Technical Efficiency and Governance: The Case of China*

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Abstract

Inefficient resource use by its enterprises may challenge the sustainability of China’s intense and prolonged growth. We investigate whether inefficiencies depend on ownership relying on a database duly representative of China’s mainland economy. Also, our stochastic frontier approach allows more flexibility to identify inefficiency’s sources. We find that, compared to matching private companies, inefficiency is systematically larger (smaller) at State Owned Enterprises (foreign owned Chinese enterprises). Furthermore, when foreign ownership comes to mainland China from the other territories of greater China (Hong Kong, Macau, Taiwan) it is slightly more conducive to lower inefficiency than when it comes from foreign countries.

I. Introduction

China has maintained an average growth rate of close to 10 percent over the last three decades. The rapid economic growth was primarily led by increases in factor inputs benefiting from a large pool of rural surplus labour and fast pace of investment growth in the post reform era from 1978 onwards. This pattern of economic growth was also facilitated by China's economic opening to the global economy, where the Chinese products were exported to the international markets via the participation in the East Asian production network. Profits generated from international markets were reinvested in the manufacturing sector, eventually making China the manufacturing centre of the world. This model had proven to be very successful until the eruption of the global financial crisis in September 2008. After the crisis, external demand has been diminishing. It is expected that external demand will remain weak for an extended period of time, as Western consumers will have to undergo a painful de-leveraging process; the financial institutions in crisis stricken nations will have to write off large bad loans; and the Western governments will have to experience large spending cuts in order to return their national indebtedness to a sustainable level.

Given external demand will likely remain weak for a lasting period of time, the sustainability of China's intense and prolonged growth has been questioned on the grounds of the large extent of inefficiency in the use of resources by Chinese enterprises. Looking ahead, while external demand is expected to remain weak, China's growth pattern is also facing increased demographic and economic constraints. First, the surplus labour is expected to run short in the near future. In 2008, it was surveyed that the Chinese surplus labour was at around 100 million.[1] Assuming an average migration rate of 18 to 20 million a year, this means that China's surplus labour is likely to run out in around 2015. That means China will run into a Lewis Turning Point (Lewis, 1953), a condition where surplus rural labour is running out and industrial wages start to rise at a fast pace. Rising labour costs will also drive down industrial profits, making labour intensive sectors less profitable and questioning their long-term survival. Second, China's factor markets are not yet fully market driven. To a large extent, Chinese enterprises – namely, those under government ownership – are subsidized by credit from the banking system (Ferri and Liu, 2010). Meanwhile, they have also been benefiting from subsidies in land, water, energy as well as from China's weak enforcement of environmental standards (Huang, 2010). With the deepening of China's economic reform, these factor prices will have to be increasingly determined by market forces. Without improvement in total factor productivity, it is likely that the current level of profits of the Chinese enterprises, especially of the state-owned companies, can no longer be sustained.

[1] China Ministry of Labor and Social Welfare (2008).

This paper investigates an issue that has not been discussed much in the literature, that is, whether inefficiency in China's industries depend on corporate governance and ownership. To address this, we rely on a unique database specifically constructed to reach a satisfactory representation of China's industries. This is a significant improvement compared with previous studies that rely on ad hoc surveys only. This database allows us to look at efficiency differences among state-owned enterprises, private-owned enterprises, and foreign joint venture companies across Chinese provinces. Furthermore, we use the stochastic frontier approach that allows more flexibility to identify the sources of inefficiency to conduct our analysis.

We find that, compared to private mainland China-owned companies of similar quality, inefficiency is systematically larger at the state owned enterprises, whereas the inefficiency is significantly smaller for Chinese enterprises featuring some form of foreign ownership. Furthermore, we also detect that there are important differences among the types of foreign participation in Chinese industries. Specifically, we show that the ownership from Hong Kong, Macau, and Taiwan proves to have systematically lower inefficiency than that from other economies. This then raises important implications for Chinese authorities as to how to shape future policies in terms of privatisation of the SOEs and modality of encouraging foreign direct investment.

This paper proceeds as follows: Section II provides a detailed survey of the literature on China's sources of economic growth, thus sets the stage to differentiate our contribution from previous works. Section III provides a detailed account of the data set used for this study and the sampling methodology to construct a representative sample of China's industrial sector. Sections IV and V, respectively, discuss our model specification and key economic results. Section VI concludes and draws the main policy implications for the future.

II. Literature Survey

Empirical analysis on China's technology efficiency and total factor productivity often suffered from the lack of good capital stock data. In one of the first studies in this field, Chow (1993) uses a Cobb-Douglas function with an exponential trend to investigate the forces behind of China's growth for the period between 1952 and 1980, most years of which were before China's economic opening and reform period. Using the data from China's planned economy based on five sectors, agriculture, industry, construction, transportation and commerce and assume an initial capital stock at 1550 to

1950 billion renminbi, he finds that there is no positive technological progress in the sample period studied. The study also confirms that there are enormous income losses during China's Great Leap Forward period (1958 to 1960) and Cultural Revolution (1966-76).

Chow and Li (2002) in a follow up study using a traditional Solow growth model find that China's TFP growth progressed by 2.6% per year over the period between 1952 to 1998. In the sample period 1978 to 1998, the estimated production function of 0.09352 exponential rate of growth was explained by a 0.051 increase in capital, a 0.012 increase in labour and a 0.0303 increase in TFP. Capital accumulation and increase in productivity account for China's economic growth in the post-reform period. The paper also confirms TFP growth for the period of 1952 to 1978 to be zero and to grow at an average exponential rate of about 0.03 from 1978 to 1998.

Using 19 sectors of industrial data and a translog function, Fujihara and Watanabe (2002) find that on average for the period of 1987 to 1992, TFP growth showed a negative sign; all industries grew at -0.34% per annum. Particularly, TFP in sectors such as mining, metal, coal and oil production, and transportation declined by 8.81, 5.61, 8.13, and 10.92%, respectively. In spite of this, positive TFP growth was observed in agriculture (3.1%), transportation equipment (3.37%), wood and furniture production (2.41%) and trade (1.15%). However, for the period between 1992 and 1997, TFP in all industries grew positively, by 2.33%, mainly led by industrial sectors such as textile, wood and furniture production, machinery and electrical appliances.

Islam and Dai (2005) apply a dual approach that allows independent price information to play a role in growth accounting to investigate the role of TFP in China's growth. They find that TFP growth for the entire period between 1978 and 2002 is at around 2.26% per annum. By breaking down the entire period into three sub periods, 1978 to 1984, 1984 to 1991, and 1991 to 2002, they find that TFP growth had slowed somewhat from 4.59% per annum during 1978-84 to 3.21% during 1991-2002. During 1984 to 1991, TFP registered a -0.6% growth per annum. The dual approach TFP growth rate estimates prove to be much lower than those of the primal approach because the former approach accounts for changes in quality or composition of inputs and the later approach did not. Both results are likely hold in broad terms. Although TFP growth has experienced some slowdown in recent years, it continues to be an important source of Chinese growth.

However, other authors have been less optimistic about China's productivity as a source of growth. Let us consider some of the contributors. Young (2000) discounts China's economic growth during the reform period by choosing among different official data sets and taking into account rises in labour participation and productivity. Young underlines statistical methods along with other systematic errors as a major contributor to the unprecedented high rate of growth of the Chinese economy. He attempts to estimate the actual real growth rate of output by making various adjustments. Due to insufficient data and other limitations, Young does not take the agricultural sector growth into account while discounting China's growth rates.

