gap between an industry in China and in frontier countries with advanced technology, it means that the technology development of the industry in China is relatively weak. Furthermore, it indicates that the industry is left behind those developed economies in terms of some key factors which will affect industry assimilation ability, including human capital, technical capacity and level of R&D input, etc. Thus poor absorptive ability naturally leads to lower R&D production efficiency. This conclusion also reveals that narrowing technological distance can bring about twofold benefits. Firstly, technology level can be improved through narrowing technological distance and secondly, R&D production efficiency is likely to be enhanced with strengthened assimilation ability.

Fourthly, the industry competition degree has no statistically significant effect on technical inefficiency. This conclusion agrees with the findings of Zhang Haiyang (2008), but is not consistent with the findings of Feng et. al (2006). This conclusion reveals that the degree of monopoly does not exert influence on technical inefficiency, and that a market with a higher degree of monopoly does not necessarily exhibit a more obvious effect of R&D input on technical inefficiency. Though industries with higher degrees of monopoly are usually endowed with such advantages as financial strength and economies of scale, they may also suffer from a lack of incentive to pursue technological breakthroughs, poor innovative awareness, and an opportunity cost for technology upgrade that is usually too heavy to bear. Therefore, the degree of monopoly does not generate significant influence on R&D production efficiency.

Fifthly, physical capital input exercises a significantly negative influence on technical inefficiency, which reflects that physical capital input is capable of enhancing R&D output efficiency. That is to say, physical capital input is complementary to R&D capital input. More physical capital input means, firstly, a larger scale economy and more output for an industry, which reflects strong technological innovation to a certain extent. It also means that in the process of enterprise technology innovation, physical capital can be utilized efficiently as a complement for R&D capital, generating higher production efficiency.

Sixthly, the coefficient of the dummy variable of industrial characteristics is positive, suggesting that there is a significant impact of industry characteristics on technical efficiency and that the R&D production efficiency in high-tech industries is lower than that in non-high-tech industries. Though since the 1990s, the Chinese government has attached great importance to the development of high-tech industries, they have not yet reached a stage where high input generates high output. R&D activities by these industries fail to achieve economies of scale. The obstacles that restrain the development of Chinese high-tech industries include fierce but low-level competition, inadequate technical base, and heavy reliance on foreign capital for R&D activities.
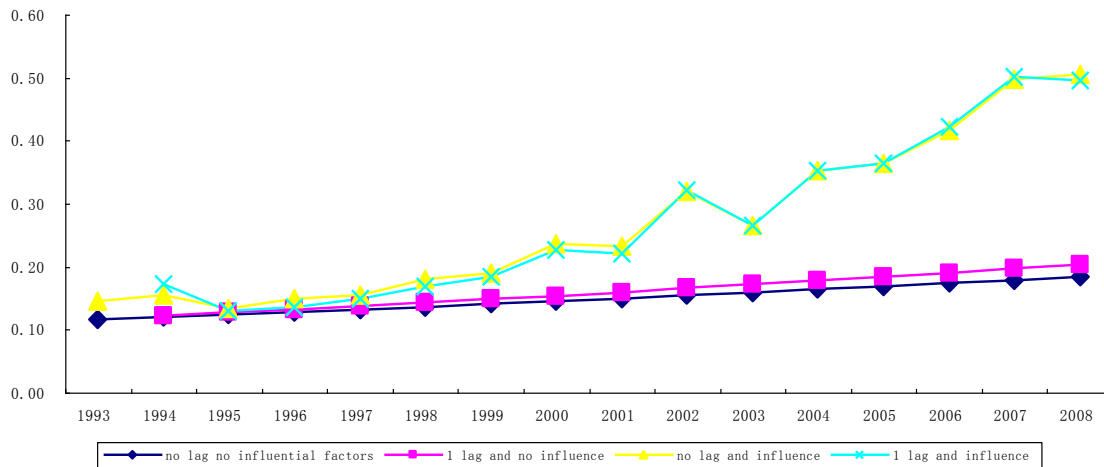
Seventhly, the coefficient of the dummy variable of property structure is negative, but the result is not significant, which indicates that state ownership has no effect on R&D production efficiency. This finding is not consistent with our expectation, that in industries with a higher share of state ownership, idle resources and ineffectual technical staff would result in low R&D production efficiency. A possible explanation to account for this discrepancy is that industries with a higher share of state ownership usually enjoy strong governmental support, making it possible for them to pour more funds into R&D activities. Most Chinese privately-owned enterprises, on the other hand, which are small in size and engage in labor-

intensive industries, are still in the process of capital accumulation; it is therefore impossible for them to invest heavily in R&D activities.

