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Ownership Structure and Determinants of Technical Efficiency: An Application of Data Envelopment Analysis to Chinese Enterprises (1986–1990)[1]

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Since economic reforms were initiated in 1978, Chinese industry has experienced dramatic changes in ownership structure and management system. Based on samples in seven three-digit industries in China during 1986–1990, this study evaluates the technical efficiency of enterprises by means of data envelopment analysis. Differences in technical efficiency between state, collective, and township–village enterprises are demonstrated. Limited dependent variable models are employed to analyze determinants of technical efficiency and the impact of various incentive schemes. *J. Comp. Econom.,* September 1998, **26**(3), pp. 465–484. Göteborg University, Box 640, SE-405 30 Göteborg, Sweden; Chinese Academy of Social Sciences, Beijing 100836, PR China; and Göteborg University, Box 640, SE-405 30 Göteborg, Sweden © 1998 Academic Press

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1. INTRODUCTION

Since economic reforms were initiated in 1978, China's industry has experienced dramatic changes in ownership structure. There are five basic ownership categories: state, urban collective, rural collective (i.e., township and village enterprises), private, and joint ventures, of which the first three—the state-owned enterprises (SOEs), urban collective-owned enterprises (COEs), and township–village enterprises (TVEs)—constitute most of the industrial sector. These three types of public enterprises, controlled by different levels of government, have coexisted for more than a decade. In 1980, the shares of gross industrial output were 76% for the SOEs, 13.7% for the COEs, and 9.9% for the TVEs, while in 1990 these shares were 54.6, 10.3, and 25.3%, respectively. The rapid development of township–village enterprises (TVEs) has been described as the most important engine driving the unprecedented growth of the Chinese economy during the past 15 years (Goodhart and Xu, 1996). At the same time, in order to improve productive efficiency, various incentive schemes have been introduced in the SOEs.

These changes characterize the Chinese gradualist enterprise reform in two respects: First, rapid expansion of the industrial sector has been accomplished essentially within the domain of public ownership (SOEs, COEs, and TVEs). Second, reforms of SOEs have emphasized the importance of management efficiency rather than mass privatization. To evaluate the success of industrial reforms it is thus necessary both to compare performance by ownership category and to investigate the impact of incentive schemes on SOEs.

This study, based on samples in seven three-digit industries during 1986–1990, evaluates the performance of Chinese enterprises with respect to technical efficiency by means of data envelopment analysis (DEA). Differences in technical efficiency between SOEs, COEs, and TVEs are demonstrated on the basis of DEA efficiency estimates. A limited dependent variable model is employed to analyze the determinants of technical efficiency and the impact of various incentive schemes.

Several studies of Chinese industries and enterprises during the reform period have concentrated on productivity growth. Recently, a majority of the studies have shown that there has been positive total factor productivity (TFP) growth in the SOE sector. However, the concern of our study is related to the level of total factor productivity across types of public ownership, that is, the comparison of technical efficiency between SOEs, COEs, and TVEs.

Jefferson (1989) compared total factor productivity of the state and collective sectors in levels. Using aggregate county-level data from 1984, he found that total factor productivity is substantially higher in the state sector than in the collective sector and suggested that it would be useful to undertake comparisons of state and collective enterprises within the same industry: perhaps textiles, apparel, or machine-building, in which there are large concentrations of collective enterprises. Following this suggestion, Murakami *et al.* (1994) investigated the differences in technical and allocative efficiency between SOEs, COEs, and different types of TVEs in China's garment industry in 1985 and 1990. They found that SOEs and COEs are much less efficient, both technically and allocatively, than cooperative TVEs and joint ventures. Our study is another attempt to investigate the differences in performance of enterprises in these three main ownership categories in China, based on comprehensive data at well-defined industry levels. We emphasize technical efficiency, which is a very important aspect of level TFP, and we use a methodology (DEA) not often used before on Chinese data.[2]

DEA has several attractive features in our context: (1) It places no restrictions on the functional form of the production relationship; (2) it focuses on individual observations, rather than on population averages; (3) it concentrates on revealed best-practice frontiers, rather than on central-tendency properties of frontiers; and (4) for each production unit, it produces a single aggregate measure of the utilization of input factors to produce desired outputs (Charnes *et al.*, 1994).

It has been suggested in several studies (e.g., Kuan *et al.*, 1988) that nonproductive capital and labor in SOEs may have produced a downward-biased measure of total factor productivity growth during the reform period. The same logic would hold for technical efficiency. To avoid this problem, we use only inputs for production purposes in our estimation of frontier production functions. Moreover, previous studies of Chinese enterprises have often used the total number of employees and total capital as input measures. In this study, however, disaggregated labor data on production workers, technicians, and management personnel are used, and capital is measured by productive capital alone. Thus it is possible to correlate technical inefficiency with respect to specific labor inputs, but more importantly, the production technology can be better estimated than by using only aggregated labor data. The results of hypothesis tests are reported regarding whether nonproductive capital and labor contributed to technical inefficiency.

We begin with a discussion of possible determinants of technical efficiency in Section 2. Data issues and preliminary analysis of single-factor productivities are presented in Section 3. Section 4 introduces the DEA model; the DEA estimates and regression results are reported and analyzed in Section 5. We summarize and draw some conclusions in Section 6.

