R&D, Technology Transfer and Productivity Growth: Evidence from Chinese Manufacturing Industries

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I really thank Finn R. Førsund, Jinghai Zheng and Yanrui Wu for very helpful comments. Financial support from National Social Science Foundation of China (grant number 06&ZD004_01) is gratefully acknowledged. The author is responsible for any errors in this article.

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Abstract: Based on an industry-level data set for Chinese large- and medium-size manufacturing enterprises over the period of 1996–2006, the paper investigates the impacts of three technology acquisition channels, i.e. in-house R&D, foreign technology transfer and domestic technology transfer, on the productivity growth by using both the output elasticity and the rate of return methods. We find that in-house R&D makes substantial and significant contributions to productivity growth in Chinese manufacturing industries, and that technology transfers, whether foreign or domestic, have no significantly positive effects on productivity growth. When the productivity growth is decomposed into technical efficiency change and technological progress by using Data Envelopment Analysis, we also find that the important role of R&D in improving industry performance is mainly attributable to the contributions of R&D to technical efficiency change.

Key Words: R&D, Technology Transfer, Productivity Growth

JEL Classification: D24, L60, O33

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1. Introduction

Technological change is an important determinant of long-run productivity growth and therefore of increases in living standards over time. Research and development (R&D), which leads to new products and processes that either increase firms' revenues or reduce firms' costs, is regarded as the fundamental driver of technological progress and endogenous growth. Therefore productivity growth should be amplified when R&D expenditures are also raised. Under the circumstance of economic globalization, another important way to achieve technological progress is to fully absorb and exploit the advanced technologies and experiences of the rest world. For developing countries in which few firms have well-established R&D operations, tapping into the existing world knowledge stock would seem to be a natural way of shortening the technology gap.

Since China' reform and opening up, the Chinese central government has been consistently emphasizing the importance of technology development and viewing technology development as an engine for the process of catching-up with advanced industrial economies and industrialization. Chinese central government has taken effective policy instruments to reform the mechanisms of science and technology and carried out the preferential policy measures towards encouraging foreign technology introduction from developed countries. As a result, in-house R&D and foreign technology transfer had a continual rise since 1978. For example, In 2007 R&D expenditures in China totaled 371 billion yuan which was about 50 times R&D expenditures in 1987. The ratio of R&D spending to GDP reached 1.49 percent in 2007, a substantial increase relative to the level of 0.61 percent in 1987. Foreign technology transfer reached 25 billion U.S. dollars in 2007, while it was only 2.5 billion U.S. dollars in 1979 (Chinese National Bureau of Statistics, 2008). Now technological progress has become a critical ingredient for sustained economic growth in China. It is believed that over the long-term, China's economic performance will ultimately depend upon its ability to acquire, adapt and innovate new technologies.

Against this background, this research draws on previous studies to offer information bearing on two questions related to R&D, technology transfer and productivity growth, which are also two important topics that have attracted considerable attention in research on technology issues in advanced industrial countries. First, are R&D and technology transfer important factors in explaining the growth of Total Factor Productivity (TFP) at the industry level? Second, if R&D and technology transfer are important factors, how great are their impacts? In practice, the main evidence related to those questions consists of econometric estimates of the output elasticity and the rate of return to R&D and technology transfer. This research uses an industry-level data set of Chinese large- and medium-size manufacturing industries over the period of 1996–2006 to systematically investigate the contribution of each of these channels to industry-level performance. Through this empirical study, this research is expected to provide an explanation for Chinese economic growth and some suggestions for Chinese technological development.

In this paper we find that R&D has a significant contribution to productivity growth in Chinese manufacturing industries, whereas direct technology transfer, whether foreign or domestic, have no significant impacts on productivity growth. When the productivity growth is decomposed into technical efficiency change and technological progress, we find that the positive impact of R&D on productivity growth seems to work mainly through technical efficiency improvement. The remainder of the paper is organized as follows. Section 2 reviews the relative literatures .Section 3 explains the conceptual and econometric framework. Section 4 describes the data. The empirical results are presented in section 5. Section 6 estimates the effects of R&D and technology transfer on productivity decompositions. Finally, section 7 provides conclusions and the policy implications.

2. Literature review

The interest in econometrically assessing the R&D investments started in the early 1960s. The earliest research to investigate the effects of R&D on productivity centered on individual industries within manufacturing and especially on the agricultural sector (Minasian, 1962, 1969; Griliches, 1964; Mansfield, 1965). As time passed and more sources of data became available, later studies tended to broaden the samples by including more industries, many firms in a single industry, or many firms in many industries. These studies, by including the knowledge stock in the Cobb-Douglas production function, tried to identify the acceleration of productivity growth which occurs due to R&D investments; However, the conceptual framework was not satisfactorily developed until the late 1970s (Griliches, 1979). From then on, a large number of empirical studies of estimating the effect of R&D investments on productivity growth have emerged in many countries. The estimated magnitudes of the R&D contribution to productivity growth span a wide range depending on the aggregation level of data, the methodology and the period being considered: some studies have found that R&D's effect on productivity is essentially zero, whereas others have found that its effect is substantial and that it exceeds that of other types of investment by a large margin. Most of the estimates, however, lie somewhere between the two extremes, and as a result, a consensus has formed around the view that R&D spending has a significantly positive effect on productivity growth, with a rate of return that is about the same size as or perhaps slightly larger than the rate of return on conventional investments.

For studies on Chinese industries during the reform era, given the transitional nature of China's industrial economy, a particular focus is on the impact of institutional reform on the performance of China's industrial enterprises. Nevertheless, increasing interests have been attached to R&D and innovation, as well as their impacts upon industry performance in the Chinese manufacturing sector. Among the existing empirical studies, the econometric evaluation of the impact of China's R&D on productivity has been a focus of analysis in recent years. Hu (2001) adopted a production function framework to analyze the impact of R&D on productivity using a cross section of innovative enterprises from Beijing, China. He found that private R&D has a strong impact on firm productivity and government R&D contributes indirectly to productivity by promoting private R&D. Hu and Jefferson (2004) used a firm-level dataset on large and medium-size industrial enterprises during the period of 1991-1997 in the Beijing area to find substantial and significant returns to R&D in the cross-section dimension. Based on a rich set of panel data covering the population of China's large and medium-size manufacturing enterprises during 1997-1999, Jefferson et al. (2006) found that the contributions of R&D expenditures to productivity are statistically significant and returns to industrial R&D appear to be at least three to four times the returns to fixed production assets.

In the context of China's opening up policy, the vast majority of the empirical literatures have emerged about the impacts of technology spillovers through foreign direct investment upon manufacturing industries' performance. For example, Liu (2002) used industry-level data of 29 manufacturing industries over the period of 1993–1998 in the Shenzhen Special Economic Zone of China to find that foreign direct investment has large and significant spillover effects in that it raises both the level and growth rate of productivity of manufacturing industries. However, it is especially noticeable that very few studies have paid attention to the relationship between direct technology introduction and productivity growth. In the existing literatures using China's data, only Hu et al. (2005) examined the contributions of domestic R&D, foreign technology transfer and domestic technology transfer, as well as their interactions, to productivity, using a large data set for China's large and medium-size enterprises during 1995 to 1999. The central findings of this research are that domestic R&D and foreign technology transfer have strong impacts on the productivity of industrial enterprises and the impacts of both domestic and foreign technology transfer on productivity are largely conditional on their interactions with in-house R&D.

