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Efficiency, technical progress, and best practice in Chinese state enterprises (1980–1994)

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Based on a sample of about 600 state enterprises from 1980 to 1994, this paper investigates the productivity performance of SOEs using Data Envelopment Analysis and a Malmquist index. Our empirical results show that the average technical efficiency was low for these firms. Considerable productivity growth was found, but it was accomplished mainly through technical progress rather than through efficiency improvement. Regression analyses indicate that large SOEs were more likely to generate productivity growth than smaller ones. The best practice firms were most likely to be found among large enterprises located in the well-developed coastal province. Wage incentives and capacity utilization had positive impacts on productivity growth. Education had a significant effect on technical efficiency. *Journal of Comparative Economics* **31** (1) (2003) 134–152. Göteborg University, Box 640, S-405 30 Göteborg, Sweden; Institute of Economics, Chinese Academy of Social Sciences, Beijing 100836, PR China.

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1. Introduction

Since economic reforms were initiated in the late 1970s, an important feature of China's economic growth has been its reliance on productivity growth (World Bank, 1997). In

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recent years, in order to boost productivity further and to sustain economic growth, China's State Planning Commission issued a set of general guidelines for restructuring the economy and accelerating the development of key industries. These guidelines emphasize the promotion of large state enterprises (SOEs) and enterprise groups and the improvement of productive efficiency through redundancies and technology upgrading.

Contrary to conventional wisdom, some recent studies argue that China's large SOEs are not stagnant fossils waiting to die. Under economic reform policies, this sector has undergone rapid change due to enhanced enterprise autonomy, the impact of market forces, rapid growth of domestic demand for upstream products, strategic integration with the world economy, and the state's policy to promote large businesses (Nolan and Wang, 1999). In conjunction with the non-state sector, large-scale enterprises have been an important engine for growth over an extended period of time in China (Smyth, 2000). These studies present a challenge to the transitional orthodoxy that only privatization can solve the industrial problems of former Communist countries. Central to this debate is the productivity performance of SOEs, especially large SOEs.

A number of empirical studies have attempted to measure total factor productivity (TFP) growth for the Chinese state-owned sector in the aggregate. Although some find that economic reform made little or no contribution to TFP growth in the state sector, most find that TFP growth in SOEs has improved since 1978, although it is still lagging behind TFP growth in township and village enterprises (Jefferson et al., 1996). However, few studies distinguish large-scale SOEs from all SOEs (Smyth, 2000). Lo (1999) is the only study that compares explicitly TFP growth in large and medium state enterprises (LMEs), SOEs as a whole, and collective enterprises (COEs). He estimates a Cobb–Douglas production function using aggregate data from 1980 to 1995. The author finds that, in terms of productivity growth, COEs performed better than both SOEs and LMEs, but LMEs performed much better than SOEs as a whole. In this paper, we investigate the productivity characteristics of SOEs with an emphasis on large enterprises.

Most previous productivity studies of the SOE sector have concentrated on average productivity growth and much of the literature has used Cobb–Douglas production function estimations. Some studies use stochastic and deterministic frontier production function estimations, but none of these has paid explicit attention to best practice SOEs. An investigation of best practice SOEs, especially the identification and characterization of those with substantial efficiency improvement and technical progress, will improve our understanding of the determinants of productivity growth in the state industrial sector. The results will also provide an interesting perspective on forming large enterprise groups with the best practice SOEs at the core.

Based on a panel data for about 600 state enterprises from 1980 to 1994, this paper uses Data Envelopment Analysis (DEA) and the Malmquist index to evaluate the productivity performance of SOEs. TFP growth is decomposed into efficiency improvement and technical progress. Production frontiers are estimated for each of the two-digit industries in our sample using disaggregated employment and material data. In this way, the best-practice SOEs are identified. The determinants of best practice SOEs and productivity growth are analyzed using regression techniques for limited dependent variable models. The plan of the paper is as follows. In Section 2, we discuss the background of our study and the relevant literature. In Section 3, we present the methodologies used. The data are

introduced in Section 4. Section 5 reports and analyzes the empirical results. Section 6 concludes.

2. Background

In spite of the rapid economic growth and swift structural changes during the last two decades, China's industrial reform is far from complete, especially with regard to SOEs. Although their share of industrial output has been steadily declining, SOEs are still of great importance in terms of urban employment and total investment in industrial fixed assets.[1] In the foreseeable future, state enterprises will continue to be replaced by non-state firms in terms of employment creation, given the recent government policy to grasp the large, release the small.[2] Although most SOEs are burdened with large financial losses, heavy debts, and substantial overstaffing, the government intends state enterprises to play a crucial role in maintaining social stability and generating sustained economic growth in China. In order to revitalize the state industrial sector, the structural adjustment program initiated by the government in 1994 focused on improving productive efficiency via redundancies and technology upgrading and on building its best SOEs into conglomerates characterized by the so-called modern enterprise system.[3]

Among Chinese economists, industrial policy is a controversial issue. Those who oppose such policies suggest that state ownership should be eliminated from all areas of industrial production except a few sectors, such as transportation and telecommunication. Following the South East Asian financial crisis, more doubts have been cast on the appropriateness of developing Japanese and South Korean style conglomerates in China. For ideological reasons, the government favors state ownership at least in some major industrial sectors. Recent changes in the international political environment and China's entry into the World Trade Organization have intensified the debate on the role of state enterprises among Chinese economists and policy analysts regarding sustainable growth, economic security, and political stability (Wang, 2000).

The unsatisfactory financial performance of most SOEs is not disputed. However, some economists argue that the management reforms in the late 1970s and early 1980s resulted in improvements with respect to efficiency and technology. The increasing losses in SOEs

[1] The SOE share in China's total industrial output has declined from 77.6 percent in 1978 to 28.8 percent in 1996. However, SOEs still employed 57.4 percent of all urban workers and undertook 52.2 percent of total investment in industrial fixed assets in 1996 (Lin et al., 1998).

[2] Once the powerhouse behind the economy's growth and employment, the dynamism of China's 1.5 million collectively owned enterprises has waned. After generating some 17 million jobs in 1993, they created just 1.4 million in 1994 and 1995, while private and individually owned enterprises created 6.6 million new jobs (World Bank, 1997).