He points out that the deflator used by the NBS are mainly based on enterprise provided implicit output deflators, which could by systematically biased, as enterprises may lack the skills or incentive to undertake serious estimation of real output. Young finds that the implicit GDP deflators systematically understate price movements. Re-running the GDP figures using official price indices, he argues that aggregate and non-agricultural GDP should be lowered by 1.7 and 2.5 percentage points respectively. Inaccuracy and inconsistencies of the survey data and the census data also contribute to the overestimation of Chinese growth. Consequently, Young made adjustments to account for the erroneous human capital contributions to economic growth. In terms of capital stock and investment, he took similar steps as the GDP deflator method.

Using his deflator discount methods, Young finds that China's GDP per capita growth is revised to 6.1% (compared with 7.8%) during the reform years. Rising participation rates further reduces output per worker to 5.2%. By removing agricultural sector, it raises the GDP growth rate but it is offset by the growth of employment, lowering the growth of productivity to 3.6%. Finally, population ageing and improving educational attainment of the workforce brings the number to 2.6%. Young thus concludes that Chinese growth record during the reforming years is far from impressive.

On his part, earlier on Krugman (1994) explained the factors behind the rapid growth of the Asian economies, stating that the rapid growth rates elevated by increased input – expansion of employment, increases in education levels, and massive investment in physical capital – are unsustainable models. He used the former Soviet Union as a historical illustration. Making the point of differentiating input growth and growth in efficiency, Krugman argued that an economy that grows only in input will hit diminishing returns eventually. On the other hand, growth in efficiency (such as by technological advances as seen in the US), can be sustained and more or less unlimited. Turning to the NIEs of Asia, Krugman attributed most of the growth to the high growth in inputs like labour and capital. Taking Singapore as an example, between 1966 and 1990, employed population rose from 27% to 51%, while educational standards of the work force also were upgraded substantially. Investment also increased at an extraordinary pace during the period. He did point out, however, that Japan's growth in the 1960s and 1970s had been driven by both input and efficiency growth. But the efficiency rate is still below that of the US. Overall, Krugman suggested that technological diffusion – thus closing the gap of efficiency between advanced and emerging economies – isn't seen across border. Diminishing returns will start to kick in eventually, and growth in East Asia would moderate.

In turn, Dollar and Wei (2007) find widespread inefficiency in the use of capital and argue that if China succeeded in allocating its capital more efficiently, it could reduce its capital stock by 8 percent without sacrificing its economic growth. Bai, Lu, and Tao (2006) use the same database but a difference sample period ranging from 1998 to 2003 to investigate whether privatization or ownership change brings about economic and social efficiency. They find that ownership reform helps increase economic efficiency in those reformed firms. Specifically, Bai et al. attribute the reduction of agency costs, measured by the ratio of administrative costs, to the improvement of economic efficiency.

III. Data and sampling methodology[2]

Our data sample is obtained from a large database of the National Bureau of Statistics (NBS) that contains more than 280,000 industrial firms with annual sales of more than 500 million yuan. The NBS started to conduct census on this category of firms in 1998 with an initial firm number of 160,000 and gradually increasing to the current number. It is estimated that the firms included in this census represent about 80 percent of all industrial value-added activities among the total Chinese firms. For the yearly data we use, it contains about 69 financial indicators including, in particular, asset, liability, revenue of major activities, profits, value-added taxes, intermediate industrial input, cash flows, debt payments, and other indicators that allow us to carry out our analysis. Given there are some major discrepancies in certain financial indicators for data before 2000, in order to avoid such problems we start our data sample – ending in 2005 – from 2001. In addition, given it is impossible to obtain the whole database, we use a sampling methodology to construct a representative sample to reflect the NBS database.

Our sample was constructed by following two methodological rules. First, we extracted a random component designed to make a closed sample of Chinese enterprises. Second, because of large

2 This section draws from Ferri and Liu (2010).

number of drop outs of firms resulting from enterprises' birth and disappearance and/or to M&A activity and also to statistical discontinuities by China's National Bureau of Statistics, we superimposed to the closed sample component an open sample component. The latter component was randomly extracted from the universe.

The closed sample component was built according to the following considerations and methodology. In order to respect the bounds represented by the necessity to minimize costs and time, we determined the dimension of the sample (n) on the basis of the financial resources of the research/project and of the tolerable error, with a confidence level of 95%. We obtained a sample composed of 5,497 units based on the following formula:

$$n = \frac{Z^2_{\alpha/2}}{\left\{\left[(N-1)\theta^2 / P(1-P)\right] + Z^2_{\alpha/2}\right\}}$$

where n is the number selected for the sample size; Z is a standardized variable with mean 0 and variance 1; 1 - α is the degree of trust; N is the total number of units in the population to be sampled; θ is the allowed error size; P is the unknown proportion (which we set at 0.5).

To select the statistical units, we used a stratified random sampling method that provides greater precision and gives a better representation – of the original population – than a simple random sample of the same size. Moreover, providing greater precision, a stratified sample generally requires a smaller sample size, although this advantage is achieved at the cost of more administrative and operative efforts vis-à-vis the simple random sample.

In this perspective, with reference to the 2001 data, we divided the population of 211,181 firms (N) into 14,250 strata, deriving from the combination of four stratification variables that we considered the most relevant for the aims of the research; the stratification variables are:

- Province (30 sub-strata);
- Ownerhip (5 sub-strata: SOE; Cooperatives; Private Enterprises; Enterprises with Capital from Hong Kong and/or Macau and/or Taiwan; Foreign Owned Enterprises);
- SITC Sectors (19 sub-strata);
- Size of employment (5 sub-strata: 0-99 Employees; 100-299 Employees; 300-499 Employees; 500-999 Employees; > 1000 Employees).

On the basis of these stratification variables, starting from the distribution of the population of the firms (N), we defined the sample design following the technique of the proportional to size allocation. According to this method, the frequencies of the statistical units in each stratum of the stratified sample are proportional to those of the stratified population. In other words, with proportional stratification, the sample size of each stratum is proportional to the population size of the stratum and this means that each stratum has the same sampling fraction. This technique is based on the assumption that selection costs and variances are about equal across strata.[3]

To overtake the practical problem of the proportional selection from the population strata containing a low number of firms, we introduced a cut-off value that excludes from the selection all the cells with a frequency less than 14 units (that means the 0.008% of the population). The allocation of the 5,497 units of the sample among the strata is shown in Tables 1A and 2A in Appendix[4] The final sample (n) is formed by summing the random samples obtained from each stratum. Finally, since our research question regards the specificity of SOEs, we oversampled SOEs within each stratum.

The open sample component was then added to the observations extracted to form the closed sample. The superimposition of this additional component should also help minimize our sampling error.

The composition of the total sample by ownership class is described in Table 3A in Appendix. The second column reports the percentage shares in the a priori base closed sample while the third column shows the shares in the a priori total sample, i.e. after oversampling SOEs and after superimposing the open sample component. Columns from 4 to 8 report the actual shares in the ex post total sample. It is possible to notice that the ex post shares are reasonably close to the a priori ones. Only the SOEs are slightly under represented. Finally, the size of the sample is on average near that of the a priori desired number, however observations in year 2004 (2005) are somewhat undersampled (oversampled).

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[3] The advantages of proportionate stratification are the following: i) it provides equal or better precision than a simple random sample of the same size; ii) the gains in precision are greatest when values within strata are homogeneous; iii) the gains in precision accrue to all survey measures.