2. DETERMINANTS OF TECHNICAL EFFICIENCY IN CHINESE ENTERPRISES

In this study, we define technical efficiency as the ratio of observed output to output on the production frontier, given the input levels. There are several factors

[2] Lau and Brada (1990) estimated a parametric deterministic frontier production function (translog) using aggregate industrial time series data from 1953 to 1985. In Färe *et al.* (1996), a comparative static DEA model was applied to Chinese state enterprise data from 1980, 1984, and 1985.

that may influence technical efficiency in Chinese enterprises; the impact of ownership structure on technical efficiency is our first concern.

Differences in incentives for government officials at different levels may result in different objectives for the enterprises they control. The key difference between TVEs and SOEs or COEs is that the former face harder budget constraints, while the latter two, especially SOEs, are usually bailed out by the government in case of losses. The consequence of the harder budget constraint is that TVE activities are more market-oriented, because they have to make a profit to survive. The performance of TVEs is related more directly to the personal economic interests of local officials, who actually control the enterprises. The salary and other informal income of township or village officials, for instance, come largely from revenues of TVEs. Profit remittances and management fees of the TVEs are also the main source of other discretionary community-government funds. On the other hand, SOE and COE supervisors are all state employees, and their basic income or welfare is not directly related to the performance of their firms. Some researchers have also pointed out that information channels linking principals (government) with agents (managerial) tend to be shorter and simpler for nonstate firms than for state-owned units (Groves *et al.*, 1994). For these reasons, COEs and especially TVEs may be thought likely to have higher technical efficiency than SOEs, given that everything else is fixed. However, SOEs also have some advantages over TVEs. The labor force of SOEs are usually more experienced and better educated. The technologies used by TVEs are often regarded as backward.

Our second concern is the impact of management reforms on technical efficiency. Several incentive schemes intended to improve management efficiency have been introduced or experimented with at various stages of the reform process since the late 1970's. Consequently, by the end of the 1980's, a variety of management systems coexisted in SOEs and COEs: contract-management responsibility, asset-management responsibility, leasing, and share systems. The contract-management responsibility system has been dominant among Chinese enterprises (over 70% of our entire sample in 1990). Before 1986 there was a reform program called the economic-responsibility system that sought to develop a profit-sharing relationship between the enterprise and the state. The program allowed enterprises to retain a substantial portion of above-quota profits as a reward for their products and fulfillment of customer contracts. Several other variations had also been introduced from 1986 (Hay *et al.*, 1994).

(1) Under contract-management-responsibility system in large and medium-sized enterprises, the enterprise was required to pay taxes and to hand over a share of profits to the state, to have funds available for investment in technical upgrading, and at the same time to link its total wage bill to economic performance. There were two new elements in the system. First, autonomy was greatly enhanced, the director was required to take decision-making responsibility.

Second, the enterprise was obliged to guarantee delivery of the contractual profit regardless of its actual performance; that is, the enterprise could retain profits only if profits exceeded the quota; otherwise, the enterprise had to make up the quota from its own funds or saving deposits.

(2) In addition to the requirements of the contract-management responsibility system, contracts under the asset-management responsibility system require an enterprise to guarantee the growth of its fixed assets.

(3) Enterprises under a leasing contract are still owned by the state, but they have become independent commodity-producers and dealers. They are mostly small, and were running at losses, or earning low profits, and were expected to separate managerial authority from ownership. Instead of profits due to the state, they payed "rents."[3]

(4) Under the share system, contracts could be constructed between enterprises and the state based on profitability, asset values, and bonus arrangements; the operation of private ownership based on share holdings and dividend payments could be mimicked to generate the same incentives to maximize profits and efficiency. Sometimes, employees were also encouraged to buy shares in their own enterprise, which linked the performance of the enterprise to the employee's income by means of potential dividends or losses. Although isolated examples could be found in the early 1980's in some TVEs (Overholt, 1993), the share system symbolized a new stage of enterprise reform when it was expanded in 1992 (Dong, 1994).

Other factors which may influence technical efficiency are regional differences (coastal vs interior), "nonproductive" capital, "nonproductive" labor, interindustry differences, and macroeconomic fluctuations. The industrial map of China is usually divided into three regions: coastal, central, and western regions. The coast is industrially much more developed than the central region, which is more developed than the west. Our data cover 15 of China's 30 provinces, among which 2 (Sichuan and Gansu) are western, 4 (Hubei, Anhui, Shanxi, and Heilongjiang) are central, and the rest are coastal. During the first decade of reforms (1978–1988), China's industrialization strategy changed from interior-oriented investments to treating the coastal region as a catalyst for industrial modernization (UNIDO, 1992). Therefore, there might be a systematic difference in technical efficiency between enterprises from coastal provinces and those from interior provinces.