The above literatures that assess econometrically China' R&D and technology introduction mainly use the firm level dataset. Moreover, shortcomings of the available data and the difficulties associated with the estimating methods make it difficult to identify with any precision the size of contributions that R&D and technology introduction make. By using an industry-level data set of Chinese large and medium-size manufacturing enterprises during the period of 1996-2007, this research will analyze the contributions of three technology acquisition channels, i.e. R&D, foreign and domestic technology transfer, to improving China's industrial performance. Compared with the existing literatures, some academic contributions in this research are as follows.

Firstly, on the basis of the expansion of Cobb-Douglas production function, not only the output elasticities but also the rates of return of R&D, foreign and domestic technology transfer will be estimated in this research. Meanwhile, Data Envelopment Analysis (DEA) will be used to decompose productivity growth of Chinese manufacturing industries into technical efficiency change and technological progress, and then the effects of three technology acquisition channels on Malmquist productivity index and its components will be re-estimated to verify the reliability of the production functions estimates.

Secondly, the available data concerning real R&D expenditures are bedeviled by the lack of a suitable price index for R&D inputs. Fortunately, China Statistical Yearbook on Science and Technology provides the detailed data about R&D expenditures which are composed of compensation for laborers, raw material expenditure, expenditure on the purchase of fixed assets and other expenditure for R&D. Based on these data, a more reliable R&D price index can be constructed to deflate the nominal R&D expenditures, which will give us an opportunity of calculating with more precision the R&D's contribution to productivity growth.

Finally, a noteworthy issue in exploring the contribution of R&D to productivity is the so-called "double counting" problem. Given that a proportion of capital and labor belongs to the R&D department, R&D machinery and R&D employees should be subtracted from the ordinary capital and labor while calculating the output elasticity and rate of return to R&D. Nevertheless, the data used in the existing literatures are not always detailed enough to allow such corrections.

In this research, the data will be corrected by subtracting the employees and expenditures devoted to the R&D department from the total numbers of employees and capital. With double counting for R&D corrected, the estimation results will be more credible than those of ignoring double counting of R&D.

3. Conceptual and econometric framework

A common approach of innovation studies is to treat R&D within a production function framework as a factor of production, symmetric with physical capital, labor, and other inputs. The R&D input is most appropriately interpreted as a stock of knowledge constructed as the sum of discounted past R&D expenditures. The model used here is essentially the same as that employed by other scholars, except that the sources of knowledge are disaggregated into three parts: domestic R&D, foreign technology import and domestic technology transfer.

The Cobb-Douglas production function is usually regarded as a starting point for most econometric studies of assessing the contribution of knowledge to productivity. In a particular industry, after accounting for time and industry differences, the production function is assumed to be the following:

$$Q_{it} = AC_{it}^{\alpha} L_{it}^{\beta} (RS_{it})^{\gamma_R} (FS_{it})^{\gamma_F} (DS_{it})^{\gamma_D} e^{\lambda t + u_i + \varepsilon_{it}} \tag{1}$$

Where Q is the industry's output, C is the industry's stock of physical capital, and L is the industry's labor input. RS, FS and DS represent the industry's stocks of R&D, foreign technology import and domestic technology transfer respectively. The term A is a constant, t is a time trend, λ captures the disembodied technical change. α, β are the elasticities of output with respect to physical capital and labor respectively, and γ_R, γ_F and γ_D are the elasticities of output with respect to three knowledge stocks respectively. u_i captures unobservable effects which are unchangeable with time, and ε_{it} is an error term.

As usual, to implement the estimation of the production function, Equation (1) can be rewritten in logs as:

$$q_{it} = a + \lambda t + u_i + \alpha c_{it} + \beta l_{it} + \gamma_R rs_{it} + \gamma_F fs_{it} + \gamma_D ds_{it} + \varepsilon_{it} \tag{2}$$

Where lower case letters denote the logarithms of variables. Under constant returns to scale with respect to the conventional measures of capital and labor, the sum of factor elasticities, $\mu=\alpha+\beta$, will be unity. For interpretive reasons, the equation can be rewritten so that the deviation from constant returns is measured explicitly, by subtracting labor from both sides of the equation (2):

$$(q_{it} - l_{it}) = a + \lambda t + u_i + \alpha(c_{it} - l_{it}) + (\mu - 1)l_{it} + \gamma_R rs_{it} + \gamma_F fs_{it} + \gamma_D ds_{it} + \varepsilon_{it} \tag{3}$$

The coefficient of the logarithm of labor (μ-1) now measures the departure from constant returns. If this coefficient is significantly different from zero, constant returns to scale for capital and labor can be rejected. Accounting for the possible effects of the restriction of returns to scale on the estimates of γ_R, γ_F and γ_D, we shall report both the estimates obtained with and without imposing constant returns to scale.

Estimating equations (3) requires very few assumptions about the production function and provides results that have a straightforward interpretation. Meanwhile, in the process of estimating the parameters of R&D and technology transfer, several econometric problems are worth noticing.

First, in estimating equation (3), we face a possible econometric problem concerning the potential correlation between the independent variables and unobservable effects. In our panel data, u_i represents time-invariant industry specific characteristics which may be corresponded to permanent differences in production technology and economic environment. However, the unobservable industry specific characteristics may be quite likely to correlate with the production inputs on the right hand side of equation (3). For example, industries with high technologies may also sustain greater than average expenditures on R&D and technology purchases. The ordinary least square estimates of the coefficients would then be subject to omitted-variable misspecification and bias. Several methods exist to correct for this bias. The habitual and convenient way to abstract from the u_i's is to compute the within regression using the deviations of the observations from their specific industry means, which is equivalent to including industry dummy variables in the total regression. Another substitute way is to use the first difference estimation in which the industry specific characteristics can be eliminated from the right hand side of equation (3). The first difference regression is as follows:

$$\Delta(q_{it} - l_{it}) = \lambda + \alpha\Delta(c_{it} - l_{it}) + (\mu - 1)\Delta l_{it} + \gamma_R \Delta rs_{it} + \gamma_F \Delta fs_{it} + \gamma_D \Delta ds_{it} + \Delta\varepsilon_{it} \qquad (4)$$

Second, multicollinearity is another possible econometric problem associated with equation (3). This problem is engendered by the fact that the variables of interest move together over time so that the estimates of the parameters tend to have large estimated variances and little statistical significance, thus it is difficult to identify accurately the contribution of each input. By contrast, since the first-difference of the logarithm of variable is approximately equivalent to the yearly growth rates of the variable, which can greatly reduce the correlations among independent variables[1], as well as control for permanent differences across industries, we are prone to use the first-differenced equation, i.e. (4), to evaluate the contribution of R&D and technology transfer to productivity growth.

Third, the inputs in production function may not be completely exogenously determined. Technical knowledge and productivity are likely to be mutually dependent—output is a function of, among other things, technical knowledge, and technical knowledge is a function of past output and expected future output, e.g. higher output leads to higher R&D expenditures and technology transfer. Under these circumstances, OLS-based estimates of the coefficients on knowledge will be biased. The solution to the simultaneity is the use of simultaneous-equation techniques or instrumental variables (IV) estimation. However, they are not always applied to explore the contribution of knowledge because the data required to use them do not always exist and the exogeneity of these instruments is then questioned raising other problems (Griliches, 1986). For this reason, we do not wipe out the possible bias induced by simultaneity.

Finally, when using equation (2) to (4) to evaluate the output elasticities, one of the most difficult tasks is to measure the stocks of the three knowledge capital. To avoid this problem, some authors have chosen to use an equation that yields an estimate of the rate of return (ROR) to knowledge instead of the knowledge elasticities. The specification is a transformation of equation (4), which assumes that the marginal products of knowledge across industries are equal.