[3] The industrial policy announced on March 25, 1994 emphasized the development of pillar industries. Five pillar industries have been designated by the government: machinery, electronics, petrochemicals, automobiles, and construction. These industries have the potential for high productivity growth and reflect China's comparative advantage in the world economy. The hope is that these pillar industries will eventually account for 5 percent of GDP, or 8 percent of industrial output, increase their share in international markets, reach international quality standards quickly, and become profitable (World Bank, 1997).

since the early 1990s were due mainly to the unfavorable external environment such as intense and sometimes unfair competition from township and village enterprises and joint ventures. Heavy social responsibilities, e.g., pension, housing, and overstaffing, were also blamed for poor performance (Lin and Tan, 1999 and Lin et al., 1998). The recent focus of the government's structural adjustment program is on introducing the modern enterprise system, a reduction of overstaffing, and technology upgrading. These measures have been accompanied by housing, pension, and other welfare reforms that were expected to reduce social burdens on enterprises. The emphasis on the modern enterprise system reflects the long-standing view of some economists that SOEs are basically reformable if effective management methods can be implemented, accompanied with reductions in staffing and technology upgrading aimed directly at boosting productivity growth.

We examine three aspects of the productivity performance of SOEs, namely, improvement in technical efficiency, technical progress, and the best practice SOEs. Our empirical evaluation provides evidence about the effectiveness of management reforms in improving the technical efficiency of SOEs. Regarding technical progress, substantial investments in relatively advanced technologies from Western countries have been made by direct purchases, technology transfers, and joint ventures. However, technical progress may differ significantly among SOEs so that an examination of the best practice SOEs sheds more light on the determinants of productivity growth in the state industrial sector and on the potential of forming conglomerates with the best practice SOEs as the core. Using an unbalanced panel from enterprise survey data from two panels (1980 to 1989 and 1990 to 1994), our study contributes to the existing literature on SOE productivity performance in China in three major ways.

First, we use a larger subset of the data for the entire data period of 1980 to 1994 and decompose productivity growth into technical efficiency improvement and technical progress. Our study involves about 600 SOEs in 17 two-digit industries and uses 6 input variables. Groves et al. (1994) used a subset of the data from 1980 to 1989 to study the effects of incentives on productivity for 437 SOEs from textiles, chemicals, building materials, machinery, and electronics industries. These authors estimated Cobb–Douglas production function for each industry with three inputs: capital, labor, and materials. Firm-specific dummies were used to capture the fixed individual effects, and time dummies were used for the technical change effect. However, TFP growth was not decomposed explicitly. Their major finding is that a strengthening of workers' incentives is correlated with higher productivity. Liu and Liu (1996) estimated stochastic production frontiers for 382 enterprises from 7 industries using a subset of the data from 1980 to 1989. The functional forms were Cobb–Douglas and translog; the inputs were capital, production workers, and technicians. These authors find that the average level of technical efficiency of the SOEs grew from 43% in 1980 to 59% in 1989, amounting to an increase of 1.6% per annum. However, technical change was not investigated in their study. Lee (1997) calculated TFP growth using the method of Gordon and Li (1995) to measure productivity in a non-market economy that allows production functions to differ arbitrarily across enterprises. The author reports that TFP grew annually at 1.9 to 2.4% during 1980 to 1987 for 769 SOEs but the growth for 1980 to 1989 was lower than for 1980 to 1987 falling in the range of 0.5 to 0.9%. Li (1997) extended the method of Gordon and Li (1995) by incorporating market power and studied 272 enterprises from 1980 to 1989 using

labor, capital, and intermediates as inputs. TFP growth was 4.68%, of which 2.29% was attributable to incentives and competition and 1.79% to factor reallocation. However, this method does not decompose TFP growth either.

There are several studies using the panel data for the entire period from 1980 to 1994, but the most relevant study is for the period 1990 to 1994 by Kong et al. (1999). Productivity growth was decomposed into efficiency change and technical progress. These authors estimate stochastic frontier production functions for 384 SOEs in four industries, i.e., building materials, chemicals, machinery, and textiles using a translog functional form with capital and labor as inputs. They find no evidence of technological change in these industries, except for machinery, and observe significant reductions of technical efficiency in the chemicals, machinery and textiles industries. As a result, chemicals and textiles experienced a negative TFP growth, whereas building materials and machinery display negligible TFP change. Their results seem to have cast doubt on the effectiveness of the industrial reform measures in China.

Second, to our knowledge, the DEA-based Malmquist index has not yet been applied to the 1980 to 1994 data. The DEA method has been employed in studies of technical efficiency and its determinants in China using other data, e.g., Zheng et al. (1998) and Sun et al. (1999). The DEA-based Malmquist index has also been calculated in Färe et al. (1996) for Chinese state enterprise data for 1980, 1984, and 1985; in Mao and Koo (1997) for efficiency change in agriculture; and in Zhang et al. (2001) for industrial enterprises in Shanghai with various ownership structures. The advantage of using the DEA-based Malmquist index is that the estimation of the production frontier requires fewer observations for each industry than does stochastic frontier estimation. Hence, we can estimate technical efficiency for two-digit individual industries, some of which have sometimes only 10 to 20 observations. For this reason, we are able to use a larger subset of the data than previous studies. Another advantage of the DEA approach is that it is not necessary to specify the distribution of technical efficiency when the production function is estimated. In the stochastic frontier case, estimated technical efficiency may be sensitive to the specification of the efficiency distribution. Compared with the stochastic frontier method, the main disadvantage of the DEA approach is that it does not provide statistical tests for the estimated production function.

Third, the original motivation of our study was to use regression analyses to identify the determinants of productivity growth and to construct the best practice technology with emphasis on large SOEs. Once TFP growth is decomposed into efficiency change and technical progress, we can identify the explanatory variables affecting a specific component. The lack of exits in the SOE sector allows a comprehensive examination of best practice techniques because the data are unusually diverse in terms of productivity performance. By separating the best practice firms from inefficient SOEs, we focus on the set of the enterprises at which specific reform policies are targeted, namely, the large SOEs in strategically important sectors.[4] The DEA method offers a straightforward analysis of the best practice firms using a two-step procedure, that is, the DEA production frontier is estimated in the first step and regression analysis is applied in the second step. Our findings

[4] Nolan (2001) is a good source for details of industrial policies.

contribute to understanding the expected complication of current industrial reforms in China.