[4] The number of observations within each stratum N_h is known, and $N = N_1 + N_2 + N_3 + ... + N_{H-1} + N_H$.

IV. Model specification and empirical implementation

We consider a standard growth model with externalities (Romer, 1986 and Lucas, 1988). The output of a firm *i* at time *t*, Y_{it}, is determined by the levels of labour input and private capital, L_{it} and K_{it}. The level of technology or multi-factor productivity is given by the parameter A. The production function is expressed as follows:

$$Y_{it} = F\left(A_{it}, L_{it}, K_{it}\right) \tag{1}$$

The parameter A_{it} describes the Hicks-neutral productivity and is assumed to be affected by a set of variables external to individual firms, Z_{it}. Equation (1) may be rewritten as:

$$Y_{it} = A_{it}\left(Z_{it}\right)F\left(L_{it}, K_{it}\right) \tag{2}$$

Equation (2) indicates that the level of total factor productivity, $TFP_{it} = A_{it}\left(Z_{it}\right)$ depends on the (embodied and disembodied) technological progress A_{it} and on external covariates, i.e., a set of growth determinants, Z_{it}. In our interest with respect to the specification of Z_{it}, we consider the contribution of type of capital ownership, R&D expenditure, the cost for staff training, and an indicator of financial costs.

Following the efficient frontier literature (see, e.g., Färe *et al*., 1994), the TFP_{it} component can be further decomposed into the level of technology, A_{it}, an efficiency measure $0 \prec \tau_{it} \prec 1$,[5] which depends on the covariates, Z_{it},, and a measurement error w_{it}, which captures the stochastic nature of the frontier:

$$TFP_{it} = A_{it}\left(Z_{it}\right)\tau_{it} w_{it} \tag{3}$$

By writing equation (2) in translog form, we thus have:

$$y_{it} = \beta_0 + \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 \frac{1}{2} k_{it}^2 + \beta_4 \frac{1}{2} l_{it}^2 + \beta_5 l_{ik} k_{ik} + \beta_6 t - u_{it} + v_{it} \tag{4}$$

where lower case letters indicate variables in natural logs [i.e., $y_{it} = \ln\left(Y_{it}\right)$], whereas $u_{it} = -\ln\left(\tau_{it}\right)$

[5] When $\tau_{it} = 1$ there is full efficiency, in this case the firm i produces on the efficient frontier.

is a non-negative random variable, and $v_{it} = \ln(w_{it})$. Neutral technology is captured by a time trend, t. Expected inefficiency is specified as:

$$E(u_{it}) = \mathbf{z}_{it}\delta, \tag{5}$$

where u_{it} are assumed to be independently but not identically distributed, z_{it} is the (1x K) vector of covariates which influence TFP via inefficiency, and δ is the (K x 1) vector of coefficients to be estimated.

We thus model the inefficiency of Chinese firms as a function of:

$$\begin{aligned} u_{it} = {} & \delta_0 + \delta_1 R\&D_{it} + \delta_2 staffeduco_{it} + \delta_3 SOE_{it} + \delta_4 hkmtw_{it} + \delta_5 fork_{it} + \\ & + \delta_6 \operatorname{int} rate_{it} + \delta_7 ROA_{it} + \delta_8 \dim en_{it} + \delta_9 gdpprSOE_{it} + \\ & + \delta_{10} gdpprhkmtw_{it} + \delta_{11} gdpprfork_{it} + \varepsilon_{it} \end{aligned} \tag{6}$$

where, *R&D* represents the R&D investments of the i^{th} firm at time *t*; *staffeduco* indicates training expenditure; *SOE*, *hkmtw*, and *fork* are dummies taking the value 1, respectively for Chinese State Owned Enterprises (SOEs), companies owned from Hong-Kong-Macau-Taiwan, and enterprises with foreign ownership; *intrate* is a proxy to measure the cost of debt and it is equal to the ratio of total financial costs and total debt for the firm *i* at the end of year *t*; *ROA* - returns on assets - is a measure of profitability and it is given by the ratio of total profits to total assets; *dimen* is a dummy equal to 1 if the average number of employees is bigger than 50 and zero otherwise; *gdpprSOE*, *gdpprhkmtw*, *gdpprfork*, are interaction terms of ownership and GDP per capita of the province. The hypothesis here is that the firms operating in richer provinces (higher per capita income) performe better.[6] Finally, ε_{it} is a white noise.

In order to estimate the parameters of the production function (4) together with the parameters in equation (6), we use a single-stage Maximum Likelihood procedure proposed by Kumbhakar (1991) and Reifschneider and Stevenson (1991), but in the modified form suggested by Battese and Coelli (1995) for panel data with time-variant technical efficiency.[7] As also discussed in

[6] In China there are 17 provinces: Xizang, Qinghai, Xinjiang, Shaanxi, Gansu, Heilongjiang, Guangxi, Guizhou, Jilin, Shanxi, Beijing City, Yunnan, Jiangxi, Tianjin, Liaoning, Hunan and Nei Mongol.

[7] MLE is used to take into consideration the asymmetric distribution of the inefficiency term (Aigner et al. 1977). Greene (1990) argues that the only distribution which provides a maximum likelihood estimator with all desirable properties is the Gamma distribution. However, following van den Broeck et al. (1994), the truncated distribution function, which better distinguishes between statistical noise and inefficiency terms, is preferred.

Kumbhakar and Lovell 2000, this stochastic approach allows the decomposition of output growth into its sources, that is, input accumulation and TFP growth. Furthermore, TFP growth can be further decomposed into technological change (or technical progress), efficiency change (i.e., technological catch-up), and scale efficiency change.

We further analyze the distributions of the productivity components based on a nonparametric kernel density estimator. Following Kumar and Russell (2002), the standard normal kernel

$$K(\psi) = \frac{1}{\sqrt{2\pi}} \exp - \frac{\psi^2}{2} \tag{7}$$

is used to derive the test statistic for the comparison of two unknown densities $f(x)$ and $g(x)$ which represent two distinct distributions. The null hypothesis $H_0 : f(x) = g(x)$ is tested against the alternative $H_1 : f(x) \neq g(x)$.[8]

The use of the test in equation (7) allows the assessment of the relevance of the output growth components of our sample of firms. Furthermore, after constructing the counterfactual growth distributions, we are able to identify the main sources of firm growth.

V. Results

V.1. Production Function Results

The parameters of the model defined by (4) and (6) are estimated simultaneously using a maximum likelihood estimator with Matlab. The results of this estimation are displayed in table 1, where we report the coefficients of the translog form.

From the estimates of technological parameters, we can retrieve information on the most appropriate specification of the production function. By using a Likelihood-Ratio (LR) test we reject the null that the production function is the Cobb-Douglas in favour of the translog form.[9]

[8] See for details Li (1996), Fan and Ullah (1999) and the parametric application in Mastromarco (2009).

[9] The LR is used to test the null hyphotesis of a Cobb-Douglas functional form, i.e., $H_0 : \{\beta_3 = \beta_4 = \beta_5 = 0\}$. The Cobb-Douglas is to be rejected: the test is equal to 710, while the critical value of the χ_3^2 (at the 1% s.l.) is equal to 10.501.