5.3. Estimation result of R&D production efficiency

In order to further predict the changing trend of R&D production efficiency, we estimate R&D production efficiency in the time-variant model with no time lag and with first-order time lag respectively (See Figure 1). From Fig.1, we can see that the estimation results of the model with no time lag and those of the model with first-order time lag are basically consistent, with the latter slightly higher than the former. The R&D production efficiency measured in the model considering environmental factors is higher than that found in the model that does not consider environmental factors. Besides, no matter which model is being employed, the R&D production efficiency in Chinese industries is at a low level, with an annual average R&D output efficiency below 0.51, and the growth rate of R&D production efficiency is very slow. This implies that the policies adopted by the Chinese government to invest heavily in technology in the past decades are ineffective in boosting R&D output efficiency and that R&D output efficiency in Chinese industries still has much room for improvement.

Figure 1. Changing trend of R&D production efficiency

6. Conclusion

This paper chose the Chinese industrial sector as a research object, based on the R&D capital as divided into the R&D capital in the same sector in the same country, the R&D capital in the same sector in other countries, the R&D capital in the other sectors in the same country, and the R&D capital in the other sectors in other countries, firstly using the knowledge production function model and the stochastic frontier production function method to empirically study the R&D production efficiency of the Chinese industrial sector, then to study how the factors of industry technical level, ownership structure, human capital, degree of trade openness, technology gap, degree of industry competition, and physical capital stock impact R&D production efficiency.

Through analysis, we can conclude that: 1) except the R&D capital in the other sectors in other countries, the other three R&D capital have a significant positive impact on the R&D production efficiency, 2) External environmental factors such as degree of trade openness, technology gap, and physical capital stock have a significant positive effect on R&D production efficiency, human capital and industry degree of competition do not have a significant positive impact on R&D production efficiency. As for industry characteristics, the technical efficiency of high-tech industries is lower than that in non-high-tech industries, and the R&D output efficiency differs little between state-owned business and non-state-owned business. 3）R&D production efficiency is improving gradually over time, but the various sectors of R&D output efficiency are still low, and development is very uneven. There are significant differences between industries.

Based on the above conclusions, the following instrumental suggestions can be given to policy-makers. Firstly, from the analysis above, we know that, apart from the independent R&D input in one industry, the R&D input from other industries and from the same industry of foreign countries can also promote R&D production efficiency. Therefore, in light of the realities of China as a developing country, we should take effective advantage of inter-industry and intra-industry technology spillover effects and focus on forward and backward association of R&D inputs to boost R&D production efficiency. In addition, the Chinese government should increase R&D inputs in all industries in general, which is not only conducive to balancing the performance of R&D production efficiency of all industries, but is also helpful in creating a benign cycle to enable the transfer of R&D input benefits among industries, and finally lead to an overall improvement of R&D output efficiency. Secondly, as was analyzed above, the R&D production efficiency varies greatly among industries with different technology levels. In order to make full use of limited R&D resources in current China, the Chinese government should allocate resources with special caution, and priority should be given to industries with higher production efficiency.

High-tech industries are an important foundation for the technology development of a nation. However, high-tech industries in China are generally suffering from an inadequate technology base, which severely impairs their technical efficiency. Therefore, the Chinese government should further make every effort to enhance the technology base and capacity of high-tech industries, and to improve their capacity to absorb and utilize advanced technology. Thirdly, from the above analysis we know that enhanced absorptive capacity can boost R&D production efficiency distinctively. As the absorptive capacity of a nation is closely linked with the improvement of human capital, the expansion of trade openness, and the narrowing of the technology gap, the Chinese government should increase the training of human capital, enhance the national level of education, further expand opening up, increase trade with the technologically advanced countries, take a series of measures to bridge the technology gap between China and developed countries, and increase absorption capacity in order to significantly enhance Chinese R&D production efficiency.

References

Arrow, K. Economic Welfare and the Allocation of Resources for Invention, in (R. R. Nelson, ed.) *The Rate and Direction of Inventive Activity.* Princeton: Princeton University Press.