3. Methodology

Following Färe et al. (1994) to define the output-based Malmquist index of productivity change, we assume that, for each time period $t = 1, \ldots, T$, the production technology $\mathbf{S}^t$ models the transformation of inputs, $\mathbf{x}^t \in \mathbf{R}_+^N$, into outputs, $\mathbf{y}^t \in \mathbf{R}_+^M$, as follows:

$$\mathbf{S}^t = \left\{ \left(\mathbf{x}^t, \mathbf{y}^t\right) \colon \mathbf{x}^t \text{ can produce } \mathbf{y}^t \right\}. \tag{1}$$

The output distance function is defined at t as

$$D_{\mathrm{o}}^t(\mathbf{x}^t, \mathbf{y}^t) = \inf\left\{\theta \colon \left(\mathbf{x}^t, \mathbf{y}^t/\theta\right) \in \mathbf{S}^t\right\} = \left(\sup\left\{\theta \colon \left(\mathbf{x}^t, \theta\mathbf{y}^t\right) \in \mathbf{S}^t\right\}\right)^{-1}. \tag{2}$$

Note that $D_{\mathrm{o}}^t(\mathbf{x}^t, \mathbf{y}^t) \leqslant 1$ if and only if $(\mathbf{x}^t, \mathbf{y}^t) \in \mathbf{S}^t$. In addition, $D_{\mathrm{o}}^t(\mathbf{x}^t, \mathbf{y}^t) = 1$ if and only if $(\mathbf{x}^t, \mathbf{y}^t)$ is on the boundary or frontier of the technology. According to Farrell (1957), this occurs when production is technically efficient. In the case of a single input and one output, under constant returns to scale, maximum feasible output is achieved when average productivity, y/x, is maximized. In our empirical work, that maximum is the best practice or highest productivity observed in our sample and is determined using DEA techniques.

To define the Malmquist index, we characterize a distance function with respect to two different time periods as follows:

$$D_{\mathrm{o}}^t\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}\right) = \inf\left\{\theta \colon \left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}/\theta\right) \in \mathbf{S}^t\right\}. \tag{3}$$

This function measures the maximal proportional change in outputs required to make $(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})$ feasible in relation to the reference or benchmark technology at t. Similarly, a distance function that measures the maximal proportional change in output required to make $(\mathbf{x}^t, \mathbf{y}^t)$ feasible in relation to the technology at $t+1$, denoted $D_{\mathrm{o}}^{t+1}(\mathbf{x}^t, \mathbf{y}^t)$ may be defined. In order to avoid choosing an arbitrary benchmark between t and $t+1$, we specify the output-based Malmquist productivity change index as the geometric mean of two Malmquist productivity indexes, one with technology at t and the other at $t+1$ as benchmarks, as follows:

$$M_{\mathrm{o}}\left(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{x}^t, \mathbf{y}^t\right) = \left[\left(\frac{D_{\mathrm{o}}^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})}{D_{\mathrm{o}}^t(\mathbf{x}^t, \mathbf{y}^t)}\right)\left(\frac{D_{\mathrm{o}}^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})}{D_{\mathrm{o}}^{t+1}(\mathbf{x}^t, \mathbf{y}^t)}\right)\right]^{1/2}. \tag{4}$$

In all definitions concerning Malmquist indexes, we assume constant returns to scale for the technology as suggested in Färe and Grosskopf (1996). The Malmquist productivity index in (4) can be disaggregated multiplicatively into two component measures:

$$\mathrm{EFFCH} = \frac{D_{\mathrm{o}}^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})}{D_{\mathrm{o}}^t(\mathbf{x}^t, \mathbf{y}^t)}, \tag{5}$$

and

$$\mathrm{TECH} = \left(\frac{D_{\mathrm{o}}^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})}{D_{\mathrm{o}}^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})}\frac{D_{\mathrm{o}}^t(\mathbf{x}^t, \mathbf{y}^t)}{D_{\mathrm{o}}^{t+1}(\mathbf{x}^t, \mathbf{y}^t)}\right)^{1/2}, \tag{6}$$

where the expression in (5) measures the change in efficiency between periods t and $t+1$, which we denote efficiency change. Expression (6) captures shifts in the frontier technology, which we denote to be the technical change component; values less than one in both cases signify deterioration in productivity. We calculate the Malmquist productivity index using non-parametric programming techniques. We assume that there are $k = 1, \ldots, K$ enterprises using $n = 1, \ldots, N$ inputs $x_n^{k,t}$ at each time period $t = 1, \ldots, T$. These inputs are used to produce $m = 1, \ldots, M$ outputs $y_m^{k,t}$. Each observation of inputs and outputs is strictly positive and we assume that the number of observations remains constant over all years, although this is usually not the case with our data. The reference, or frontier, technology in period t is constructed from the data as:

$$\mathbf{S}^t = \left\{ \left(\mathbf{x}^t, \mathbf{y}^t\right) \colon y_m^t \leqslant \sum_{k=1}^{K} z^{k,t} y_m^{k,t},\ m = 1, \ldots, M, \right.$$
$$\sum_{k}^{K} z^{k,t} x_n^{k,t} \leqslant x_n^t,\ n = 1, \ldots, N, \text{ and}$$
$$\left. z^{k,t} \geqslant 0,\ k = 1, \ldots, K \right\}. \tag{7}$$

It exhibits constant returns to scale and strong disposability of inputs and outputs (Färe and Grosskopf, 1996).