Table 1. Estimation Results

Parameter	Estimate	Std.Err.	t-Ratio
β_0	7.1735	0.3521	20.3717
β_1	-1.4915	0.0588	-25.3738
β_2	2.3501	0.1130	20.7973
β_3	0.3216	0.0077	41.7762
β_4	0.0610	0.0346	1.7619
β_5	-0.2187	0.0153	-14.2728
β_6	0.0800	0.0158	5.0734
δ_0	2.3457	0.1385	16.9328
δ_1	-0.8321	0.1308	-6.3594
δ_2	-0.3288	0.2087	-1.5758
δ_3	1.0038	0.1307	7.6814
δ_4	-0.6719	0.1583	-4.2433
δ_5	-0.6244	0.1037	-6.0210
δ_6	0.4776	0.1590	3.0033
δ_7	-3.8867	0.1858	-20.9199
δ_8	0.2198	0.0963	2.2832
δ_9	-0.0001	0.0000	-8.6133
δ_{10}	0.0000	0.0000	3.3870
δ_{11}	0.0000	0.0000	2.1310
σ_u	0.4034	0.0714	5.6502
σ_v	0.7207	0.0400	18.0401

Number of observations: 1583, log-likelihood: -1925.5. The estimates $\beta_{0,...,5}$ are the parameters of the translog production function (equation 4), β_6 is the coefficient of the time trend. The estimates $\delta_{0,...,11}$ are the parameters of the inefficiency model (equation 6), σ_u the estimate of the standard deviation of the efficiency, and σ_v is the estimate of the standard deviation of the statistical noise.

The coefficients of the translog production function cannot be directly interpreted economically, therefore in Table 2 we report the estimated values of the output elasticities calculated at the average value for each input. The results displayed are based on variable means for the whole panel in the observation period 2001-2005. As expected, all elasticities are positive and significant: output is elastic especially with respect to labour (about 0.70), while the output elasticity with respect to capital is much lower (around 0.29).[10]

Table 2. Output Elasticities

	Capital	Labour
Elasticity	0.29***	0.70***
Standard Error	0.02	0.04

***: significant at 1 per cent level;

**: significant at 5 per cent level;

*: significant at 10 per cent level.

Table 3. Returns to Scale

$\sum \beta_j$	Standard Error
0.99***	0.033
$H_0 : \sum_j \beta_j = 1$	

***: H_0 rejected at the 1 per cent level;

**: H_0 rejected at the 5 per cent level;

*: H_0 rejected at the 10 per cent level.

[10] The high labour elasticity is not surprising and confirms the evidence of other studies on different countries.

To investigate the technology embodied in the production function of firms, we conduct tests on the presence of linear homogeneity. The null hypothesis of the test is to see whether the sum of the estimated elasticity is not statistically different from one. If we reject the null hypothesis, then we can infer that the technology presents increasing (decreasing) returns to scale when the sum of elasticity is above (below) unity. Table 3 shows that the hypothesis of constant returns to scale can be rejected and Chinese firms exhibit decreasing returns to scale.

V.2.1. TFP and Efficiency

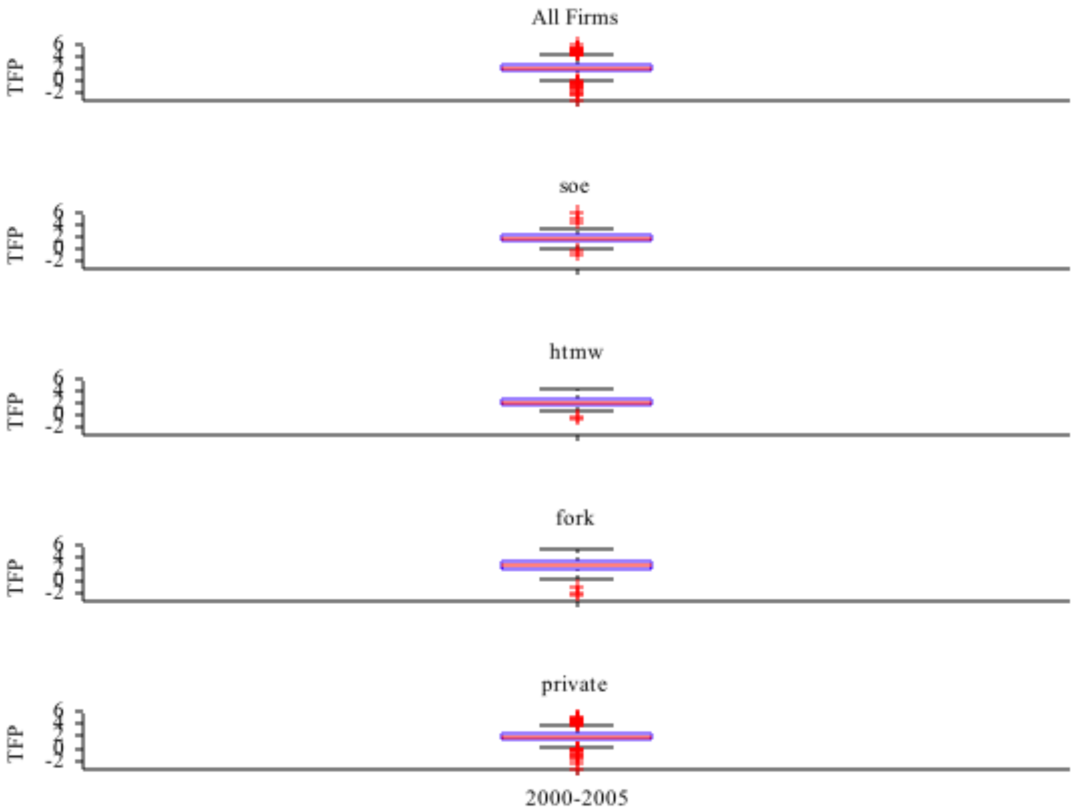
Before exploring the determinants of inefficiency and the TFP components (sections V.2.1 and V.3), it might be interesting to investigate how total factor productivity and efficiency differ across Chinese enterprises according to the ownership of each firm. For this purpose, in Figure 1 we have approximated the inefficiency distributions for the four ownership types: Chinese State Owned Enterprises (*SOE*), companies owned from Hong-Kong-Macau-Taiwan (*hkmtw*), enterprises with foreign ownership (*fork*) and privately owned firms (*private*).

The results show some differences in efficiency more than TFP across different ownership.