[1] In our database, the correlations between the corresponding variables are as follows: cor(LnRS, LnFS)=0.81, cor(LnRS, LnDS)=0.85, cor(LnFS, LnDS)=0.78; and cor(ΔLnRS, ΔLnFS)=0.13, cor(ΔLnRS, ΔLnDS)=0.25, cor(ΔLnFS, ΔLnDS)=0.09.

Since by definition the elasticity of R&D stock γ_R is equal to $\frac{\Delta Q}{\Delta RS}\frac{RS}{Q}$, term $\gamma_R \Delta rs$ can be rewritten as $\frac{\Delta Q}{\Delta RS}\frac{RS}{Q}\frac{\Delta RS}{RS}=\frac{\Delta Q}{\Delta RS}\frac{\Delta RS}{Q}$. The fraction $\Delta Q/\Delta RS$ is the marginal product of R&D stock (termed as ρ_R) which is interpreted as the rate of return to R&D. In order to estimate ρ_R, the variable ΔRS (representing the change of R&D stock) is needed. Most of the previous studies have usually assumed that R&D capital does not depreciate so that the difference of R&D capital (ΔRS) is equal to the current R&D expenditures (termed as R)[2], i.e. $\Delta RS = R$, then the term $\gamma_R \Delta rs$ can be rewritten as $\rho_R (R/Q)$. Similarly, the terms $\gamma_F \Delta fs$ and $\gamma_D \Delta ds$ in equation (4) can also be rewritten as $\rho_F (F/Q)$ and $\rho_D (D/Q)$ respectively, where F and D represent the expenditures on foreign and domestic technology transfer respectively, and ρ_F and ρ_D represent the rate of return to the corresponding variables. Therefore, the equation (4) can be transformed into the following form:

$$\Delta(q_{it}-l_{it})=\lambda+\alpha\Delta(c_{it}-l_{it})+(\mu-1)\Delta l_{it}+\rho_R(\frac{R}{Q})_{it}+\rho_F(\frac{F}{Q})_{it}+\rho_D(\frac{D}{Q})_{it}+\Delta\varepsilon_{it} \quad (5)$$

Compared with equation (4), the main advantage of equation (5) is that the relevant variables on the right hand side are the intensities of R&D and technology transfer to output which are easily measured. Meanwhile, it must be made in mind that there are at least two potential problems with this rate of return approach (Hall and Mairesse, 1995). First, the rate of return estimated using equation (5) is a gross rate of return. To obtain the net rate of return we need to subtract the (unknown) depreciation rate for R&D and technology transfer; thus the problem of depreciating incurred when estimating the stocks of R&D and technology transfer is not really avoided. Second, the timing of the relationships among R&D, technology transfer and productivity growth is not clear, so applying various lag structures of variables in the regression seems to be appropriate. Fortunately, Mairesse and Sassenou (1991) in their survey point out that R&D expenditures by firms is very stable over time, most of the variation is in the cross-section. In this paper we experiment with the timing of both the three technical variables and sales revenue and confirm that it has little impact on the regress results and the intensity coefficients do indeed seem to be unbiased.

Taking the advantages and disadvantages of the output elasticity and the rate of return method into account, we will use the two different methods to evaluate the effects of the three technology acquisition channels on productivity growth.

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[2] According to the Perpetual Inventory Method (PIM) which will be described in section 3 of this paper, $\Delta RS_{it}=RS_{it}-RS_{it-1}=R_{it}+(1-\delta)RS_{it-1}-RS_{it-1}=R_{it}-\delta RS_{it-1}$. When the depreciation rate δ equals to zero, then $\Delta RS_{it}=R_{it}$.

4. Data and variables

4.1 Data

The main data for this research, which span the population of Chinese large and medium-sized manufacturing enterprises[3], are drawn from the China Statistical Yearbook on Science and Technology published by China statistics press. Large and medium-sized enterprises dominate Chinese industry, in 2006 accounting for 64 percent of China's total industrial value added. In addition, the correlative price indexes are necessary in order to eliminate the influences of price fluctuation on output and inputs. Price indexes are drawn from Chinese Statistical Yearbook that National Bureau of Statistics of China (NBS) reports each year. Our sample spans a period of eleven years from 1996 to 2006 and includes data for 29 two-digit manufacturing industries every year; therefore a balanced panel data which is composed of 319 observations is constructed.

In our sample, the R&D expenditure is measured by intramural expenditure on technical development which refers to the actual expenditure made for scientific and technological activities by the survey units during the reference period, including service expenses, professional expenses for scientific research, management expenses for scientific research, purchases of fixed assets with investment in non-capital construction, capital construction expenditure for scientific research and others. Foreign (domestic) technology transfer is measured by an industry's expenditure on disembodied technology purchased from foreign (domestic) providers, such as patent licensing fee and payment for blueprints of technology and so on.

4.2 Variables

4.2.1 R&D stock and technology transfer stock

In order to estimate the elasticities of output with respect to R&D, foreign and domestic technology transfer, stock measures for each of the three technology variables are needed. Knowledge accumulated through these technological activities in the past generates benefits in the present and the future. However, knowledge depreciates and becomes obsolete not only because new knowledge replaces old knowledge but also because the appropriability of knowledge decreases as the diffusion of that knowledge takes place with the passage of time. Following the methods of Griliches (1979), by using a perpetual inventory model like that commonly used for physical capital, we construct the stocks of R&D, foreign and domestic technology transfer as the discounted sum of past expenditures on respective activity.

We first construct the R&D capital stock. R&D stock has been viewed as a measurement of the current state of technical knowledge, determined, in part, by current and past R&D expenditures. The perpetual inventory method defining R&D capital stock is the following:

$$RS_{it} = R_{it} + (1 - \delta) RS_{i,t-1} \tag{6}$$

Where RS is the R&D stock for industry i in year t; δ is the depreciation rate of R&D capital, and R is industry i's gross R&D investments in year t. To implement the equation, we must first calculate the price index for R&D expenditures, the initial R&D stock and the depreciation rate.

As Mansfield (1984) points out, the available data concerning real R&D expenditures are

[3] To define large and medium-sized enterprises, China's National Bureau of Statistics (NBS) uses either of two industry specific criteria: annual production capacity or original vale of the productive fixed assets. For further elaboration of the criteria used to classify firm size, see the web site of the China's NBS (http://www.stats.gov.cn/english/statisticalstandards/).

bedeviled by the lack of a suitable price index for R&D inputs. The usual R&D price deflator used in the past literatures is either the GNP deflator or a weighted average (with almost equal weights) of the consume price index and assets price deflator. Fortunately, China Statistical Yearbook on Science and Technology provides the detailed data for R&D expenditures which are composed of compensation for laborers, raw material expenditure, expenditure on the purchase of fixed assets and other expenditure for R&D. Based on these data, we construct the R&D price index as the following:

R&D price index = (compensation for laborers/R&D expenditures) ×consumer price index+ (raw material expenditure/R&D expenditures) × row material price index+(expenditure on the purchase of fixed assets/R&D expenditures) × fixed assets price index+(other expenditure for R&D/R&D expenditures) × other expenditure price index.

The yearly price indices for consumer, row material and fixed assets are from China Statistical Yearbook (CSY). It is a pity that CSY does not provide the relevant price indices for each manufacturing. In addition, because of the implication of other expenditure for R&D is not clear, we represent other expenditure price index by the arithmetical average of consumer price index, row material price index and fixed assets price index. Using the constructed R&D price index to deflate the nominal R&D expenditures, we get the real R&D expenditures for 29 manufacturing industries during the year of 1996-2006.