In China, SOEs are supposed to provide some major social services to their employees, such as housing, medical care, and even primary school education. Hence, fixed assets consist of two parts: productive (industrial) capital and

[3] More than 10,000 small industrial and commercial enterprises in China began to operate on a lease system in 1986, leased either to individuals or to collectives. According to a survey, 95% of the 5735 leased enterprises in the six large cities of Beijing, Shanghai, Shenyang, Guangzhou, Chongqing, and Wuhan were successful. (People's Republic of China Year Book, 1987, p. 306).

nonproductive capital. It is not obvious how nonproductive capital affects technical efficiency. Labor has similar constituents: productive (industrial) labor as well as nonproductive labor. Besides this nonproductive labor, overstaffing is also a severe problem in the SOEs. It was reported by UNIDO in 1992 that 80% of the SOEs were 15–20% overstaffed.

Reforms have not been pursued at the same pace in different industries. As a result, light industries now have a relatively high concentration of TVEs, while heavy industries are still subject to a higher degree of government control. The expansion of nonstate enterprises has served as a lever forcing often reluctant state firms in the direction of market-oriented behavior. The Jefferson and Rawski (1994) calculation (and also calculations by Singh *et al.* (1993)) shows that profitability within the state industry is lowest in provinces where non-state industry has grown most rapidly. Singh et al. also reported that large provincial shares of nonstate industrial output are associated with high levels of total factor productivity in state industry, suggesting that robust growth of the nonstate sector not only squeezes profits and but also motivates greater efficiency in the state sector. Therefore, there may be systematic patterns in the distribution of efficiency across industries.

The size of the enterprises may also be related to technical efficiency. Statistical authorities in China classify enterprises as large, medium, or small according to their fixed capital. All TVEs are classified as small. Government policies concerning enterprise reforms have treated small enterprises differently from large and medium ones; for instance, small SOEs, mostly inefficient ones, have been exposed to more drastic incentive schemes such as leasing. Meanwhile, the government still intends to control the economy through large and medium enterprises. The size may matter for reasons other than reform. Large enterprises usually provide better working conditions and social welfare. They are usually strategically important to the government, and they are equipped with advanced machinery and privileged supply of other industrial resources. Thus they are in much better condition in attracting highly skilled workers, technicians, and managers.

Macroeconomic fluctuations may affect technical efficiency in the public sector to a large extent. One of the objectives of the public enterprises in China is to generate employment opportunities. When they face downturns in production, they usually do not lay off workers, especially in the case of SOEs. Failure to adjust employment in response to output fluctuations may have a very strong effect on measured technical efficiency. On the other hand, in 1989 and 1990, during the recession period of the Chinese economy, hundreds of thousands of TVEs went bankrupt. As to the employment behavior of TVEs, there are no guaranteed positions for either managers, engineers, or workers, though local resident workers have the priority for keeping their jobs when there are layoffs. Particularly, the existence of migrant labor in TVEs in well-developed regions allows for greater wage and employment flexibility and makes it easier for the adjustment of employment to temporary supply or demand shocks (Goodhart and Xu, 1996).

3. DATA ISSUES

The data used in the study were provided by the Institute of Economics, Chinese Academy of Social Sciences.[4] Data collection was supported by the World Bank. To make the technologies used comparable across SOEs, COEs, and TVEs, relatively large TVEs were chosen purposely. However, on average, the TVEs in our sample are still smaller than small SOEs and COEs. Seven three-digit industries were selected from the data sets for this study: coal mining, clothing manufacturing, paper manufacturing, daily-use chemicals, cement manufacturing, daily-use metal fabrication, and daily-use electrical appliances.

The clothing industry, daily-use chemicals, and daily-use electrical appliances are all typical light industries with many TVEs. Paper manufacturing also contains a significant number of COE and TVE producers. In 1986, 27% of machine-made paper and cardboard was produced by rural industry. China has been the world's largest cement producer since the middle of the 1980's; in 1986, the share of rural industry (mostly by TVEs) in cement output was 22%. In 1986, rural industry produced 26% of the coal in China (Byrd and Lin, 1990).

There are six main variables in the study: five inputs (three productive labor categories, productive capital, and materials) plus industrial output (gross value of industrial output). To reduce reporting errors in the data, we checked the main variables used for maximum (sometimes minimum) values of single-input productivities, for shares of productive labor by category in the total labor, and for the share of productive capital in the total capital. Thus we checked nine dimensions, i.e., five input productivities and four input shares. Out of 1927 observations, 168 were deleted as outliers. These were extreme observations such as production units with productivity as high as a hundred times average values. Consequently, on average, we end up with 0.84% of total observations deleted in each dimension. To avoid adjusting the data in accordance with the DEA estimates, the checking was conducted only once and done independently of DEA estimates.

Definitions of variables are as follows:

(1) Industrial output: We use gross value of industrial output in current prices as the measure of output. Since we include materials as an input in the production function estimation, this is the proper measure rather than value-added. Besides, it is difficult to obtain reasonable deflators for capital and material inputs.[5] The study is thus confined to cross-sectional comparisons of technical efficiency

[4] A more detailed description of the data can be found in Liu *et al.* (1995).