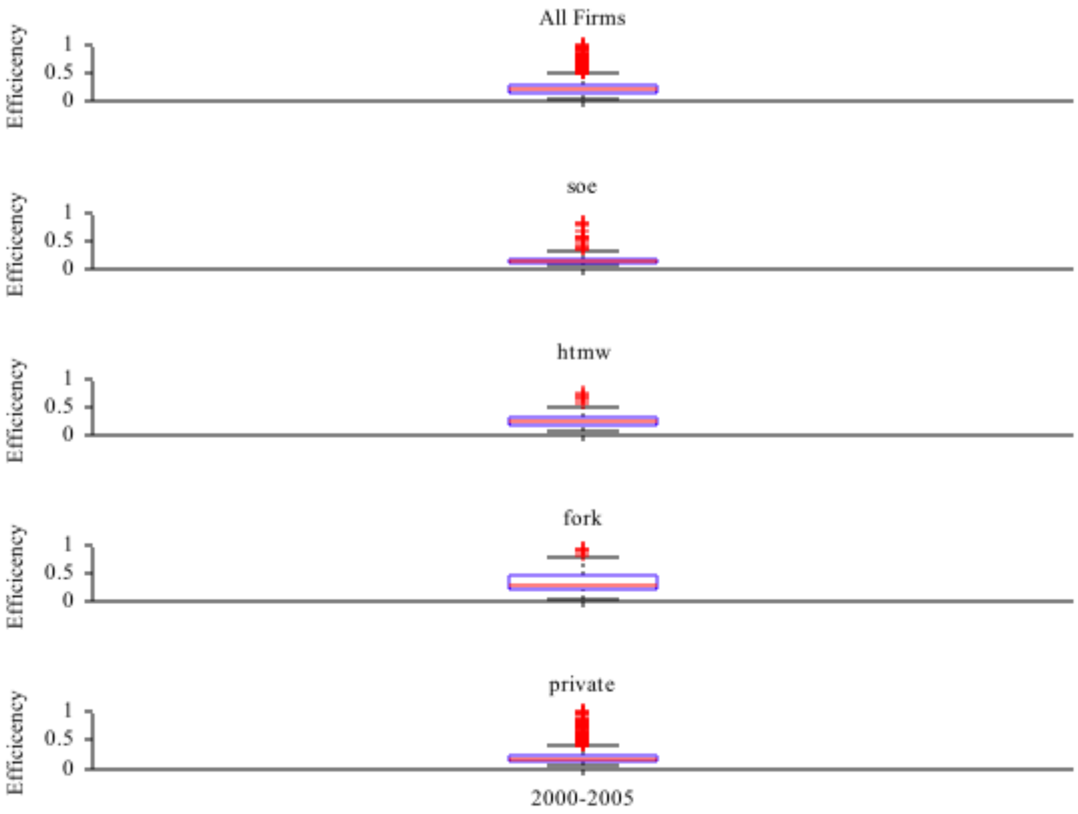
The dispersion of total factor productivity across different ownership, shows that there are not notable differences among Chinese firms during the observation period 2000-2005 (Figure 1; Panel a). Differently, the efficiency distributions seem to be more widely dispersed for foreign ownership and Chinese State Owned enterprises, meaning that the distance between efficient and inefficient firms is greater in these two groups (Figure 1; Panel b).

Figure 1: Chinese Enterprises (2000-2005): Total Factor Productivity and Efficiency distributions by Ownership

Panel a.



Panel b.



V.2.2 Efficiency results

In this section, we investigate the statistical relevance of inefficiency and we analyze the determinants of inefficiency, that is, the factors that have an impact on firms' TFP.

The first issue is thus the testing of the statistical (and economic) relevance of firms' inefficiency. The stochastic approach allows us to explicitly test for the presence of technical inefficiency in a specific production process. We test the null of the joint significance of the coefficients in equation (6), that is, $\left(H_0 : \gamma = \delta_0 = ... = \delta_{11} = 0\right)$. The test is based on the variance parameters

$$\gamma = \frac{\sigma_u^2}{\bar{\sigma}^2}, \qquad \bar{\sigma}^2 = \sigma_u^2 + \sigma_v^2 \tag{8}$$

which are derived from equations (4) and (6). These parameters can be used to perform a diagnostic likelihood-ratio test.[11] The LR test statistic is approximately distributed following a mixed chi-square distribution. We find that the null hypothesis is decisively rejected at the 1 per cent level of

[11] Coelli et al. (1998) point out that if $\gamma = 0$, the deviations from the frontier are entirely due to noise.

significance.[12] That is, these results allow us to reject the null hypothesis of <u>no</u> inefficiency at the 1 significance level.

We are thus able to investigate the factors that exert an impact on firms' efficiency, and hence, on TFP. The analysis is based on equation (6), whose estimates are reported in Table 1. Our findings are as follows:

- Technological investment *R&D* has negative sign and is statistically significant, indicating that its impact on efficiency is positive (δ_1 table 1). Therefore, we find that firms with high levels of internal innovative activities perform well because of the benefits they get in terms of technical efficiency. While this finding supports the hypothesis that the ability to innovate is a crucial dimension of firm performance (see, Griliches 1979), it shows that the channel through which R&D efforts have an impact on production is by enhancing efficiency.
- With regards to the results of human capital variable, *staffeduco*, we see that the coefficient (δ_2 table 1) is statistically significant and has the right sign, suggesting that the expenditure in labour training increases efficiency. This outcome might be determined by the measure of human capital used in the estimation, which is based on the staff education costs, thus, is a proxy of specific human capital (Becker, 1975). We find that the channel through which training positively affects firm output is through a labour enhancing efficiency effect (Benhabib and Spiegel 1994, Tallman and Wang 1994).
- The result for *intrate* (δ_6 table 1) confirms our expectations: Companies with higher costs of debt are less efficient.
- The coefficient on *ROA* (δ_7 table 1) has negative sign, revealing that firms with higher profitability are significantly more efficient.

Among the factors affecting efficiency, the model (6) incorporates the types of firms ownership: *SOE*, *hkmtw* and *fork*. The reference group contains the privately owned firms. The inclusion of these variables allows us to test the effect of different ownership on Chinese firms' performance. In deriving equation (6), we assume that the channels through which ownership affects private output act via efficiency. The empirical results support this choice. The coefficients of *hkmtw* and *fork* have a statistically significant negative sign (δ_4 and δ_5 table 1), suggesting that foreign capital participation has a positive impact on firms efficiency. On the other hand, the coefficient on *SOE* (δ_3 table 1) has a positive sign and is statistically significant, suggesting that Chinese State owned

[12] Test statistic LR=415.17, with a critical value of 24.049 for 11 degrees of freedom (for the critical values see Kodde and Palm 1986).

enterprises (SOEs) are significantly less efficient.

Moreover we argue that firms operating in richer province perform better, therefore we include the interaction terms of ownership and GDP pro capita of the province in equation (6). We find that the coefficient on *gdpprSOE,* (δ_9 table 1) has a negative sign and it is statistically significant, suggesting that state owned firms operating in richer province are significantly more efficient. The coefficients on *gdpprhkmtw* and *gdpprfork*, (δ_{10} and δ_{11} table 1) are significant with positive sing, although very low (equal to zero). Indeed, they demonstrate that the effect of foreign capital on efficiency is almost constant and does not depend on the level of GDP pro capita in the province.

V.3. Growth decomposition results

To understand the relative importance of the different sources contributing to firms output, we look at the different distributions in the output and productivity growth. As explained by Quah (1996, 1997) and Kumar and Russell (2002), this approach includes all the distribution moments and thus is to be preferred to the standard regression analysis which considers the conditional mean and the variance.

To test for the changes in the growth distributions among different firms in the period under consideration, we use a non parametric test on the closeness between two distributions based on a kernel nonparametric estimator (Li 1996, Fan and Ullah 1999) and adapted to stochastic estimators by Mastromarco (see Aiello, Mastromarco and Zago, 2010).

Specifically, using kernel smoothing methods we estimate non-parametrically the density functions corresponding to output growth distributions determined by just all of the growth components except one (input accumulation, TFP growth, technological change, scale effects and efficiency changes). Once densities are estimated, the Li (1996) test enables us to ascertain whether the differences between actual growth distribution and counterfactual distributions are statistically significant. The test is based on measuring the distance between two densities through the mean integrated square error (see Appendix in Mastromarco, 2010 and Aiello, Mastromarco and Zago, 2010). Kumar and Russell (2002) adopt non-parametric methods and calculate the growth decomposition as an identity. We employ stochastic frontier and the parametric method permits to disentangle inefficiency from random error. Therefore, it is necessary to adapt the Li (1996) and Kumar and Russell (2002) decomposition to the case of stochastic frontier estimation. This implies we must control for the issue of random error in the growth decomposition (where the true components are replaced by the estimated ones plus error). To do this, we follow an ad hoc method based on the computation of the growth rate from SFA estimates and subtract the noise of the estimation. The Kumar and Russell (2002) identities decompose the growth of labour productivity in the two periods into changes in efficiency, technology changes and changes in the capital–labour ratio. Our identities decompose output growth into input accumulation and TFP growth. TFP growth is further decomposed into efficiency, scale effects and technological changes plus random error. Moreover, while Kumar and Russell (2002) estimate y = f (x)−u, where y is output, f (x) is the production technology and u is inefficiency, we instead estimate y = f (x) − u + v, thus distinguishing between u and v, the estimated random noise.