As for the initial R&D stock, with the assumption of pre-sample R&D expenditures growing at a rate of g, the R&D stock at the beginning of the year is defined by the following equation:

$$\begin{aligned} RS_{i1} &= R_{i1} + (1-\delta)R_{i0} + (1-\delta)^2 R_{i-1} + \cdots = R_{i1} + \frac{1-\delta}{1+g} R_{i1} + (\frac{1-\delta}{1+g})^2 R_{i1} + \cdots \\ &= R_{i1} \sum_{S=0}^{\infty} (\frac{1-\delta}{1+g})^S = R_{i1} \frac{1+g}{\delta+g} \end{aligned} \tag{7}$$

Assuming that a depreciation rate of 15 percent of R&D stock which has been most frequently used previously in this type of estimation and a pre-sample growth rate of 5 percent in real R&D expenditures[4], the initial R&D stock is 5.25 times the R&D expenditures in 1996((1+0.05)/(0.15+0.05)=5.25). On the basis of the initial R&D stock and equation (6), we can compute the R&D stocks of the 29 manufacturing industries during 1996-2006.

Similarly, the stocks of foreign and domestic technology transfer can be computed by the same method as the measurement of the R&D stock. The difference is that the expenditures on the two technology transfers are deflated by the fixed assets price index because there are no detail data on the compositions of technology transfers in the statistical yearbook. Besides this, with the assumption of the depreciation rate of 15 percent and the pre-sample growth rate of 5 percent in expenditures on technology transfers, the perpetual inventory method (equation (6)) can be in the same way used to compute the stocks of the two technology transfers.

4.2.2 Output, labor and capital

The output at constant price is constructed by deflating the sales revenue of each manufacturing during 1996-2006 by ex-factory price index of industrial products. Although measuring value added instead of sales revenue is more appropriate, the required data are not available in our database. As Mairesse and Hall (1996) find, however, the elasticity of R&D is not

[4] To verify the stability of estimation results, we will change the depreciation rate and the pre-sample growth rate of expenditures and report the results of experimentation with the assumption of different parameters in section 4 of this paper.

seriously biased when sales revenue is used instead of value added. Another area of potential distortion is the immeasurable improvements of output, i.e. better quality, increased product variety, etc. Since the price indices of China statistical agencies fail to fully account for these intangible improvements, our output record will be underestimated and the R&D elasticity downward biased. Labor is measured simply by the total number of employees because there is no available information on the labor working hours of industry.

Our measure of physical capital (C) is the original value of equipment instead of fixed assets which are not available in our database, so the physical capital will be underestimated and accordingly its elasticity may be downward biased. Growth theory suggests that capital input must be a measure of "productive stock", implying that its efficiency declines as it get old. The usual approach of measuring physical capital stock is the perpetual inventory method which has already been used in the computation of knowledge stock, i.e. $C_{it} = I_{it} + (1 - \sigma)C_{i,t-1}$ and $C_{i1} = I_{i1}\left[(1+d)/(\sigma+d)\right]$, where C is physical capital stock, I is the expenditures on physical capital, σ is the depreciation rate, and d is the pre-sample growth rate of physical capital. The key parameters of computing the equipment stock in this paper are set in the following: The value of equipment is deflated by fixed assets price index, the depreciation rate of equipment is assumed as 15 percent which is computed by zhang et al. (2008), and the pre-sample growth rate of equipment is set to 5 percent (i.e., the initial stock of equipment is 5.25 times the expenditures on equipment). Then equipment stock can be computed by using the perpetual inventory method described above.

Another noteworthy issue in exploring the contribution of R&D to productivity is the so-called "double counting" problem which originated with Schankerman (1981) and has been echoed by Cuneo and Mairesse (1984) and Griliches and Mairesse (1984). Given that a proportion of capital and labor belongs to the R&D department, we should subtract R&D machinery and R&D employees from the ordinary capital and labor. Nevertheless, the data are not always detailed enough to allow such corrections. In our database, we have the data on R&D employees but no data on R&D machinery, so the data is corrected by subtracting the employees devoted to the R&D department from the total numbers of employees. After correcting double counting for R&D employees, it is usually believed that the estimation results will be more credible than those of ignoring double counting of R&D, therefore we will mainly report the results of data corrected in the following text.

4.3 Descriptive statistics

When calculating the average ratios of the expenditures on R&D, foreign and domestic technology transfer to sales revenue across 29 two-digit manufacturing industries during 1996-2006, as listed in table 1, we find several patterns. As a whole, most manufacturing industries, other than tobacco processing industry and printing and record medium reproduction industry, invest far more in R&D than in technology transfer, which reflects that R&D is the main foundation of innovation capacity in Chinese industry. From the R&D intensity in table 1, we also find that the huge differences of innovation capacity among manufacturing industries: R&D tends to be relatively more intensive in technologically advanced industries, such as machinery, electric equipment, medical and pharmaceutical products, electronic and telecommunications equipment, etc., in which the R&D intensities are more than 2 percent. Nevertheless, the R&D intensities in those traditional industries, i.e. leather, food processing, petroleum processing, and tobacco, are less than 0.5 percent. We also find that foreign technical providers make a great role in shaping industry's innovation capacity; however, in sharp contrast to their foreign counterparts, domestic suppliers seem to be an insignificant source of technology transfer.

[Insert Table 1 Here]
[Insert Table 2 Here]

Table 1 also summarizes the results of the estimation of the three technology stocks per firm in 2006. The absolute size of R&D stock per firm is large in ferrous metals, transport equipment and tobacco processing industries, whereas it is very small in the furniture, leather and garments industries, which reflects the great differences in R&D investments of different industries. In addition, the stock of domestic technology transfer per firm is much less than that of foreign technology transfer per firm which in turn is less than R&D stock per firm for most of industries.

Table 2 presents the time mode of three technical variables for the period of 1996-2006. R & D intensity in Chinese manufacturing industry has a continually rising trend during 1996-2001, but decreases during 2001-2003, and then tends to increase after 2003. The intensity of foreign technology transfer tends to decline; meanwhile, the intensity of domestic technology transfer only has a little change during the period of 1996-2006. The time pattern of the three technical stocks per firm is basically the same as that of three technical intensities. These changes reflect that in recent years the indigenous innovation capacity increases gradually and dependence on foreign technologies tends to reduce.

5. Empirical results

This section analyzes the impacts of R&D and technology transfer on productivity growth. We first estimate the output elasticities of the three technical stocks using equation (4), and then compute their rates of return using equation (5).

5.1 Elasticity estimates

Table 3 shows the results obtained for the production function estimates when constant returns to scale is not imposed by using different estimation techniques. In order to check the estimates' robustness, column (1), (2) and (3) of table 3 report the regression estimates of R&D, foreign and domestic technology transfer respectively, and column (4) of table 3 reports the estimates with the three technical stocks included in a regression. In avoiding double counting of R&D employees we distinguish between the employees working with R&D production and other workers as two separate labor inputs. The R&D personnel have been subtracted from the total labor because the latter includes both R&D- and non-R&D personnel. Column (5) of table 3 also gives the estimates with the measure of labor which has not been corrected for double counting of R&D employees. In addition, to compare the effects of the stocks and expenditures of the technical variables on productivity growth, column (6) of table 3 presents the estimates with the technical expenditures used as the independent variables. Table 4 shows the same estimates in format when constant returns to scale imposed. The key results reported in table 3 and 4 can be summarized as follows.