[5] Jefferson *et al.* (1992) demonstrated that during the latter half of the 1980's, particularly in the state sector, intermediate input prices rose more rapidly than output prices.

among enterprises. However, this measure also has its problems. For instance, due to the strategic importance of the coal industry, the price of coal, especially in the state sector, has long been subject to government price controls. Using gross value as the measure of coal output may underestimate the state sector's technical efficiency in coal production.[6]

(2) Productive labor (production workers, technicians, and management): The SOE and COE data give the year-end number of total employees, production workers, temporary workers, apprentices, technicians, management, service personnel and others. Our measure of production workers is the sum of production workers, temporary workers, and apprentices. In the TVE data, there are production workers, technicians, managers, sales agents, and purchasing agents. Our measure of management personnel is the sum of the last three.

According to our calculations, TVEs had the highest share of production workers (between 78 and 90% on average), while SOEs had the lowest (71 to 73%). TVEs had on average about 5% technicians, while SOEs and COEs were slightly lower. In 1986 and 1987 TVEs had the lowest share of management personnel, but highest in 1988, 1989, and 1990.

(3) Productive capital: Total capital consists of two components: productive and nonproductive, both measured at their historical prices.[7] Productive capital includes structures, machinery and equipment for industrial production, whereas nonproductive capital refers to apartment buildings for employees, hospitals, and sometimes even schools. To obtain the value of productive capital net of depreciation, we multiplied the net value of total capital by the share of productive capital in total capital at original prices. The differences in shares of net productive capital across ownership categories are considerable. The typical share of productive capital was about 78% for SOEs, 91% for TVEs. Section 5 reports regression results regarding the relationship between nonproductive capital and technical efficiency.

(4) Materials: Materials are measured as values in current prices.[8] From the TVE data we added the inventory of raw materials and energy at the beginning of the year minus the inventory at the end of the year plus consumption of raw materials and energy within the year. For the SOEs and COEs, we added up the purchase of materials, of fuels, and of energy; it is not completely clear to what extent these figures reflect actual usages during the period.

[6] Similar problems may occur in other industries as well, since the dual-price system was still functioning in some industries during the data period.

[7] This is a special problem with Chinese capital data. Since there is no information on the age structure of the capital stock in the data, even if proper capital deflators are available, we cannot get a capital measure in current prices (e.g., in 1986 price).

[8] The use of current prices for cross-section estimates does not eliminate entirely the measurement problem, since pricing regimes differ across ownership types and quality differences between SOE and TVE products are not accounted for.

In 1988, productivity of production workers (mean 35,300 Yuan per worker) in SOEs was higher than in TVEs (24,000 Yuan), but COEs had the highest productivity (37,700 Yuan per worker). The productivity of productive capital was also the highest (6.76) in COEs, but the lowest in SOEs (3.66), with TVEs in between (5.46). Productivity of materials was highest in TVEs (4.46) and lowest in SOEs (1.99).

4. DEA MODELS AND MEASUREMENT OF TECHNICAL EFFICIENCY

The DEA model was introduced by Charnes, Cooper, and Rhodes in 1978. It was the consequence of the development of the measurement of productive efficiency (Farrell, 1957), frontier production functions (Aigner and Chu, 1968), and numerical aspects of mathematical programming. Important contributions can also be found in Färe *et al.* (1985). Numerous applications of the DEA method have appeared in economics and management journals, covering industries from farming and air transportation to social insurance and banking.

The DEA approach is illustrated in Fig. 1. The straight line OG represents a deterministic production frontier under constant returns to scale (CRS), while the concave envelope EABCF represents the frontier under variable returns to scale (VRS). X is an index of inputs and Y an index of output. With these two frontiers, several technical efficiency measures can be considered for a unit producing at D. (1) HJ/HD measures input-oriented efficiency under variable returns to scale (VRS), denoted as E1(VRS); (2) ND/NL measures output-oriented efficiency under VRS, denoted as E2(VRS); (3) HI/HD measures input-oriented efficiency under constant returns to scale (CRS), denoted as E1(CRS); (4) ND/NG (=HI/HD) measures output-oriented efficiency under CRS, denoted as E2(CRS).[9] By construction, these efficiency measures can take values between 0 and 1. All the measures can be calculated by solving standard linear-programming (LP) problems. For instance, E2(VRS) for enterprise m can be obtained numerically by solving the LP problem;[10]

$$1/E2_m = \max_{\lambda_{m1}, \ldots, \lambda_{mM}} \theta_m \qquad m = 1, \ldots, M \tag{1}$$

$$s.t.\ \theta_m y_m \leq \sum_{i=1}^{M} \lambda_{mi} y_i \tag{2}$$

[9] The efficiency measures and the notations we use in this study are due to Førsund and Hjalmarsson (1979).

[10] Except for different notation, the presentation here is identical to that in Färe *et al.* (1994, p. 75).