This approach enables us to investigate the decomposition of output growth in 1241 Chinese manufacturing firms for the period 2001-2005 and identify the main sources of firm growth provided one knows the counterfactual output distribution.

The output growth rate $\left(\frac{\dot{Y}}{Y}\right)$ is decomposed into the contribution due to weighted input growth $\left(\frac{\dot{X}}{X}\right)$, where X represents the weighted sum of the inputs k and l) and TFP growth, $\left(\frac{T\dot{F}P}{TFP}\right)$. This is done by comparing the kernel distribution at the beginning and at the end of the period under investigation, i.e., 2002 versus 2005.

Because the number of observations is low, we do not rely on the asymptotic distribution of the test statistic (Kumar and Russell 2002), but perform a bootstrap approximation of the distribution. 2000 realizations of the test statistic are generated under the null hypothesis that $f(x) = g(x)$ (sample size: 1200).[13]

First, we perform an analysis of the importance of TFP by testing the null hypothesis

$$H_0 : f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{X}}{X}\right)$$

[13] Since the asymptotic distribution of the test statistic is standard normal, one expects that with increasing sample size, the difference between simulation results and standard normal distribution will become smaller. A small simulation study helps to assess the extent of the small-sample-bias problem. 2000 replications of two standard normally distributed random variables are generated (sample sizes: 50, 100, 250, 500, 1200)(see Mastromarco 2010).

We thus test the null that the output growth distribution $f\left(\frac{\dot{Y}}{Y}\right)$ can only be explained by the input accumulation growth, i.e., $g\left(\frac{\dot{X}}{X}\right)$. If the null hypothesis is rejected, then one can conclude that the TFP variations contribute to significantly explain the variations in the output growth distribution.

The test results are reported in Table 4, which shows that the null can be rejected: Indeed, we obtain a value of around 1.33, where the critical value is 1.06 at the 5% significance level. Therefore, we can infer that output growth for our sample of manufacturing firms is significantly affected by the TFP growth.

Table 4. Test Results

H_0	T	%10	%5	%1
$f\left(\frac{\dot{Y}}{Y}\right)=g\left(\frac{\dot{X}}{X}\right)$	1.33	0.67	1.06	2.03
$f\left(\frac{\dot{Y}}{Y}\right)=g\left(\frac{T\dot{F}P}{TFP}\right)$	0.83	0.67	1.06	2.03
$f\left(\frac{\dot{Y}}{Y}\right)=g\left(\frac{\dot{X}}{X}+\left(\frac{T\dot{F}P}{TFP}-\frac{\dot{A}}{A}\right)\right)$	18.46	0.67	1.06	2.03
$f\left(\frac{\dot{Y}}{Y}\right)=g\left(\frac{\dot{X}}{X}+\left(\frac{T\dot{F}P}{TFP}-(\varepsilon-1)\left(\frac{\varepsilon_L}{\varepsilon}\frac{\dot{L}}{L}+\frac{\varepsilon_K}{\varepsilon}\frac{\dot{K}}{K}\right)\right)\right)$	0.04	0.67	1.06	2.03
$f\left(\frac{\dot{Y}}{Y}\right)=g\left(\frac{\dot{X}}{X}+\left(\frac{T\dot{F}P}{TFP}-\dot{u}\right)\right)$	0.11	0.67	1.06	2.03

Notes:

The critical values are based on the simulation results, $N=1200$.

Second, in order to assess the contribution of input growth, we test the null hypothesis that the output growth distribution $f\left(\frac{\dot{Y}}{Y}\right)$ is equal to the TFP growth distribution, i.e., $g\left(\frac{T\dot{F}P}{TFP}\right)$:

$$H_0: f\left(\frac{\dot{Y}}{Y}\right)=g\left(\frac{T\dot{F}P}{TFP}\right)$$

If the null is rejected, then it is possible to conclude that input accumulation can significantly explain the changes in the output growth distribution. The results of the test show that input growth is not important: we cannot reject the null since the test is around 0.83 against a critical value of 1.06 for a statistical significance level at 5% .

Furthermore, the TFP growth $\left(\frac{T\dot{F}P}{TFP}\right)$ is decomposed into technical change $\left(\frac{\dot{A}}{A}\right)$, scale effects, and the contribution of efficiency (or catch-up effect, $\dot{u}$).[14]

If TFP growth plays an important role, which is indicated by the evidence emerging from our sample of manufacturing firms, the identification of the precise sources of this contribution is a relevant issue to be addressed. The importance of technical change, scale effects and efficiency in explaining the variations in the TFP growth distribution is determined by testing whether the output growth distribution is equal to the distribution considering input accumulation growth and TFP growth determined by just two (out of three) of these components. More formally, the following three hypotheses help to understand the contribution of each component:

$$H_0 : f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{X}}{X} + \left(\frac{T\dot{F}P}{TFP} - \frac{\dot{A}}{A}\right)\right); \text{ (Technological Change)}$$

$$H_0 : f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{X}}{X} + \left(\frac{T\dot{F}P}{TFP} - (\varepsilon - 1)\left(\frac{\varepsilon_L}{\varepsilon}\frac{\dot{L}}{L} + \frac{\varepsilon_K}{\varepsilon}\frac{\dot{K}}{K}\right)\right)\right); \text{ (Scale Effects)}$$

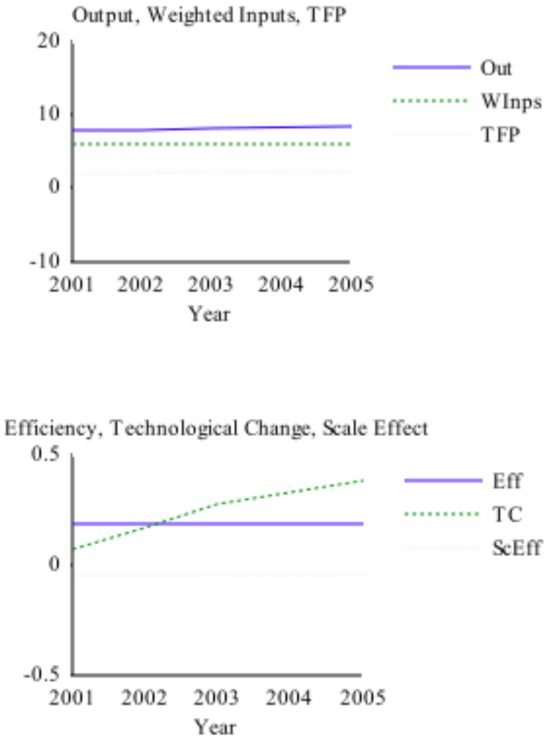
$$H_0 : f\left(\frac{\dot{Y}}{Y}\right) = g\left(\frac{\dot{X}}{X} + \left(\frac{T\dot{F}P}{TFP} - \dot{u}\right)\right); \text{ (Efficiency)}$$

where ε_K and ε_L are the output elasticity with respect to physical capital and labour respectively and $\varepsilon_K + \varepsilon_L = \varepsilon$.