Barro, R. J. (1991). Economic Growth in a Cross Section of Countries, *The quarterly journal of economics,* 106(2):407-443.

Battese, G. E. and Coelli, T. J., 'Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India', *Journal of Productivity Analysis*, 1992.3 (1 –2), pp.153–169.

Battese, G. E. and Coelli, T. J. (1995). A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data, *Empirical economics*, 20(2):325-332.

Benhabib, J. and Spiegel, M. M. (1994). The Role of Human Capital in Economic Development Evidence From Aggregate Cross-Country Data, *Journal of Monetary economics*, 34(2):143-173.

Coe, D. T. and Helpman, E. (1995). International R&D Spillovers, *European Economic Review*, 39(5):859-887.

Cohen, W. M. and Levinthal, D. A. (1989). Innovation and Learning: The Two Faces of R&D', *The economic journal*, pp. 569-596.

Feng, G., Liu, J. and Xu, Z. (2006). Study On the Factors On Chinese Industries R&D Efficiency [J], *China Industrial Economy*, 11, pp. 46-51.

Feng Z. X.,Wang. Q and Hou. XH. (2011). Government Investment, Degree of Marketization and Technological Innovation Efficiency of China's Industrial Enterprises. *The Journal of Quantitative & Technical Economics*, (4):3~17.

Ge X. H. and Chen L. (2009). The Technological Progress Effect of International R&D Spillovers, *The Journal of Quantitative & Technical Economics*, (7):86~98.

Griliches, Z. (1979). Issues in Assessing the Contribution of Research and Development to Productivity Growth, *Bell Journal of economics*, 10(1):92-116.

Hai-yang, Z. (2008). R&D Production Efficiencies and Determinants in Chinese Manufacturing', *Studies in Science of Science* 5, pp.970-978.

Kunbhakar, S. and Lovell, C. (2000). *Stochastic Frontier Analysis*, New York: Cambridge University Press.

Liangke, X. (2010). How Human Capital and R&D Investments Influence TFP, *The Journal of Quantitative & Technical Economics*, 4:78-94.

Lichtenberg, F. R. and Pottelsberghe De La Potterie, B. V. (1998). International R&D Spillovers: A Comment, *European Economic Review*, 42(8):1483-1491.

López-Pueyo, C., Barcenilla-Visús, S. and Sanaú, J. (2008). International R&D Spillovers and Manufacturing Productivity: A Panel Data Analysis, *Structural Change and Economic Dynamics*, 19(2):152-172.

Wan-Goo Kang (2002). *Focusing on the Effect of Education and Technology Adoption on the Economic Growth*, A Dissertation presented to the Faculty of the Graduate School, University of Missouri Columbia, August.

Wang, E. C. and Huang, W. (2007). Relative Efficiency of R&D Activities: A Cross-Country Study Accounting for Environmental Factors in the DEA Approach, *Research Policy*, 36(2):260-273.

Wu, Y. (2008). Measurement On R&D Output Elasticity of China'S Industrial Sector, *China Economic Quarterly*, 7:869-889.

Xiaoping, L. and Lu Xianxian. (2010). International Trade, Pollution Industry Transfer and Chinese Industries'CO_2 Emissions, *Economic Research Journal*, 1(1):15-26.

Xiaoping, L. and Zhongdi, Z. (2006). International Trade, R&D Spillover and Productivity Development: Based On the Analysis of Chinese Industry's Panel Data, *Economic Research Journal*, 2(2):31-43.

Zhang, A., Zhang, Y. and Zhao, R. (2003). A Study of the R&D Efficiency and Productivity of Chinese Firms, *Journal of Comparative Economics*, 31(3):444-464.

Zhu, Y. and Xu, K. (2006). The Empirical Research on R&D Efficiency of Chinese High-Tech Industries [J], *China Industrial Economy*, 11:38-45.

Contact Information

Jianping Liu, Business School, Hubei University. 368 Youyi Avenue, Wuhan 430062, Hubei, P.R. China. E-mail：liujp621@163.com.

Shixiong Cheng, Business School, Hubei University. 368 Youyi Avenue, Wuhan 430062, Hubei, P.R. China. E-mail：csxcsx007@foxmail.com; csxcsx007@163.com.