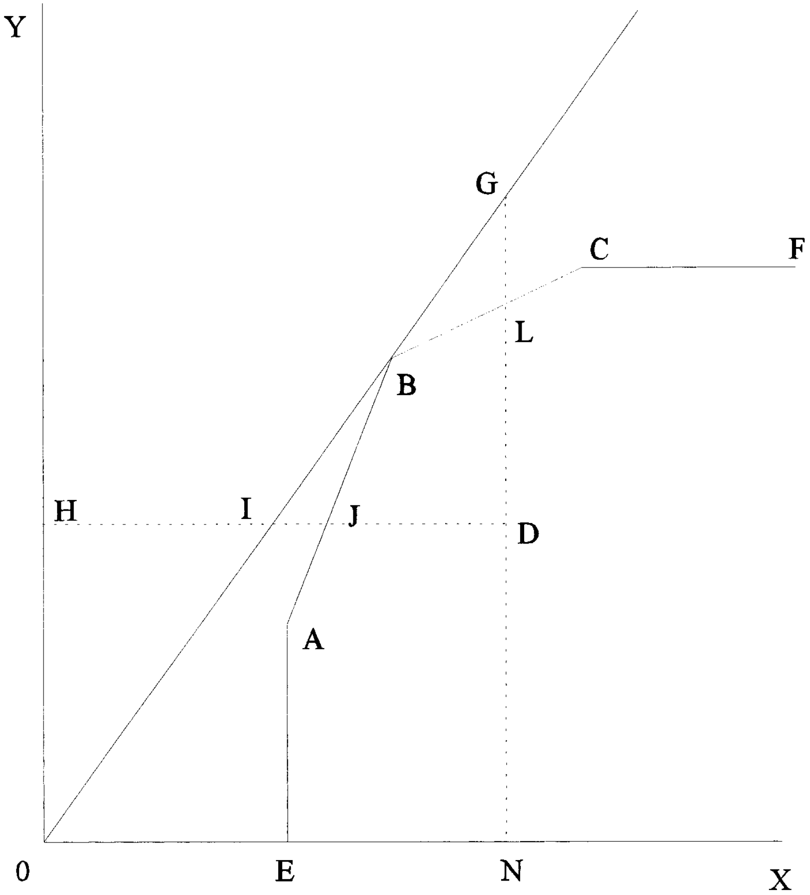

FIG. 1. Illustration of frontiers and efficiency measures.

$$x_{mj} \geq \sum_{i=1}^{M} \lambda_{mi} x_{ij} \qquad j = 1, \ldots, J \tag{3}$$

$$\sum_{i=1}^{M} \lambda_{mi} = 1 \tag{4}$$

$$\lambda_{mi} \geq 0, \tag{5}$$

where y represent output and x inputs, J is the number of inputs, and M is the number of cross-section observations (production units).

Restriction (2) implies that the volume of output y_m must be less than or equal to output at the production frontier. Restriction (3) states that input used by unit m must at least equal the input required at the frontier. Restriction (4) is the condition for VRS. If this restriction is omitted, CRS is implied.

In empirical applications, depending on the objective of studies, appropriate efficiency measures should be chosen accordingly. We concentrate on the output-oriented efficiency measures E2 (CRS) and E2 (VRS). The main reason for this is that Chinese industries have been expanding in recent years to meet increased demand, while there has been a shortage of nonlabor industrial inputs (capital and materials). It would be desirable for policymakers to know how much more output could be produced if enterprises improved their technical efficiency given limited inputs.

In practice, usually both CRS and VRS frontiers are estimated. If the technology is close to CRS, then the two estimates are similar; hence, a test can be carried out by comparing the estimates from the two frontiers. When they give quite different estimates, the VRS results should usually be preferred.

Tulkens and van den Eeckaut (1995) discussed various options regarding application of DEA models to panel data. One involves computing a sequential frontier, i.e., efficiency is computed each year on the basis of all observations generated up to that year. With our data, for instance, the first year would consist of only 1986 data, while the last year would include all observations from 1986 to 1990. This approach may be preferable when the time period T is large, because it implies that the technology of the last period might not be available in the first period. When T is small, ignoring technical change, a single intertemporal frontier can be constructed from all the data. Since our data are not comparable between years, we ignore the panel nature of our data and construct cross-sectional frontiers for each industry instead.

5. EMPIRICAL RESULTS

We first report the DEA results and discuss the efficiency rankings in several dimensions. Then, the efficiency scores, E2 (VRS) of all seven industries are pooled together and used as dependent variables in regression analysis. The OLS method is used for the simple linear model, and maximum-likelihood for the Tobit model.

5.1. DEA Efficiency Estimates

Overall, the number of units with efficiency estimates (VRS) lower than 30% is negligible (less than 10% of the total observations), in contrast to the number of frontier and near frontier units. Efficiency rankings based on the E2 (VRS) measure are presented in Tables 1 and 2. Efficiency rankings based on the E2 (CRS) are not reported formally here, but we will mention them whenever it is necessary. Results from all seven three-digit industries over the

TABLE 1

Technical Efficiency E2 (VRS) by Ownership, Scale, and Year

Categories	*N*	Mean	Min	Max	Std
Ownership					
SOE	949	0.77	0.185	(255)	0.204
COE	450	0.80	0.107	(179)	0.220
TVE	360	0.84	0.073	(200)	0.228
Scale					
Large	216	0.87	0.206	(97)	0.169
Medium	357	0.79	0.185	(88)	0.187
Small	1186	0.78	0.073	(449)	0.227
Year					
1986	305	0.82	0.156	(121)	0.203
1987	320	0.80	0.199	(114)	0.209
1988	379	0.79	0.073	(139)	0.216
1989	377	0.79	0.107	(135)	0.215
1990	378	0.78	0.134	(125)	0.225
Industry					
Coal	312	0.75	0.203	(99)	0.232
Clothing	238	0.82	0.107	(99)	0.216
Paper	262	0.82	0.185	(80)	0.180
Chemical	220	0.75	0.169	(80)	0.253
Cement	320	0.80	0.073	(118)	0.204
Metals	173	0.87	0.345	(76)	0.150
Electrical	234	0.77	0.252	(82)	0.217
Management					
Share	9	0.78	0.206	0.99	0.243
Responsibility	1045	0.78	0.073	(340)	0.216
Leasing	8	0.74	0.514	0.88	0.106
Assets	222	0.84	0.203	(106)	0.207
Others	475	0.81	0.107	(188)	0.214

Note. Numbers in parentheses represent the number of best-practice units.