To calculate the productivity of enterprise k' between t and $t+1$, we solve four different linear-programming problems: $D_{\mathrm{o}}^t(\mathbf{x}^t, \mathbf{y}^t)$, $D_{\mathrm{o}}^{t+1}(\mathbf{x}^t, \mathbf{y}^t)$, $D_{\mathrm{o}}^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})$, and $D_{\mathrm{o}}^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})$. For each $k' = 1, \ldots, K$,

$$\left(D_{\mathrm{o}}^t\left(\mathbf{x}^{k',t}, \mathbf{y}^{k',t}\right)\right)^{-1} = \max \theta^{k'} \quad \text{subject to:}$$
$$\theta^{k'} y_m^{k',t} \leqslant \sum_{k=1}^{K} z^{k,t} y_m^{k,t}, \quad m = 1, \ldots, M,$$
$$\sum_{k=1}^{K} z^{k,t} x_n^{k,t} \leqslant x_n^{k',t}, \quad n = 1, \ldots, N, \quad \text{and}$$
$$z^{k,t} \geqslant 0, \quad k = 1, \ldots, K. \tag{8}$$

This linear programming problem is the basis for DEA and the distance function estimates are referred to as DEA efficiency estimates in the literature.

Two of the distance functions used to construct the Malmquist index require information from two periods. The first of these is computed for observation k' as

$$\left(D_{\mathrm{o}}^t\left(\mathbf{x}^{k',t+1}, \mathbf{y}^{k',t+1}\right)\right)^{-1} = \max \theta^{k'} \quad \text{subject to:}$$
$$\theta^{k'} y_m^{k',t+1} \leqslant \sum_{k=1}^{K} z^{k,t} y_m^{k,t}, \quad m = 1, \ldots, M,$$

$$\sum_{k=1}^{K} z^{k,t} x_n^{k,t} \leqslant x_n^{k',t+1}, \quad n = 1, \ldots, N, \quad \text{and}$$
$$z^{k,t} \geqslant 0, \quad k = 1, \ldots, K. \tag{9}$$

In empirical applications, the above formulations may produce results of technical regress, which are usually difficult to interpret. In this study, when the frontier for year $t + 1$ is generated, the best practice observations from the year t will also be included to impose a restriction of no technological regress.

4. Data

4.1. Source

The data come from two enterprise surveys conducted by the Chinese Academy of Social Sciences (CASS) in 1990 and 1996. The first survey, which was used in Groves et al. (1994; 1995), Liu and Liu (1996), Lee (1997), and Li (1997), contains annual data for 769 state-owned enterprises between 1980 and 1989. The second survey, sponsored by the University of Michigan, is a follow-up survey for the period 1990 to 1994. The data for the entire period of 1980 to 1994 has been used in Li and Liang (1998), Lee (1999), and Dong and Putterman (2001). Kong et al. (1999) used only the second survey. As in Lee (1999), we tried to use a matched data set of 681 SOEs from the two surveys. After excluding SOEs with missing or invalid observations, we had a smaller data set with cross-section observations ranging between 440 and 616 for 1980 to 1994. The cross-section observations for 1990 to 1994 include only those that appeared in 1980 to 1989. The follow-up survey contains 10% fewer firms than the first survey. Firms that dropped out in the follow-up survey tended to be small firms with poorer performance than those included in both surveys. More than 300 variables are covered in the data, including details of enterprises' real and financial accounts, price information, and internal incentives. The sample enterprises represent 36 two-digit industries in mining, logging, utilities, and manufacturing and are located in four provinces, namely, Jiangsu, Jilin, Shanxi, and Sichuan. However, due to the limited number of observations in some industries, we chose 17 two-digit industries for our estimations.

4.2. Output, inputs, and their deflator

When dealing with a comprehensive panel data set, a common practice is to estimate a production function with value-added as the output variable, and the capital stock and total employment as inputs. Because this type of data covers different two-digit industrial sectors, using value-added plus capital and total employment to estimate a value-added production function would make observations across different two-digit industries more comparable. Unfortunately, the variables involved in the analysis are limited to labor and capital. To extend the analysis to more variables, a practice followed in this line of research is to use gross output plus capital, employment, and intermediate inputs in the estimation of production functions for the entire data set. However, this method would make the cross

industrial observations less comparable, since the intermediate inputs used in one two-digit industry may not be used in another.

In this study, we take a third approach and use a two-step procedure both to overcome the comparability problem and to extend our analysis to variables other than labor and capital. To take care of the comparability problem, we assume that each two-digit industry has its own production function so that regression analyses can be carried out after production functions for individual industries have been estimated. Another advantage of this approach is that disaggregation of inputs other than labor and capital is more reasonable. For one thing, material inputs within each industry are more comparable. For another, energy usage is also more comparable within a two-digit industry than across the industries.

To approximate the production technology in individual industries more precisely, disaggregated labor inputs of production workers, technicians, and management personnel are chosen. For intermediate inputs, annual costs of material, electricity, coal, and oil are available. Because the cost shares of coal and oil in the total cost of non-labor inputs are negligible, coal and oil are excluded from our analysis. The deflator for materials is constructed using the annual percentage increase in the materials price reported in the data, and the deflator for electricity is from the China Statistical Yearbook (State Statistical Bureau, 1993). Capital is measured as total net fixed assets for production purpose in fixed prices. The capital deflator comes from the China Statistical Yearbook (State Statistical Bureau, 1993, 1994, 1995).

Output is measured as gross output at fixed 1980 prices and comes directly from the data set. Using the 1980 price as a base to convert outputs in later years to a comparable measure is a controversial issue in Chinese enterprise studies. In Li (1997), 1990 market price deflators are used to reflect the real value of output produced in SOEs. However, according to Chinese practice and for comparison purposes, SOEs have been required to calculate and report their gross output value by simply multiplying the quantities of their outputs with fixed prices issued by the statistical authorities. Since the establishment of the People's Republic of China, there have been only five different fixed price tables issued by the government in 1952, 1957, 1970, 1980, and 1990 (State Statistical Bureau, 1993). Hence, gross output in current price may consist of values calculated using both market and planned prices. Therefore, the price deflator obtained by dividing gross output in current price by gross output in fixed price is not really a consistent deflator.[5]

4.3. Reform and characteristic variables

Several variables may be helpful in identifying the determinants of technical efficiency and productivity growth. Since the financial performance of many SOEs has not been satisfactory, an assessment of the relationship between profitability and productivity is interesting. We use annual profit as the variable to examine this correlation. Regarding the impact of incentive schemes on enterprise productivity, several relevant variables are

[5] If one divides output in current prices in 1980 or 1990 by output in fixed prices using 1980 or 1990 prices, most results give values other than unity.

available in the data set; these include flexible wage (bonus), retained profits, and the relative salary of managers to that of workers. Other factors affecting productivity may include the education levels of employees (the proportion of employees with high school education or higher), investment in fixed capital, capacity utilization, age of the enterprise, and the proportion of non-production workers to the total.