The results for the capital to labor ratio for all estimation regressions are not altered essentially. The coefficient on the labor variable is not significantly different from zero for all the regressions in table 3, which shows that the hypothesis of constant returns to scale is accepted for the first-differenced estimates. The corrections for double-counting of R&D employees tend to increase the R&D capital coefficients across the columns of table 3 and 4, which are consistent with the studies of Schankerman (1981) and Cuneo and Mairesse (1984) who find that the "double counting" corrections increase the R&D elasticity. We also find that the coefficients with the measured stocks used as dependent variables are obviously larger than those with the expenditures used as dependent variables. The most important finding from table 3 and 4, in any case, is that the R&D capital coefficients remain fairly high and statistically significant and the coefficients on foreign and domestic technology transfer are quite small and insignificant whether the constant returns to scale imposed or not.

[Insert Table 3 Here]
[Insert Table 4 Here]

A common result across the regressions, i.e., column (1) and (4) of table 3, is that the estimates on R&D are positive and quite significant, with the results indicating that R&D has a significant impact on productivity growth. Specifically, the estimate of R&D elasticity is about 0.15 when the R&D stock is separately included in the regression (column 1 of table 3), while it decrease to 0.14 when the three technical variables are all included in the regression (column 4 of table 3). The R&D coefficients have almost similar changes when constant returns to scale imposed (table 4). As a whole, the coefficients of R&D remain stable in magnitude. The findings are consistent with similar studies carried out in other countries confirming the positive and statistically significant correlation between R&D and output. Our findings are also consistent with the studies using Chinese firm data which affirm the significant role of R&D for productivity (Hu, 2001; Hu and Jefferson, 2004; Hu et al., 2005; Jefferson et al., 2006). Despite the estimates of the R&D elasticity from those studies vary on the basis of the sample, the central tendency which is cited frequently runs from about 0.10 to about 0.20 (Griliches, 1988; Mairesse and Sassenou, 1991). Our estimate of the R&D elasticity of around 0.15 lies in the range of central tendency. The organizational culture of R&D- intensive firms expedites the discovery of new knowledge, practices and innovations that favor productivity performance; as a result, productivity growth should be amplified when R&D expenditures are raised. At the same time, we should highlight once again a fact which has already been pointed out by other previous studies (Mairesse and Sassenou, 1991): the estimates in the first-differenced, which control for permanent differences across industries, usually have an R&D output elasticity which is much smaller than that in the cross-section estimates. Because the cross-section estimates neglect the differences across industries which are correlated with the presence of R&D capital, we regard the first-differenced estimates as more reliable parameters.

Although the estimates on R&D are statistically significant, those on foreign technology transfer are statistically insignificant. From column (2) and (4) of table 3 and 4, we can see that the coefficients of the foreign technology transfer are positive but not significant, showing that the market-mediated technology imports have no significant impacts on productivity growth. At first sight the insignificant contribution of foreign technology transfer to productivity may be surprising, because along with china's institutional reform and economic opening, many technologically lagging firms learn to innovate by first imitating technologies created in developed countries. For China in which few firms have well-established R&D operations, utilizing the advanced technologies of developed countries would seem to be a natural way of shortening the technology gap. However, technological market failures that compromise the ability to appropriate returns to technology transfer reduce the volume and sophistication of technologies that can be transferred through markets (Caves, 1996). More importantly, Chinese firms usually pay much attention to hardware imports that do not match the skill level of this country and neglect software introduction. In the meantime, the absorptive capacity to technology has been ignored by Chinese firms in the process of purchasing foreign technologies. For example, according to Gilboy (2004), Chinese firms tend to import technology by purchasing foreign manufacturing equipment, often in complete sets such as assembly lines. Throughout the 1980s and 1990s, such hardware accounted for more than 80% of China's technology imports, whereas licensing accounted for only 9%, "know-how" services 5% and consulting 3%. Over the last decade, large- and medium-sized Chinese industrial firms have spent less than 10% of the total cost of imported equipment on indigenizing technology, which is much lower than the average for industrial firms in OECD countries (about 33%). The unreasonable structure of technology imports and absence of absorptive capacity in Chinese industrial firms substantially limit the contribution of foreign technology imports to productivity growth.

The estimated coefficients of domestic technology transfer are also statistically insignificant, whether we impose constant returns to scale in the production function and whether we correct the double counting of R&D employees in the labor input. This phenomenon can be explained as follows. Compared with the technologies in developed countries, the technological level in China, as a whole, is backward. The technologies are characterized by competitiveness and exclusiveness among domestic industrial enterprises, which cause enterprises to take effective measures to protect their own core technologies. Due to the need for technological confidentiality, one enterprise is unwilling to sell its technologies to the other domestic enterprises so as to there is very few technological transactions among domestic enterprises. In addition, the immature and imperfect technology market in China also limits technology transfer among domestic enterprises. The above interpretations can be verified by the data reported in table 1 and 2 which show that the intensity of domestic technology transfer is much smaller than that of R&D and foreign technology transfer. In a word, both the technology competitiveness among domestic enterprises and the imperfect technology market in China cumber the domestic technology exchanges, which result in the insignificant contribution of domestic technology transfer to productivity growth.

5.2 Rate of return estimates

Because of the difficulty of measuring technical stock, an alternative approach to evaluating the productivity of technology, i.e. the rate of return method, is often used. The rate of return method actually estimates the correlation between the growth rate of labor productivity and the technical intensities which are denoted as the ratio of contemporaneous technical variables to sales revenue in this paper. The results of estimating equation (5) are shown in table 5 with constant returns to scale not imposed, similar estimates in format are reported in table 6 with constant returns to scale imposed.

As we can observe in the first column of table 5, with constant returns to scale not imposed, the coefficient on the intensity of R&D expenditures is about 1.87 which is statistically significant at the 5 percent level of significance and it decreases to about 1.86 in column (4) where the intensities of technology transfer are included in the regression. When constant returns to scale is imposed in the production function (table 6), the coefficient of the R&D intensity is around 1.78 whether other technical variables are included in the regression or not. Obviously, the estimated rate of return to R&D with CRS not imposed is higher than that with CRS imposed. Another finding, as can be observed in column (4) and (5) of both table 5 and 6, is that the magnitude of the rate of return to R&D keeps almost unchanged according to whether the labor used to produce R&D is removed from the labor inputs in the production function.

Table 5 and 6 also reveal that while the intensity of R&D is a significant determinant of productivity growth, the intensities of foreign and domestic technology transfer are not: the coefficients of those variables are quite insignificantly different from zero across the columns of table 5 and 6, which are consistent with the findings of the insignificant impacts of technology transfer stock on productivity growth contained in the aforementioned results. In a word, we do not find a significantly positive relationship between the productivity growth and technology transfers whether we use either the output elasticity or the rate of return method.

[Insert Table 5 Here]
[Insert Table 6 Here]

It is especially noticeable that the estimate of the rate of return of 1.78-1.87 to R&D expenditures is strikingly high. The range of the estimated rate of return to R&D in the previous literatures runs from zero to nearly 0.60, with a central tendency between 0.20 and 0.30 (Griliches, 1988; Mairesse and Sassenou, 1991). Our estimate of the rate of return to R&D is much higher than that of the previous studies using the database in developed countries, but similar to Hu and Jefferson's (2004) estimate of 1.64 for Chinese machinery industry and lower than 1.95 for Chinese chemical industry. They are also similar to Mansfield's (1980) estimate of 1.78 and substantially lower than Link's (1981) estimate of 2.31 of rate of return to basic research for the US manufacturing sector.