5-year period are sorted by various categories as indicated in the tables. When the maximum value for a specific category is 1.0, the number of best-practice units is instead reported in parentheses. Because the frontiers give different average values of technical efficiency (about 70% under CRS and 80% under VRS), and the number of best-practice units is also quite different (343, or 19%, CRS; 634, or 36%, VRS), we shall discuss mainly the VRS results. In the following discussion, we are considering VRS unless otherwise mentioned.

By ownership categories (Table 1), SOEs are the least efficient (mean 77%), TVEs most efficient (84%), and COEs in between (80%). The differences in technical efficiency between SOEs, COEs, and TVEs are all statistically signif-

TABLE 2

Technical Efficiency E2 (VRS) by Province

Provinces	*N*	Mean	Min	Max	Std
Hubei (C)	161	0.76	0.107	(46)	0.231
Sichuan (W)	129	0.70	0.198	(28)	0.236
Guangdong	44	0.95	0.654	(29)	0.098
Zhejiang	21	0.93	0.538	(15)	0.138
Jiangsu	162	0.78	0.186	(40)	0.201
Anhui (C)	32	0.82	0.318	(12)	0.217
Hebei	397	0.81	0.261	(164)	0.203
Liaoning	89	0.83	0.248	(38)	0.208
Shanxi (C)	159	0.84	0.283	(64)	0.176
Gansu (W)	59	0.77	0.203	(21)	0.217
Heilongjiang (C)	73	0.78	0.206	(26)	0.230
Shanghai	61	0.88	0.236	(39)	0.218
Guangxi	202	0.76	0.073	(52)	0.216
Fujian	87	0.85	0.169	(36)	0.196
Shangdong	83	0.72	0.258	(24)	0.239

Note. Numbers in parentheses represent the number of best-practice units. C, central; W, western; all others are coastal.

icant at the 1% level.[11] Under VRS, 26% of SOEs are on the production frontier, but only 12% under CRS; 55% of TVEs are on the VRS frontier, only 33% for CRS; the corresponding figures for the COEs are 40 and 24%. Hence, the number of fully efficient enterprises sorted by ownership also depends very much on the shape of the production frontier.

Large enterprises are the most efficient with a mean of 87%, and small enterprises the least efficient (78%). The difference is statistically significant at the 1% level. From 1986 to 1990, a negative trend in technical efficiency is shown in Table 1. This may be due to the economic recession at the end of the data period (1989–1990).

Metal has the highest efficiency estimates (mean 87%, Table 1); clothing and paper manufacturing averaged 82%. Note that these two industries are typical light industries, where there is a large concentration of TVEs and a higher degree of competition was expected. However, our efficiency rankings cannot be used to judge relative efficiency across industries because different industries may achieve different levels of average technical efficiency due to their industrial structures. We shall not comment on the rankings of the share and the leasing contract systems (78 and 74%, respectively) for lack of observations (nine and

[11] In particular, z(SOE vs TVE) = 5.10, z(SOE vs COE) = 3.69; and z(COE vs TVE) = 2.52; where z is the standard normal test statistics; the critical value at the 1% level is 2.33.

eight observations, respectively). However, the difference between the contract responsibility system and the asset-management system (78% vs 84%, $z = 3.89$) is statistically significant at the 1% level.

As shown in Table 2, provinces from the coastal region (Guangdong, 95%; Zhejiang, 93%; Shanghai, 88%; and Fujian, 85%) were the most efficient, and the difference between Guangdong and Shanghai, for instance, is statistically significant at the 5% level ($z = 2.21$). Otherwise there is no clear relationship between technical efficiency and the degree of industrialization of the regions; e.g., central Shanxi came next at 84%, but coastal province Jiangsu averaged only 78%. Ownership, scale, management, and region seem to play a role in determining technical efficiency, but so far we have not controlled for other factors. Mean technical efficiency in each of the seven industries is at least 75%. The average SOE value seems high compared to the results reported in Wu (1993), where one of the main findings was that SOEs averaged only 50–60% of their potential output.[12] We actually carried out two sets of estimations: one with the full data set (1927 observations, not reported here) and the one reported here (1759 observations). Efficiency rankings from both estimations were identical except that exclusion of outliers increased average efficiency and the number of observations on the production frontier.