As the results show, only the third null hypothesis can clearly be rejected (a test value of 18.46, against the usual 1.06 critical value for a 5% statistically significance level), meaning that only the change in technology has a significant role in explaining the TFP growth (Table 4).

[14] TFP contains the measurement error.

Figure 2. Output Decomposition

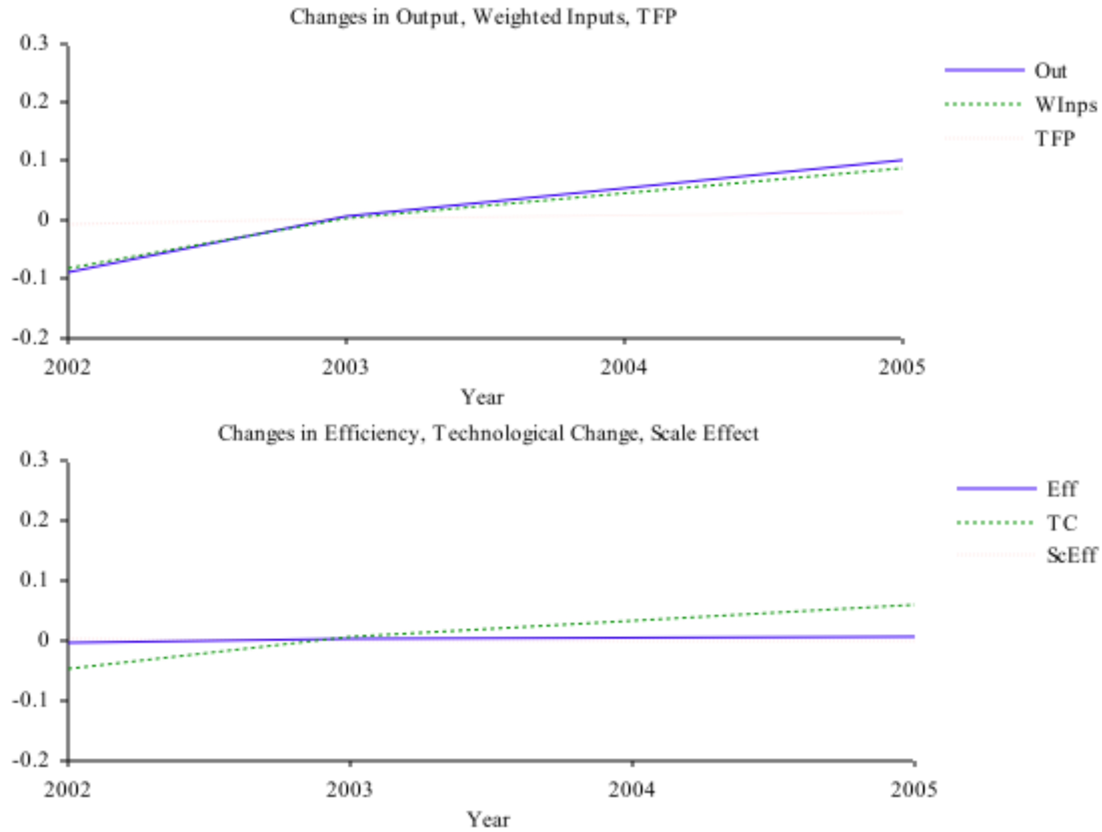


In sum, the tests presented in this section, based on a comparison of empirical distributions smoothed via a kernel estimator, show that TFP growth is useful in explaining the output growth distribution for the sample of Chinese manufacturing firms considered in the period 2001-2005. Whereas input accumulation seems do not play a significant role. Moreover, among the components of the TFP growth, the change in technology is the most significant for the TFP growth. We can therefore imply that the technological change significantly influences Chinese firms' output growth.

Turning to discuss the distribution of the output components, we find that the TFP is important in explaining the performances of Chinese manufacturing firms (Figure 2). Moreover, we find that efficiency has been the most important TFP element up to 2002. After 2002, technological change prevails (second graph in Figure 2). In terms of growth rates, we observe that output growth depends on input accumulation until 2003 and after 2003, it depends on TFP (Figure 3).

Another key result emerging from our analysis is that the efficiency change, i.e., the technological catch-up, is the most important component of TFP growth in 2001 and 2002 (second graph in Figure); during the following years, the technological change becomes the leading TFP component.[15]

Figure 3. Output Growth Decomposition



VI. Robustness Checks

We check to see if our results are robust to a non parametric estimation of the model. One of the main results of this study is that state owned enterprises are less efficient than Chinese enterprises with foreign participation. The other important finding is that the types of foreign participation affects the efficiency: the ownership from Hong Kong, Macau, and Taiwan proves systematically to have lower inefficiency than that from other economies.

The robustness check stems from our awareness of the problems linked to the adoption of a parametric approach. Thus, in order to validate our results, we implement the non-parametric Data Envelopment Analysis (DEA) to estimate productive efficiency. An advantage of Data Envelopment Analysis (DEA), popularized by Charnes et al. (1978), over SFA is that it does not

[15] The estimated measurement error is the difference between TFP growth on one hand and the sum of efficiency growth, technological changes and scale effects on the other.

make any assumption, either about specific parametric functional form for the production frontier nor regarding distributional assumptions on the noise and inefficiency component. However, one of the most common critique of the DEA approach is that does not consider measurement error and it is extremely sensitive to outliers (Aigner and Chu, 1968; Timmer, 1971; Koop, Osiewalski and Steel, 1999) which can cause a bias in the estimated production frontiers and efficiency measures. Moreover, the standard DEA efficiency measures are point estimates and, therefore, it is not possible to construct standard errors and confidence intervals. The parametric or econometric approach, on the other hand, imposes a specification on the production function which of course can be overly restrictive. The parametric approach, SFA, does, however, have the advantage of having a well-developed statistical theory which allows for statistical inference. Hence, using SFA we can test the specification as well as different hypotheses on the efficiency term and on all the other estimated parameters of the production frontier such as input elasticities, scale economies, efficiency, etc.

Simar and Wilson (1998, 2000) propose a general methodology for bootstrapping in frontier models to analyze the sensitivity of efficiency scores relative to the sampling variations of the estimated frontier (i.e., to estimate the bias and variance, and to construct confidence intervals). We check to see how robust our results are following their method which is based on statistically well-defined models and allows for consistent estimation of the production frontier, corresponding efficiency scores as well as standard errors and confidence intervals. We thus estimate the effects of possible explanatory variables on efficiency using the double-bootstrap procedure for a truncated regression model proposed by Simar and Wilson (2007) to improve the robustness of statistical inference in the second stage. Using this method we assume that the observation are independent and identically distributed ignoring the time dependence due to time dimension (however this assumption is justified by the short time pan in our dataset). Another important assumption we make in adopting the two stage approach proposed by Simar and Wilson (2007) is the separability condition of the efficiency factors and the production set: the covariates are assumed to affect the output only through the inefficiency (see p. 35 in Simar and Wilson, 2007). If this condition is not supported by the data, the authors suggest to apply the parametric one stage approach of Battese and Coelli (1998) - used in this paper -.

Table 5 presents our robustness checks when we use this methodology. The non-parametric estimations confirm our basic results which were obtained with parametric stochastic frontier estimation, i.e. that the positive effect of foreign participation on efficiency depends crucially on the type of ownership. Specifically, the ownership from Hong Kong, Macau, and Taiwan enhances efficiency more than other foreign participations (δ_4 is significant and with negative sign).