We are particularly interested in two characteristic variables, namely, scale and administrative level. According to the statistical authority in China, SOEs are classified into three scale groups: large, medium, and small. SOEs are supervised at different levels of government: central, province, region, and county. Centrally administered SOEs are usually large and county managed ones are usually small. Depending on the number of observations available for each two-digit industry, 17 two-digit industries were chosen for analysis. These are: Coal, Construction materials and other non-metal mining, Food manufacturing, Textiles, Animal skin product manufacturing, Paper and paper products manufacturing, Printing, Chemicals, Medicine, Rubber product manufacturing, Construction materials and other non-metal mine products, Black metal production and processing, Machinery, Communication and transportation equipment manufacturing, Electrical machinery and material manufacturing, Electronics and communication equipment manufacturing, Industrial instrument and measurement equipment manufacturing.

The industries that were left out have too few observations, namely, less than four. Although deterministic frontier methods such as DEA usually require fewer observations than stochastic frontier methods, the lack of cross-section observations for some industries has undesirable effects on estimation results. For example, when there are only about 10 observations in each cross-section, average technical efficiencies tend to be unusually high. In the next section, DEA and Malmquist estimation results are discussed by industrial sector. The numbers of best practice SOEs are reported by scale, administration level, and province. Regression analyses are performed on estimated technical efficiency measures, productivity growth and its components.

5. Empirical results

5.1. DEA and Malmquist index results

The estimates of technical efficiency, productivity growth (the Malmquist index), efficiency change, and technical progress are reported in Tables 1 and 2. The productivity growth measure is the Malmquist index in the tables. Since the DEA efficiency estimate, $0 < D_0^t(\mathbf{x}^t, \mathbf{y}^t) \leqslant 1$, is the reciprocal of the Farrell technical efficiency measure, we use it as our technical efficiency measure following Førsund and Hjalmarsson (1979). The results are presented for four groups of industries. The machinery and textile industries have a relatively larger number of cross-section observations so that each is treated individually. All other industries are grouped into either heavy industries or light industries, although their efficiency estimates were calculated according to their individual industrial frontiers. The estimation strategy was to keep as many observations as possible and detailed data cleaning work was kept to a minimum due to the relatively large size of the data set. Therefore, we deleted only non-positive observations and a few misreported observations

Table 1
Technical efficiency and Malmquist index for SOEs for selected years (1980–1994)

Technical efficiency

	Machinery industry			Textile industry			Heavy industries			Light industries		
Year	N	Mean	Std	N	Mean	Std	N	Mean	Std	N	Mean	Std
1980	108	0.62	0.22	64	0.73	0.16	145	0.71	0.24	123	0.68	0.35
1982	138	0.54	0.21	86	0.67	0.19	186	0.75	0.23	154	0.78	0.23
1984	145	0.56	0.22	93	0.48	0.23	196	0.78	0.21	164	0.78	0.23
1986	145	0.52	0.21	94	0.48	0.28	200	0.76	0.22	172	0.79	0.23
1988	143	0.52	0.20	95	0.49	0.26	200	0.75	0.22	173	0.79	0.22
1989	146	0.52	0.22	95	0.48	0.27	201	0.76	0.23	174	0.78	0.23
1990	141	0.68	0.19	89	0.69	0.20	177	0.87	0.16	176	0.86	0.17
1992	142	0.63	0.19	90	0.69	0.20	177	0.84	0.18	177	0.81	0.21
1994	142	0.62	0.21	90	0.66	0.22	177	0.75	0.23	177	0.68	0.30
1980–1989 average	10	0.55	0.21	10	0.54	0.26	10	0.75	0.23	10	0.77	0.25
1990–1994 average	5	0.65	0.20	5	0.69	0.20	5	0.80	0.22	5	0.80	0.23

Malmquist productivity index (growth rate of TFP)

	Machinery industry		Textile industry		Heavy industries		Light industries	
Year	Mean	Std	Mean	Std	Mean	Std	Mean	Std
1980–1981	0.94	0.27	1.04	0.15	1.04	0.70	1.00	0.31
1982–1983	1.13	0.25	1.16	0.72	1.10	0.23	1.16	0.52
1984–1985	1.11	0.21	1.02	0.18	1.04	0.29	1.10	0.25
1986–1987	1.10	0.27	1.04	0.21	1.06	0.20	1.14	0.36
1988–1989	1.04	0.23	0.93	0.24	1.01	0.21	1.10	0.37
1989–1990	1.13	0.52	1.21	0.69	1.14	0.56	1.20	0.46
1991–1992	1.06	0.18	1.00	0.16	1.06	0.28	1.05	0.17
1993–1994	1.07	0.20	1.12	0.27	1.10	0.17	1.12	0.27
1980–1989 average	1.09	0.32	1.03	0.37	1.07	0.37	1.12	0.41
1990–1994 average	1.05	0.21	1.03	0.22	1.08	0.29	1.06	0.22

prior to the DEA estimations. Fortunately, there are only a handful of values for the Malmquist index and its components that seemed to be too high; these are excluded as outliers later in the regression analysis.

In Table 1, the levels of technical efficiency for SOEs in China fall mainly in the 50% to 80% interval. The average efficiency for 1990 to 1994 was obviously higher than that for 1980 to 1989, which might be due to the exit of some poor performance small SOEs during the latter period. Since the data were collected separately for the two periods, we need to interpret the difference with caution. In addition, there is a visible negative trend in efficiency level during 1990 to 1994. Regarding the Malmquist indexes in Table 1, productivity growth is found consistently in all the sectors, with the exception of textiles from 1988 to 1989 and machinery from 1980 to 1981. The average growth rate ranges from 3% to 12% for the period of 1980 to 1989 and from 3% to 8% for 1990 to 1994. These results are much more optimistic than the ones reported in Kong et al. (1999).