5.2. Limited Dependent Variable Model Estimation

Regression analysis is used to investigate the determinants of technical efficiency. Due to a relatively large number of fully efficient DEA estimates, the distribution of efficiency is truncated above from unity. Applying the OLS method would produce biased parameter estimates. One way to get around this problem is to employ a limited dependent-variable model; we chose a censored-regression model (Tobit model; Tobin, 1958).[13] A censored sample is a random sample with a certain range of observations distorted to a constant (Kmenta, 1990), in our case, unity from above.

The underlying assumption of the censored-regression (Tobit) model is that technical efficiency is normally distributed in terms of the population while the sample distribution of the DEA efficiency scores is a mixture of continuous and discrete distributions. This assumption may be more reasonable for enterprises in a planned economy than in a market economy where there is little room for inefficient enterprises in the long-run. Standard stochastic frontier production function models often assume skewed distributions of technical efficiency, e.g.,

[12] Wu's other main findings are that the technical efficiency of rural industrial firms, although low on average, has been increasing over time and that productivity growth of rural industrial enterprises, and their contribution to total GDP, have been much higher than those of the state sector.

[13] For a selective survey on statistical inference and nonparametric efficiency, see Grosskopf (1996). Some studies using regression analysis on DEA estimates are Nyman and Bricker (1989), Bjurek *et al.* (1992), McCarty and Yaisawarng (1993), and Brännlund *et al.* (1996).

half-normal, truncated normal, or exponential. Given a certain sample efficiency distribution such as ours, the standard stochastic frontier model may lead to the conclusion that the probability of a production unit being fully efficient is much higher than its being extremely inefficient (e.g., less than 20%). However, in a planned economy, especially in the state sector, enterprises survive almost regardless of their economic and technical performance. One does observe technically efficient enterprises in such an economy, but the majority may be average performers. Thus one could imagine that the efficiency distribution of state enterprises would be less skewed than the distribution in a market economy. In our sample, about 54% of the observations came from SOEs, 26% from COEs, and 20% from TVEs. So the sample is still generally representative of a planned economy, but according to our DEA estimates there are a relatively large number of fully efficient enterprises (36%). The Tobit model gives the parameter estimates of the original normal distribution of technical efficiency while taking account of the censored distribution of the DEA efficiency scores. We are particularly interested in the original normal distribution, because under this distribution the probability of a production unit being fully efficient will be about the same as it is for its being extremely inefficient.

Since we pooled the efficiency scores from all seven industries for the entire period, industry and time dummies were included in the regression analysis. There are also dummies for provinces, management systems, and size of enterprises. The ratio of total productive labor to total employment was used as a reverse measure of nonproductive labor, because sometimes the productive and nonproductive labor do not add up to the total number of employees at the end of the year. We thus chose to rely on the ratio of productive labor to the total number of employees. To investigate the contribution of nonproductive capital in the production process, the ratio of productive capital to the total capital was used as another explanatory variable.

Regression results are shown in Table 3.[14] Parameter estimates from the simple linear model and the Tobit model are basically the same, except that the Tobit model gives higher parameter estimates in absolute values.

In contrast with straight DEA estimates, the regression results show much larger gaps between SOEs and TVEs, and between sizes of enterprises, because other factors have now been controlled for. SOEs were the least efficient and TVEs the most efficient, with COEs in between.

Regression results in Table 3 shows that size has positive effects; large scale (0.20) almost compensated for the effect of SOE ownership (−0.23). These differences are all statistically significant at the 1% level. A Wald test also indicates that the difference between SOEs and COEs is statistically highly significant; this result is more reliable than the comparison between SOEs and

[14] Since we are mainly interested in inferences about the population of Chinese enterprises, marginal effects are not discussed.

TABLE 3

Determinants of Technical Efficiency E2 (VRS)

Independent variables (OBS: 1759)	OLS		Tobit		Other statistics
	Estimates	*T* values	Estimates	*T* values	
Intercept	0.8995	14.137	1.0918	11.291	Log-likelihood
Clothing	0.0838	4.542	0.1172	4.194	(OLS): 360.9
Paper	0.0608	3.304	0.0686	2.504	(Tobit): −666.3
Chemicals	−0.0029	−0.153	0.0056	0.199	
Cement	0.0615	3.573	0.0820	3.192	
Metal	0.1364	6.709	0.1920	6.184	R^2:
Electrical	−0.0129	−0.661	−0.0264	−0.91	0.16 (OLS)
Sichuan	−0.0316	−1.324	−0.0326	−0.936	
Guangdong	0.1285	3.71	0.2508	4.327	
Zhejiang	0.1195	2.536	0.2514	3.079	Estimated σ (Tobit):
Jiangsu	0.0160	0.709	0.0069	0.21	0.28 (43.7)
Anhui	0.0168	0.425	0.0182	0.308	
Hebei	0.0620	3.202	0.0941	3.281	
Liaoning	0.0434	1.622	0.0697	1.735	
Shanxi	0.0960	4.179	0.1336	3.899	Marginal effects
Gansu	−0.0033	−0.105	−0.0075	−0.162	(Tobit)
Heilongjiang	0.0200	0.685	0.0383	0.884	Conditional mean:
Shanghai	0.0863	2.77	0.1609	3.255	0.2997
Guangxi	0.0043	0.203	0.0022	0.072	
Fujian	0.0910	3.326	0.1295	3.142	Scale factor: 0.3715
Shangdong	−0.0757	−2.638	−0.1120	−2.66	Productive labor:
1987	−0.0103	−0.636	−0.0184	−0.754	0.0257 (0.743)
1988	−0.0183	−1.12	−0.0300	−1.218	
1989	−0.0199	−1.211	−0.0330	−1.337	Productive capital:
1990	−0.0347	−2.112	−0.0558	−2.264	−0.0997 (−26.205)
Share	−0.0639	−0.888	−0.1584	−1.55	
Responsibility	−0.0196	−1.453	−0.0322	−1.595	
Leasing contract	−0.0640	−0.877	−0.1214	−1.177	
Assets management	−0.0096	−0.52	−0.0160	−0.573	Wald test of
SOE	−0.1310	−7.611	−0.2290	−8.653	SOE−COE=0 (Tobit)
COE	−0.0950	−5.15	−0.1630	−5.772	χ^2: 90.62
Large	0.1433	8.496	0.2021	7.845	*P* value: 0.00000
Medium	0.0534	3.863	0.0604	2.978	
Productive labor	0.0541	0.989	0.0693	0.83	
Productive capital	−0.1653	−4.384	−0.2683	−4.654	