Table 5: Robustness Check for Empirical Methodology

Results of Truncated Regression Analysis

Parameter	Estimate
δ_0	2.0359*
δ_1	-0.0575
δ_2	0.1534
δ_3	0.0613*
δ_4	-0.0860*
δ_5	0.0099
δ_6	-0.1681*
δ_7	-0.3807*
δ_8	0.1579*
δ_9	0.0000
δ_{10}	0.0000
δ_{11}	0.0000
δ_{12}	2.0359

Notes: * implies significance at the 5 percent level. The estimation is done according to Algorithm 1 and 2 of Simar and Wilson (2007) with 1,000 bootstrap replications for bias correction and 2,000 for confidence intervals of the estimated regression coefficient. The regressor is the DEA estimate of the unobserved inefficiency score of the countries. Estimations are done in MatLab.

VI. Concluding Remarks

This paper investigates an issue that has not been discussed much in the literature, that is, whether inefficiency in China's industries depend on corporate governance and ownership. To address this, we rely on a unique database specifically constructed to reach a satisfactory representation of China's industries. This is a significant improvement compared with previous studies that rely on ad hoc surveys only. This database will allow us to look at efficiency differences among state-owned enterprises, private-own enterprises, and foreign joint venture companies across Chinese provinces. Furthermore, we use the stochastic frontier approach that allows more flexibility to identify the sources of inefficiency to conduct our analysis.

We find that, compared to private companies of similar quality, inefficiency is systematically larger at the state owned enterprises, whereas the inefficiency is significantly smaller for Chinese enterprises featuring some form of foreign ownership. Furthermore, we also detect that there are important differences among the types of foreign participation in Chinese industries. Specifically, we show that the ownership from Hong Kong, Macau, and Taiwan proves systematically to have lower inefficiency than that from other economies. This then raises important implications for Chinese authorities as to how to shape future policies in terms of privatisation of the SOEs and modality of encouraging foreign direct investment.

Appendix

Table 1A. Distribution by Sector and Presence of SOEs

By Sector	A PRIORI COMPOSITION OF THE TOTAL SAMPLE % Share	EX POST COMPOSITION OF THE TOTAL SAMPLE % Share	SOEs % Share
06-Coal mining and dressing	1.22	1.10	2.74
08-Ferrous metals mining and dressing	0.41	0.35	0.00
09-Nonferrous metals mining and dressing	0.17	0.08	0.00
07-Petroleum and natural gas extraction	0.00	0.00	0.00
10-Nonmetal minerals mining and dressing	0.39	0.45	0.00
11-Logging and transport of timber and bamboo	0.00	0.00	0.00
12-Fishing	---	0.00	0.02
13-Food processing	6.16	5.62	9.15
14-Food production	1.89	1.95	3.90
15-Beverage production	0.81	0.75	1.56
16-Tobacco processing	0.00	0.01	0.00
17-Textile industry	10.32	9.93	2.54
18-Garments and other fiber products	5.30	5.58	0.28
19-Leather, furs, down, and related products	2.64	2.67	0.12
20-Timber, bamboo, cane, palm fiber and straw	1.95	1.86	0.53
21-Furniture manufacturing	1.03	1.07	0.02
22-Papermaking and paper products	2.42	2.45	0.81
23-Printing and record medium reproduction	2.25	2.13	7.75
24-Cultural, educational, and sports goods	1.33	1.41	0.02
25-Petroleum processing and coking	0.39	0.41	0.00
26-Raw chemical materials and chemicals	6.52	6.34	5.23
27-Medical and pharmaceutical products	0.88	0.93	0.49
28-Chemical fiber	0.43	0.43	0.00
29-Rubber products	0.82	0.88	0.26
30-Plastic products	4.66	4.68	0.97
31-Nonmetal mineral products	7.19	6.97	7.16
32-Smelting and pressing of ferrous metals	2.15	2.02	0.26
33-Smelting and pressing of nonferrous metals	1.39	1.21	0.00

34-Metal products	5.37	5.45	1.93
35-Ordinary machinery manufacturing	7.98	7.55	7.02
36-Special purposes equipment manufacturing	4.06	3.89	4.97
37-Transport equipment manufacturing	4.44	4.35	8.18
39-Electronic equipment	5.88	3.62	1.36
40-Electric equipment and machinery	3.58	4.57	1.46
41-Electronic and telecom equipment	1.25	2.21	0.83
42-Instruments, cultural, and office machinery	1.95	1.76	0.85
43-Other manufacturing	0.06	0.87	0.32
44-Electric power, steam, and hot water	3.00	2.77	19.78
45-Gas production and supply	0.00	0.00	0.00
46-Tap water production and supply	1.93	1.68	12.23

Table 2A. Distribution by Province and Presence of SOEs

	A PRIORI COMPOSITION OF THE TOTAL SAMPLE	EX POST COMPOSITION OF THE TOTAL SAMPLE	SOEs
By Province	% Share	% Share	% Share
Zhejiang	16.40	16.58	2.52
Guangdong	15.10	16.47	7.09
Jiangsu	17.00	16.47	1.64
Shandong	8.60	8.81	3.98
Shanghai City	5.80	5.99	2.09
Fujian	4.50	4.75	1.95
Liaoning	4.80	4.33	12.24
Henan	3.60	3.44	5.42
Hebei	2.80	2.97	4.75
Tianjin	2.50	2.34	6.98
Hunan	2.40	2.31	4.67
Beijing City	2.40	2.20	7.25
Sichuan	2.00	1.86	1.85
Hubei	1.70	1.60	2.88

Jiangxi	1.50	1.23	3.78
Shanxi	1.10	1.22	4.99
Anhui	1.20	1.16	0.83
Guangxi	1.00	0.95	4.53
Jilin	1.10	0.95	3.90
Heilongjiang	0.90	0.83	4.02
Guizhou	0.80	0.78	3.31
Shaanxi	0.70	0.56	3.15
Chongqing	0.50	0.52	0.04
Nei Mongol	0.50	0.48	0.97
Gansu	0.50	0.43	2.11
Yunnan	0.40	0.43	1.36
Xinjiang	0.20	0.19	1.06
Xizang	0.10	0.07	0.49
Ningxia	0.10	0.07	0.00
Qinghai	0.00	0.03	0.16

Table 3A.

	A PRIORI COMPOSITION OF THE SAMPLE		EX POST COMPOSITION OF THE TOTAL SAMPLE				
	BASE CLOSED SAMPLE	TOTAL SAMPLE	2001	2002	2003	2004	2005
By Ownership Class	% Share	% Share	% Share	% Share	% Share	% Share	% Share
SOE (110+141+143+151)*	9.1	16.2	15.1	14.4	13.8	15.8	11.4
Private (from 159 to 190)*	64.2	59.0	54.8	56.0	57.6	59.8	62.2
Hong Kong, Macau, Taiwan (from 200 to 240)*	13.1	12.0	14.6	14.2	13.8	12.1	13.1
Foreign owned (300 or larger)*	13.1	12.0	13.0	13.1	13.0	12.3	13.1
Cooperatives (120+130+140+142+149)*	0.5	0.8	2.6	2.3	1.8	0.0	0.2
Total	100	100	100	100	100	100	100
Total number of enterprises	5,000	7,500	6,814	7,165	7,790	5,597	9,276

Notes: * numbers in bracket indicate the classification codes used by National Beureau of Statistics to classify enterprises by ownership.

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