The decomposition of productivity growth into efficiency change and technical progress is reported in Table 2. Efficiency improvements were rather rare in all four sectors, which is consistent with Kong et al. (1999). The average rates of efficiency change are negative for both the 1980s and for 1990 to 1994. Turning to the rate of technical progress in Table 2,

Table 2
Efficiency change and technical progress in SOEs for selected years (1980–1994)

	Machinery industry		Textile industry		Heavy industries		Light industries	
Year	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Efficiency change								
1980–1981	0.87	0.24	0.91	0.15	0.89	0.65	0.95	0.28
1982–1983	1.06	0.24	0.69	0.27	1.01	0.18	1.02	0.48
1984–1985	0.94	0.20	0.96	0.17	0.97	0.22	1.00	0.20
1986–1987	1.05	0.26	0.99	0.18	0.97	0.15	0.83	0.24
1988–1989	0.98	0.21	0.84	0.21	0.95	0.18	0.95	0.19
1989–1990	1.08	0.46	1.10	0.65	1.06	0.51	1.03	0.36
1991–1992	0.89	0.16	0.92	0.15	1.01	0.26	0.94	0.13
1993–1994	1.01	0.18	0.96	0.14	0.99	0.14	0.96	0.21
1980–1989 average	0.99	0.29	0.93	0.30	0.98	0.33	0.98	0.29
1990–1994 average	0.94	0.17	0.95	0.16	0.95	0.24	0.94	0.17
Technical progress								
1980–1981	1.08	0.07	1.15	0.09	1.33	0.79	1.06	0.12
1982–1983	1.07	0.08	1.83	1.06	1.10	0.13	1.14	0.19
1984–1985	1.18	0.07	1.06	0.05	1.07	0.06	1.10	0.10
1986–1987	1.05	0.03	1.05	0.06	1.09	0.12	1.53	0.76
1988–1989	1.06	0.04	1.12	0.18	1.07	0.11	1.16	0.29
1989–1990	1.04	0.05	1.11	0.20	1.07	0.12	1.16	0.18
1991–1992	1.20	0.12	1.09	0.09	1.05	0.08	1.12	0.14
1993–1994	1.06	0.07	1.16	0.22	1.12	0.09	1.18	0.19
1980–1989 average	1.10	0.09	1.14	0.41	1.11	0.26	1.17	0.38
1990–1994 average	1.12	0.13	1.09	0.13	1.21	0.56	1.14	0.17

most of the productivity growth came from technical progress. The period averages are over 10% annually, with the exception of textiles at 9% in the 1980s.

In Table 3, we calculated the distribution of frontier best practice enterprises for different scales, administrative levels, and provinces. A higher percentage of small scale enterprises produce on their industry production frontier than enterprises of other sizes for most of the period, with the exception of large scale enterprises in 1994. Enterprises supervised by region and county governments usually have a higher proportion of frontier producers. In 1990, the proportion of best practice increased dramatically in ministry, province, and region administrated SOEs. However, this proportion decreased rapidly for all administration levels from 1990 to 1994, which probably explains the decrease in average technical efficiency during the period. Turning to the provinces, Jiangsu had a higher percentage of best practice SOEs than other provinces.

5.2. Regression analysis

Two regression results are presented in Table 4, one for technical efficiency estimates and another for best practice. The Tobit model is used when technical efficiency is the dependent variable. Parameter estimates from this regression measure the magnitude of the impact on technical efficiency when the explanatory variables change. The Logit model is estimated when using technical efficiency estimates converted to a binary variable for

Table 3
The distribution of best practice SOEs (1980–1994)

Number of best practice and its proportions by scale

	Large SOEs			Medium SOEs			Small SOEs		
Year	Total	Best	Share	Total	Best	Share	Total	Best	Share
1980	102	19	0.19	219	48	0.22	119	27	0.23
1985	135	31	0.23	294	53	0.18	177	44	0.25
1989	132	30	0.23	298	64	0.21	186	49	0.26
1990	135	38	0.28	291	87	0.30	146	54	0.37
1994	136	30	0.22	293	52	0.18	146	31	0.21

Number of best practice and its proportions by administration

	Ministry			Province			Region			County		
Year	Total	Best	Share	Total	Best	Share	Total	Best	Share	Total	Best	Share
1980	36	4	0.11	40	5	0.13	323	75	0.23	34	8	0.24
1985	47	5	0.11	53	7	0.13	443	102	0.23	55	10	0.18
1989	47	5	0.11	54	11	0.20	446	103	0.23	61	20	0.33
1990	46	11	0.24	58	18	0.31	434	139	0.32	41	13	0.32
1994	46	5	0.11	59	11	0.19	436	95	0.22	41	4	0.10

Number of best practice and its proportions by province

	Jiangsu			Jilin			Shanxi			Sichun		
Year	Total	Best	Share	Total	Best	Share	Total	Best	Share	Total	Best	Share
1980	137	38	0.28	67	13	0.19	93	15	0.16	143	28	0.20
1985	172	47	0.27	122	25	0.20	149	22	0.15	163	34	0.21
1989	173	51	0.29	125	31	0.25	155	29	0.19	163	32	0.20
1990	185	74	0.40	126	36	0.29	118	32	0.27	154	41	0.27
1994	186	61	0.33	126	20	0.16	119	17	0.14	155	18	0.12

the dependent variable, with 0 indicating less than 100% efficient and 1 indicating best practice enterprises. This regression analyzes the factors that affect the probability of an SOE producing on the production frontier, i.e., a best practice enterprise.

The explanatory variables are: age of the enterprise, the ratio of flexible wage to total wage, the proportion of high school graduates or higher in total employees (the education variable), capacity utilization, and dummies for province, scale, administration level, industry, and year.[6] Explanatory variables that were excluded from our final estimations are: total profits, retained profits, relative salary of managers to that of workers, investment in fixed capital, and the proportion of non-production workers to the total. These variables were not statistically significant in our preliminary estimations and often had much more missing observations than those that were retained in the final estimations.