Note. Intercept stands for coal, Hubei, 1986, other systems, small scale, and TVEs. Except for productive labor and productive capital, all the variables are dummies.

TVEs, because SOEs and COEs use the same accounting system and their samples were jointly collected.

According to the Tobit model results under VRS (Table 3), given that other things are equal, SOEs are 23 percentage points less efficient than TVEs and 6.6 percentage points less efficient than COEs. Large enterprises are 14 percentage points more efficient than the medium ones and 20 percentage points more efficient than small ones. Differences among management systems are not significant statistically, and the magnitudes of those for which we had sufficient observations are not high either.

Guangdong, Zhejiang, Shanghai, Shanxi, and Fujian again are ranked high. Guangdong and Fujian are the provinces in which special economic zones were developed in the early period of the economic reform and large overseas investments were attracted. Zhengjiang is a typical well-developed coastal province even before the reform. Shanghai has always been China's industrial center, even maintaining relatively high production efficiency before the reform period.

The decline in technical efficiency over time (although not statistically significant), especially during 1989–1990, most certainly reflects business cycle conditions.

The explanatory variable related to nonproductive labor (the ratio of productive labor to total employees) has a positive sign in both tables, but is not statistically significant and its magnitude is also considerably smaller than that for capital. Nonproductive capital appears to be positively correlated with technical efficiency, and is statistically highly significant. A 1% increase in nonproductive capital brings up technical efficiency by 0.27 percentage points (Table 3). Although this result is not obvious prior to estimation, it is interpretable in that the higher the ratio of the nonproductive capital, the better the welfare conditions for the employees, and as a result, more-productive workers, technicians, and managers could be attracted to the enterprise. Besides, enterprises with large proportions of nonproductive capital are usually of strategic importance to the government and are often given privileges with regard to acquisition of high quality industrial (and nonindustrial) resources.[15] The gap between TVEs and SOEs is noteworthy, but one should be somewhat cautious in drawing conclusions, since the TVE data came from a different accounting system than the data for SOEs and COEs.

6. SUMMARY AND CONCLUSIONS

With respect to technical efficiency, relatively large TVEs surpassed SOEs by a large margin during the study period (1986–1990); urban COEs were less efficient than TVEs, but more efficient than SOEs. However, these results should be interpreted with caution, because there are other factors (such as the differ-

[15] Another possible interpretation is that enterprises with high technical efficiency and high profits retained more profit that could be directed to welfare-enhancing activities. These may in addition have had an efficiency-wage effect on labor. Note that if technical efficiency motivated more accumulation of nonproductive capital, the parameter estimate associated with nonproductive capital will suffer from simultaneity bias.

ences in product quality and in input and output pricing across ownership types) that were not accounted for in the study.[16]

The scale of production was also positively correlated with technical efficiency. Coastal provinces were preponderant among the most efficient. The proportion of nonproductive labor was not highly correlated with technical efficiency, but the proportion of nonproductive capital was positively correlated with technical efficiency at a high level of statistical significance and with considerable magnitude.

Some important explanatory variables in the regression analysis were not statistically significant, including the one related to nonproductive labor and those for types of management system. Our investigation on the impact of management reforms is thus inconclusive, partly because of data problems but mainly because of limitations of the methods used. Beyond that, comparative static and even dynamic studies of management reforms are required. To obtain more significant parameter estimates, the entire data-set for the 39 two-digit industries (covering 148 three-digit industries) could be utilized by forming a DEA frontier for each industry (three-digit or two-digit) and then by pooling the efficiency scores from all industries to perform a regression analysis as in this study. The difference in technical efficiency between SOEs and COEs is interesting. Given that larger size has no negative effect on technical efficiency, small scale COEs are still more efficient than small-scale SOEs because small SOEs are larger than small COEs, on average. Further analysis of the impact of management reforms on small SOEs should be conducted.

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[16] It may be that part of the SOE–TVE difference is due to the fact that inefficient, loss-making, small-size TVEs exit, while SOEs with same characteristics do not.

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