Why is the estimated rate of return to R&D in Chinese industry so high? We can provide some preliminary arguments according to the possible econometric problems in the equation. Firstly, we note that R&D intensity can be defined either as R&D over sales revenue or as R&D over value added. Since sales revenue is much higher than value added, the first ratio is considerably smaller than the latter which amplify the estimated rate of return to R&D. Using value added which is unfortunately unavailable to us instead of sales revenue may attenuate the rate of return to R&D. Secondly, there may be a problem of endogeneity of R&D intensity in equation (5). In principle, we should use all of the predetermined variables in the estimation regression; however, few variables are likely to be truly exogenous given the available data to us. Failing to resolve the possible endogeneity issue may result in the upward bias of the estimates of R&D returns.

Another convictive explanation for the strikingly high estimates of R&D returns is that our estimates by using the industry-level data capture the social return to R&D which is defined as including both the return earned by the original innovator and any gains that spill over to other firms not involved in the R&D effort. Scherer (1982, 1984) believes that it is important to follow R&D from industry of origin to industry of use, as many firms "purchase" R&D from other firms implicitly when buying certain products and services. For each industry, R&D inputs from other industries are inputted through the use of a technology flow matrix based on information on industries of origin and use of inventions culled from patent data or input-output flows between industries. If spillovers to R&D exist within an industry, then the estimated return to R&D will be higher when computed using industry-level rather than firm-level data. According to this view, our estimated return to R&D using industry-level data includes not only the impact of R&D from one's own industry on productivity growth but also the impact of "inter-industry technology flows" on productivity growth. Given that the estimates of the social return to R&D average more than 100 percent in the previous productivity literatures, our estimates of return to R&D seem to be not too surprising.

5.3 Robust check

We investigate the robustness of the above estimates by experiment with various ways of measuring the technical stock and physical capital stock. To test the sensitivity of the estimates of R&D and technology transfer to the different parameters assumption, we recalculate the regression using both the output elasticity and the rate of return method. To save space we only report the estimates with constant returns to scale imposed and the double counting of R&D employees corrected. The estimates for output elasticity and the rate of return are reported in table 7 and 8 respectively.

When the depreciation rate of R&D is set to 25 percent which is the high end of the orders of magnitude obtained by Pakes and Schankerman (1984) using patent renewal data and applied by Hall and Mairesse (1995) in their empirical study, the output elasticity of R&D is about 0.14 (column 1 of table7).When the pre-sample growth rate in R&D expenditures is set to 15 percent, the elasticity of R&D is around 0.13 (column 2 of table7). While the depreciation rate and the pre-sample growth rate of expenditures are set to 25 percent and 15 percent respectively, the elasticity of R&D is slightly decreased to 0.12(column 3 of table7). Although one may expect that the choice of the R&D depreciation rate would significantly affect the R&D elasticity, it does not. Many researchers, such as Griliches (1980) and Harhoff (1998), have tried different depreciation rates (10, 15, 20 and 30%) and find that R&D elasticity remains stable. In this paper using a higher depreciation rate when constructing R&D capital stocks makes little difference to the estimates. In the same way, the different choice of the pre-sample growth rate of R&D expenditures also does not affect the estimates significantly. In table 7 we also find that with the assumption of the different parameters, the coefficients of technology transfer, whether purchased from foreign and domestic, are still statistically insignificant, showing the stability of our estimates.

Other parameters that can affect the estimation results are the misspecification of the equipment stock variable. With the assumption of the 15 percent of depreciation rate of equipment, using a 15 percent of pre-sample growth rate for equipment instead of 5 percent, we recalculate the regression and find that the elasticity of R&D increases to 0.17(column 4 of table 7) which is higher than the above estimates but the difference is not large. In the assumption of 15 percent of pre-sample growth rate for equipment we also estimate the rates of return to R&D and technology transfer (table 8). The estimated marginal product of R&D is 1.96 which is higher than the aforementioned estimate of 1.78 when constant returns to scale imposed. We also find that the estimated rates of return to technology transfer, whether foreign and domestic, are still insignificant.

[Insert Table 7 Here]
[Insert Table 8 Here]

As a matter of fact, using all the possible parameters, we have tried a number different ways of measuring these variables but too little effect. The various measures we tried turn out to be very good substitutes for each other and the choice between them has little practical import. The resulting differences in our estimates, even when they are statistically significant, are nonetheless quite small and not very meaningful. In particular, they do not substantially alter the order of magnitude and the significance of the coefficients of our interest, γ and ρ.

6. Estimating the effects of R&D and technology transfers on productivity decompositions

We have thus far examined the effects of R&D and technology transfer on the productivity growth of manufacturing industries using Cobb-Douglas production function estimation. Now we use Data Envelopment Analysis (DEA) to decompose total factor productivity into technical efficiency change and technological progress, and then run regressions to examine the contributions of R&D and technology transfer to the Malmquist productivity index and its components.

The output-based Malmquist productivity change index is commonly expressed in the following form:

$$M_o^{t+1}(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} \frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)} \right]^{\frac{1}{2}} \quad (8)$$

Where y is the output and x is the input vector of the manufacturing being evaluated. D_O is an output distance function. The distance function is the inverse of the out-oriented efficiency score, which can be calculated by solving different linear programming problems (Fare et al., 1994). The superscripts on D_O indicate the time period within which the efficiency scores are calculated. The superscripts on x and y indicate the time period of the data used in the calculation of the efficiency scores. The ratio outside the brackets on the right-hand side of equation (8) represents the change in technical efficiency from period t to t+1, and the bracketed term in (8) captures the geometric mean of the shift in production frontier. As a result, the Malmquist index is decomposed into the technical efficiency change and the technological change of the industry. The value of the Malmquist index more than one signifies the improvement in productivity from t to t+1.

To examine the effects of R&D and technology transfer on the Malmquist productivity index, we run the regression:

$$M_{it} = \lambda + \varphi_R \Delta rs_{it} + \varphi_F \Delta fs_{it} + \varphi_D \Delta ds_{it} + \Delta\omega_{it} \quad (9)$$

Where M represents the Malmquist productivity index, and φ represents the coefficient estimates. Since the Malmquist index indicates the annual change of productivity growth, we transform the explanatory variables, i.e. R&D, foreign and domestic technology transfer, into first differences.

The regression results are reported in the first column of table 9. It can be seen that R&D is the most statistically significant factor affecting the Malmquist productivity index, and that technology transfers (foreign and domestic) are not associated with productivity growth in a statistically significant manner, which are consistent with the estimation results obtained by using both the output elasticity and the rate of return methods described above.

[Insert Table 9 Here]

The decomposition of the Malmquist index provides a way of measuring the channels of R&D and technology transfer affecting productivity growth. In column (2) and (3) of table 9, we report the results of similar regressions of the technical efficiency change and technological progress, i.e., a shift of the production frontier, respectively. It can be seen that R&D is highly statistically significant for technical efficiency change but not for technological progress. In contrast, foreign technology transfer has a statistically significant positive effect on technological progress but not on technical efficiency change. The estimate on domestic technology transfer is still not statistically significant in any of the regressions in table 9.

From the above observation, we know that the significant role of R&D in improving productivity growth is mainly attributable to the contributions of R&D to technical efficiency. Under the circumstance of the relatively backward technology level in Chinese manufacturing, indigenous R&D can greatly improve the technical efficiency of each manufacturing; however, it can not shift the production frontier of the manufacturing sector upward markedly. In addition, basic research in Chinese manufacturing sector is relatively weak and as a result it can not substantially support the development of applied research, which further cumbers the shift of production frontier of the manufacturing sector. The unreasonable structure of R&D investments in manufacturing sector may be another complementary interpretation. In any case, notwithstanding working only through technical efficiency improvement not through technological progress, R&D still greatly facilitate the productivity growth of manufacturing sector, which is consistent with the estimates obtained by using either the output elasticity or the rate of return method.