[6] For the education variable, values greater than 1 were excluded since it was defined as a percentage of the total employment. Observations with a capacity utilization larger than 300% were deleted, because quite a few firms, over 10% on one account, were operating above their 100% production capacity. This value of 300% falls into the interval between 2 and 4 standard deviations of the mean capacity utilization in the data.

Table 4
Determinants of technical efficiency and best practice

	Dependent variable: Technical efficiency Tobit model		Dependent variable: Best practice binary Logit model	
Variable	Coefficient	Std	Coefficient	Std
Constant	0.5711***	0.0368	−1.5795***	0.3478
AGE	0.0012***	0.0003	0.0038	0.0027
WP	0.0984***	0.0229	0.6513***	0.2174
ED	0.0431**	0.0203	0.0795	0.1982
KG	0.1270***	0.0192	0.4169**	0.1969
PROV1	0.1252***	0.0090	0.7978***	0.0861
PROV2	−0.0290***	0.0101	−0.1352	0.1025
PROV3	−0.0376***	0.0098	−0.0578	0.1045
S1	0.0162	0.0108	0.2862***	0.1021
S2	−0.0188**	0.0083	−0.2043**	0.0804
ADM1	−0.0891***	0.0179	−0.6023**	0.1908
ADM2	−0.0364**	0.0167	−0.2633*	0.1663
ADM3	−0.0179	0.0128	−0.1168	0.1296
Sigma	0.2535***	0.0027		
Chi-squared			1040.66***	
OBS	6487		6487	

Notes. AGE is the age of the enterprise; WP is the flexible wage; ED refers to education; KG stands for capacity utilization. PROV stands for Province, of which number 1 is Jiangsu, number 2 is Jilin, number 3 is Shanxi, and the fourth, Sichuan is the omitted category. S stands for the scale of the enterprise, of which number 1 refers to large, number 2 is the medium firm, and small scale is the omitted category. ADM is the administration level and 1 stands for central and ministry level, 2 for provincial, 3 for region, and county level is the omitted category. Industry and time dummies were used but the results are not reported here.

*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.

In Table 4, the coefficients for flexible wages, capacity utilization, and Jiangsu province show statistically significant positive effects for both technical efficiency and the probability of producing at the production frontier. On the other hand, central government control over the enterprise lowers technical efficiency and decreases the probability of becoming a best practice enterprise. Education has a significant positive effect on technical efficiency, but its effect on the probability of a firm becoming a best practice enterprise is not statistically significant. This result probably shows that SOEs with a well-educated labor force can perform better than the average enterprise, but to become a best practice SOE other complementary factors like incentives and investment in new technology may be necessary. In contrast to education, large scale increases the probability of becoming a best practice enterprise, but it is not associated with higher technical efficiency in a statistically significant manner. This may imply that the performance of large SOEs is rather diverse because large inefficient firms stay in the sample for a long period due to few bankruptcies. In terms of augmenting technical efficiency, capacity utilization is the most effective (0.1270), with flexible wage second (0.0984) and education third (0.0431).

Table 5
Determinants of productivity growth, efficiency change, and technical progress

	Productivity growth OLS method		Efficiency change OLS method		Technical progress Tobit model	
Variable	Coefficient	Std	Coefficient	Std	Coefficient	Std
Constant	0.9494***	0.0266	0.9030***	0.0238	1.0191***	0.0169
WP	0.1318***	0.0239	0.0976***	0.0213	0.0379**	0.0149
ED	0.0207	0.0408	0.0137	0.0364	0.0058	0.0255
KG	0.0524**	0.0214	0.0333*	0.0191	0.0194	0.0133
PROV1	0.0303***	0.0076	0.0211***	0.0067	0.0074	0.0047
PROV2	0.0177**	0.0086	0.0092	0.0077	0.0103*	0.0054
PROV3	0.0099	0.0085	0.0060	0.0076	0.0036	0.0053
S1	0.0138	0.0090	0.0144*	0.0081	−0.0008	0.0056
S2	−0.0026	0.0070	0.0012	0.0063	−0.0027	0.0043
ADM1	0.0332**	0.0154	0.0261*	0.0138	0.0058	0.0096
ADM2	0.0221	0.0143	0.0181	0.0128	0.0003	0.0089
ADM3	0.0181*	0.0110	0.0145	0.0098	0.0034	0.0068
R^2	0.0528		0.0172		Sigma	0.1313
F-value	9.22***	0.4275	3.58***	0.1323	Sig-level	0.0000
OBS	5903		5903		5903	

Notes. See Table 4 for identification of the variables.

In Table 5, the Malmquist productivity index, efficiency change index, and technical progress index are used as dependent variables.[7] Since the three indexes are in first-differences, we transformed some of the explanatory variables, e.g. flexible wage, education, and capacity utilization, into first differences. Flexible wage is the most statistically significant factor affecting productivity growth and its components. Capacity utilization has a statistically significant positive influence on productivity growth but it seems to work mainly through efficiency improvement rather than through technical progress. The dummy for Jiangsu province is highly statistically significant for productivity growth and efficiency change but not for technical progress. Large scale is positively associated with the rate of efficiency improvement but only at the 10% level of statistical significance.

In Table 6, the regressions involve binary dependent variables converted from the Malmquist productivity index and its two components, with 0 indicating negative or no change and 1 indicating positive change. These regressions examine the probability of a positive change in the three productivity indexes, regardless of magnitude, when the quantitative explanatory variables change over time. They can be analyzed jointly with the regressions in Table 5. For example, an explanatory variable may be positively correlated with the rate of productivity growth, but it may not be positively correlated with the probability of a productivity breakthrough, i.e., a positive change in productivity regardless

[7] For the Malmquist index and its components, observations with values larger than 2 were excluded from the regressions. The criteria take the usual two standard deviations from the mean as a rough reference. For instance, assuming that a typical mean for the Malmquist index is 1.10 and a typical standard deviation 0.30, two standard deviations from the mean on the positive side are 1.70 each. To save more observations, we take a somewhat larger number, in our case 2.