Although foreign technology transfer does not guarantee a higher rate of productivity growth and technical efficiency change, it affects technological progress significantly. Chinese manufacturing enterprises usually focus on large-scale introduction of foreign equipment and production lines, which may result in the upward shift of the production frontier; however, because of the lack of software support and technical absorptive capacity, the technical efficiency does not improve correspondingly. To integrate the two effects, we can find from column (1) of table 9 that foreign technology transfer has no statistically significant impacts on the Malmquist productivity index.

7. Conclusions

By an industry-level data set of Chinese large- and medium-size manufacturing enterprises over the period of 1996–2006, we investigate the impacts of three technology acquisition channels, i.e. in-house R&D, domestic technology transfer and foreign technology transfer, on the industry' productivity growth using both the output elasticity and the rate of return method. With the different assumptions (such as constant returns to scale in the production function, the depreciation rate used to compute the technical capital stock, and the choice of whether to include an adjustment for double counting of R&D employees in the labor inputs), we find that there is strong evidence for the significant contribution of R&D to productivity growth in Chinese manufacturing industries, whereas technology transfer, whether foreign or domestic, have no significant impacts on productivity growth. When the productivity growth is decomposed into technical efficiency change and technological progress, we find that the significantly positive impact of R&D on productivity growth seems to work mainly through technical efficiency improvement rather than through technological progress.

The contribution of R&D to productivity growth means that creating a favorable innovation environment is of great significance for China's sustainable economic growth. China's government should further take effective policy instruments to reform the mechanism of science and technology activities, to improve the intellectual property system, and to strengthen the protection of intellectual property rights, which will substantially stimulate Chinese enterprises to investment in R&D. After all, it seems to be impossible to introducing the advanced and core technologies from developed countries by means of direct technology transactions. International experiences have also showed that the fundamental driving force of innovation stems from national enterprises. No other than base upon domestic innovation can China initiatively grasp the adjustment of economic structure and transformation of the economic growth pattern.

At the same time, under the circumstance of economic globalization, developing countries should also pay much attention to exploit and absorb the advanced technical achievements in developed countries. Over the past two decades, Chinese government has carried out the preferential policy measures towards encouraging foreign direct investments and introduction of foreign technologies from developed countries. However, due to the absence of absorption capacity to imported technologies and ignorance of the software support, direct foreign technology introduction does not make corresponding contributions to the productivity growth in Chinese manufacturing industries. The introduction of foreign technologies in the next step should keep to the features of resource endowments and the principle of comparative advantages in China. It is only appropriate technology introduction that will ultimately enhance China's productivity and economic performance.

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Table 1

Technology intensity and technology stocks in manufacturing sectors

	R/Y	F/Y	D/Y	RS/N	FS/N	DS/N
	Average1996-2006(%)			2006(million Yuan)		
food processing	0.44	0.14	0.02	746.56	154.86	31.97
food production	0.89	0.26	0.03	985.95	175.47	39.33
beverage production	1.23	0.78	0.04	2565.52	930.49	56.47
tobacco processing	0.46	0.73	0.08	6093.65	6270.32	1051.89
textile industry	0.94	0.52	0.05	852.67	352.69	46.42
garments and other fiber products	0.66	0.38	0.01	427.87	125.92	9.87
leather,furs,down and related products	0.43	0.30	0.01	301.63	104.58	6.99
timber,bamboo,cane,palm fiber and straw products	0.98	0.19	0.02	726.55	105.24	14.61
furniture manufacturing	0.62	0.20	0.02	242.64	19.80	18.82
papermaking and paper products	1.35	0.84	0.07	1702.49	638.91	60.67
printing and record medium reproduction	1.02	1.10	0.05	655.52	392.86	38.38
culture, educational and sports goods	0.97	0.08	0.02	438.74	24.50	4.61
petroleum processing and coking products	0.45	0.30	0.04	3345.11	1310.39	282.32
raw chemical materials and chemical products	1.79	0.52	0.09	3691.17	717.97	151.24
medical and pharmaceutical products	2.36	0.27	0.22	3337.44	286.01	254.68
chemical fiber	1.70	1.09	0.13	5627.13	2327.93	298.19
rubber products	1.57	0.36	0.04	2512.10	374.82	53.23
plastic products	1.57	0.62	0.04	962.57	256.32	15.80
nonmetal mineral products	1.44	0.39	0.08	989.99	172.65	46.05
smelting and pressing of ferrous metals	1.53	0.80	0.07	9116.09	2663.93	604.34
Smelting and pressing of nonferrous	1.30	0.46	0.08	3764.41	862.96	174.15
metal products	1.29	0.39	0.03	1021.81	171.09	17.73
ordinary machinery	2.74	0.57	0.06	2689.55	397.83	55.01
equipment for special purposes	2.68	0.31	0.07	3178.25	279.27	104.54
transport equipment	2.30	0.53	0.05	6316.75	1138.75	161.99
electric equipment and machinery	2.70	0.72	0.11	3692.59	534.36	99.05
electronic and telecommunications equipment	2.22	0.66	0.02	5935.06	1334.83	39.25
instruments, meters, cultural and office machinery	2.19	0.42	0.03	2075.84	314.19	28.23
other manufacturing	1.08	0.22	0.04	678.33	53.50	23.04

Notes: The intensities of the three technical inputs are calculated by current prices. The three technical capital stocks are constructed by perpetual inventory method with a depreciation rate of 15 percent and a pre-sample growth rate of 5 percent in technical expenditures. N denotes the number of firms in an industry.

Table 2

Time series of technology intensity and technology stocks (1996-2006)

	R/Y (%)	F/Y (%)	D/Y (%)	RS/N (million Yuan)	FS/N (million Yuan)	DS/N (million Yuan)
1996	1.17	1.00	0.08	954.87	1206.62	66.54
1997	1.22	0.76	0.04	1007.26	1207.45	63.60
1998	1.31	0.60	0.05	1069.26	1182.55	66.46
1999	1.37	0.46	0.04	1223.05	1181.07	66.36
2000	1.53	0.51	0.06	1452.89	1146.30	70.24
2001	1.57	0.52	0.06	1586.54	1095.42	76.49
2002	1.56	0.59	0.06	1826.51	1141.11	88.59
2003	1.36	0.43	0.06	1966.41	1043.91	100.63
2004	1.43	0.24	0.06	1929.52	880.51	108.42
2005	1.50	0.15	0.05	2357.38	855.73	125.30
2006	1.49	0.12	0.04	2574.97	775.60	130.65

Notes: The intensities of the three technical inputs are calculated by current prices. The three technical capital stocks are constructed by perpetual inventory method with a depreciation rate of 15 percent and a pre-sample growth rate of 5 percent in technical expenditures. N denotes the number of firms in an industry.

Table 3

Estimates of the output elasticities (constant returns to scale not imposed)

	Stocks					Expenditures
	Correction				No correction	Correction
	(1)	(2)	(3)	(4)	(5)	(6)
constant	0.0992	0.1154	0.1127	0.1016	0.1006	0.1067
	(6.72)***	(8.60)***	(8.41)***	(6.81)***	(6.75)***	(7.87)***
ΔLn(C/L)	0.4237	0.4764	0.5024	0.3983	0.4053	0.4463
	(2.87)***	(3.28)***	(3.49)***	(2.67)***	(2.72)***	(3.10)***
ΔLn(L)	0.0111	0.0872	0.1127	-0.0144	0.0035	0.0420
	(0.08)	(0.65)	(0.84)	(-0.10)	(0.02)	(0.31)
ΔLn(RS)	0.1503			0.1448	0.1391	0.0655
	(2.15)**			(2.02)**	(1.94)*	(2.91)***
ΔLn(FS)		0.0601		0.0542	0.0566	0.0044
		(1.31)		(1.18)	(1.23)	(0.67)
ΔLn(DS)			0.0109	0.0005	0.0004	-0.0016
			(0.55)	(0.02)	(0.02)	(-0.34)
R^2	0.2809	0.2736	0.2700	0.2794	0.2609	0.2869
F-value	38.6259	37.2865	36.6320	23.4091	21.4032	24.2597

Notes: The three technical capital stocks are constructed with a 15 percent depreciation rate. Numbers in brackets are t-statistics of the estimated parameters. *** indicates that the estimated parameter is significantly different from zero at the 1% level of significance, * *at the 5% level, and *at the 10% level.

Table 4

Estimates of the output elasticites (constant returns to scale imposed)

	Stocks					Expenditures
	Correction				No correction	Correction
	(1)	(2)	(3)	(4)	(5)	(6)
constant	0.0999	0.1231	0.1225	0.1007	0.1009	0.1102
	(8.35)***	(19.83)***	(18.66)***	(8.39)***	(8.40)***	(14.38)***
ΔLn(C/L)	0.4125	0.3859	0.3853	0.4128	0.4018	0.4030
	(10.71)***	(10.53)***	(10.45)***	(10.71)***	(10.23)***	(10.88)***
ΔLn(RS)	0.1522			0.1424	0.1397	0.0666
	(2.34)**			(2.11)**	(2.07)**	(3.01)***
ΔLn(FS)		0.0655		0.0535	0.0567	0.0045
		(1.45)		(1.18)	(1.25)	(0.69)
ΔLn(DS)			0.0124	0.0005	0.0004	-0.0015
			(0.63)	(0.02)	(0.02)	(-0.32)
R^2	0.2834	0.2751	0.2707	0.2819	0.2635	0.2892
F-value	58.1372	55.8353	54.6481	29.3608	26.8480	30.3968

Notes: The three technical capital stocks are constructed with a 15 percent depreciation rate. Numbers in brackets are t-statistics of the estimated parameters. *** indicates that the estimated parameter is significantly different from zero at the 1% level of significance, * *at the 5% level, and *at the 10% level.

Table 5

Estimates of the rate of return (constant return to scale not imposed)

	Correction				No correction
	(1)	(2)	(3)	(4)	(5)
constant	0.0844	0.1129	0.1086	0.0856	0.0842
	(4.80)***	(7.82)***	(7.68)***	(4.76)***	(4.68)***
ΔLn(C/L)	0.5274	0.5072	0.5088	0.5302	0.5353
	(3.71)***	(3.53)***	(3.55)***	(3.71)***	(3.75)***
ΔLn(L)	0.1506	0.1197	0.1256	0.1507	0.1663
	(1.14)	(0.90)	(0.94)	(1.13)	(1.25)
R/Y	1.8662			1.8570	1.8571
	(2.48)**			(2.30)**	(2.30)**
F/Y		0.0868		-0.5118	-0.5239
		(0.07)		(-0.38)	(-0.39)
D/Y			8.3853	1.9278	1.6479
			(0.98)	(0.21)	(0.18)
R^2	0.2847	0.2693	0.2717	0.2800	0.2620
F-value	39.3344	36.4962	36.9330	23.4823	21.5162

Notes: Numbers in brackets are t-statistics of the estimated parameters. *** indicates that the estimated parameter is significantly different from zero at the 1% level of significance, * *at the 5% level, and *at the 10% level.

Table 6

Estimates of the rate of return (constant returns to scale imposed)

	Correction				No correction
	(1)	(2)	(3)	(4)	(5)
constant	0.0989	0.1236	0.1200	0.1002	0.1002
	(8.16)***	(15.26)***	(16.07)***	(7.92)***	(7.92)***
ΔLn(C/L)	0.3712	0.3828	0.3784	0.3741	0.3633
	(10.10)***	(10.04)***	(10.20)***	(9.82)***	(9.37)***
R/Y	1.7853			1.7813	1.7729
	(2.38)**			(2.22)**	(2.20)**
F/Y		0.0597		-0.5188	-0.5346
		(0.05)		(-0.38)	(-0.40)
D/Y			8.0074	1.7801	1.4774
			(0.93)	(0.19)	(0.16)
R^2	0.2839	0.2698	0.2720	0.2793	0.2605
F-value	58.2959	54.3779	54.9765	29.0027	26.4505

Notes: Numbers in brackets are t-statistics of the estimated parameters. *** indicates that the estimated parameter is significantly different from zero at the 1% level of significance, * *at the 5% level, and *at the 10% level.

Table 7
The effects of different parameters on elasticity estimates

	σ =0. 15, d=0. 05			σ =0. 15, d=0. 15
	δ =0. 25 g=0. 05	δ =0. 15 g=0. 15	δ =0. 25 g=0. 15	δ =0. 15 g=0. 05
	(1)	(2)	(3)	(4)
Constant	0.1004 (9.01)***	0.0986 (7.19)***	0.0999 (8.30)***	0.0862 (6.72)***
ΔLn(C/L)	0.4147 (10.92)***	0.4018 (10.65)***	0.4050 (10.79)***	0.3886 (10.41)***
ΔLn(RS)	0.1360 (2.50)**	0.1282 (1.89)*	0.1223 (2.22)**	0.1726 (2.50)**
ΔLn(FS)	0.0483 (1.48)	0.0404 (0.99)	0.0412 (1.32)	0.0476 (1.04)
ΔLn(DS)	-0.0013 (-0.08)	0.0011 (0.06)	-0.0004 (-0.03)	0.0026 (0.13)
R^2	0.2890	0.2779	0.2839	0.2701
F-value	30.3743	28.8118	29.6416	27.7356

Notes: Numbers in brackets are t-statistics of the estimated parameters. *** indicates that the estimated parameter is significantly different from zero at the 1% level of significance, * *at the 5% level, and *at the 10% level.

Table 8

The effects of different parameters on rate of return estimates

	σ =0. 15, d=0. 15
Constant	0.0900
	(7.05)***
ΔLn(C/L)	0.3459
	(9.48)***
R/Y	1.9630
	(2.42)**
F/Y	-0.9145
	(-0.67)
D/Y	3.1931
	(0.34)
R^2	0.2668
F-value	27.2952

Notes: Numbers in brackets are t-statistics of the estimated parameters. *** indicates that the estimated parameter is significantly different from zero at the 1% level of significance, * *at the 5% level, and *at the 10% level.

Table 9

The effects of the technical variables on the Malmquist index and its components

	(1)	(2)	(3)
	Productivity growth	Technical efficiency change	Technological progress
Constant	0.0476	-0.0689	0.1242
	(2.57)***	(-4.95)***	(9.55)***
ΔLn(RS)	0.4749	0.5248	-0.0732
	(4.32)***	(6.36)***	(-0.95)
ΔLn(FS)	0.0913	-0.0323	0.1143
	(1.18)	(-0.55)	(2.10)**
ΔLn(DS)	0.0073	0.0305	-0.0279
	(0.21)	(1.17)	(-1.14)
R^2	0.0663	0.1352	0.0118
F-value	7.8420	16.0574	2.1501

Notes: Numbers in brackets are t-statistics of the estimated parameters. *** indicates that the estimated parameter is significantly different from zero at the 1% level of significance, * *at the 5% level, and *at the 10% level.