Table 6
Probability of productivity growth, efficiency change, and technical progress

Logit model results

	Productivity growth		Efficiency change		Technical progress	
Variable	Coefficient	Std	Coefficient	Std	Coefficient	Std
Constant	−0.3476	0.2564	−1.1338***	0.2793	−0.1307	0.3472
WP	0.9166***	0.2346	0.7173***	0.2427	0.8508**	0.3401
ED	0.3129	0.3962	−0.0464	0.4046	0.1772	0.5595
KG	0.4455**	0.2098	−0.0141	0.2155	0.1654	0.3422
PROV1	0.3858***	0.0745	0.0768	0.0775	0.3032**	0.1231
PROV2	0.1551*	0.0850	0.0367	0.0897	0.1878	0.1447
PROV3	−0.0012	0.0826	0.0821	0.0865	0.0245	0.1373
S1	0.1897**	0.0893	−0.0704	0.0930	0.1635	0.1501
S2	−0.0048	0.0683	−0.0084	0.0723	0.0200	0.1113
ADM1	0.2007	0.1519	0.2592*	0.1565	0.0396	0.2580
ADM2	0.2410*	0.1403	0.0888	0.1476	0.0142	0.2259
ADM3	0.1174	0.1061	−0.0142	0.1131	0.1620	0.1712
Chi-squared	397.36***		199.87***		844.23***	
OBS	5903		5903		5903	

Notes. See Table 4 for identification of the variables.

of magnitude. Again, flexible wage has a statistically significant positive impact on the probability of an enterprise having a productivity breakthrough through improvement in both technical efficiency and technical progress. In Jiangsu province, enterprises achieve productivity breakthroughs mainly through technical progress. Although large SOEs are more likely to have a productivity breakthrough at the 5% significance level, they appear to achieve this through technical progress rather than by efficiency improvement, which has a negative but not statistically significant coefficient. Compared with the results in Table 5, having large scale does not guarantee a higher rate of productivity improvement, although it increases the probability of a breakthrough in productivity growth. The education variable is not significant in any of the regressions in Tables 5 and 6.

Overall, the decomposition and the corresponding regressions indicate that the explanatory variables can be grouped into two categories. First, both education and capacity utilization affect technical efficiency. Whereas education has a statistically significant impact on technical efficiency in levels, its impact on technical efficiency in first differences is not statistically significant. Capacity utilization has a positive impact on productivity through technical efficiency both in levels and in first differences. Second, the incentive variable, flexible wage, has a significant positive impact on all measures of productivity growth and technical efficiency. However, causality between productivity and flexible wage might well run in both directions (Groves et al., 1994).

6. Conclusions

The measured average efficiency levels of the sample SOEs were low, sometimes around only 50%, in the 17 two-digit industries. This result is consistent with the findings in Liu and Liu (1996) and Kong et al. (1999), although differences arise depending on industries.

For 1980 to 1989, the positive TFP growth reconfirms the result of Groves et al. (1994), Liu and Liu (1996), and Li (1997). However, our decomposition attributes this growth overwhelmingly to technical progress rather than to efficiency improvement, which differs from the interpretation of Liu and Liu (1996). Perhaps the truth lies somewhere in between because, during a period of rapid technical progress, improvement in technical efficiency can be obscured in the data. For 1990 to 1994, TFP growth continued in the sampled enterprises, contradicting the results reported by Kong et al. (1999) but more in line with the positive impact of corporatization on productivity reported in Lee (1999). Turning to the decomposition, the source of this contradiction comes from the positive effect of technical progress in our findings, while average technical efficiency worsened at the same time, which is consistent with the stochastic frontier results in Kong et al. (1999).

To echo the study on large SOEs by Lo (1999), in our regression analyses, large SOEs were found significantly correlated with the best practice and productivity breakthrough. Large SOEs were also associated with higher levels of technical efficiency improvement at the 10% statistical significant level. However, their associations with higher levels of productivity growth and higher probabilities of efficiency breakthrough were not statistically significant. These findings may imply that even large SOE is not a homogeneous group in terms of technical efficiency and TFP growth. Besides large scale, best practice SOEs were characterized by stronger incentives and higher capacity utilization; they were most likely to be found in the coastal province (Jiangsu) assuming everything else constant. In general, our results corroborate the overall assessment of the productivity performance of the SOE sector by Jefferson et al. (1996).

Although we find considerable productivity growth for our sample of SOEs, throughout the time period, it was accomplished mainly through technical progress rather than through efficiency improvement. On average, technical efficiency declined but this should not be taken to indicate the general failure of the reform programs with the SOE sector. As the economy was moving gradually to a market system, inefficient SOEs remained so that average technical efficiency could have been higher if these inefficient SOEs had exited in the 1980s. Since the structural adjustment program was initiated in 1994, about 40 million workers have been laid off, most of these from the SOE sector. Hence, getting rid of inefficient SOEs is costly in terms of social stability.

The government's effort to promote technical progress in the SOE sector appears to have been successful according to our empirical findings. Some large best practice SOEs may have played the role of productivity leaders throughout the data period. As they improve their production efficiency and technology, it would have been difficult for others to catch up. Hence, the average and the best practice SOEs may belong to entirely different categories in terms of technology, quality of human capital, managerial capacity, and external environment. Therefore, the recent government policy that encouraged takeovers of less efficient SOEs by more efficient ones may be a reasonable alternative to bankruptcy. In general, our empirical findings support recent government policies concerning redundancies, technical upgrading, and corporate governance. These policies address the key problems in the SOE sector, i.e., low efficiency, lack of international competence, and the unclear relationship between the control rights and the state ownership. Since our analysis indicates that the performance of the SOEs is rather diverse, a reasonable reform strategy would separate the large SOEs from the smaller ones and the

best practice enterprises from the inefficient enterprises. If the ultimate goal is to privatize SOEs, privatization is more likely to succeed in the absence of policy burdens and when the modern enterprise system has become well established in China as the experiences in Eastern Europe and the former Soviet Union demonstrate.

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